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A Mathematical Morphological Deep Neural Network for the Classification of Periapical Radiographs in the Diagnosis and Treatment of Dental Diseases

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Certification

This is to certify that Grace Lawumi **Tam-Nurseman** with matriculation number LCU/PG/001249 carried out this research work titled "A Mathematical Morphological Deep Neural Network for the Classification of Periapical Radiographs in the Diagnosis and Treatment of Dental Diseases" in the Department of Computer Science, Faculty of Natural and Applied Sciences, Lead City University, Ibadan, Oyo State, Nigeria, for the award of Doctoral degree (PhD) Computer Science and that this work has not been previously submitted

Dr Wilson Sakpere Date

(Supervisor)

Dr Wilson Sakpere Date

(Head of Department)

Dedication

This research work is dedicated to my late mother and my late elder brothers Victor Okorotie and Alex Okorotie all of whom I lost during the course of this study.

Acknowledgement

My special thanks go to Lead City University for creating the enabling environment to carry out this research. The university library is not left out for the provision of needed materials.

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Though the above mentioned institutions and persons have assisted in the process of this research work, I alone stand responsible for the errors, if any, found in the work.

Abstract

One of the best ways to diagnose a disease in medical practice objectively is through medical imaging. The importance of medical imaging cannot be overemphasized. In dentistry, dentists often use radiographs, especially in finding hidden dental structure, bone loss, malignant or benign masses, and cavities that cannot be examined during a visual examination. The use of dental radiographs also helps dentists to detect hidden dental diseases early. This study is a continuation of previous work which bothered on the development of an expert system for the diagnosis and prognosis of 20 Common dental diseases using Bayesian network. The work was developed using several symptoms associated with dental disease for diagnosing dental diseases (D1- D20). The study was limited to symptomatic diagnosis which however has some obvious gaps such as the uncertainty in the reasoning associated with Bayes rule, the use of Pain as a parameter among others that were filled through the use of deep learning tools on dental periapical radiographs through an improved model. The improved model was developed integrating mathematical morphology (MM) operations (dilation, erosion, opening and closing) in the convolution layer of CNN, for data preprocessing and quality feature extraction. With its high sense of intelligence (artificial) obtained during training, the system receives dental images and analyses them automatically for various clinical findings with which 6 dental disease problems were solved. With an achieved accuracy of 99.78%, it can be established that this system can be used in dental clinics with high confidence giving very little or no-error-diagnosis. To make this system more scalable and robust, more dental diseases should nbe added through other MM based theory like lattice, topology and random functions other than set theory-based MM used in this study.

Keywords: Mathematical Morphology (MM), Dilation, Erosion, Opening, Closing, Convolutional Neural Network (CNN)

Word Count: 285

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List of Acronyms

Abbreviations	Meaning
AI	Artificial intelligence
ANN	Artificial neural network
CNN	Convolutional neural network
DL	Deep learning
HDD	Hard disk drive
HTML	Hyper text markup language
ML	Machine Learning
MM	Mathematical morphology
RAM	Random access memory
XAMPP	X(cross-platform) Apache MYSQL PHP,and Perl

List of Apendices

Chapter One

Introduction

1.1 Background to the Study

A deep mathematical morphological neural network for the classification of periapical radiographs in the diagnosis and treatment of dental diseases is a continuation of a previous work**.** The previous study background was on diagnosing and prognosing dental diseases using symptoms as parameters. The system was developed using Bayes rule as a mathematical model. It was an exploratory and experimental work that exploited the knowledge of dental experts to develop an expert system that could diagnose 20 common dental diseases given their various symptoms. The study design and development were on simple IF-THEN rules.

An expert system as in previous study is one of the sub units of Artificial Intelligence (AI) that is domain-specific. It is developed using the specialized knowledge of a human expert to solve problems. Human expert as used in this context refers to one who has a special skill acquired through a period of training formally or informally and such skill or knowledge is not commonly available to anybody. In today's technology, the output of any applied expert system technology is termed expert system. Expert system technology includes the use of special tools such as programming languages and special hardware designs[1]. One who develops an expert system limits his or her scope to just what is needed to solve a specific problem.

Artificial Neural Network (ANN) algorithms for medical diagnosis and treatment today is relying heavily on state-of-the-art technology such as deep learning to assist medical doctors confirm and reconfirm their subjective diagnosis, hence this study.

This study adopted the fundamental question concerning the difference between biological neural network and artificial neural network which seeks to know whether the strength of the electric potential of a signal traveling along an axon is the result of multiplicative process and the mechanism of the postsynaptic membrane of a neuron adds the various potentials of the electric impulses or an additive process and the mechanism of postsynaptic membranes only accept signals of certain maximum strength? The state-of-the-art technology Convolutional Neural Network (CNN), is a product of the answer to the first phase of the question where ANNs are developed from the multiplicative process and the addition of the various potentials of the electric impulses of the mechanism of the postsynaptic membrane of a neuron.

Three key objectives make up this study; Number one is to design and develop a mathematical morphological neural network. Number two is the use of dental periapical radiographs as basic dataset thereby developing a dental diagnostic model and number three is the treatment plan to be included to treat the diagnosed dental diseases.

This study in a bit to answering the adopted question framed its research question to seek a way to apply CNN differently yet get expected or better output. The study experimented on the additive process of an ANN and accepting the signals of certain maximum strength of the mechanism of the postsynaptic membranes thereby employing the services of the operations of mathematical morphology which are basically dilation and erosion. In other words, this experimental study shifted from the regular or conventional approach of CNN by replacing the convolution layer of CNN with Mathematical Morphology (MM) operations. With the outburst of CNN, ANN model developers and designers are so carried away especially in feature extraction such that little or no attention is given to ancient technologies like MM. The MM is more mentioned in literature for segmentation and filtering applications than feature extraction. The presence of CNN has drifted developers' minds away from realizing the powerful feature extraction ability in MM. Most literature articles on automated medical diagnosis are on the application of CNN.

Addressing the application of deep learning (DL) in disease diagnosis, Bakator and Radosav obtained more than 300 articles, among which 46 were presented in more details[2]. The findings showed that CNN was more widely represented. Mulrenan *et al* reviewed literature on the use of AI for covid-19 diagnosis on CT and chest X-ray with an electronic search of 312 studies among which some were removed on basis of duplicate and some others as irrelevant[3]. All of the reviewed articles were diagnostic performances of CNN and none included MM.

Kumar *et al* also reviewed various literatures on different disease diagnosis with various AI methods among which were Naïve Bayes, Generative Adversarial Networks (GAN), Convolutional neural networks (CNN), without a mention of MM[4].

In this study set theory based MM is used both for preprocessing and feature extraction. As a feature extractor, it replaced the conventional convolution layer of CNN. That is to say that the addition of the multiplicative process is replaced with additive process and taking maximum or minimum depending on a particular MM set theory operation applied. At this point, it is noteworthy to say that some studies in the past had done similar works in which addition of the multiplicative process was replaced with additive process and taking maximum or minimum. Most of these past studies employed lattice based operations as basic computational model.

Gerhard Ritter in an International Conference proceeding on Pattern Recognition in 1996 presented a paper on a general approach to morphological neural network[5]. This author also adopted the fundamental question of the difference between biological neural network and ANN but applied lattice based operations to the latter query as a basic computational model, which provided a strong biological basis for morphological neural networks.

Shen *et al* proposed a study on a morphological neural network to address the difficulty in determining suitable morphological operations and structuring elements when given an image[6].

Franchi *et al* proposed a study on morphological and convolutional neural network that is trained from scratch to replace the standard max pooling in CNNs with a learned morphological pooling[7].

The second objective upon which this system is developed is the dental disease diagnosis. People who suffer from one ailment or the other are best described as patients. Dental patients are people who suffered from dental disease(s). One best way to diagnose dental disease(s) is the use of medical radiological equipment such as X-rays, Magnetic Resonance Imaging (MRI), Computerized Tomography (CT) scan to mention but a few. The use of radiological equipment is advantageous to doctors as they help in the detection of diseases which are not symptomatic and beyond what the ordinary eye can see during physical examination. The radiological equipment such as X-rays help dentists to detect hidden dental diseases early. A disease when detected at the point when it is not symptomatic certainly gives good prognosis because the chances of altering its natural course with adequate interventions are very high which in turn halts the progression of the disease[8].

In defining this model, dental periapical radiograph is a key data for the research besides the primary parameters of MM and CNN, thereby resulting in a model that diagnoses dental disease. Automated disease diagnosis models abound but not much is done on dental diseases.

Mulrenan *et al* reviewed 23 articles on the application of AI for automated medical diagnosis. Eleven out of these reviewed papers were on chest X-ray for covid-19 diagnosis, 12 were on CT scan for same disease[9]. Rogers *et al* in decades past reviewed 58 articles bothering on different diseases among which non was dental disease[10]. Among the several articles on automated disease diagnosis reviewed by Kumar *et al*, is void of dental disease[11].

The third objective which is the inclusion of telemedicine is a gap in previous study filled in this study. This aspect of the study is necessary especially to this part of the world as there is serious brain drain of medical practitioners as reported by Ojoma Akor in an article published in DailyTrust[12]. The brain drain is as a result of among other reasons, lack of conducive work environment, delay in payment. This has caused developing nations like Nigeria fall short of the world health organisation (WHO) recommended doctor-to-population ratio of 1:600 to 1:4000-5000 as reported by same author in the same article.

1.2 Statement of the Problem

In recent years, computer applications have evolved to the extent that computer models today are made to learn and apply learned skills to reasoning and making predictions. CNN of course is the state-of-the-art computer algorithm. A lot of detection, prediction, pattern recognition, computer vision works etc. have been credited to the power behind CNN. The ANN model developers and designers are so carried away with CNN especially in feature extraction that little or no attention is given to ancient technologies like mathematical morphology (MM). Few literatures where MM is mentioned are applied as a tool for image segmentation and filtering. The outburst of CNN is a kind of blind folded developers such that the powerful ability in MM for feature extraction is not recognized or relegated to the background.

In this study, a set-based MM operations was integrated into the convolution layer of CNN. Convolution operation of multiplying node outputs with corresponding weights and taking summation of the weighted products are going to be replaced with morphological operations of adding nodes' output with corresponding weights and taking maximum or minimum values.

The key problems addressed in this study are the gaps of previous study[13]. The previous study bothers on the diagnosis of 20 dental diseases using Bayes' rule. The work was developed using several symptoms associated with dental disease for diagnosing dental diseases (D1- D20). The study was limited to symptomatic diagnosis which however has its shortcomings. For example, in dentistry, one of the key symptoms is pain. Pain as a parameter in medical science is highly subjective in the sense that individuals have different pain threshold[14]. What one individual may perceive as pain may just be mere discomfort for another as they have different maximum level of pain tolerance[15]. This problem of pain perception by different individuals results in a dental doctor's subjective diagnosis where a dental disease may be under or over diagnosed. The best bet to this problem is the use of a radiologic diagnostic tool as proposed in this study. The role of radiological diagnosis in every field of medicine and specifically dentistry cannot be over emphasized. It is a key path to objective diagnosis. Experts in the field use radiological results as evidence and confirmation to their subjective diagnosis. Early detection of hidden dental diseases is made possible with radiographs. And this helps curb the danger in progression of the disease. However, radiographs have their shortcomings. In some cases, especially in emergency situations, the images produced by the radiological machines may pose quality problems which could pose difficulty in analyzing, thereby causing misdiagnosis. Besides emergencies, images generally suffer from what is known as environmental noises, patients' special conditions in photography, lighting conditions, and technical constraints of imaging devices which could cause images to have low quality[16]. With the MM operations, dental periapical images are preprocessed and made to have a sharpened view. With these sharpened images, an intelligent model is trained to understand and recognize the dental image patterns which will help dental professionals and learners in;

i. Clearly showing the disparity between CNN and MM-NN

ii. Early detection of incipient dental diseases.

iii. Prompt intervention including early preventive and curative approaches

iv. Enabling statistical evaluation of the correlation between radiologic and clinical diagnosis

v. Eliminating the problem of dental doctors having difficulty in identifying key parts in a dental image.

vi. Eliminating time wasted in identifying areas of interest in a dental image.

Another shortcoming of previous work was the use of Bayes' rule. Bayes' rule is a way of using mathematics to determine the conditional probability of an event. This means using a mathematical formula to give the probability of an event given prior knowledge of another event. In the work, prior knowledge of an event which was the disease prevalence and symptom scores in the sample population determined the posterior (disease to be diagnosed) distribution. In non-mathematical terms, the Bayesian theorem in the work explained the probability of a claim (disease) given the currently available data (symptoms). Now the probability of both disease and symptom is represented as P(D) and P(S) respectively, and the likelihood function of the symptom given disease represented as P(S/D) was derived from subjective estimates. This constitutes a problem in disease diagnosis as there is so much uncertainty in the reasoning associated with Bayes rule. Bayes rule begins with a prior probability distribution P_D (as used in previous study) which is determined by an existing knowledge (prevalence of the disease in the sample population) at a given period of time say t_1. When a new piece of knowledge arrives at say time t_2, P_D, the prior knowledge changes to posterior probability distribution P(D/S). Disease prevalence (D) and disease symptom (S) are the determinants of P(D/S). In determining P(D/S) with a new knowledge best described as prevalence of disease in previous study, its inverse P(S/D), the likelihood function of the symptom S given disease D plays a key role, as shown in Equation 1.1.

$$P(D|S) = \frac{P(S|D) * P(D)}{P(S)} \qquad (1.1)$$

P(D/S) in the formula is the prediction which is highly conditional, therefore subjective. It therefore means that use of Bayes rule in diagnosis is from the description of an event rather than from some form of physical and radiological examination.

This study in overcoming the shortcoming of Bayes rule, introduces MM neural network to learn the content of a dental periapical radiographs to diagnose dental diseases in order to arrive at an objective diagnosis.

Furthermore, previous work is desktop-based and it can only run locally on a computer device.

To make this system accessible irrespective of location and time, the proposed system is web based

Lastly, existing work did not include a treatment plan for diagnosed dental diseases. Treatment according to Collins's dictionary is medical attention given to a sick or injured person or animal. The consequences of lack of treatment are that one could face far more serious than it was diagnosed. For example, untreated periodontitis could result in cardiovascular disease, tooth mobility, decrease in masticatory function, and eventual tooth loss[17,18]. Other diseases such as respiratory infections and diabetic complications could result from the lack of treatment for dental diseases. This study included a treatment plan whereby, users could have live interactive section with a dental professional through online chat, telephone call, or text messages.

1.3 Aim and Objectives of the Study

This study aims to close the gaps of previous work as stated in the statement problem; design and implement a web-based mathematical morphological neural network model that can diagnose common dental diseases through Periapical radiographs alongside carrying out a treatment planning. The above aim was accomplished through the objectives listed below.

1. Design a web-based MM neural network architecture that can provide a radiologic diagnosis of dental disease through periapical radiographs alongside providing a platform for treatment planning

2. Implement objective 1 (the designed system) through the replacement of the convolution operations with mathematical morphological operations.
3. Evaluate the implemented system.

1.4 Research Question

The ability to correctly identify images at the early age of computer vision was quite turbulent. But with time, as researchers crave the need for improvement, they achieved positive results either by way of adding to mathematical functions or by filter increment or arrangement of an existing model. Durand D'souza in his study said 1 in every *4* images was incorrectly identified. The desire to reduce the error kept burning and during AlexNet work, it was reduced down to 1 in every 7. With further improvement, for example, in Google's Inception network, only 1 in every 25 images is incorrectly or wrongly identified[19]. With the same desire to do something new, the research question:

1. In what way can CNN be applied differently yet achieve great accuracy?
2. How would the answer to qustion1 be beneficial to upcoming researchers in the face of limited dataset?
3. In what way(s) would answer to question1 be beneficial to automate medical diagnosing through radiographs.

1.5 Significance of the Study

The role played by radiological diagnosis in every field of medicine and specifically dentistry cannot be over emphasized. It is a key path to objective diagnosis. Experts in the field use radiological results as evidence and confirmation to their subjective diagnosis. Early detection of hidden dental diseases is made possible with radiographs. And this helps curb the danger in progression of the disease. However, radiographs have their shortcomings. In some cases, especially in emergency situations, the images produced by the radiological machines may pose quality problems which could pose difficulty in analyzing, thereby causing misdiagnosis.

Besides emergencies, images generally suffer from what is known as environmental noises, patients' special conditions in photography, lighting conditions, and technical constraints of imaging devices which could cause images to have low quality[20].

This research work would help in;

1. Clearly showing the disparity between CNN and MM-NN
2. Bringing back MM into the picture of modern research in deep learning
3. Seeing to the problem of uneven distribution and shortage of dental doctors in Nigerian hospitals through the provision of a treatment planning platform
4. Encouraging future researcher to experiment on other ways to develop intelligent deep ML algorithms.
5. Medically, it will help in;
   i. Early detection of incipient caries.
   ii. Prompt intervention including early preventive and curative approaches
   iii. Enabling statistical evaluation of the correlation between radiologic and clinical diagnosis
   iv. Eliminating the problem of dental doctors having difficulty in identifying key parts in a dental image.
   v. Eliminating time wasted in identifying areas of interest in a dental image.
   vi. Sharpening dental images for a better and easy diagnosis.

1.6 Scope

The study is focused on the design, and implementation of a web-based mathematical morphological neural network algorithm to classify dental periapical radiographs.

1.7 Limitations of the Study

The study is limited to experimenting on integrating set theory based mathematical morphology operation into a convolutional neural network algorithm to carry out radiologic diagnosis. A definitive clinical diagnosis is impossible in some cases.

The system cannot elucidate soft tissue affectation from dental disease. In other words, the study is limited to the diagnosing of common dental diseases through periapical radiographs only. Therefore, no form of physical examination on patients or other forms of diagnosis expected as part of this study.

1.8 Operational Definition of Terms

The following terms, according to how they are used in this study, are operationally defined thus:

Activation Function

An activation function is a mathematical function in an artificial neural network that determines which node is activated or fired after receiving a weighted sum of input from a linear transformation.

Algorithm.

A sequence of defined steps taken to solve a problem.

Artificial

Things made through human skills, opposed to natural

Convolution

Convolution is a mathematical operation that permits the combination of two sets of information In simple terms, it is the combination of two functions, say f(t) and g(t) to give a third function.

Dilation

Just like the literal meaning of the process of being made wider or larger, dilation as used in this study is one of the operations of Morphology that adds pixels to the boundaries of an image, thereby increasing the size of the image.

Erosion

The dictionary definition of erosion is the process by which the surface of the Earth gets worn down by means of natural elements such as wind, water, etc. It has to do with removal though as used in this study but it is that of pixels from image boundaries.

Gradient Descent

Gradient Descent is an algorithm that is used to locate the least possible error (loss function) value in a machine learning algorithm.

Intelligence

The ability to learn and apply learned skill to solve a problem.

Loss Function

Loss function is a measure of how confused a model is in predicting. It is the difference between the predicted value and the actual value.

Machine Learning

Data-based algorithms used in training a computer system to enable them learn patterns, make accurate prediction without being precisely programmed.

The science of getting computers to learn and improve their learning over time in an accurate and automatic manner, by giving them data and information

Morphology

In this study, the term morphology was used to refer to the shape, (form appearance of the images) and structure (size)of an image.

Periapical

Periapical as used in this study refers to an intraoral dental X-ray type, therefore, periapical radiograph implies static images generated from the use of a periapical dental x-ray machine.

Pooling

Pooling is a term used when the feature map passed from the convolution layer of a CNN is spatially reduced.

Radiographs

Radiographs are static images generated following the passage of x-rays through a patient. It is what the layman and non-imaging clinicians refer to as an x-ray. All images used in this study are static and not dynamic or fluoroscopic.

ReLU

ReLU stands for Rectified Linear Unit. It is a non-linear activation function that is piecewise in nature. ReLU outputs an input directly if it is positive, else it will output zero.

Softmax

Softmax is an activation function used at the output layer of a neural network that takes a vector and creates a probability distribution.

Telemedicine

It is the provision of healthcare services by medical practitioners and healthcare givers via telecommunication tools

1.9 Outline of The Thesis

Design and Implementation of a Web-Based Mathematical Morphological Neural Network for Dental Disease Diagnosis and Treatment using Periapical Radiographs is a study that experimented on the additive process of a deep ANN and accepting the signals of certain maximum strength of the mechanism of the postsynaptic membranes thereby employing the services of the operations of mathematical morphology which are basically dilation and erosion.

It seeks a way to apply CNN differently yet get expected or better output. The outcome of this experimental work resulted in the diagnosis of dental disease which entails a treatment plan to close gaps of previous study upon which the entire study is built on.

The rest of the study is organized as follows; chapter two identified the key concepts of the study and explained some relevant theories as well as related literatures. The study approach, design, data type and data collection method, algorithm, and experimental setup comprise the subjects of chapter three. Chapter four highlights the study findings and results while chapter five on summary and conclusions highlights what has been achieved in this study, problems encountered and their solutions as well as suggestions for further improvement.

Chapter Two
Literature Review

This chapter reviews some theoretical frameworks that are related to this study. Before the review, an overview of the basic concepts which are fundamental to this research, beginning from Machine learning (ML), mathematical morphology (MM), through convolutional neural network (CNN) to dentistry and diseases that are related to dentistry alongside treatment planning is systematically outlined.

2.1 Conceptual Framework

The study is on the general knowledge of artificial intelligence under which Deep Learning (DL) is housed. MM is one of the key focus in this study as its importance as well as capability in pattern recognition and feature extraction is part of the aim of the study. The dataset with which the study achieves its objectives and some other concepts that filled gaps of previous study are discussed as framework of this study

2.1.1 Artificial Intelligence Overview

There are different definitions of AI. All of the several definitions boil down to a computer having the intelligence of human and making decisions on its own without a human intervention. John McCarthy referred to as the father of Artificial Intelligence defines artificial intelligence as "the science and engineering of making intelligent machines especially intelligent computer programs[21]. The beginning of AI was when a scientist Alan Turing posed a replaceable question: Are there digital computers which can do well in the imitation game? With "Can machines think?" The imitation game is a game to test if a machine can successfully take the place of a human which today is known as the Turing test. The game was a game played by two humans and a machine. John McCarthy argued that if the machine could successfully pretend to be human to a knowledgeable observer then you certainly should consider it intelligent. This test would satisfy most people but not all philosophers. The observer could interact with the machine and a human by teletype (to avoid requiring that the machine imitate the appearance or voice of the person), and the human would try to persuade the observer that it was human and the machine would try to fool the observer[22]. In 1956, John Mccarthy, an American mathematician who at Dartmouth proposed a research conference tagged "The Dartmouth Summer Research Project on Artificial Intelligence" and that was the first time the phrase "artificial intelligence" was heard. John Mccarthy was also the inventor of LISP programming language in a space of two years after the Dartmouth conference[23].
After the Dartmouth conference, between 1956 and 1975, the concept of AI was well received by people and organizations as there was a lot of investment on AI. Within these years, specifically 1959, Massachusetts Institute of Technology (MIT) set up the first AI laboratory that was founded on the principle that vision, robotics, and language are the keys to understanding

intelligence, and ultimately how the human mind works[24]. During this period, "MYCIN", a rule based expert system that can use artificial intelligence to identify bacteria causing severe infections, such as bacteria and meningitis, and to recommend antibiotics with the dosage adjusted for patient's body weight was developed by Edward H. Shortliffe. MYCIN system was also used for the diagnosis of blood clotting diseases. It was the first artificial intelligence diagnosis system[25] Arguably, expert systems were introduced formally in the 1960s and exp… tween … sys… e co… After the g… of interest i… blue, a…

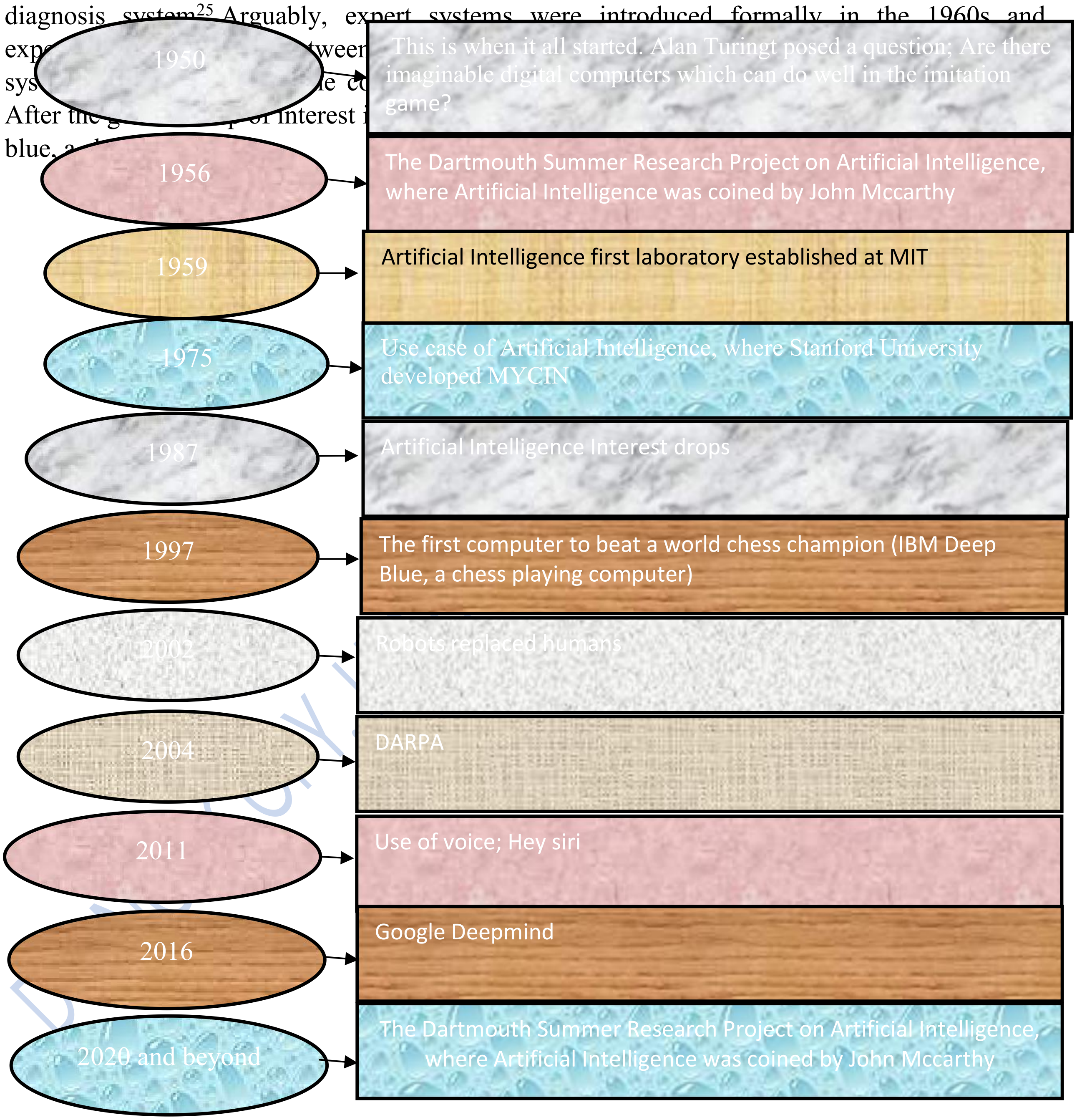

Figure 2.1 Artificial Intelligence history and evolution. Image by author

which beat the world chess champion was created in 1997. In 2002, robots replaced humans in so many sphere of life, and 2004 through to 2016, DARPA came up, and the first use of voice was recorded as well as Google Deepmind. Figure 2.1 depicts how AI evolved gradually to what we have today as state-of-the-art technology in Computer science/Engineering.

AI over the years evolved through advance research in Machine Learning (ML), ANN, DL to CNN as depicted in Figure 2.2

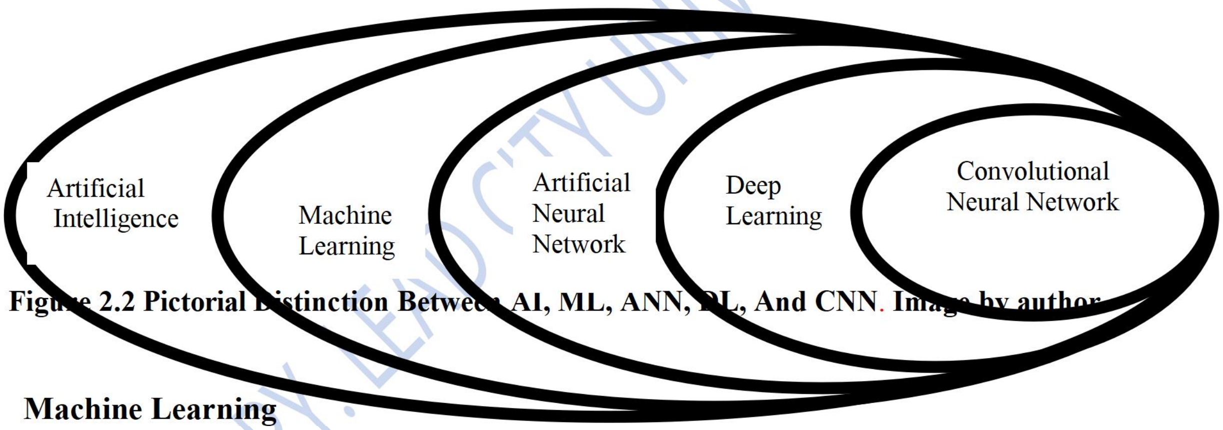

Figure 2.2 Pictorial Distinction Between AI, ML, ANN, DL, And CNN. Image by author

2.1.2 Machine Learning

Machine learning as depicted in Figure 2.2 is a subset of AI concerned with the question of how to construct computer programs that automatically improve with experience[26]. It is a dominant problem-solving techniques in many areas of research Kristian Kersting clearly made a remark on the difference between ML and AI thus; if you can write a very clever program that has, say, human-like behavior, it can be AI. But unless it automatically learns from data, it is not ML[27]. That was a logical interpretation of ML. For an AI program to be termed ML, there must be learning and availability of data. Therefore, the concept of ML is established on the idea that a computer system can be trained either from interacting with the environment, past experience, or from data. Today's ML evolved from developing computer models from predefined equations supplied with data to setting up parameters about the data and making the computer learn through some form of supervision. Making a machine, a non-living thing to learn sounds funny. The question here is, according to Alan Turing, "can machines learn?" And how does a machine learn? Is machine learning similar to human learning? To answer all of these questions, we have to understand what learning is.

Dale H. Schunk in a book titled "Learning Theories; An Educational Perspective" defined learning as an enduring behavioural change, or the ability to behave in a given fashion, which results from practice or other forms of experience[28]. An in-depth analysis of the definition of learning three criteria was identified by the author. Number one the author saw that learning involves a change in behavior or in the capacity for behavior. What this means is that learning is visible when people begin doing something different from usual. And the result of learning is observed in the outcomes of the learner.

The number two criterion according to the author is that learning endures over time for learning to take place, time must be involved though not forever and not for too short a time like a few seconds. The third is that learning occurs through constant practice and observation of others.

Mimicking human ability in learning is major areas of research in which models are developed to learn and behave as humans in areas like speech and pattern recognition. Research in computer science/engineering is ongoing to bridge the gap between machines and humans in learning and prediction making. In other words, machines should be able to see and perceive things the exact way as humans and apply this gained knowledge to carry out a needed task as/and even better than humans in terms of speed and accuracy.

2.1.2.1 Brief History of Machine Learning

The technology of AI is being embedded in almost everything one can think about. Measuring up with consumers' expectations by organizations means relying heavily on present-day AI technology and the algorithms associated with it to make things easier[29]. Such technology as machine learning algorithms that enables computers to communicate together and with humans, drive cars autonomously, detect fraud, give assistance in directions and traffic, tracks search history, recommend ads based on search history, etc.

Machine learning history started back in the 1940s. The level it has reached today is a result of the combination and contribution of individual inventions in the form of frameworks and algorithms at different times. In 1943, a neurophysiologist and mathematician wrote a paper captioned A Logical Calculus of Ideas Immanent in Nervous Activity. In this paper, the first mathematical model of a neural network was proposed and it triggered many theoretical investigations up to the present day about neural networks[30]. The theory was illustrated by modeling a neural network with electrical circuits. In a space of 7 years Alan Turing in 1950 posed a question, "Can machines think?", in a paper called Computing Machinery and Intelligence while at the University of Manchester. This question made men of creative minds never stopped thinking about how to make a machine reason and behave like a human. The idea behind this question posed by Alan Turing is without any human intervention a machine should be able to take its own decision and this is about behind AI[31]. Turing didn't stop at posing a question, he invented the "Turing Test" to test whether or not a computer has intelligence; that is, if a computer is capable of thinking like a human being.

The idea of computer's ability to learn did not die in Turing as other researchers like Arthur Samuel put the idea into practice by writing the first computer learning program in 1952. The program was a game of checkers that helped improved an IBM computer better at playing it. The term Machine Learning was also coined by Arthur Samuel in later years precisely 1959[32]. As research work on computer intelligence continued, the first artificial neural network aimed at pattern and shape recognition, called Perceptron was designed by Frank Rosenblatt in 1958[33]. Perceptron was developed using McCulloch and Pitts model and it could classify data into two classes of 1 and 0 with adjustable weights and a bias of 1 with the aid of supervised learning rule. John Mccarthy American mathematician in 1956 proposed at Dartmouth a research conference. The conference was tagged The Dartmouth Summer Research Project on Artificial Intelligence and that was the first time the phrase artificial intelligence was heard. John Mccarthy was also the inventor of LISP programming language in a space of two years after the Dartmouth conference[34]. Going advance in the quest for making computers reason and make decision without the intervention of human, simple cells and complex cells in the human visual cortex were described by Hubel and Wiesel in 1959[35]. The authors researched into how pattern recognition process is achieved in steps by the combined efforts of both simple and complex cells. It was these two authors who in their paper described in details how that in recognizing a pattern, cells at their different levels carry out specific task in learning and identifying patterns How that edges and bars of particular shape or orientations are responded to by simple cells, while complex cells besides responding to edges, they are spatially invariant. That the spatial invariance is achieved by "summing" the results of several simple cells that all prefer the same orientation (e.g. horizontal bars) but different receptive fields (e.g. bottom, middle, or top of an image). It was from the work of these authors that CNN models derived their basis.

ADALINE and MADALINE, two instances of neural network model by Widrow and Hoff in 1959 were developed at Stanford University[36]. ADALINE, could detect binary patterns and does prediction of what the next could be in a stream of bits while MADELINE, could eliminate echo on phone lines.

"Gradient Theory of Optimal Flight Paths" is a paper by Henry J. Kelley, a professor of aerospace and ocean engineering at the Virginia Polytechnic Institute published in 1960. It was a work on control theory that was used to develop the basics of a continuous back propagation model used in training neural networks. This control theory concept brought about the modification of input during feedback and over the years, the author's concept is widely recognized and applied to AI models.

Alexey Ivakhnenko considered as the father of deep learning who was a Mathematician was the researcher whose research work is recorded for creating the first working deep learning networks in 1965. The author developed a family of inductive algorithms for computer-based mathematical modeling of multi-parametric datasets that features fully automatic structural and parametric optimization of models which was applied to neural networks. Alexey Ivakhnenko learning algorithm for his deep learning model used deep feed forward multilayer perceptrons using statistical methods at each layer to find the best features and forward them through the system. The author in 1971 developed an 8-layer deep network from the group method of data handling he developed some years back which demonstrated a successful learning process in a computer identification system called Alpha[37].

Hubel and Wiesel's work so inspired other researchers like Dr. Kunihiko Fukushima who in a study proposed a self-organizing neural network model for a mechanism of pattern recognition that was spatially invariant in the 1980s. Dr. Kunihiko Fukushim's model can recognize stimulus patterns based on the geometrical similarity (Gestalt) of their shapes without affected by their positions.

Yann Le Cun, a postdoctoral computer science researcher and his team in the 1990s built on the work done by Kunihiko Fukushima. Le Cun *et al* developed a CNN which could recognize handwritten digits. He called it LeNet (after LeCun), first modern application of CNN.The authors in their paper, "Gradient-Based Learning Applied to Document Recognition", trained a convolutional neural network with the MNIST (Modified National Institute of Standards and Technology) dataset of handwritten digits[38]. He applied back-propagation to train Fukushima's artificial neural network, the method has a 1% error rate and about 9% reject rate on zip code digits.

After LeNet by Yann LeCun in the 1990s and 2012, not much was done because CNN models needed a large amount of data and computing resources to train. This brought about a major drawback for CNN at that period. But shortly after in 2012, a paper by Krizhevsky *et al* titled ImageNet classification with deep convolutional neural networks revisited deep learning[39]. In this work, a large, deep convolutional neural network was trained to classify 1.2 million high-resolution images into different classes. The neural network was made up of 60 million parameters and 650,000 neurons, consisted of five convolution layers, some of which were followed by max-pooling layers, and three fully-connected layers with a final 1000-way softmax. The work entered into a variant of the model in the ILSVRC-2012 (ImageNet Large Scale Visual Recognition Challenge) competition and achieved a winning top-5 test error rate of 15.3%, compared to 26.2% achieved by the second-best entry. One of the sources of great achievement in this work was the availability of large sets of data, namely the ImageNet dataset with millions of labeled pictures, and vast computing resources such as the use of GPUs, ReLU activation function, regularization technique called dropout and data augmentation. The success of this work brought about a revolution in computer vision. A lot of fantastic and challenging works have been developed thereafter.

2.1.3 Artificial Neural Network

ANN is a Machine Learning model that is inspired by the human brain. It is a collection of nodes interconnected such that each node carries out a simple computation. The nodes are arranged in layers hierarchically, starting with the input layer where the system communicates with its environment, followed by hidden layer(s) for information processing and lastly the output layer where processed information is passed or communicated to its environment. The layers in ANN each contains one or neurons where computation takes place. Data from the input layer passes through all the layers wherein each node classifies the characteristics and information of the previous layer before passing the results on to other nodes in subsequent layers[40]. Unlike machine learning that makes “decisions according to what it has learned from the data, ANN arranges algorithms in a fashion that it can make accurate decisions by itself The computational capability of an ANN is determined by the number of the hidden layers it contains.

2.1.3.1 Artificial Neural Network Topologies

ANN are of two topologies: Feed forward and Feedback.

I. Feed forward: Feed forward NN as shown in Figure 2.3 is the simplest type of ANN with input layer, hidden layer(s) and output layer[41]. In a feed forward network, an image pixel intensity values are fed into the input layer as input values. These input values move only in one direction from the input nodes through the nodes in the hidden layer to the output layer. Within the nodes in the hidden layer, some mathematical operations are applied to the numerical values that arrive there. The results of the mathematical operations on the numerical values are sent to the neurons at the output layer where output is generated. Feedforward ANNs have fixed inputs and outputs and does not have loops.[42] They are used mostly in pattern generation, pattern recognition and classification.

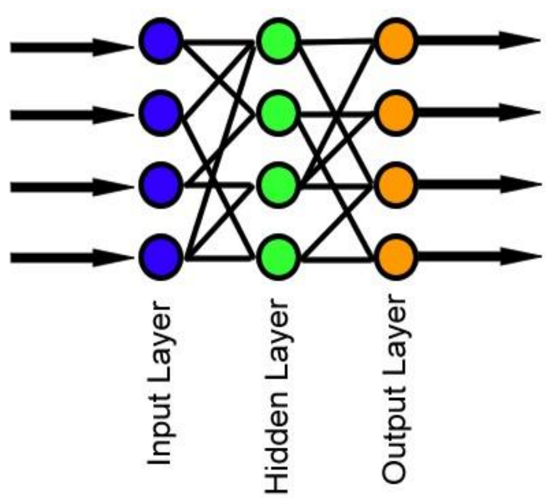

Figure 2.3 simple Feedforward ANN[43]

II. Feedback topology: The feedback topology as shown in Figure 2.4 is a NN that has feed-back paths. Signals in this type of network system travel in both directions using loops unlike the feed forward network that is one directional without a loop. Feedback NN experience changes in its parameters until it gets to equilibrium and as a result of these changes the network becomes a non-linear dynamic system. Each feed forward output that is undesirable is accompanied with some adjustment of weights and this continues until a desirable output is generated or achieved. Feed forward architectures are mostly used in content addressable memories[44].

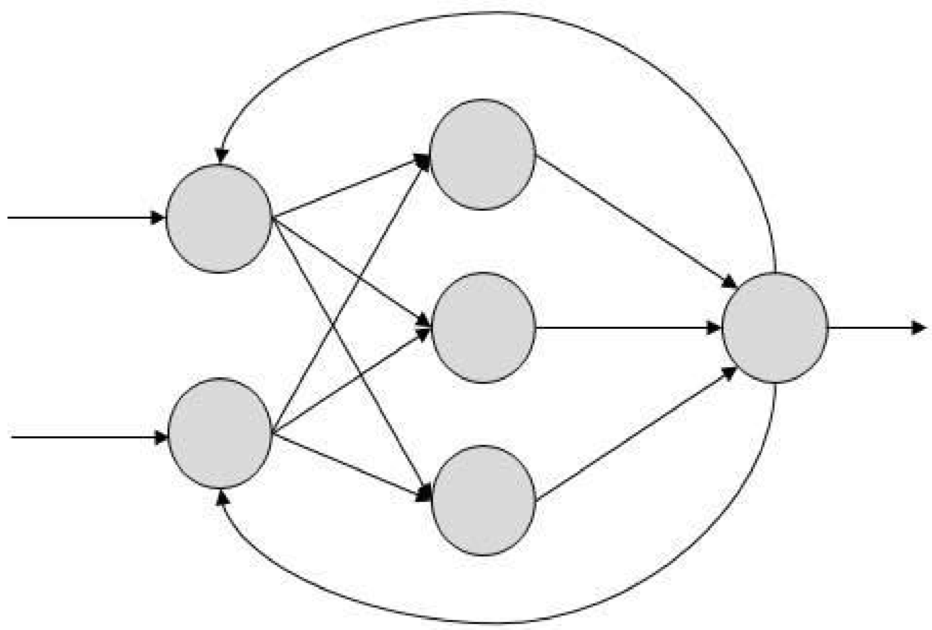

Figure 2.4 Feedback Neural Network

Source:https://www.tutorialspoint.com/artificial_intelligence/artificial_intelligence_neural_networks.htm

2.1.4 Deep Learning

Deep Learning (DL) neural networks are neural networks under the big umbrella of ML that are structured after the functioning of human brain neurons. It is a term used for "stacked neural networks. DL is a form of ANN with 3 layers and above. It is significantly known for its layer depth.

Each layer of nodes in deep-learning networks trains on a distinct set of features based on the previous layer's output. More complex the features of an object are recognised at deeper layers of a DL because there is a recombination and aggregating activity from previous layers as shown in Figure 2.5.

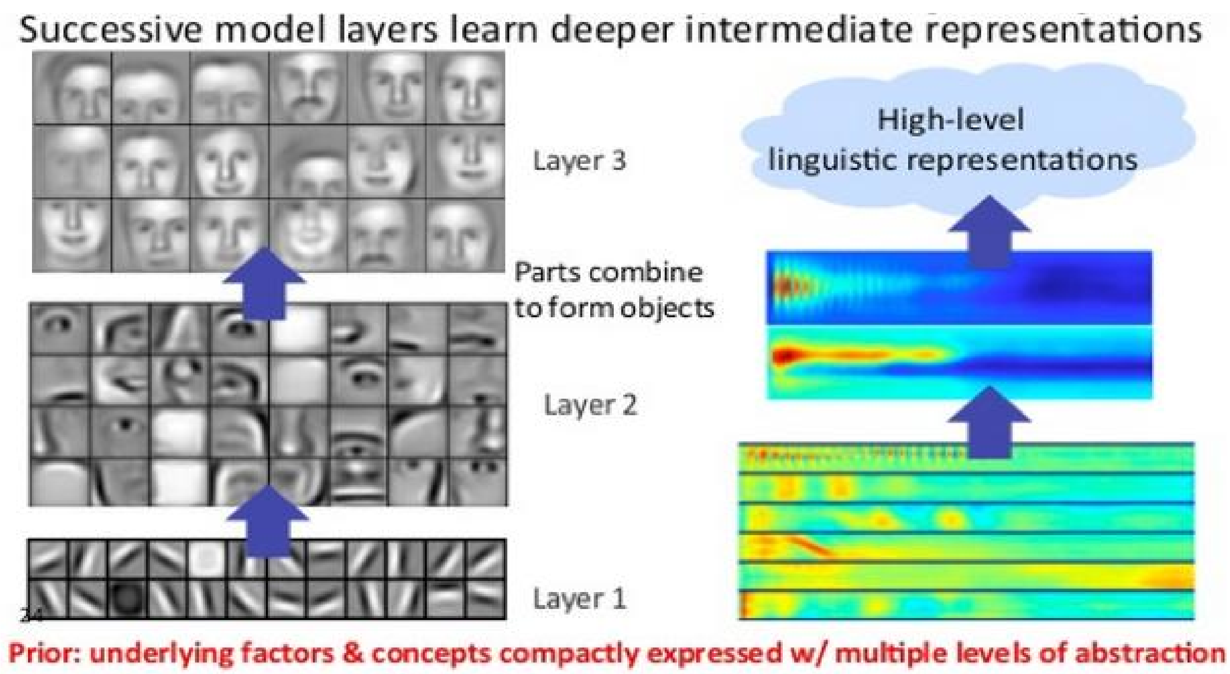

Figure 2.5 Ascending order of deep learning image feature extraction

Source: http://wiki.pathmind.com/neural-network

2.1.5 **Convolutional Neural Network (CNN)**

CNN also known as ConvNet is a special class of deep (multiple layers) neural network employed in the analysis and processing of images. Multiple layers is one key factor that differentiates CNN from other types of neural network. The innovation of DL has gained so much recognition because of its learning ability through the handling of large amount of data in the last few decades. Monumental growth in Artificial Intelligence brought about machine closer to human in terms of learning and reasoning. The development of artificial neurons after the neurons of a human brain bridged the gap between human and machine capabilities yearned for by earlier researchers in the 1950s.[45] Further bridging of the gap between human and machine by enthusiastic researchers went deeper to make machine not only reason but see as human, a field known as machine Vision.

The peculiarity of CNN as a deep learning algorithm is the employment of convolution as a layer. Convolution is a mathematical function that expresses how the shape of a function is modified" by another thereby producing a third function which is the modified function[46].

Convolution in the context of neural networks is a linear operation that involves the multiplication of a set of weights with the input", much like a traditional neural network. As a deep learning algorithm, CNN assigns importance (learnable weights and biases) to various aspects/objects of input images differentiating one input image from the other. The architecture of CNN is fashioned after the "connectivity pattern of human brain neurons and its organization of the Visual Cortex[47].

Some key and striking improvement of CNN over ANN is the reduction of parameters of ANN in CNN. And for this reason, solving complex tasks which was not very possible with ANN became easier as developers could develop larger models[48].

Again, CNN is spatially invariant. What this means; judging from David Hubel and Torsten Wiesel's work in 1959 from which CNN was inspired, how that edges and bars of particular shape or orientations could be recognized by simple cells while complex cells recognise what the simple cell recognises even though they are of different orientation or particular shape or of both particular orientations and when these edges and bars are shifted around the scene. Hubel and Wiesel's study exposes the behavior of complex and simple cells, how that complex cells no matter the orientation or position of a shape is able to recognize it and that it is not so with simple cells as they can only recognize shapes of particular orientation[49]. CNN has so many important features such as image feature learning and feature extraction. Feature extraction ability of CNN progresses as input propagates toward the deeper layers. Edges and simple features are detected at the first initial layers while complex features at the deeper layers[50].

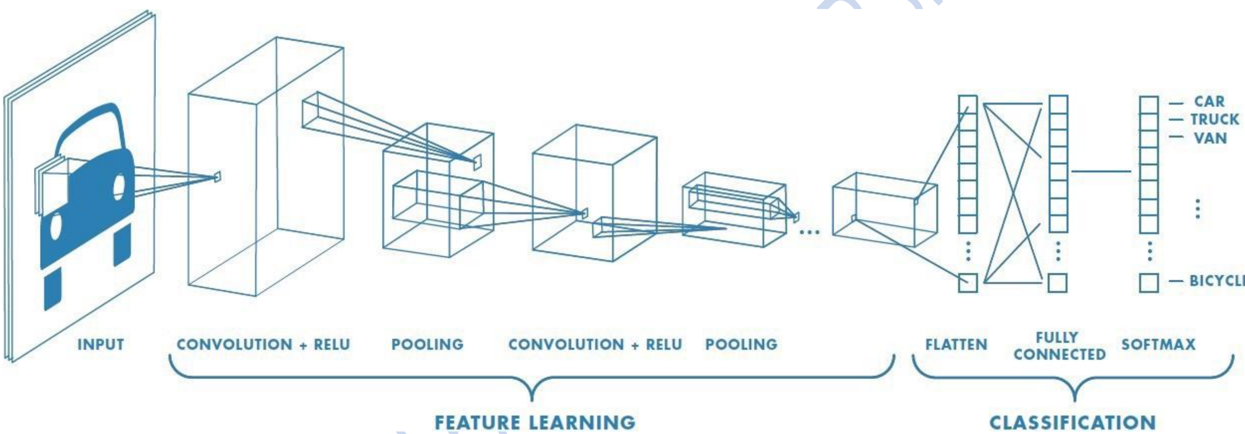

Figure 2.6 CNN Diagram

Source; (slide 12 introduction to convolutional neural networks (Stanford University, 2018))

2.1.5.1 Convolutional Neural Network Features and their Operations

CNN is composed mainly of four layers. Convolution layer, activation layer, pooling layer, and fully connected layer"

I. **Convolution Layer**: Convolution layer is Central and peculiar with CNN. It is the most involved layer in CNN. It is the presence of convolution layer which is a key layer that the name Convolutional neural network came to be. The "convolution" layer can be seen as the bran of

CNN as processing of input data takes place in this layer *"Convolution"* in the context of a CNN is a special operation performed in the convolution layer.

A convolution is a linear operation that involves the multiplication of a set of weights with the input, much like a traditional neural network. A convolution operation is the simple application of a filter to an input that results in activation. The filter slides over the image and looks for patterns. Where that part of the image matches the filter's pattern, the filter returns a large positive value, and when there is no match, the filter returns zero or a smaller value. Convolution put in a simpler language is a "function that focuses on an image in parts, processes each part, and provides the output. Mathematically put, convolution is a mathematical operation that takes an image represented as a matrix of pixel values and a filter or kernel as inputs and carries out a dot multiplication on them to give an output depicted in Figure 2.7. The size of the filter is much smaller than the size of the image which helps us to process small parts of the image. Note that the size of the filter is the same as the size of the part of the image which needs to be focused on.

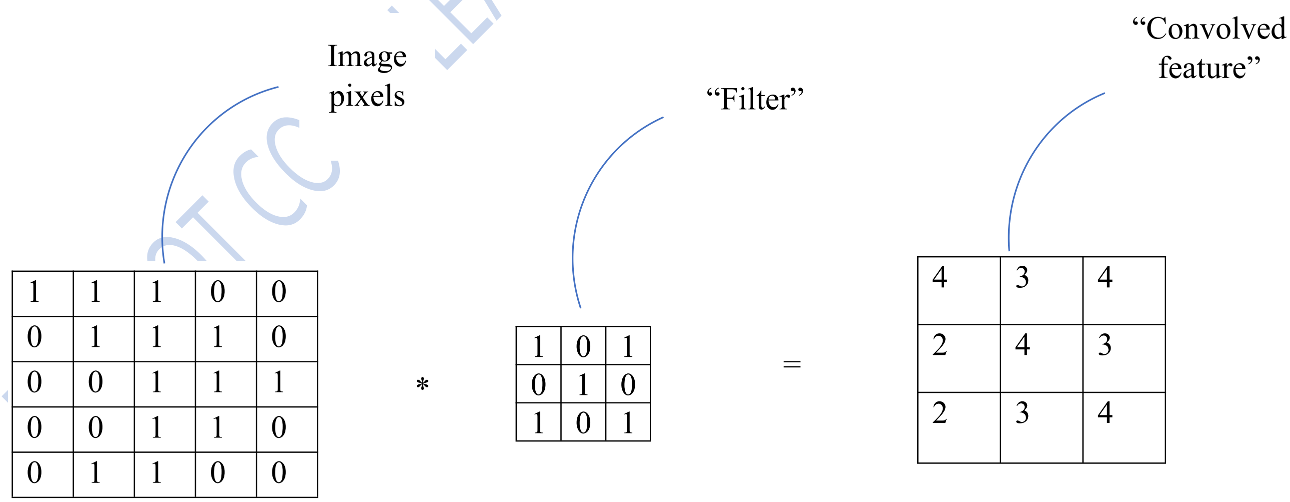

Figure 2.7 Image-filter convolution

Filters are usually square and are commonly 3x3, 5x5, or 7x7 matrix in size. The kernel or filter moves over the image. As it moves over the image, it checks for patterns in that section of the image by way of learning different portions of the image. The major reason for sliding the filter over the input image is to identify some key features in the image and map it onto an output. There are some key steps taken in the process of feature extraction; the first step is to multiply the filter size values of the image by the filter values. That is, each element in the filter is multiplied by an element in the corresponding location in the image. Then all the results are summed up, which gives one output value, that is, a scalar value. The sliding of the filter is repeated over the image until the filter slides over every pixel value of the input image. The filter moving over the image is done systematically, a process called stride. Strides could be a step, or two or three etc.

The convolution process of CNN is demonstrated with an image matrix of 5 by 5 and a filter of 3 by 3 with a stride of 1 in below 9 steps

Step 1

1	**1**	**1**	0	0
0	**1**	**1**	1	0
0	**0**	**1**	1	1
0	0	1	1	0
0	1	1	0	0

*

1	**0**	**1**
0	**1**	**0**
1	**0**	**1**

=

4		

$(1 * 1) + (1 * 0) + (1 * 1) + (0 * 0) + (1 * 1) + (1 * 0) + (0 * 1) + (0 * 0) + (1 * 1) = 4$

Step 2

1	**1**	**1**	**0**	0
0	**1**	**1**	**1**	0
0	**0**	**1**	**1**	1
0	0	1	1	0
0	1	1	0	0

*

1	**0**	**1**
0	**1**	**0**
1	**0**	**1**

=

4	**3**	

(1 * 1) + (1 * 0) + (0 * 1) + (1 * 0) + (1 * 1) + (1 * 0) + (0 * 1) + (1 * 0) + (1 * 1) = 3

Step 3

1	1	**1**	**0**	**0**
0	1	**1**	**1**	**0**
0	0	**1**	**1**	**1**
0	0	1	1	0
0	1	1	0	0

*

1	**0**	**1**
0	**1**	**0**
1	**0**	**1**

=

4	**3**	**4**

(1 * 1) + (0 * 0) + (0 * 1) + (1 * 0) + (1 * 1) + (0 * 0) + (1 * 1) + (1 * 0) + (1 * 1) = **4**

Step 4

1	1	1	0	0
0	**1**	**1**	1	0
0	**0**	**1**	1	1
0	**0**	**1**	1	0
0	1	1	0	0

*

1	**0**	**1**
0	**1**	**0**
1	**0**	**1**

=

4	**3**	**4**
2		

(0 * 1) + (1 * 0) + (1 * 1) + (0 * 0) + (0 * 1) + (1 * 0) + (0 * 1) + (0 * 0) + (1 * 1) = **2**

Step 5

1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

*

1	0	1
0	1	0
1	0	1

=

4	3	4
2	4	

(1 * 1) + (1 * 0) + (1 * 1) + (0 * 0) + (1 * 1) + (1 * 0) + (0 * 1) + (1 * 0) + (1 * 1) = 4

Step 6

1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

*

1	0	1
0	1	0
1	0	1

=

4	3	4
2	4	3

(1 * 1) + (1 * 0) + (0 * 1) + (1 * 0) + (1 * 1) + (1 * 0) + (1 * 1) + (1 * 0) + (0 * 1) = 3

Step 7

1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

*

1	0	1
0	1	0
1	0	1

=

4	3	4
2	4	3
2		

(0 * 1) + (0 * 0) + (1 * 1) + (0 * 0) + (0 * 1) + (1 * 0) + (0 * 1) + (1 * 0) + (1 * 1) = 2

Step 8

1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

*

1	0	1
0	1	0
1	0	1

=

4	3	4
2	4	3
2	3	

(0 * 1) + (1 * 0) + (1 * 1) + (0 * 0) + (1 * 1) + (1 * 0) + (1 * 1) + (0 * 0) + (0 * 1) = 3

Step9

1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

*

1	0	1
0	1	0
1	0	1

=

4	3	4
2	4	3
2	3	4

(1 * 1) + (1 * 0) + (1 * 1) + (1 * 0) + (1 * 1) + (1 * 0) + (1 * 1) + (0 * 0) + (1 * 1) = 4

Each kernel size in the image feature matrix represents a section of the image. However, kernel size can be increased or decreased depending on the size of the image to be viewed at a time

II. **Activation Layer**: The output of the Convolution layer is made to pass through what is known as activation function. An activation function is very important in the building process of ANN. Activation function makes ANN learn and makes sense of something really complicated and Non-linear complex functional mappings between the inputs. They introduce non-linear properties to the network. Their main purpose is to convert an input signal of a node in ANN to an output signal

The activation function has the effect of adding non-linearity to the convolutional neural network. If the activation function was not present, all the layers of the neural network could be condensed down to a single matrix multiplication.

Activation functions are very important in the process of building an Artificial Neural Network. Activation function makes ANN to learn and make sense of something really complicated and Non-linear complex functional mappings between the inputs[51]. They introduce non-linear properties to the network. Their main purpose is to convert an input signal of a node in ANN to an output signal.

Commonly used activation functions are sigmoid function and ReLU (Rectified Linear Unit)

III. Pooling Layer: The second key layer in CNN architecture is the pooling layer. The function of the pooling layer is to downsample (reduce the dimension) the output of the convolution layer. What this means is that it reduces the dimensionality of the feature maps by combining a set of values into a smaller number of values. Although it reduces dimensionality it retains relevant information and eliminates only irrelevant information. This is where the down sampling sets in. Over fitting and reduction of computing parameters is also achieved in this layer. Two common types of pooling layers are max pooling and average pooling. Max Pooling selects the maximum pixel value for each patch of the feature map while average pooling calculates the average pixel value for each patch on the feature map. Between max and average pooling, max is used often than average because max selects the brighter pixel values from the image. These values have the closest similarities of the features[52]. It is noteworthy to say that pooling layer of CNN does not parameters (weights) that need to be learned during neural network training. However, its layers are associated with two hyper parameters; stride(s) and filter size (f). Stride determines the number of steps the filter moves over the pixel values of an image. Commonly used stride is 2. The commonly used filter size in pooling is also 2. Figure 2.8 shows an image of a max pool with a filter size of 2x2 and stride 2.

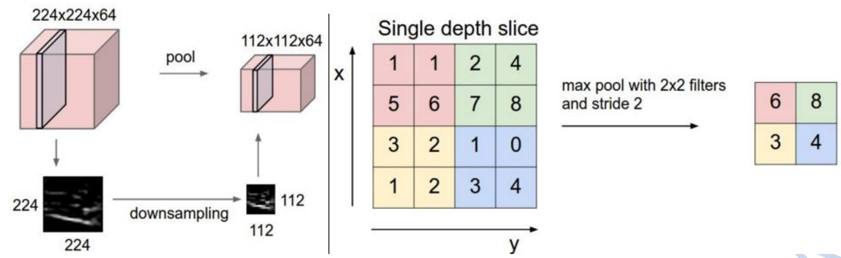

Figure 2.8 CNN pooling layer

Source; (extracted from https://leonardoaraujosantos.gitbook.io/artificial-inteligence/machine_learning/deep_learning/pooling_layer)

Fully Connected Layer: The convolution layer of a CNN is to identify patterns. This layer lacks the ability to make decisions as to classify patterns. For this reason, the fully connected layer (FC) becomes very necessary especially in classification models. Fully connected layer is the last layer of a CNN. This layer works as the normal neural network. It receives an output from either the last pooling layer or convolution layer that is flattened as its input. The final fully connected layer in the architecture contains the same amount of output neurons as the number of classes to be recognized. The fully connected layer based on the features extracted through the previous layers and their different filters performs classification. Classification in FC layer is made possible because every input vector but not every weight (extracted features from previous layer is flattened and received as a vector) from the previous layer influences every output of the output vector.

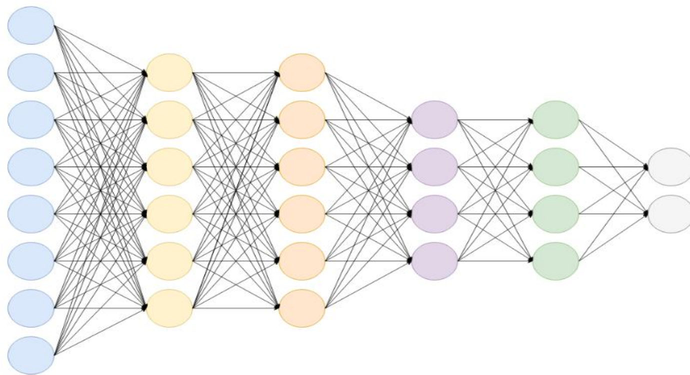

Figure 2.9 Fully connected network

Source: https://towardsdatascience.com/convolutional-neural-network-17fb77e76c05

Unlike the convolution layer, each neuron in this layer is connected with another neuron from the next layer as depicted in Figure 2.9, and each such connection has a particular weight. "Each neuron in a fully connected layer applies a linear transformation to the input vector through the weights matrix. As a result, all possible connections layer-to-layer are present, meaning every input of the input vector influences every output of the output vector" [53]. In a FC, the output size is specified by the number of columns in the weights matrix.

2.1.5.2 The working and Characteristics of CNN

Artificial neural networks are a simulation of real biological neural network in a computer. A neural network, either biological or artificial, consists of a large number of simple units of neurons that receive and transmit signals to each other. As seen in Figure 2.10, the human brain consists of interconnected neurons that transmit electrochemical signals.

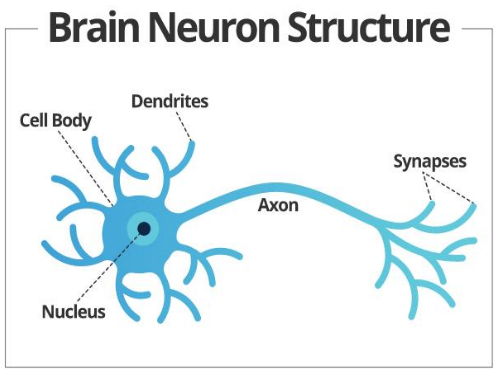

Figure 2.10 Structure of biological neuron

Source: https://www.linkedin.com/pulse/neural-network-srasthy-chaudhary

These neurons in their interconnected nature process data to give information. Neurons vary in many forms but a typical neuron is made up of a cell body having a nucleus, *dendrites* and axon. The dendrites extend from the cell body of the neuron, receive information from other neurons. The cell body collects information from the dendrites, relays this information to other parts of the neuron and maintains the general functioning of the neuron. The axon is the part of the neuron that communicates or sends information out to other neurons. It also stores information. It does so at the axon terminal called synapses[54]. A synapse is able to increase or decrease the strength of the connection between neurons.

These brain neurons are like organic switches. They can change their output state depending on the strength of their electrical or chemical input. Because the output of any given neuron is input to thousands of other neurons, learning occurs by repeatedly activating certain neural connections over others, and this reinforces those connections. This makes them more likely to produce a desired outcome given a specified input. This learning involves feedback. When the desired outcome occurs, the neural connections causing that outcome become strengthened[55].

A typical neural network (NN) architecture is composed of layers of neurons that are fully connected. A simple NN consist of input layer, hidden layer and output layer. Each layer consists of one or more nodes, represented by small coloured circles in Figure 2.11 below.

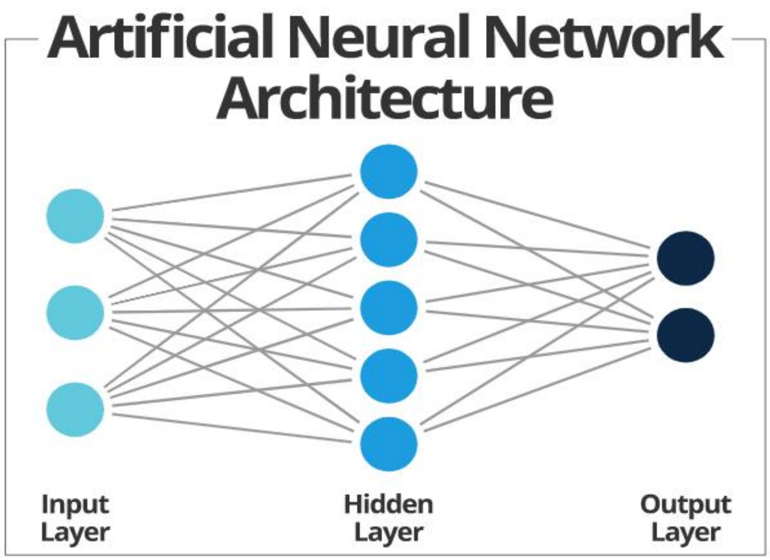

Figure 2.11 Structure of Artificial Neural Network

Source: https://www.linkedin.com/pulse/neural-network-srasthy-chaudhary

The lines between the nodes indicate the flow of information from one node to the next. In this particular type of neural network in Figure 2.9 the information flows only from the input to the output (that is, from left-to-right). Other types of neural networks have more intricate connections, such as feedback paths.

The interconnected arrangement of the nodes in ANN is analogous to biological neurons in the human brain. The input layer mimics the dendrites, the hidden layer where data is processed is likened to the cell body while the synapses of the axon is comparative to the output layer of the biological neural network. The input layer transmits signals to the neurons in the next layer, which is the hidden layer. The hidden layer is usually about 10% the size of the input layer[56]. The hidden layer extracts relevant features or patterns from the received signals. Those features or patterns that are considered important are then directed to the output layer, which is the final layer of the network[57].

The basic artificial neuron model involves a set of adaptive parameters, called weights and biases. These weights are used as multipliers on the inputs of the neuron, which are added up. The sum of the weights times the inputs are called the linear combination of the inputs.

The nodes of the input layer of NN are passive, meaning inputs at this layer are not modified. They receive a single value on their input and duplicate the value to their multiple outputs. Relatively, the nodes of the hidden and output layer are active[58]. This means they modify the data. The modification is done by passing the data through what is called a mathematical function. The mathematical functions are statistical functions that are combined with biological principles to solve complex problems in ANN. Mathematical functions are of different types depending on what the system intends to achieve. Some of the Mathematical functions are Sigmoid, Hyperbolic Tangent, Softmax, Softsign, Rectified Linear Unit (ReLU), Exponential Linear Units (ELUs).

2.1.5.3 Advantages of CNN over ANN

The involvement of a special type of layer named convolution layer makes CNN different from other machine learning technique. The convolution layer is able to detect and learn patterns such as edges, lines and corners from image and image-like input. In other words, CNN can capture or are able to learn relevant features from an input image which is not possible with Conventional ANN. Conventional ANN learns over time through what is called back-propagation algorithm. ANNs have weights and hidden layers. Input features are fed into the layers of an ANN directly and these features are multiplied with the weights in the hidden layers alongside other mathematical operations and then an output is generated in the output layer. In most cases, the output from the first iteration is somehow far from the expected or target output. In order to get expected or very close to expected result, a process called back-propagation is done. The back-propagation process involves adjusting the weights of the layers so that in the next iteration the output moves closer to the expected result. Another key difference is in the architecture of these networks. In CNN only the last layer is fully connected which utilizes the output from the convolution and pooling layers to predict a class in the case of a classification problem whereas, in ANN, all the layers are fully connected. A filter convolves over the input image in the convolution layer to extract features in CNN which makes it the most different from other ANN architecture. Convolution here is moving the filter over the input image with a given size of step known as stride. This could also be seen as breaking the image into the same size of the filter each of which is convolved with the filter. The filter goes through the patches of images, performs an element-wise multiplication, and the values are summed up as demonstrated in Section 2.1.5.1 (Convolutional Neural Network Features and their Operations).

There is also the difference in how weights are utilized. In CNN there is weight sharing. Each kernel slides over an entire image thereby extracting features from the image. Since the same kernel slides through all the pixels of the image, the same weights are shared reducing computational cost against ANN that uses different weights in all the connecting channels. CNN therefore can be used to process very large images with less computation and memory cost compared to ANN[59]. Due to the above stated qualities, CNNs have so far given state of the art results in image classification.

2.1.5.4 Application Areas of CNN

State-of the-art Convolutional Neural Networks have been very successful in solving many problems in the domain of machine learning. CNN because of its precise results when applied to real-world problems has found itself in many disciplines including medical sciences. Two key areas of CNN application are computer vision (scene labeling, face recognition, action recognition, and image classification) and natural language processing (that is, the fields of speech recognition and text classification)[60]. CNNs are deployed for the recognition of structure of an image because it is modeled after the visual cortex of the human brain. Different parts of the human brain are responsible for processing different pieces of information, and these parts of the brain are arranged in order of layers. By this, information that comes into the brain is processed by each level of neurons, provides insight, and passes the information to the next, more senior/advanced layer[61].What it means is that visual information that enters the brain through the eyes, travels through neurons in the brain regions, passes through different layers of increasing complexity, that is , from simple cells to complex cells according to Hubel and Wiesel where they described simple cells and complex cells in the human visual cortex capable of identifying image structures starting from simple visual representations such as edges, lines, curves etc. and then use the edges, lines or curves to detect simple shapes in the second layer and then use these shapes to detect higher-level features, such as, faces or full bodies in higher layers.. The last layer is then a classifier that uses these high-level features[62]. This is exactly how CNNs are modeled.

CNNs when given large number of images to train, can learn to adjust their artificial neurons' connection weights (strength) such that, after training, they are able to recognize image structures no matter their size and position, and are able to classify such images that they have never even seen before. This detection ability is achieved by scanning feature maps over an input image. The idea is that the neuron will output a large number if it detects a pattern that looks like its weights' pattern on the input image. By training the network, these weights actually change such that they look like patterns of the input image. CNN for its powerful ability to recognize image is applied in computer algorithms for:

a. **Face/image Recognition**: Facial recognition is a way to identify or verify an individual's identity through *image*, **video or any audiovisual element of the face**[63]**.** Two variants are performed in the facial recognition process. First is to register or digitally onboard a face and associate it with an identity and stored in database of the system. Second is to verify a registered face. A captured facial image by the camera is sent into the system as data". It is then authenticated by crossing it with the existing data in the database of the system, taking into consideration some key features due to the multidimensionality of the structure of the face.

b. **Image Classification:** Image classification is the process of categorizing and labeling groups of pixels or vectors within an image based on specific rules. When a human being opens his/her eyes, the objects seen are easily identified. Humans identify and group objects no matter the position or colour. It is not so with computers. Computers don't find such task of easily identifying objects quite as easy and this is where deep learning comes in. Computers are trained with several images and mathematical models in order to identify images and classify them when given the task to do so. They learn features to look for from the several images they are trained with coupled with some mathematical operations. The best and most accurate results in machine image classification have been credited to CNN. The accuracy of CNN to image classification is because CNN is modeled after biological neurons. Neurons in CNN known as artificial neurons filter through an input image to identify small areas of the input image such as corners and edges. And these small areas combine in higher layers of the artificial neural system to until the entire image is learnt.

Yadav and Jadhav applied CNN based algorithm on a chest X-ray dataset to classify pneumonia. They evaluated three techniques; linear support vector machine classifier with local rotation and orientation free features, transfer learning on two convolutional neural network models: (Visual Geometry Group i.e., VGG16 and InceptionV3), and a capsule network training through experiments. The findings on this work presented CNN-based method as the best of all three methods because they can learn and select features automatically and effectively[64].

Mishra *et al* classified images that make their way into their Smartphone devices through various social-media text-messaging platforms into three broad categories: document-based images, quote-based images, and photographs. Various convolutional neural networks (CNN) based models were trained on their self-made dataset and compared their results to find our task's optimum model. The research work achieved an accuracy of 95%. Every image that got into their phones were automatically grouped into the number of categories that were defined. A lot of CNN models for image classification abound. There are the ones that Can Classify Fashion Images using Fashion-MNIST dataset into different fashion categories as defined during training[65].

c. Text Classification: Several text classification methods based on CNN have been developed. These CNN based text classification works of late have shown very high performance and accuracy. Wang *et al* proposed CAPTCHA recognition methods based on deep CNN. This work overcame the problems of low efficiency and poor accuracy of traditional CAPTCHA recognition methods. The work improved on memory consumption and achieved an accuracy of above 99.9%.[66]Xiao and Cho proposed a neural network architecture that utilized both convolution and recurrent layers to efficiently encode character inputs. It achieved comparable performances with less parameters[67].

Yao *et al* proposed a novel Graph Convolutional Network (GCN) for text classification. GCN captures document and word relationships, and global word co-occurrence information utilize limited labeled documents well[68].

Wu *et al* reviewed Text Classification Methods based on Deep Learning (Convolutional Neural Network-Based (CNN-Based), Recurrent Neural Network-Based (RNN-based, Attention Mechanisms-Based and so on). In their review, many studies proved that text classification methods based on deep learning outperform the traditional methods. This is because text classification methods based on deep learning is void of cumbersome feature extraction process and have higher prediction accuracy for a large set of unstructured data.[69]

d. **Action recognition:** Action recognition systems are specially used for surveillance. They are used for monitoring scenes to check treacherous actions and to prevent crimes. Arunnehru*et al* in a paper titled "Human Action Recognition using 3D Convolutional Neural Networks with 3D Motion Cuboid Surveillance Videos used an advanced approach to propose for suspicious action recognition in intelligent video surveillance. They used 3D-CNN with 3D motion cuboid for action detection and recognition in real-time surveillance video to stop crimes. The experiments were conducted on KTH and Weizmann dataset and the outcome is a tremendous performance[70]. Human Activity Recognition with Convolutional Neural Networks is a paper by Bevilacqua *et al* in which the authors used CNN to classify human activities. The research work used raw data obtained from a set of inertial sensors. They got a promising result[71].Ankita *et al* proposed a model that combined convolutional layers with long short-term memory (LSTM), along with the deep learning neural network for human activities recognition. The model extracts feature and categorizes them with some model attributes automatically. They used a dataset of UCI-HAR for Samsung Galaxy S2 in the proposed architecture for various human activities. The work achieved an accuracy of 97.89%for activity detection capability than traditional algorithms, which is a very good one[72]. Zeng *et al* developed a work based on CNN, to automatically extract discriminative features for activity recognition. They carried out their "experiments on three public datasets, Skoda (assembly line activities), Opportunity (activities in kitchen), Actitracker (jogging, walking, etc.) the work when applied in real life situation achieved higher accuracy than existing state-of-the-art methods of that time[73].

2.1.6 Mathematical Morphology Overview

Oxford Dictionary on Lexico.com defines morphology as a branch of biology that deals with the form and structure of animals and plants. Form and structure in layman terms could simply be translated to mean size and shape respectively.

Mathematical Morphology (MM) as the name sounds is heavily mathematized according to Bloch *et al* as it borrowed concepts and tools from various branches of mathematics and mathematical theory that deals with shapes, their combinations or their evolution: algebra (lattice theory), topology, discrete geometry, integral geometry, geometrical probability, partial differential equations, etc.[74].

In terms of image processing, morphology is used to extract image components for representation and description of region, shape, such as boundaries, skeletons, and the convex hull. Image segmentation, edge detection, noise removal, and image enhancement are some of its usages. In image processing, morphology probes the structure of an input image with what is known as a structuring element to understand the geometric properties of the image. With the probing, it eliminates irrelevant parts and retains only relevant parts[75]. The resultant effect is to make the image simple for analysis, It either modifies or tends to modify geometric features of images[76]. Structuring element used to probe an image for image processing is positioned at all possible locations in the image and compares with corresponding neighborhood of pixels to determine the effect of the dilation or erosion on the input image.

2.1.6.1 Brief History of Mathematical Morphology

Georges Matheron and Jean Serra" are household names in MM. They are founding fathers of MM. MM dates back to 1964 when Georges Matheron, "mining engineer from the Corps des Mines, working with the B.R.G.M. (i.e., geological survey) in Paris studied the geometry of porous media in relation to their permeabilities. At the same time, Jean Serra, a civil engineer from the Ecole des Mines de Nancy and also a PhD student under the supervision of Georges Matheron had to quantify the petrography (i.e., the macroscopic and microscopic study of rocks) of iron ores, in order to predict their milling properties.[77],[78]

Georges Matheron introduced MM as a technique for analyzing geometric structure of metallic and geologic samples while Jean Serra extended to image analysis. Their main goal was to characterize physical properties of certain materials, e.g., the permeability of a porous medium, by examining their geometrical structure. Their investigations have led to a new quantitative approach in image analysis, nowadays known as mathematical morphology[79].

Morphology is founded on the basis of set theory. Therefore, its operation is defined by set arithmetic. Sets in mathematical morphology represent objects in an image. Objects in image in this context are the pixel value of the image. For binary image, it is the pixel value of the image where the x, y coordinates intersect each other at a point in the coordinate plain. It is denoted as Z^2 because the sets are members of 2-D integer space. For the Grayscale image, it is denoted as Z^3. The third component in the grayscale image besides the 2-D is the discrete intensity value of the pixel.

The concept of set reflection and translation are also used in mathematical morphology[80].

Reflection as regards image processing is a transformation representing a flip of the image. Images may be *reflected* in a point, a line, or a plane. In reflection the set of points in B (x, y) coordinates are replaced by (-x, -y). Translation on the other hand "slides" an object or image a fixed distance in a given direction. The original object and its translation have the same shape and size, and they face in the same direction.

During Jean Serra's PhD research period, after Georges Matheron introduced MM as a technique for analyzing geometric structure of metallic and geologic samples, Serra came up with the idea of using structuring elements. The idea of using structuring elements is to interact or probe the shape of an image. Probing the shape of an image is more or less like looking through a window of a particular opening to view through the image for areas of interest (AOI). This is achieved by positioning the structuring element at all possible locations in the image and it is compared with the corresponding neighborhood of pixels.

Structuring element has some striking characteristics: size, shape and origin. The size of the structuring element acts as a 'window' over which the interaction takes place. Besides acting as a window, the size of a structuring element also helps to differentiate image objects or features[81]. Georges Matheron said, knowledge about an object depends on the manner in which we probe it[82]. Probe here means to observe. And this observation is done using a structuring element of a particular size and shape.

The size of a structuring element can be a **3** × **3**square, **5** × **5** square**,** **7** × **7** square**,** or even **21** × **21** square. These various sizes of the structuring element can be likened to setting the observation scale. Observation scale here answers the question: how large or small of the image do you want to view at a time?

Figure 2.12 shows the arrangement of ones and zeros in a pattern within a matrix which gives the shape of the structuring element.

0	**1**	**0**
1	1	1
0	1	0

Figure 2.12 Shape of a structuring element

The pixel of interest that is to be processed is identified by the origin of the structuring element as shown in figure 2.13. The origin of a structuring element is not restricted to the centre of a matrix. It can be placed in any position of the matrix.

0	**1**	**0**
1	1	1
0	1	0

Figure 2.12 Shape of a structuring element with origin at the centre

2.1.6.2 Morphological Operators

In image processing, there are some basic steps taken to pre-process an image to enhance the it for further analysis**.** Such enhancement of images for further analysis could be achieved through morphological operations on the image. Morphological operations remove undesirable elements such as noise, blurriness, distortions etc. from an image structure. Two fundamental operators of mathematical morphology which make image processing possible are dilation and Erosion.

Other operators such as opening, closing, thickening and thinning were derived from dilation and erosion.

I. Dilation

Dilation means to grow or expand. Dilation operator denoted as a plus sign inside a circle ⊕, increases the size of an object. The extent to which the object size increases depends on the nature and shape of the structuring element.

Dilation is defined as;

$$X \oplus B = \{P \in Z^2 | p = x + b, \\ x \in X, b \in B\}$$

Where;

X = set points of the image

B = set points of structuring element

P = summation of the Input image set points (X $\{x_1, x_2\}$) and the structuring element set points (B $\{b_1, b_2\}$) at particular points.

ii. Erosion operator

The erosion operation is a complement of the dilation operation in context with the operation effect. That is, erosion operation causes object to lose its size. The erosion of an image A by structuring element B causes shrinking of the image.

iii. **Opening and Closing**

Opening and closing help to separate and join objects.

a. Opening Operation: Morphological opening involves the application of erosion, followed by dilation. Opening operation detaches objects that are touching but should not be, and enlarges holes inside the objects. By repetitively applying erosion and dilation, image details which are smaller than the structuring elements can be eliminated without affecting its global geometric features. It smoothens contours by suppressing small islands. So, opening operation is simply an erosion operation followed by a dilation operation. Opening operation is defined as:

$(A \circ B) = (A \Theta B) B$

b. Closing operation: Morphological closing involves the application of dilation, followed by erosion joins broken objects and fills in unwanted holes in objects. It smoothens the contours by filling in narrow gulfs and eliminates small holes. It involves one or more dilations followed by one erosion.

c. $(A \bullet B) = (A B) \Theta B.$

2.1.7 X-Rays

X-rays are electromagnetic radiation from high-energy[83]. X-ray imaging creates pictures of the inside of the body. The images of the parts of the body are shown in different shades of black and white. This is as a result of different amounts of radiation absorbed by different body tissue. While calcium in bones absorbs x-rays the most, fat and other soft tissues absorb less, and air in lungs absorb the least. Therefore, bones look white, soft tissue look gray and lungs look black in X-ray images[84].

X-rays can be traced to Wilhelm Conrad Rontgen a physicist, a Wuerzburg University professor in Germany. In 1895, Wilhelm Conrad Rontgen observed X-rays, a significant scientific advancement that ultimately benefited a variety of fields, most of all medicine, by making the invisible visible. Working with a cathode-ray tube in his laboratory, Roentgen observed a fluorescent glow of crystals on a table near his tube. The tube that Roentgen was working with consisted of a glass envelope (bulb) with positive and negative electrodes encapsulated in it. The air in the tube was evacuated, and when a high voltage was applied, the tube produced a fluorescent glow. Roentgen shielded the tube with heavy black paper, and discovered a green colored fluorescent light generated by a material located a few feet away from the tube[85]. He dubbed the rays that caused the x-rays glow because of their unknown nature[86]. X-rays are electromagnetic energy waves that act similarly to light rays, but at wavelengths approximately 1,000 times shorter than those of light. Rontgen holed up in his lab and conducted a series of experiments to better understand his discovery. He learned that X-rays penetrate human flesh but not higher-density substances such as bone or lead and that they can be photographed. Rontgen's discovery soon became an important diagnostic tool in medicine, allowing doctors to see inside the human body for the first time without surgery. Figure 2.14 below shows a sample of an X-ray photo

.

Figure 2.14 A sample of an X-ray photo[87]

2.1.7.1 Dental X-Ray and Types

Dental x-ray images (radiographs) were among the first X-ray images obtained of humans[88]. The discovery of X-ray by Professor Wilhelm Conrad Roentgen in 1895 was instantly recognized. This is because Roentgen's discovery showed a great potential for diagnosing internal medical conditions. Roentgen in his discovery also found out that the rays could pass through human tissue but they could not pass through bone and teeth, rather, created a shadow. He learned how to make pictures from these shadows and from this learning, carried out his first experiments a film of his wife's hand[89].

Drotto Walkhoff in December 28, 1895, exactly fourteen days after Roentgen's first publication and discovery of X-rays, took the first dental X-rays. It took Walkhoff 25 minutes of X-ray exposure to produce the image. And that image he captured was a radiograph of his own teeth[90]. Thereafter, the next line of dental X-ray history is credited to prominent New Orleans dentist Edmund Kells who took the first dental X-ray of a living person in the US in 1896 and reported on the role of radiographs in dentistry. A member of the faculty at the Indiana University School of Dentistry, R. Raper, further advanced dental radiography by writing the first book titled "Elementary and dental radiography[91,92].

After the initial hype of medical X-ray application had passed, it took several years before radiography became an integral part of dental practice[93]. When it did, however, technological improvements such as faster film speed, improved image quality, and patient comfort were made to each aspect of the radiographic imaging chain to address specific practical or diagnostic challenges in dentistry. Today, x-rays are a normal part of a routine dental examination.

2.1.7.2 Dental Radiographs

X-rays as stated in section 2.1.7 are high-energy electromagnetic radiation. Since the discovery of X-rays in 1895, it has been a common imaging test that's been used especially in medical sciences. X-rays are similar to visible light, but unlike light, x-rays have higher energy and can pass through most objects. X-rays with their high-frequency energy waves when they penetrate through the body or the target organ are absorbed, reflected off, or traversed through the body[94].

Medical x-rays are used to generate images of tissues and structures inside the body. The images produced by X-rays are formed on an x-ray detector placed on the other side of a patient. The x-ray detectors are of many types, a common one among them is photographic film. The x-ray images formed on these detectors are called radiographs[95].

Dental radiographs constitute the main data and are also the heart of this study besides CNN and MM. One of the primary diagnostic tools used in dentistry to determine disease states and roll out necessary treatment plan is radiographs[96].

Dental radiographs are very important part of dental care. Dental doctors get a more complete view of what's happening in the mouth of dental patients." Dental radiographs are achieved through two major X-ray groups: Intraoral and Extraoral.

i. Extraoral X-rays; Dental radiographs achieved through extraoral X-rays are made with the photographic film placed extraorally parallel to the teeth to be imaged, such that the tooth of interest comes in the center and the beam is directed through the opposite side buccal soft tissue without exposing the crowns of opposite side teeth. Extraoral X-ray provide important information about the jaw and skull" besides the teeth.

a. Panoramic View: Panoramic X-rays show the whole teeth structure with jaws and teeth in single view. They give a much larger perspective, including all of the teeth, joints, and nasal areas. This type of X-rays are used to detect different infections or problems present in teeth such as cysts, fractures, tumors, impacted teeth and dental caries etc.

b. Cephalometric projections: Show entire side of the head. These X-rays are used to examine teeth in relation to the jaw and profile of the individual".

ii. In**traoral Radiographs:** Intraoral Radiographs are the most common type of dental X-ray images. To achieve these images, the "X-ray film is placed inside the mouth of the patient. Here the dental doctor is looking for cavities and checking the status of developing teeth. They also give the dental doctor the ability to view tooth roots, check the health of the bone and even diagnose periodontal disease. There are different types of intraoral X-rays, among which is periapical. Each one shows different aspects of the teeth. The study focused on periapical radiographs.

a. Periapical Radiographs: The term periapical is a combination of two terms Peri, (a prefix meaning “around” or “about”) and apical (meaning "apex" or end of tooth root) and its objective is to capture the tip of the root on the film[97]. These will give dentists a complete view of one or more teeth including all of the primary components such as the crown and the supporting bone structure. It is used to determine teeth caries in a particular tooth, because it allows a dentist to visualize the whole tooth as well as the teeth surrounding cavities of bone.

Figure 2.15 shows an example of a Periapical radiograph. Periapical radiographs are chosen in this study because they are the most common dental radiographs.

Figure 2.15 Periapical X-ray Type

Source: https://www.colgate.com

II. Bitewing X-ray: The bitewing types of X-ray are when the patient bites on cardboard tab as demonstrated in Figure 2.16.

Figure 2.16 Bite-wing X-ray

Source: https://www.colgate.com

Normally four bitewings are taken as a set. They may be taken as often as every six months for people with frequent cavities or every two or three years for individuals with good oral hygiene and no cavities. In this view, the crown portions of the Upper and lower teeth are visible. It shows how the lower and upper teeth meet when the mouth is closed. These X-rays are used to check different dental diseases present in the upper and lower teeth particularly gum disease and cavities between teeth.

iii. Occlusal View: This type of X-ray captures all the upper and lower teeth in one shot while the film rests on the biting surface of the teeth[98]. This X-ray type is typically used to assess tooth development among children. The primary teeth can be observed along with the developing permanent teeth while giving you a view of the mouth floor as seen in Figure 2.17.

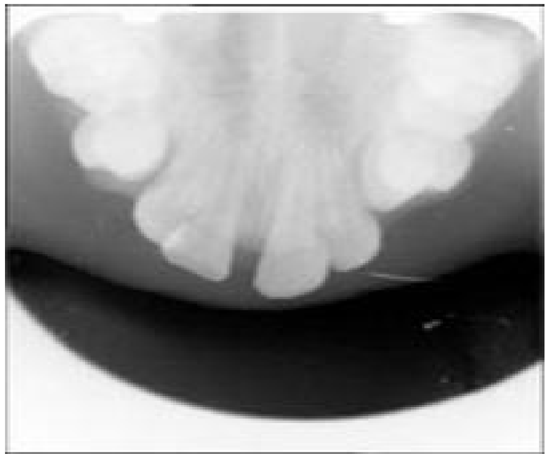

Figure 2. 17 Occlusal X-ray

Source: https://www.colgate.com

2.1.7.3 Why Dental Images Are Processed

One of the most important operations in computer vision and Image Processing is segmentation. Segmentation as defined as the process of partitioning or decomposing a digital image into smaller segments to extract information for further analysis and decision making. For the purpose of this research work, dental images were partitioned in order to extract areas of interest to see if a dental X-ray image has a defection or not. "Dentists often use X-rays especially in finding hidden dental structure, bone loss, malignant or benign masses and cavities that cannot be examined during visual examination[5]. The use of X-rays helps dentists to detect hidden dental diseases early. Early detection of a disease at a point in its natural history when it is not yet symptomatic is key to medical disease good prognosis. Early detection of disease may allow for interventions that alter its natural course, thereby halting disease progress and preventing the onset of adverse outcome[99].

2.1.7.4 Application of Processed Dental X-ray in Artificial Neural Networks

Processed dental radiographs (denoised images) are not processed for the fun of processing it. After dental X-ray image is denoised and areas of interest extracted, it can be used to train an artificial neural network system that will be able to diagnose, classify, predict to mention but a few.

An artificial neural network (ANN) attempts to simulate the network of neurons in the human brain[100]. By this, computers are made to learn from example (by way of training) in order to make decisions and predictions like a human. ANN is inspired by the animal neurons also known as brain cells t*o* aid machines with intelligence without explicit programming.[101]

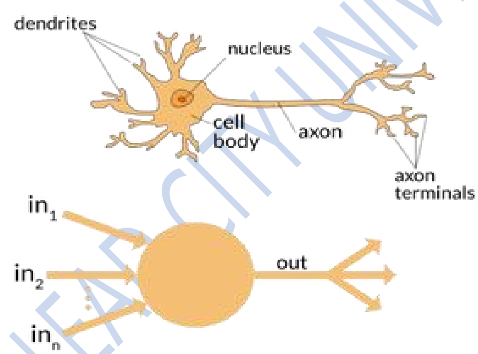

Figure 2.18 Biological Neurons[102]

The biological brain as seen in Figure 2.18 receives the stimulus from the outside world through the dendrites, does the processing on the input in the cell body, and then generates the output to other neurons through the Axon. As the task gets complicated, multiple neurons form a complex network, passing information among themselves. Artificial neural network mimics a similar behavior. In Figure 2.19 below image the nodes represent human brain neurons.

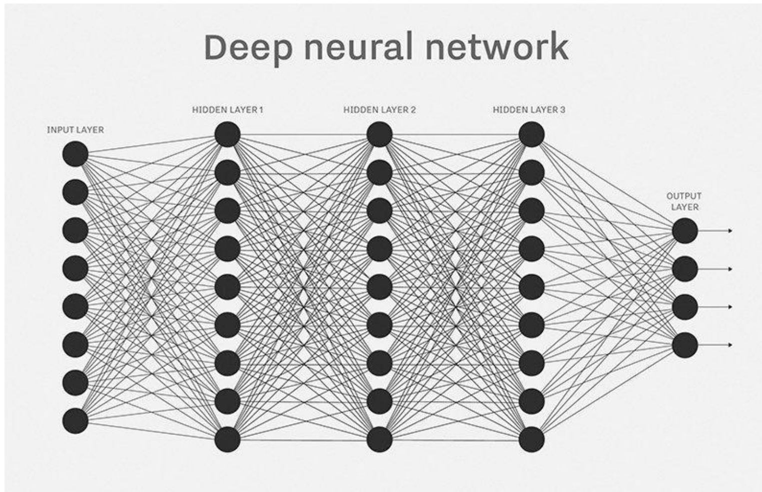

Figure 2.19 Deep neural network diagram

Source:https://searchenterpriseai.techtarget.com/definition/neural-network

The first sets of nodes are the input neurons. They receive the raw input information from the outside world.

The neurons in ANN are highly connected as demonstrated in Figure 2.20. The connections are weighted. Data goes through each unit in the network as input, thereby causing the network to learn. The inputs are multiplied with their corresponding weight and summed together.

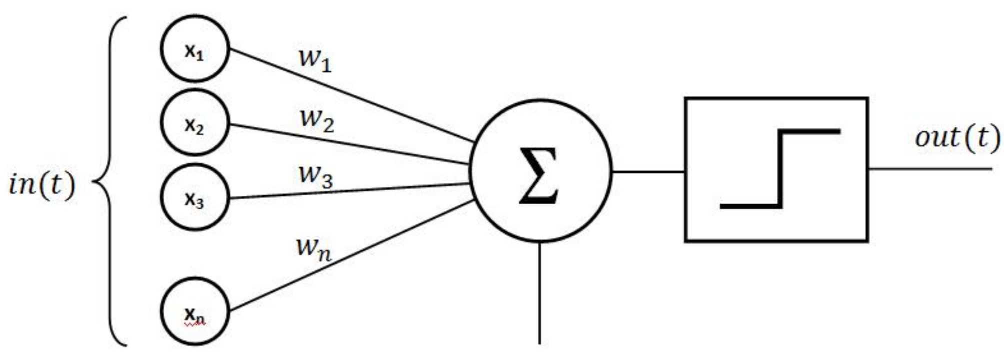

Figure 2.20 Graphical representation of mathematical model of a neural network

$$x_1w_1 + x_2w_2 + x_3w_3 + \ldots + x_nw_n$$

Each successive node (neuron) receives the output from the node preceding it, rather than from the raw input. The last sets of neurons are the output neurons which produce the output of the system. The neurons between the input and output neurons are known as the hidden neurons. The hidden neurons constitute the processing unit of the ANN. They transform the input into something the output unit can use by causing some activation function on the inputs at every unit of the network. The activation function is a mathematical model represented below. Activation function is of many types. For the purpose of this work, the activation function types to be used are ReLU and Softmax functions.

$Y = Activation(\sum(weight * input) + bias$

Where;

Weight * input = dot products between inputs and their corresponding weight (W*X)

$\sum$ (Weight * input) = "sum of dot products between inputs and their corresponding weights(W*X)

Activation = "mathematical function ReLU (f(x)) that converts an input signal of a node in a ANN to an output signal.

Bias = "Bias is a constant which helps the model in a way that it can fit best for the given data[103].

2.1.8 Overview of Dentistry

The American Heritage Science Dictionary defined dentistry as the branch of medicine that deals with the diagnosis, prevention, and treatment of diseases of the teeth, gums, and other structures of the mouth. Dentistry is a branch of medicine that consists of the study, diagnosis, prevention, and treatment of diseases, disorders and conditions of the oral cavity, commonly in the dentition but also the oral mucosa, and of adjacent and related structures and tissues, particularly in the maxillofacial (jaw and facial) area[104].

Figure 2.21 displays the oral cavity which is the first section of the mouth, also known as the mouth cavity. The mouth is made up of a space that is bordered in the front and to the sides by two alveolar arches, which contain the teeth. Toward the back, it is bordered by the isthmus of the fauces. This entire structure is also called the mouth;

the structures within the mouth allow us to taste and masticate (chew) food, to swallow food and drink, and to manipulate the air that comes up from the voice box so that we can form words.

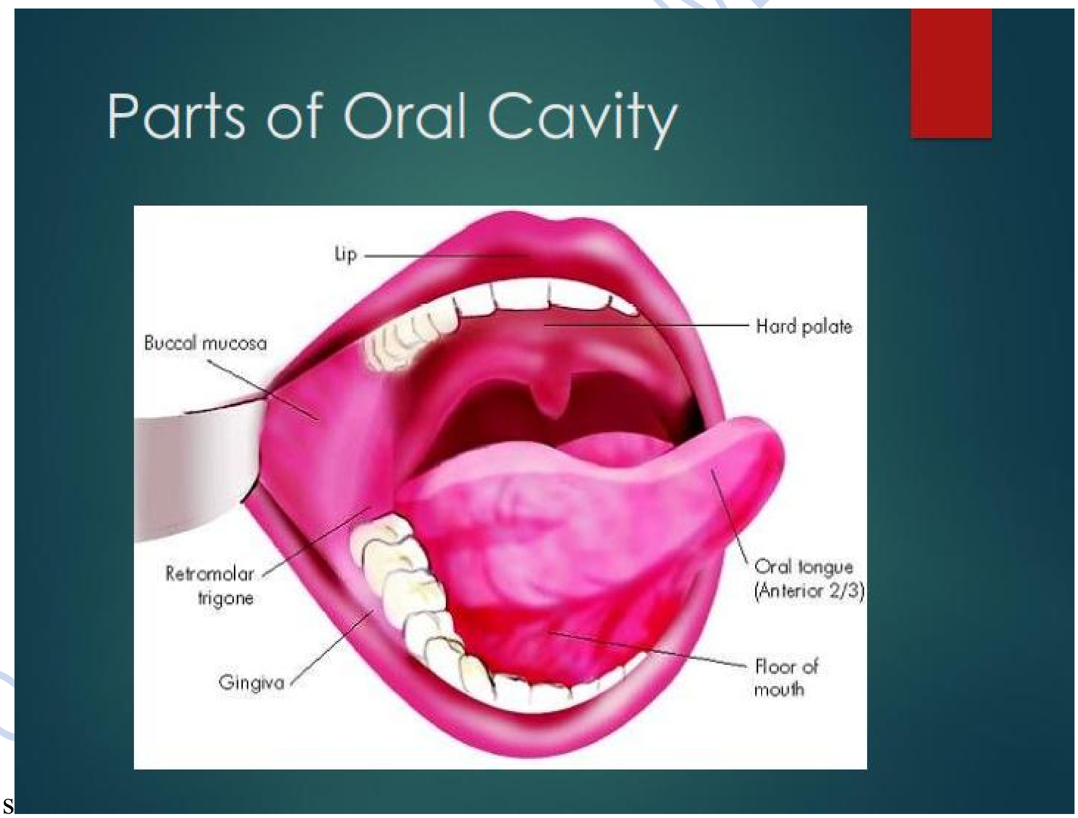

Figure 2.21: Dental Oral Cavity[105]

Dentistry is widely considered necessary for complete overall health. Doctors who practice dentistry are known as dentists. The dentist's supporting team which includes dental assistants, dental hygienists, dental technicians, and dental therapists aid in providing oral health services[106].

2.1.8.1 Brief History of Modern Dentistry

Since prehistoric times, when people have had issues with their teeth, there have been other people there to help. How we care for our teeth have changed over the past several thousand years, and today we call the professionals who care for teeth dentists".

"It was between 1650 and 1800 that the science of modern dentistry developed. The English physician Thomas Browne in his letter to a Friend (c. 1656 pub. 1690) made an early dental observation with characteristic humour."

The "French surgeon Pierre Fauchard became known as the "father of modern dentistry. Despite the limitations of the primitive surgical instruments during the late 17th and early 18th century, Fauchard was a highly skilled surgeon who made remarkable improvisations of dental instruments, often adapting tools from watch makers, jewelers and even barbers, that he thought could be used in dentistry. He introduced dental fillings as treatment for dental cavities. He asserted that sugar derivate acids like tartaric acid were responsible for dental decay, and also suggested that tumors surrounding the teeth and in the gums could appear in the later stages of tooth decay[107]. He also suggested that substitutes could be made from carved blocks of ivory or bone. He also introduced dental braces.

Fauchard was the pioneer of dental prosthesis, and he discovered many ally made of gold, he discovered that the teeth position could be corrected as the teeth would follow the pattern of the wires. “Waxed linen or silk threads were usually employed to fasten the braces. His contributions to the world of dental science consist primarily of his 1728 publications Le chirurgien dentiste or The Surgeon Dentist. The French text included "basic oral anatomy and function, dental construction, and various operative and restorative techniques, and effectively separated dentistry from the wider category of surgery.[110]

After Fauchard, the study of dentistry rapidly expanded. Two important books, Natural History of Human Teeth (1771) and practical treatise on the diseases of the Teeth (1778), were published by British surgeon John Hunter. In 1763 he entered into a period of collaboration with the London-based dentist James Spence. He began to theorize about the possibility of tooth transplants from one person to another. He realized that the chances of an (initially, at least) successful tooth transplant would be improved if the donor tooth was as fresh as possible and was matched for size with the recipient. These principles are still used in the transplantation of internal organs. Hunter conducted a series of pioneering operations, in which he attempted a tooth transplant. Although the donated teeth never properly bonded with the recipients' gums, one of Hunter's patients stated that he had three which lasted for six years, a remarkable achievement for the period[108].

Major “advances were made in the 19th century, and dentistry evolved from a trade to a profession. The profession came under government regulation by the end of the 19th century. In the UK the Dentist Act was passed in 1878 and the British Dental Association formed in 1879.” In the same year, Francis Brodie Imlach was the first ever dentist to be elected President of the

Royal College of Surgeons (Edinburgh), raising dentistry onto a par with clinical surgery for the first time[109].

2.1.8.2 Radiologic Appearances of Common Dental Diseases

Potential benefits of imaging studies include diagnosis of illness, and the severity or benign nature of that process, is made quickly and accurately. Medical imaging is essential not only at initial diagnosis, but for treatment planning also. It is essential for the monitoring of how a disease is responding to treatment i.e. whether a treatment plan should continue, adjusted or stopped[110]. Listed below are six dental diseases treated in this study.

1. **Dental Caries**. Dental caries is perhaps the most prevalent chronic disease[111]. Confirming Norman Tinanoff, two authors, Rathee and Sapra also said dental caries is reported to be the most common and one of the oldest diseases found in humans[112]. The authors also said caries is a Latin word meaning decay and it was originally used to describe a hole in the teeth as seen in Figure 2.22.

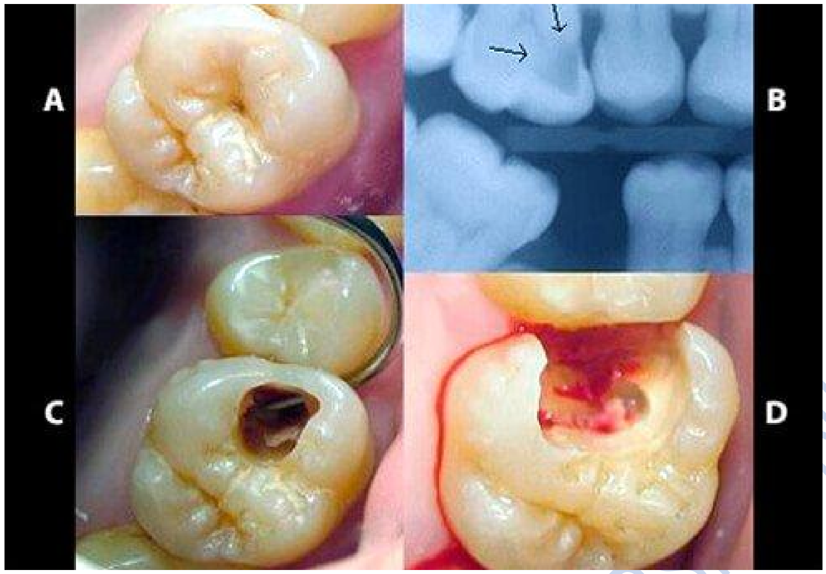

Figure 2.22 Dental caries.

Source: https://www.onhealth.com/content/1/dental_procedures

Etiologically dental caries is a dietary related bacteria action. When acid-producing bacteria and fermentable carbohydrate interact over time, the enamel gets softened and begins to decay, and that results to dental caries. Dental caries develops in both the crowns and roots of teeth[113].

2. **Periodontitis**. Periodontitis is a term built from two words; "periodont-" meaning structure surrounding the teeth and "itis" meaning inflammation[114].

Figure 2.23 Periodontitis[115]

Putting these two words together, periodontitis therefore is an inflammation of the structure surrounding the teeth as depicted in Figure 2.23. Periodontitis appears on periapical x ray as widening of the periodontal ligament space and bone loss[116].

Fractured Tooth. Fractured tooth also known as tooth crack is "when a piece of a tooth's chewing surface breaks off" as seen in Figure 2.24. Tooth fracture in most cases is due to traumatic injuries to the teeth and oral structures. If the early stage of breaking down the hard enamel is not treated, a cavity forms.

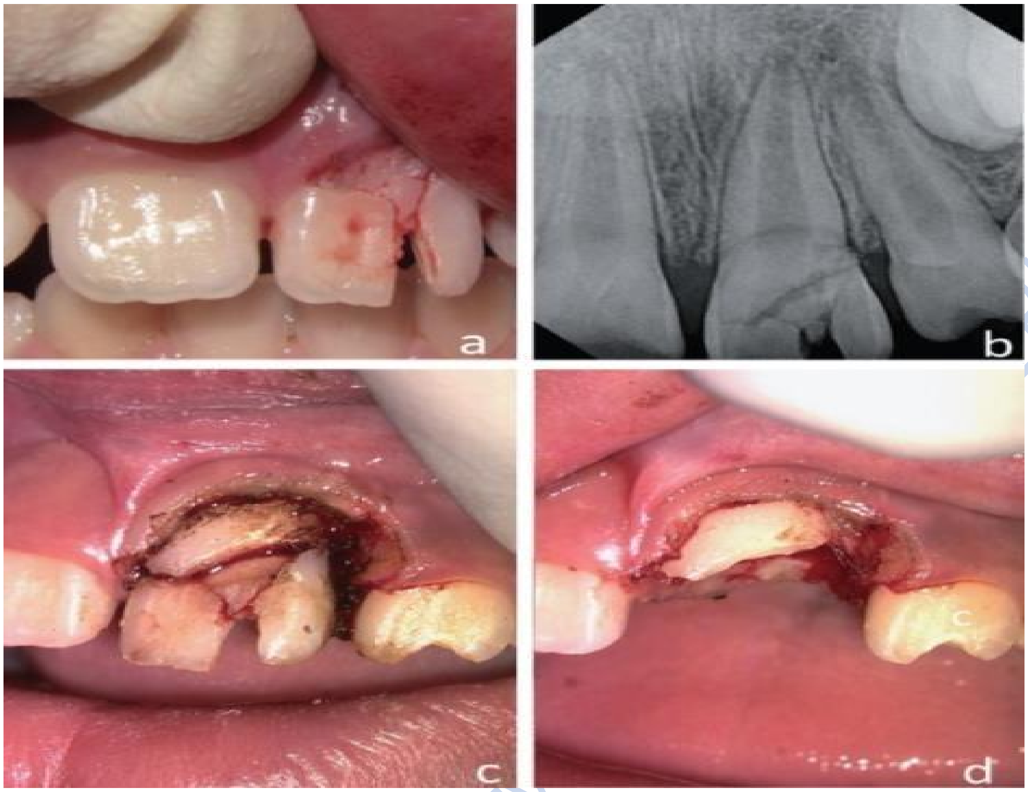

Figure 2.24 Fractured tooth

Source:https://pocketdentistry.com/9-radiographic-interpretation-of-traumatichttps://pocketdentistry.com/9-radiographic-interpretation-of-traumatic-injuriesinjuries

The traumatic injuries are caused by either a direct or indirect impact to the tooth[117]. The amount or severity of damage to the tooth results from the impacting object's shape, energy and the direction of the object[118].

3. **Dental Cysts**. Figure 2.25 is an image of dental radiograph. Dental cysts are small pockets of fluid which could be sterile or contain infectious material usually found around the roots of dead or infected teeth, within the gums, around impacted wisdom teeth, in maxillary sinuses or within the jawbone[119].

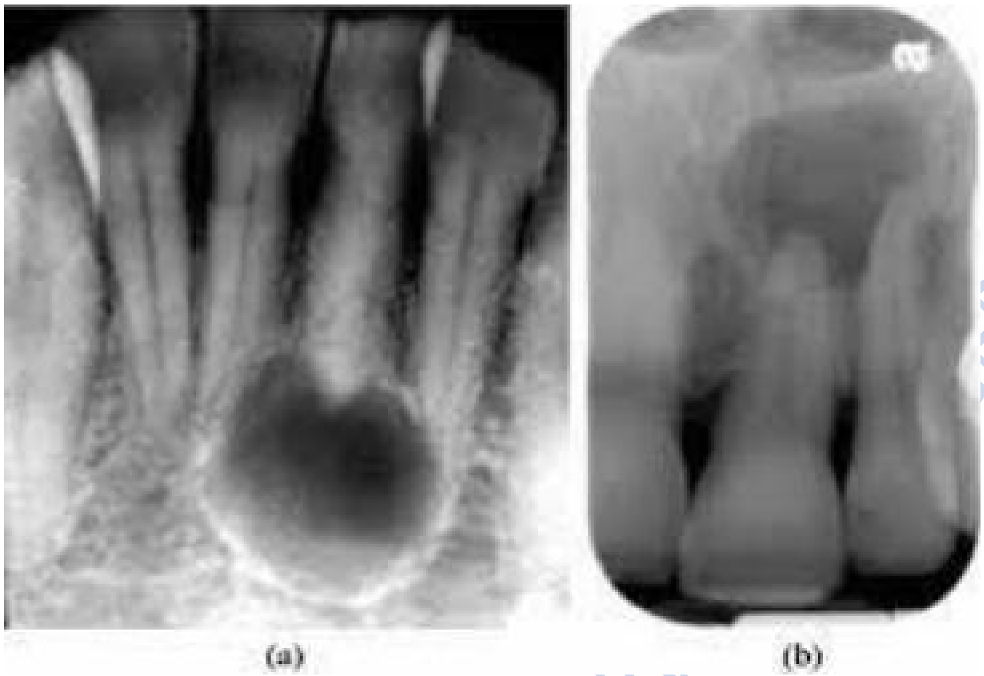

Figure 2.25 Dental Cysts

Source:https://www.researchgate.net/figure/Types-of-dental-cyst-a-Radicular-cystb-Follicular-cyst_fig1_322946738

There are three types of dental cysts; Periapical cyst, dentigerous cyst, and odontogenic keratocyst. All of these cyst types have their peculiar characteristics. Periapical cyst is the most common dental cyst amongst the these three types and it is referred to either as a radicular cyst, or apical periodontal cyst, or root end cyst, or simply dental cyst[120]

4. **Impacted Tooth**. Failure of a tooth to erupt into the dental arch within expected developmental window is termed tooth impaction in dentistry. In other words, the tooth does not break through the gum because there is eruption obstruction. The tooth is retained permanently unless exposed surgically or extracted[121]. Tooth impaction may be caused by various reasons such as overcrowding or tooth coming in position or direction. Figure 2.26 is a periapical X-ray radiograph of an impacted tooth

Figure 2.26 Impacted teeth

Source:https://upload.wikimedia.org/wikipedia/commons/e/e6/Impacted_Wisdom_Tooth_aka_Lower_Left_Third_Molar_38_RVG_IO

5. **Dental Cavities**. Dental cavities result when a hole is formed in the tooth as a result of decay. Decay is caused by bad bacteria on the teeth. The bacteria break down the food and drinks we consume into acid and then this acid helps to break down the hard coating on our teeth called enamel.

Figure 2.27 Stages of Tooth Decay

Source: https://www.drugs.com/cg/dental-cavities.html

No pain is felt at the earlier stage of dental decay but the longer it goes untreated the more the hole gets deeper and gets to the points that can cause severe pain. Figure 2.27 shows the different stages of tooth decay.

2.1.9 Telemedicine

Telemedicine is the remote delivery of health care services through telecommunication technology. A situation whereby the participants are not physically present but via telecommunication. Telemedicine is a word coined by World Health Organization in the 1970s[122]. WHO coined this word to fit and describe the services medical practitioners and health givers render services off their physical zone through telecommunication tools. With these telecommunication tools, diagnosing a disease, giving treatment plan, carrying out surgeries, and a lot more are practiced today. The meaning of telemedicine should not twisted to mean a specialty in the medical field but rather a tool to disperse traditional medical practice beyond the walls of the typical medical practice.[123],[124]. Telemedicine could be between two medical doctors or more working as a team or between patient and a doctor.

2.1.9.1 The Practice of Telemedicine in Nigeria

The use of telemedicine started far back in 2007 when the National Space Research and Development Agency and Federal Ministry of Health inaugurated their first project in six Federal Medical Centers and two teaching hospitals across the country[125]. Between 2007 and date, the adoption of telemedicine in Nigeria didn't stride for known factors such as illiteracy, access to internet, awareness, etc.

In respect of internet access, a survey conducted by the Alliance for Affordable Internet (A4AI) at nine low and middle income countries (Colombia, Ghana, India, Indonesia, Kenya, Mozambique, Nigeria, Rwanda, and South Africa), reported that only one in every ten people in these countries have meaningful connectivity[126]. A4AI defined meaningful connectivity as regular access with fast speeds, enough data and sufficient devices which billions of people in its focused countries of research lack. A4AI from its findings, concluded that 81 percent meaningful connectivity gap exists in Nigeria, in which they claimed that only 6.6 per cent of the rural population and 16.4 per cent of the urban have meaningful connectivity. From A4AI report, it can be concluded that telemedicine is out of the reach of a large number of Nigerians as it is access only through meaningful internet connectivity. And for the number that has internet connectivity, the problem of bad internet quality poses as a challenge to accessing telemedicine.

Inadequate information and communication technology (ICT) infrastructure is also another barrier to the effective adoption of telemedicine in Nigeria as revealed in a study by Sani *et al*[127].

Femi Obikunle published an article in The Guardian: Successes, challenges of telemedicine adoption in Nigeria clinical settings, where he listed 8 barriers to the adoption of telemedicine in Nigeria, among which he mentioned high-speed Internet, which is in agreement with A4AI[128].

Femi Obikunle also wrote on lack of education and skills to appreciate telemedicine by rural inhabitants. Obikunle did not fail to mention the fact that Nigeria lacks locally trained experts, and training facilities on how to develop telemedicine platforms. Obikunle concluded by saying that if the barriers to telemedicine adoption are not given serious consideration, it may spell an immeasurable healthcare doom for Nigerian future inhabitants.

2.1.9.2 Benefits of Telemedicine

Ojoma Akor published an article on DailyTrust on the report from the maiden Nigerian medical association (NMA) annual lecture series in Abuja where he said the association president, Professor Innocent Ujah stated that Nigeria lost over 9,000 medical doctors to the United Kingdom, Canada and the United States of America between 2016 and 2018[129]. The author in his article said Professor Innocent Ujah, quoting (WHO) data, said Nigeria has a doctor-to-population ratio of about 1:4000-5000, which falls far short of the WHO recommended doctor-to-population ratio of 1:600.

In a critical situation like the mentioned above, telemedicine with its benefits is one sure way to closing the wide gap created. Telemedicine operates upon the platform of ICT. This is to say that with the adoption of telemedicine, foreign medical experts including the Nigerian emigrated doctors can be reached and be of help to the medical sector while they fix the cause of brain drain in the country. It is one major means to bringing to the doorsteps of the Nigeria populace that falls short of the WHO recommended doctor-to-population ratio of 1:600.

William *et al* in their paper said telemedicine will allow the underserved a better opportunity to receive the quality care they deserve[130]. The authors in a narrative review discussed the benefits of telemedicine in postoperative care. Some of the benefits listed are increased accessibility along with reduced wait times, excellent clinical outcomes, enhanced patient satisfaction, and cost savings for patients and health care systems.

Telemedicine has recorded successes in developed nations like America where diagnosis and treatment of a range of urological conditions achieved success. Medication follow-up, metabolic kidney stone counseling, kidney stone and cancer surveillance via telemedicine platforms have also recorded successes[131].

Young *et al* also carried out a study on the impact of telemedicine in pediatric postoperative care[132]. The study came out with findings that patients reported pretty high satisfaction with virtual visits and benefitted from reduced wait times, yet, received care of comparable duration and quality. The authors concluded with a remark that virtual visits provide an efficient way to conduct postoperative visits, reducing wait times and increasing physician efficiency while retaining high satisfaction and quality of care.

Finkelstein *et al* compared virtual visits with conventional in-person visits with respect to clinical outcomes, family experience and costs in a pediatric urology surgical population in a study and concluded that pediatric postoperative care virtual visits are associated with shorter wait times, decreased missed work and school, and clinical outcomes similar to those of in-person visits. Telemedicine appears to reduce the costs associated with these brief but important encounters[133].

2.2 Theoretical Frameworks of CNN Models and Their Architectures

The idea of ANN dates back to the 1900s and the first application of this idea was on image classification. Thereafter improvement by twerking or replacement of older models' feature or the other has brought about a clear difference between the modern models of ANN and the classical

2.2.1 **LeNet Model**

The first application of CNN was by Yann LeCun and his team in 1998. They developed CNN which could recognize handwritten digits and was named LeNet after the principal author, LeCun. The system was trained with the application of back-propagation to Fukushima's artificial neural network. Due to limitations of computational resources at that time, the system was developed only with few layers and few filters. The architecture as shown in Figure 2.28 has two convolution layers, two average pooling layers, two fully connected layers and an output layer with Gaussian connection and 60,000 parameters.

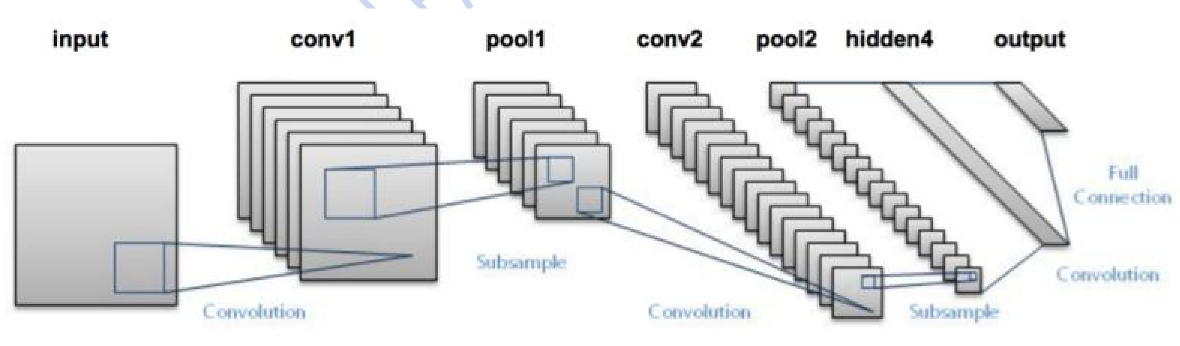

Figure 2.28 LeNet architecture[134]

The authors of LeNet model used Tanh as the activation function across the entire model and it was built for a specific purpose; "Optical Character Recognition (OCR)"

There are some clear drawbacks about LeNet model;

- With just 2 convolution layer and 2 pooling layers, LeNet architecture is shallow compared to modern architectures.
- The possibility of slow learning cannot be ruled out from LeNet judging from the shallow network of 2 convolution and 2 pooling layers
- The model will likely suffer from extracting detailed features from more complex images other than the hand written digits of 0-9. This means that when a classification problem with a more complex image is trained using LeNet architecture, accuracy will be very low
- Tanh activation function has the problem of vanishing gradient as the layers of a CNN increases. That is, the inability of a feedforward network to propagate gradient information from output end back to the layers around the input end of the model.

2.2.2 **AlexNet**.

In 2012, a paper by Krizhevsky*et al* titled ImageNet classification with deep convolutional neural networks revisited deep learning. In this work, a large, deep convolutional neural network was trained to classify 1.2 million high-resolution images into different classes. The neural network was made up of 60 million parameters and 650,000 neurons, consisted of five convolution layers as shown in Figure 2.29, some of which were followed by max-pooling layers, and three fully-connected layers with a final 1000-way softmax. The tanh activation function that was used in LeNet-5 replaced with ReLU. AlexNet was the first GPU based CNN model and was 4 times faster than previous models.

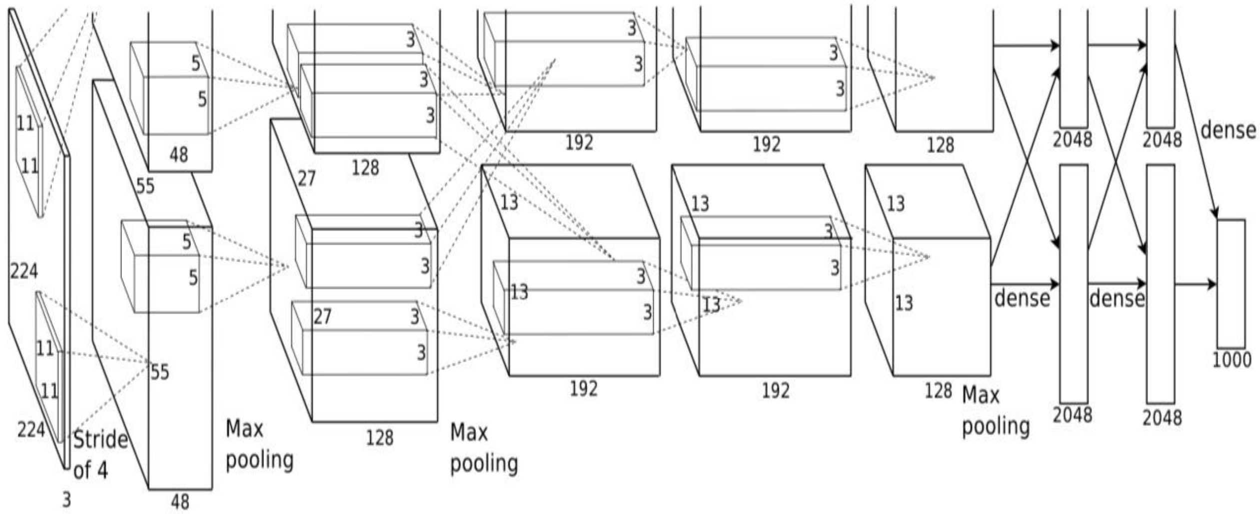

Figure 2.29 AlexNet architecture[135]

The work entered into a variant of the model in the ILSVRC-2012 (ImageNet Large Scale Visual Recognition Challenge) competition and achieved a winning top-5 test error rate of 15.3%, compared to 26.2% achieved by the second-best entry. One of the sources of great achievement in this work was the availability of large sets of data, namely the ImageNet dataset with millions of labeled pictures, and vast computing resources such as the use of GPUs, ReLU (Rectified Linear Unit) activation function, regularization technique called dropout and data augmentation.

Though the success of this work brought about a revolution in computer vision it has its drawbacks such as the model depth compared with later CNN architectures like VGGNet, GoogleNet, etc. AlexNet convolution filters were 5 by 5 which is quite large as large filters were discouraged" shortly after.

2.2.3 **VGGNet (2014)**

Karen Simonyan and Andrew Zisserman from the University of Oxford in 2014 proposed a paper "Very Deep Convolutional Networks Large Scale Image Recognition" that focused on the effect of the convolutional network depth on its accuracy in the large-scale image recognition setting. VGGnet (Visual Geometry Group) made an improvement over AlexNet by replacing large kernel-sized 11 filters in the first convolutional layer and 5 filters in the second convolutional layer with multiple 3X3 kernel-sized filters one after another. Displayed below in Figure 2.30 is an image of VGG architecture.

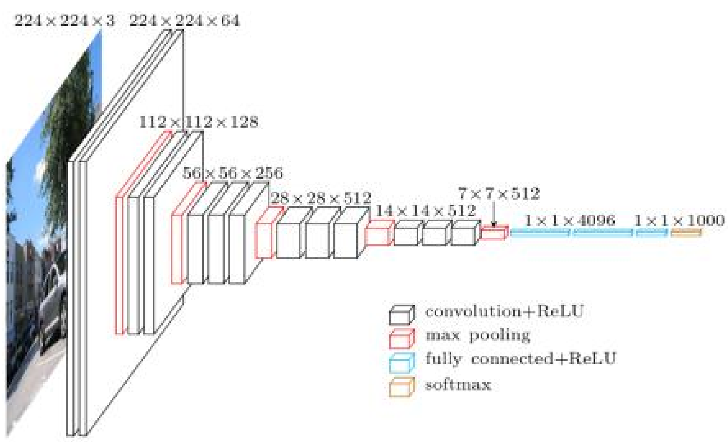

Figure 2.30 The VGG architecture.

Source:http://www.nvidia.cn/content/tesla/pdf/machine-learning/imagenet-classification -with-deep-convolutional-nn-pdf.

VGGNet increased the number of layers from eight layers in AlexNet. It has a variant of 16 and 19 layers. VGG16 has a total of 138 million parameters, convolutional layer kernels of size 3x3 with a stride 1 and maxpool kernels of size 2x2 with a stride of two. VGGNet was the runner up of the ImageNet Large Scale Visual Recognition Challenge (ILSVRC)"classification the benchmark in 2014[136].

Though VGGNet replaced AlexNet Tanh activation function with ReLu, VGGNet is still likely going to have vanishing gradient as a result of the depth of the models (16 and 19).

2.2.4 ZFNet (2013)

Figure 2.31 is an architectural image of ZFNet. ZFNet is a work by Matthew D Zeiler and Rob Fergus", the ILSVRC 2013 winner is a convolutional neural network motivated by visualizing intermediate feature layers and the operation of the classifier.

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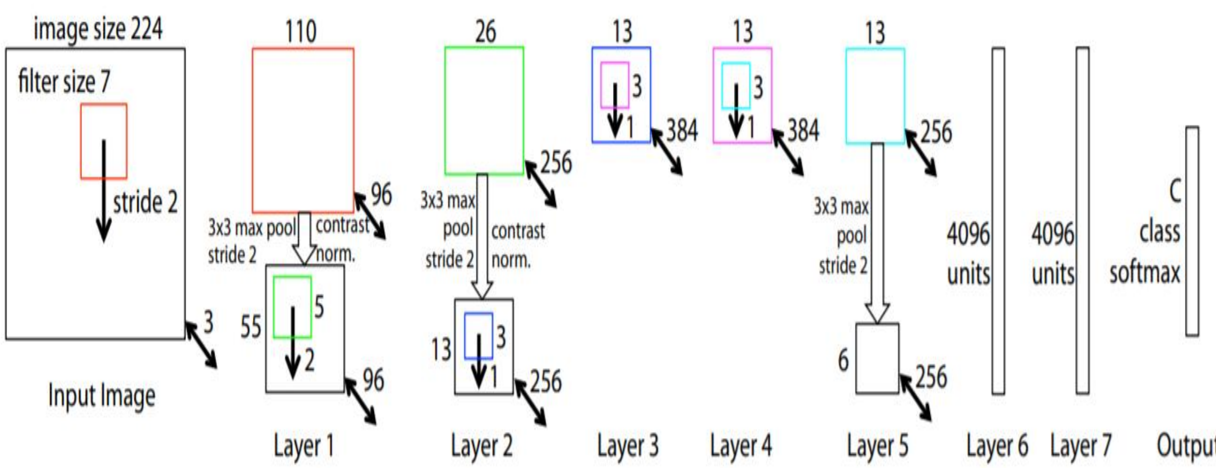

Figure 2.31 The ZFNet architecture.
Source:https://arxiv.org/pdf/1311.2901.pdf

The system used an input image size of 224x224x3 with 96 convolutions of 7x7 with a stride of 2. Next to this is a ReLU activation and then a 3x3 max pooling with stride 2 and local contrast normalization. A local contrast normalized and pooled 256 filters of 3x3 each followed the max pooling. The third and fourth layers are 384 kernels of 3x3 each. The fifth layer has 256 filters of 3x3, followed by 3x3 max pooling with stride 2 and local contrast normalization. The sixth and seventh layers housed 4096 dense units each. Finally, we feed into a Dense layer of 1000 neurons i.e. the number of classes in ImageNet[137]. The filter sizes and the stride of the convolutions are reduced in **ZFNet c**ompared to AlexNet. It achieved a top-5 error rate of 14.8% which is now already half of the prior mentioned non-neural error rate.

2.2.5 **GoogleNet**

GoogLeNet the winner of the ILSVRC 2014 competition is a 22-layer deep convolutional neural network that's a variant of the Inception Network, a Deep Convolutional Neural Network developed by researchers at Google.

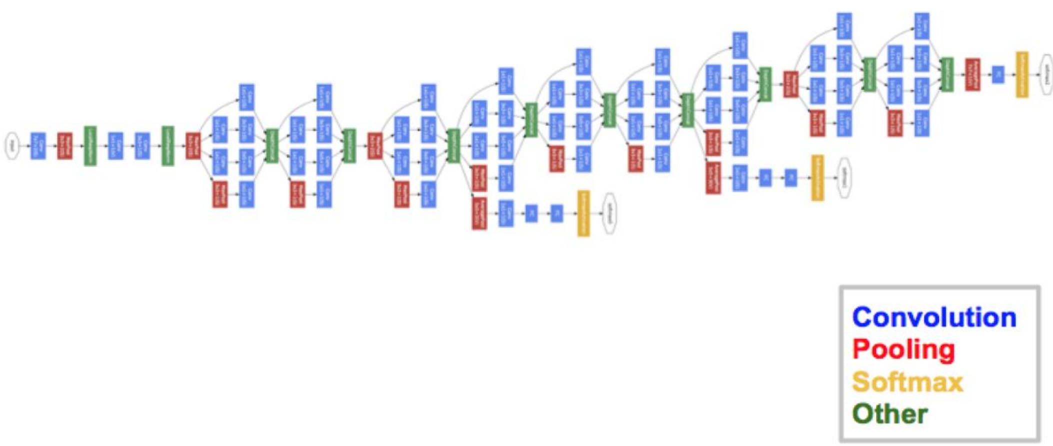

Figure 2.32 GoogleNet architecture
Source:http;//images.app.ggoogle/nXhAr9UPK6xbhzfy8

The GoogLeNet architecture as shown in Figure 2.32, presented in the ILSVRC14 solved image classification and object detection. It achieved a top-5 error rate of 6.67%! GoogleNet used a CNN inspired by LeNet but implemented a novel element which is dubbed an inception module. It used batch normalization, image distortions and RMSprop. In terms of parameters, GooggleNet is a reduced version of AlexNet from 6 million to 4 million.

2.3 Review of Related Works

In literature, many studies about Convolutional Neural Network, mathematical morphology, and morphological neural network employed for various purposes like interpretation of images, diagnosis of various diseases, segmentation of images, pattern recognition, prediction, classification and many more have been carried out. The first application of CNN was by Yann LeCun and his team in 1998. They developed CNN which could recognize handwritten digits and was named LeNet after LeCun. "The system was trained with the application of back-propagation to Fukushima's artificial neural network. Due to limitations of computational resources at that time, the system was developed only with few layers and few filters. Thereafter Alex Krizhevsky et al. published the paper " ImageNet Classification with Deep Convolutional Neural Networks describing the winning AlexNet model; this paper has since been cited 38,007 times[138].

Abdullah S. AL-Malaise AL-Ghamdi *et al*[139]developed a CNN-based multiclass model that classified cavity, filling, and implant achieving 96.51% accuracy.

Aslan *et al* proposed a study using two deep learning architectures; Artificial Neural Networks (ANN) and a hybrid structure[140]. ANN based segmentation was used to automatically detect positive COVID-19 cases using Chest CT X-ray images. Lung segmentation (preprocessing) in CT images, were given as input to the proposed architectures. The second proposed architecture, hybrid structure contains a Bidirectional Long Short-Term Memories (BiLSTM) layer, which takes into account the temporal properties. The results proved outstanding success in infection detection with a COVID-19 classification accuracy of the first architecture 98.14%, and 98.70%

in the second hybrid architecture. Therefore, proposed second hybrid architecture is more successful for COVID-19 detection.

A study titled Peri-Implant Bone Loss Measurement Using a Region-Based Convolutional Neural Network on Dental Periapical Radiographs by Cha *et al* is an automated assistant system for calculating the bone loss percentage and classifying the bone resorption severity using a deep convolutional neural network (CNN) [141]. A modified region-based CNN (R-CNN) was trained using transfer learning based on Microsoft Common Objects in Context dataset. The system aimed at detecting the marginal bone level, top, and apex of implants on dental periapical radiographs. The findings of this work were that there was no statistically significant difference found between the modified R-CNN model and dental clinician for detecting landmarks around dental implants. Therefore, the modified R-CNN model can be utilized to measure the radiographic peri-implant bone loss ratio to assess the severity of peri-implantitis.

Lee *et al* carried out a study to evaluate the discriminating performance of deep convolutional neural networks (CNNs), with various transfer learning strategies, on the classification of specific features of osteoporosis in Dental panoramic radiographs (DPRs) [142]. The authors collected a dataset containing 680 images from different patients who underwent both skeletal bone mineral density and digital panoramic radiographic examinations at the Korea University Ansan Hospital between 2009 and 2018.They used four study groups to evaluate the impact of various transfer learning strategies on deep CNN models: a basic CNN model with three convolutional layers (CNN3), visual geometry group deep CNN model (VGG-16), transfer learning model from VGG-16 (VGG-16_TF), and fine-tuning with the transfer learning model (VGG-16_TF_FT). From the findings of the study the best performing model achieved an overall area under the receiver operating characteristic of 0.858. Also, transfer learning and fine-tuning improved the performance of a deep CNN for screening osteoporosis in DPR images.

Application of Transfer Learning Using Convolutional Neural Network Method for Early Detection of Terry's Nail" is a paper by Muhamad *et* al presented in an "International Conference on Electronics Representation and Algorithm (ICERA 2019) [143]. The research work was conducted to detect a disease called terry's nails based on digital images using Convolutional Neural Network (CNN). The architecture used in the CNN is Tensorflow Inception-V3 model with transfer learning method. The results of the experiments" yielded 95.24% accuracy.

Khan and Aslam investigated on four deep-learning techniques DenseNet121, ResNet50, visual geometry group (VGG) 16 and 19 for diagnosing "COVID-19 by using X-ray images. In the study, it was reported that VGG-16 and VGG-19 models have better performance than the others[144]. The study came up with an overall classification accuracy of 99.3%.

Yabo *et al* developed a deep learning-based framework for coronary artery segmentation on coronary computed tomographic angiography (CCTA). Mask R-CNN was used for the coronary artery segmentation. Prior to the Mask R-CNN training, the lung region was masked to avoid the interferences from pulmonary vessels. The network was trained using 20 patients' CCTA datasets and tested using another 5 patients' CCTA datasets. The mean of the Dice similarity coefficient (DSC) were 0.90±0.01 respectively, which demonstrated the segmentation accuracy of the proposed method[145].

Muramatsu *et al* developed a computerized system to detect and classify teeth in dental panoramic radiographs for automatic structured filing of the dental charts[146]. The system can also be used as a preprocessing step for computerized image analysis of dental diseases. The authors used one hundred dental panoramic radiographs for training and testing an object detection network using fourfold cross-validation method. The detected bounding boxes were then classified into four tooth types, including incisors, canines, premolars, and molars, and three tooth conditions, including nonmetal restored, partially restored, and completely restored, using classification network.

"Deep Learning at Chest Radiography: Automated Classification of Pulmonary Tuberculosis by Using Convolutional Neural Networks is a work by Lakhani and Sundaram. The work evaluated the efficacy of deep convolutional neural networks (DCNNs) for detecting tuberculosis (TB) on chest radiographs[147]. Their findings came to a conclusion that Deep learning with DCNNs can accurately classify TB at chest radiography with an area under the curve (AUC) of 0.99. A radiologist-augmented approach for cases where there was disagreement among the classifiers further improved accuracy of the work.

Nouri *et al* proposed a CNN architecture based automatic diagnosing system for detecting positive COVID-19 via using X-ray images[148]. The CNN model is a five convolution layered serial network which was trained from scratch. Discriminative features were extracted from the CNN model which was used to feed machine learning algorithms like k-NN, SVM and DT. The study recorded 98.97% accuracy by the SVM classifier which is also the most efficient.

Yadav and Jadhav researched on how to apply convolutional neural network (CNN) based algorithm on a chest X-ray dataset to classify pneumonia[149]. They evaluated three techniques through experiments (linear support vector machine classifier with local rotation and orientation free features, transfer learning on two convolutional neural network models: Visual Geometry Group i.e., VGG16 and InceptionV3, and capsule network training from scratch. The results of their experiments showed that data augmentation generally is an effective way for all three algorithms to improve performance. Also, transfer learning is a more useful classification method on a small dataset compared to a support vector machine with oriented fast and rotated binary (ORB) robust independent elementary features and capsule network. In transfer learning, retraining specific features on a new target dataset is essential to improve performance. And, the second important factor is a proper network complexity that matches the scale of the dataset.

Singh and Sehgal proposed a technique for numbering and classification of panoramic dental images[150]. They worked with a dataset of 400 dental panoramic images collected from various dental clinics. The image data set was augmented by applying various transformations. The dental images were pre-processed segmented using fuzzy c-mean clustering and subjected to vertical integral projection to extract a single tooth. The 400 dental images were divided into 240 training samples and 160 testing samples. They used a 6-layer deep convolution neural network (DCNN) consisting of 3 convolution layers and 3 fully connected layers to do a classification of tooth as canine, incisor, molar and premolar." An accuracy of 95% was achieved for augmented database and 92% for original dataset with the proposed algorithm.

A paper by Lakhani e*t al* provided a high-level overview of how to build a deep neural network for medical image classification, and codes that can help those new to the field begin their informatics projects[151]. The aim of the tutorial was to spark interest and provide a basic starting point for those interested in machine learning in regard to medical imaging. "The tutorial assumed basic understanding of CNNs, some Python programming language (Python 3.6, Python Software Foundation, Wilmington DE), and is more of a practical introduction to using the libraries and frameworks. The tutorial also highlighted some important concepts but due to space constraints did not cover everything in full detail.

Rikiya Yamashita *et al* in their article focused on the basic concepts of CNN and their application to various radiology tasks, and discussed its challenges and future directions in the field of radiology[152]. How the unavailability of well-labeled data in medical imaging due to the cost and necessary workload of radiology can be taken care of through other efficient techniques such as data augmentation and transfer learning. Although these methods exist, well-annotated large medical datasets are still needed since most of the notable accomplishments of deep learning are typically based on very large amounts of data. Different application areas of CNN (classification, segmentation, detection, and others.) were discussed in this work.

Kaushik and Kumar reviewed and compared some works on various segmentation techniques[153]. They found in their research work that CNN is one the most powerful tool in image segmentation technique. Besides reviewing papers on image segmentation techniques, detailed analysis of CNN, possible advantages and fields CNN were also included in the paper.

Chen *et al* proposed using faster regions with convolutional neural network features (faster R-CNN) in the Tensor Flow tool package to detect and number teeth in dental periapical films[154]. The authors proposed three post-processing techniques to supplement the baseline faster R-CNN according to certain prior domain knowledge. First a filtering algorithm to delete overlapping boxes detected by faster R-CNN associated with the same tooth. Next a neural network model to detect missing teeth. Finally, a rule-base module based on a teeth numbering system is to match labels of detected teeth boxes to modify detected results that violate certain intuitive rules. The intersection-over-union (IOU) value between detected and ground truth boxes were calculated to obtain precisions and recalls on a test dataset. The results indicate that machines already perform close to the level of a junior dentist. However, the precision and recall of the classification work that provided each detected tooth an FDI number was unsatisfactory until certain post-processing procedures were applied. The performance of the proposed automatic system was very close to the level of a junior dentist who was selected as a control in this study.

Benkarim *et al* applied a patch-based approaches in the segmentation of biomedical images and it showed promising results over the most common approach, which is the use of registration to warp the atlases to the target space and then the warped atlas label maps are fused into a consensus segmentation based on local appearance information encoded in form of patches[155]. They also proposed a common formulation for two widely-used label fusion strategies, i.e., similarity-based and a particular type of learning-based label fusion. The proposed framework was evaluated on subcortical structure segmentation in adult brains and tissue segmentation in fetal brain MRI. As conclusion, the combination of learning-based label fusion and native atlas patches yields the best performance with reduced test times than conventional similarity-based approaches.

Ozaki and Motokawa developed a neural network model to get an accurate assessment of dental developmental age which is a prerequisite to obtaining occlusal harmony and correct masticatory function[156]. They used fuzzy logic and neural network for practical application by inputting data readily obtainable by simple clinical visual inspection. They used six hundred and thirty-five patients ranging in age from 27 to 184 months to optimize the systems. The dental ages of 50 additional patients estimated clinically by 2 expert pediatric dentists were compared to those obtained by the 2 optimized computer models. An average error of 11 to 18 months was observed with either computer model, while clinically the error averaged 12 to 14 months. The authors with the implementation of the methods achieved reasonable accuracy without exposing patients to X-rays.

An “effective teeth recognition method using label tree with cascade network structure by Zhang *et al* applied deep learning technique to medical field for the teeth detection and classification of dental periapical radiographs. The work was able to detect and distinguish teeth from different positions in an input X-ray image. The proposed approach reaches a high precision and recall of 95.8% and 96.1% in total, which is a big improvement in such a complex task[157].

Moulli *et al* developed a morphological convolutional neural network for digit recognition. The authors incorporated morphological operators into the convolution layer using counter harmonic mean to produce an enhanced feature map[158].

A novel mathematical morphology based algorithm for shoreline extraction from satellite images by Rishikeshan and Ramesh presented a flexible mathematical morphology-driven approach for shoreline extraction algorithm from satellite imageries[159]. The key features of the work are the preservation of actual size and shape of the shorelines, run-time structuring element definition, semi-automation, faster processing, and single band adaptability. The proposed approach was tested with various sensor-driven images with low to high resolutions. “Accuracy of the developed methodology was assessed with manually prepared ground truths of the study area and compared with an existing shoreline classification approach. The proposed approach was found successful in shoreline extraction from the wide variety of satellite images based on the results drawn from visual and quantitative assessments.

Lira *et al* presented a method for automatic segmentation and feature extraction for dental radiographs. The proposed method was implemented using traditional mathematical morphology and matching techniques. Further works include the development of a more sophisticated pre-processing pipeline, test of other morphological operators to improve the segmentation and the development of a more robust technique for seed identification[160].

Segmentation of dental radiographs in medical imaging using neutrosophic orthogonal matrices is a paper by Ali *et al*[161]. In this paper, a new fuzzy clustering algorithm based on the neutrosophic orthogonal matrices for segmentation of dental radiographs was proposed. This algorithm transforms image data into a neutrosophic set and computes the inner products of the cutting matrix of input. Pixels are then segmented by the orthogonal principle to form clusters. The experimental validation on real dental data sets of Hanoi medical university hospital, Vietnam showed the superiority of the proposed method against the relevant ones in terms of clustering quality. Experimental results on the real dental X-ray image datasets showed that the proposed method out-performed the relevant fuzzy clustering scheme. It also showed that the proposed method achieved better validity index values. Future research of this work is to be conducted on improving the method by an idea of boolean matrix and enhance the computational time by parallel strategy.

A paper by Amer and Aqel presented method to extract wisdom teeth automatically from panoramic images that consist from three stages, pre-processing region of interest (ROI) extraction and post-processing. The obtained results from the proposed method showed that it could successfully extract the wisdom teeth, the segmented images can be used later in classification system to classify the extracted teeth as wisdom teeth or not, and then classify the wisdom teeth according to a specific problem that is, impaction. Future work should be to implement the algorithm[162].

Oladele and Yetunde developed a dental expert system with the intention of solving real life problem. The system is a desktop-based medical expert system for diagnosis and prediction of dental diseases. The dental expert system is an open loop system which will be handled by Medical Practitioners in the Dental field who selects the symptoms of the patient and the expert system work on these symptoms based on symbolic rules to arrive at the best ailment together with the cause, prevention, and diagnosis. Another significance of this expert system is that it will also serve as a management system to keep past and existing records of patient's data. The dental expert system was able to show that automating the management and administration of treatment is more reliable and efficient than the manual approach of the existing system. The system was developed using the Coactive Neuro-Fuzzy Expert system model. Speed and accuracy was achieved in the computerized system which will prevent mix up or confusion in the documentation of patients' information. It reduces the stress involved in treatment administration to patients considering the tight schedule of most medical practitioners the reliability and efficiency of the developed system is also higher than that of the existing system. Updating and maintenance of the program can be done easily. It is interactive and easy to use. The Expert System has taken care of the lapses in the existing manual system to a great extent and has designed a more efficient, accurate and speedy method of preparing enrollment report[163].

A prototype expert system for diagnosis and suggestion of treatment for oral cancer presented by Khosravi *et al* receives input from user, analyses it and reforms it. It is able to diagnose Oral cancer and give appropriate treatment. However, the designed system lacks clinical review to ascertain correctness of result. It only acts based on user's answers and can't study the correctness of user answers[164].

Expert system for determining the level of stress before pediatric dental treatment by Bucur *et al* is a web based expert system prototype that evaluates the clinical cooperation of the patients before initiating any dental treatment[165]. This is because the need for a good communication with the young patient enables the dentist get a successful result in pediatric. The goal of the expert system is to determine the exact anxiety level in patients. The work establishes the opportunity of medical intervention considering the patient's anxiety and related symptoms. The system greatly eases clinical work by helping the dentist to take the best medical decision at the beginning of the young patient's treatment. The research variables are independent variable and dependent variables. These variables were established and measured with digital and nominal scale.

Eyad *et al* presented an automated dental image segmentation algorithm that handles bitewing and periapical dental images based on mathematical morphology[166]. Also, grayscale contrast stretching transformation to improve the performance of teeth segmentation was presented with very low failure rate.

Raju and Modi proposed feature extraction technique for dental X-ray image using Fourier descriptor features for shape analysis and Gray Level co-occurrenceMatrix(GLCM) properties such as Energy, Contrast, Correlation and Homogeneity to describe the texture of the extracted Tooth[167]. In the algorithm, both shape and texture analysis of the extracted tooth are explored as features. However, the algorithm fails when two images have similar texture and shape properties." Future work will involve finding a novel feature extraction technique which explores the geometry of teeth which remains inherently unique to each individual.

A Survey: "Segmentation in Dental radiographs for Diagnosis of Dental Caries" by Krithigaand Lakshmi is a paper which reviewed some influential papers in the dental x-ray segmentation literature[168]. According to this paper, among the methods proposed only very few are fully automatic. Some methods were not accurate in segmenting caries due to improper teeth segmentations and some of them due to noise, low contrast and unusual arrangement of teeth. The future work will focus on retrieving dental radiographs using content-based retrieval systems.

Krithiga*et al* developed an automatic segmentation of caries from dental radiographs using wavelet and watershed transform. The work is aimed at easing the difficulty in identifying caries from the raw data obtained directly from X-ray acquisition device due to poor image quality. The result analysis showed that the watershed transform algorithm performs well in segmenting the caries when compared to Euler's min-max method. The segmented caries area can be used for automatic dental applications such as human identification, dental diagnosis systems etc. Further, the severity of dental caries can be performed on a larger dataset[169].

Reddy *et al* proposed a dental processing algorithm and implemented it using a specialized object oriented image processing software. The work bothers on the classification of dental caries based on several criteria, (1)According to the rapidity of the process, (2) whether the lesion is a new one attacking a previously intact surface or Recurrent, (3).According to the extent of attack, etc. The algorithm yielded a successful result, however it is limited to caries detection[170].

Rad *et al* presented a method for segmentation and feature extraction for dental radiographs. The proposed method was implemented using traditional image processing techniques, by using level set for segmentation, after image enhancement. Some features of dental radiographs were extracted using texture statistics techniques by gray-level co-occurrence matrix. The experimental results showed that it is a promising technique for segmentation which can be used for human identification or dental diagnosis systems. For the future work a better solution to distinguish each particular tooth in segmentation step and evaluation of segmentation methods are expected[171].

A study was conducted by Na`am *et al* to overcome the difficulties in identifying proximal caries through image processing of panoramic dental x-ray image[172]. The image processing method used in this study is Multiple Morphological Gradients. These image processing results can be used to appropriately identify proximal caries and the level of severity. Based on the results of this study, further research is needed to compare the results of Panoramic Dental X-Ray processed by multiple morphological gradients (mMG) with the results of bitewing Dental X-Ray from any proximal caries Patients.

A paper by Krizhevsky *etal* titled ImageNet classification with deep convolutional neural networks revisited deep learning. In this work, a large, deep convolutional neural network was trained to classify 1.2 million high-resolution images into different classes. The neural network was made up of 60 million parameters and 650,000 neurons, consisted of five convolution layers, some of which were followed by max-pooling layers, and three fully-connected layers with a final 1000-way softmax. The work entered into a variant of the model in the ILSVRC-2012 competition and achieved a winning top-5 test error rate of 15.3%, compared to 26.2% achieved by the second-best entry. One of the sources of great achievement in this work was the availability of large sets of data, namely the ImageNet dataset with millions of labeled pictures, and vast computing resources[173].

Dr. Kunihiko Fukushima being inspired by the findings of Hubel and Wiesel's work on simple and complex cells, proposed a paper titled: Neocognitron: A Self-organizing Neural Network Model for a Mechanism of Pattern Recognition Unaffected by Shift in Position. The proposed paper is a neural network model for a mechanism of visual pattern recognition. The network is self-organized by learning without a teacher, and acquires an ability to recognize stimulus patterns based on the geometrical similarity (Gestalt) of their shapes without being affected by their positions. The network got a nickname neocognitron. The structure of neocognitron is similar to the hierarchy model of the visual nervous system proposed by Hubel and Wiesel. The system is made up layers of which the first is "S-cells" while the second is made of "C-cells" similar to Hubel and Wiesel's simple and complex cells respectively. The result of the system showed that the response of the C-cells of the last layer is not affected by the pattern's position at all. Neither is it affected by a small change in shape nor in size of the stimulus pattern[174].

2.4 Summary of Literature Reviewed

Several literatures have been reviewed to know what exists in scholarly literatures related to this study. The reviewed literatures informed this study some gaps and areas that are presently making rounds. Among the reviewed literatures, some gaps that are observed discussed in this section.

LeNet was the first application of CNN by Yann LeCun and his team in 1998. The model was developed to recognize handwritten digits and was named LeNet after the principal author. The system was developed only with only a few layers and few filters due to limitations of computational resources at that time. A major shortcoming of LeNet is that it was designed for a specific size input and it didn't do well in colour image recognition[175].

A paper by Lakhani e*t al* provided a high-level overview of how to build a deep neural network for medical image classification, and codes that can help those new to the field begin their informatics projects. The aim of the tutorial was to spark interest and provide a basic starting point for those interested in machine learning in regard to medical imaging. "The tutorial assumed basic understanding of CNNs, some Python programming language (Python 3.6, Python Software Foundation, Wilmington DE), and is more of a practical introduction to using the libraries and frameworks. This work had space constraints and therefore did not cover everything in full detail[176].

MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications is a work by Howard *et al.* The authors demonstrated vision application embedded MobileNets for mobile devices based on depthwise separable convolutions. In this work, a reasonable amount of accuracy was traded off for size and latency. The work was limited to mobile devices[177].

An Introduction to Deep Morphological Networks is a work by Keiller *et al*, where the convolution filters were replaced with non-linear filters of mathematical morphology. The authors failed to subject same data set to implement a CNN model in order to compare performance between the morphological network with that of CNN[178].

Krizhevsky *et al* developed a model that could classify 1.2 million high-resolution images into different classes. The neural network was made up of 60 million parameters and 650,000 neurons, consisted of five convolution layers some of which were followed by max-pooling layers, and three fully-connected layers with a final 1000-way softmax. The model was trained with ReLU as an activation function to add non linearity to the model. AlexNet was the first GPU based CNN model and was 4 times faster than previous models. Though the success of this work brought about a revolution in computer vision it has its drawbacks such as the model depth compared with later CNN architectures like VGGNet, GoogleNet, etc. AlexNet convolution filters were 5 by 5 which is quite large as large filters were discouraged" shortly after [179].

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Chapter Three

Methodology

This chapter introduces the research methodology for this quantitative and experimental study regarding designing and developing a mathematical morphological neural network for the classification of dental periapical radiographs to diagnose dental diseases. In a bit to answer the key research question; In what way can CNN be applied differently yet achieve great accuracy, the research work was experimented with integrating MM operations into the CNN convolution layer to diagnose dental diseases using dental periapical radiographs.

This chapter describes the research methods that were used in the study; the study design, the place(s) of data collection, the various methods used to collect data, the study population, sample size, data, as well as system framework, experimental setup and the model's various algorithms.

3.2 Research Approach

This study achieved its research objectives and was able to answer the research question through a mixed research method of quantitative and qualitative approaches. The approaches allowed for the collection and analysis of the various data types that were needed to design and implement the system. The data collection and analysis methods were approached in both methods. The six common types of dental diseases to diagnose in this study were decided through a closed-ended questionnaire, where several dental diseases were listed for the participant to tick the six most common dental diseases from his professional experience. Catherine Dawson[180] in her book Practical Research Methods when explaining the advantages and disadvantages of open and close questionnaire said close questions are easy for participants to tick their opinion and by that, the likelihood of responses to all questions are increased. The results of this questionnaire were analyzed with the use of Microsoft office Excel. This quantitative method was easier as respondents didn't have to explain opinions rather, just a tick. From Hajic and Simonett comparisons of qualitative and quantitative image analysis[181], this study depended more on quantitative methods since the study involved the use of probabilistic statements such as error rates associated with identification and classification

Qualitative approach was employed in the aspect of treatment planning. The idea to apply telemedicine was exploratory as we exploited the knowledge of dental professionals on how best to apply treatment planning to the diagnosed dental diseases online. The key materials and data needed to establish an effective treatment planning were sorted from dental experts through interviews.

3.3 Research Design

This research is both experimental and exploratory. It is experimental because it attempts to experiment on integrating MM operations into the convolution layer of CNN thereby replacing the mathematics of convolution with that of set theory. The system was developed with dental periapical radiographs as the core dataset. At this point of using dental radiographs as training and testing dataset, the experiences of dental experts were explored; what they look at for in dental radiographs and the steps taken to planning a treatment.

The study is designed to reveal the possibility of shifting from the regular application of CNN algorithm on image and pattern recognition.

3.4 Data Acquisition

In every research work, data collection plays an important role. To get substantive findings in research work, necessary information is gathered through some form of data gathering methods. Usually, these data collection methods in most cases are guided by the research question formed at the onset of the research work. It is a key process of the work without which the research work remains a mere idea. There are different styles and methods of data collection but the result is the same; data is collected. The data that is acquired for this study are periapical dental radiographs and treatment planning for six common dental diseases.

We chose to use periapical radiographs because being a result of an intraoral x-ray, it is more detailed and common than the extra oral X-rays[182].

To achieve the objectives of this research work, data (secondary) was collected. Benchmark dental dataset were collected from UFBA_UESC_DENTAL_IMAGES_DEEP *and* https://data.mendeley.com/. The benchmark dataset was used for both training and testing of the model. Besides the benchmark dataset, random dataset was also collected in renowned hospitals.

In this work, we chose to use interviews and questionnaires as our key research instruments because it is one of the ways we talked to knowledgeable people one-on-one in the discipline (dentistry) we have chosen to work in. we drafted a list of questions to guide us in asking questions during the interview (see appendix A). Knowledge acquired from interviews and questionnaires guided us in developing a telemedicine software which was one of the gaps filled in previous work.

Rubin and Rubin in Qualitative Interviewing said "the researcher is looking for rich and detailed information, not for yes-or-no, agree-or-disagree response" [183]. In the light of this, we talked to knowledgeable dental experts in the listed data collection centres in Section 3.4 under Site and Participant Selection**,** which certainly made us explore thoroughly dental diseases and related treatment plans, which can be transformed into an abstract machine to help experts confirm their subjective diagnosis, upcoming dental doctors learn and the society at large to benefit from.

Besides in-depth qualitative interviewing and questionnaires, we also got data through participation. This was to enable us to get familiarized with the various people (dental doctors, dental assistants, dental technologists, etc.) involved in dentistry, the language, and allow future interviewees to get to know us before we start asking them questions. Another excellent reason is building trust and a comfortable interview environment.[184]

Participant observation as mentioned earlier is another major data collection instrument that we used besides other non-significant methods. The Oxford English dictionary defines observation as the ability to notice things, especially significant details. Observation in this context is a way to gather data by watching people and activities in their natural settings. Here we established a rapport so that people will go about their business as usual when we show up.

Another key data collected is the treatment plan. The treatment plan is one of the vital data needed to carry out this study. It is a very sensitive area in medical science. This is because a good diagnosis with poor or no treatment amounts to the risk of a patient's life. The key data here was the measures taken in giving treatment plans and not the treatment itself as the study didn't concern itself with the automation of drug prescription. With the knowledge acquired, we designed and developed a form to extract personal details from the patient for an online dental doctor for a treatment plan.

The above-stated methods of data collection for this study gave us a clue into how dental doctors analyze dental radiographs and how these dental radiographs are mapped to dental diseases and treatment plans.

All of these data collected formed the basis for this study as they were used for the training and testing of the model as well as develop a telemedicine application that took care of treatment planning.

3.5 Site and Participant Selection.

Dental radiographs being the core dataset play a major role in the model training. As a result, the appropriate places for data collection (dental radiographs) were renowned hospitals with instruments (digital X-ray machines) to get radiographs of dental patients. The hospitals we applied for data collection were;

1. Lead city University Hospital, Ibadan
2. Federal College of Dental Technology Enugu, Enugu State.
3. Lily Hospital Warri
4. Dentoba Dental Clinic, Warri
5. Teem Clinic & Dental Services, Ekpan, Warri.
6. Dental Centre, Military Hospital, Awolowo road, Ikoyi, Lagos

7. 68 Nigerian Army Reference Hospital Yaba, Lagos State.
8. Central Hospital, Warri, Delta State.

We applied to the above-mentioned hospitals with a letter of introduction (letter in appendix A) from the Head of the Department of Computer Science Lead City University, our ethical code, and a copy of our research proposal. Our application went through the ethical committees of the various hospitals after which we were invited for interview at different times by the above listed hospitals/clinics. Among the listed data collection centres, Lily hospital gave us full approval for data collection through email. (email copy from Lily hospital found in appendix B) while the rest of the data collection centres verbally approved our applications.

On Time factor, data was collected in all of the hospital/clinics except List numbers 6, 7, and 8. We got Digital data in Lead City University Hospital and Lily hospital while the rest were hardcopy periapical X-ray images.

The first hospital visited is Lily Hospital. Lily hospital is located at Warri central, Warri, in Delta state of Nigeria. It is a multi-specialty hospital with state-of-the-art facilities and equipment. With these state-of-the-art facilities and equipment, data collection was easy as we transferred over two thousand digital dental radiographs from a DICOM file to our storage facility (external hard disk). DICOM is an acronym for Digital Imaging and Communication in medicine. It is a format internationally accepted for the retrieval, storage, viewing, and transfer of medical images. It serves as a file format and networking protocol. Images stored in DICOM format are viewed using DICOM viewers (computer software applications that can display DICOM images) A typical DICOM file contains besides the images, the patient's other information such as name, sex, ID, and birth date.

Data collection from the remaining hospitals on the list was cumbersome as dental radiographs were scanned physically with a scanning machine and stored in our storage facility.

Dentoba Dental Clinic and Teem Clinic & Dental Services are also Warri-based hospitals, at Refinery Road and Ekpan respectively.

Dental Centre, Military Hospital, Awolowo road, and 68 Nigerian Army Reference Hospital are military hospitals located at Ikoyi and Yaba respectively in Lagos State.

Federal College of Dental Technology Enugu is in the southwest of Nigeria. It is a training Institution for Dental Technologists and Therapists. It also provides Clinical Services for Oral Health-related problems in the area of preventive, Curative, and Restorative Dentistry.[185]

In choosing participants for our data collection, we adopted convenience and purposive sampling methods. It was a most convenient sampling method for us because most of the hospitals we visited, were attended to by the people in charge of the various dental departments. Therefore, they were the most accessible to us. We also adopted the purposive sampling method as what we needed was patients' folders with dental radiographs. And so, we requested to work with less-than-doctor staff who could just sort out folders with radiographs for us. The reason we choose this approach was that we are seeking participants who have knowledge or idea of most of what we needed. The doctors are not in a better position to provide us with such materials.

3.6 Data Sorting/Analysis.

Data collected from their various sources without being organized and structured remains mere figures useful for nothing. For proper decision-making, useful information is extracted from collected raw data through data analysis.

Qualitative data analysis encompasses the process that qualitative researchers employ to make sense of their data.[186] The reason why data was gathered from several hospitals is that training a convolutional neural network system requires several data. As a result, several data were collected in their thousand.

The physical data were collected with a scanning machine. The dental x-ray films are of three sizes.

(1) size 0 for small children (22 mm × 35 mm).

(2) size 1, which is relatively narrow and used for views of the anterior teeth (24 mm × 40 mm)

(3) size 2, the standard film size used for adults (30.5 mm × 40.5 mm)

We choose to use the biggest size which is the size 2, the standard film size used for adults (30.5 mm × 40.5 mm). Therefore, the folders of adults were sorted for the data collection. Dental radiographs of a folder were arranged collectively in a scanner and scanned as shown in Figure 3.1. The collectively scanned films were cropped into their films as shown in Figure 3.2a, b, c and d

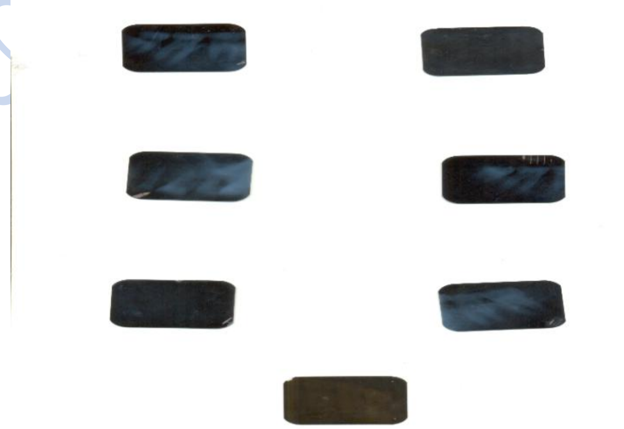
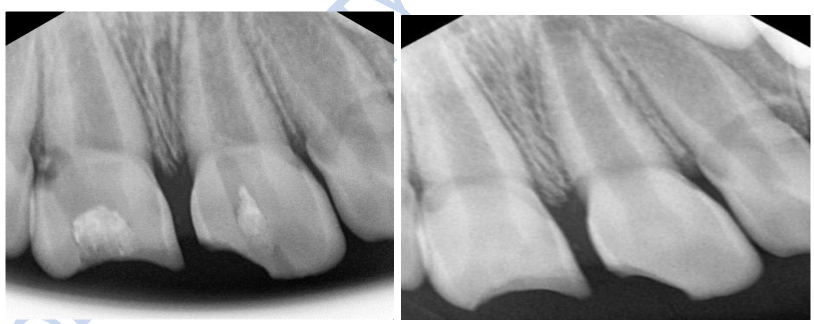


Figure 3.1 Scanned standard film size periapical radiographs

a b c d

Figure 3.2 a-d cropped images of periapical radiographs

There were also digital radiographs that were collected from hospitals operating on digital X-ray machines. All that we did was copy the images from the hospital storage into our storage. The digital images were clearer compared to the scanned images. Below in Figure 3.3a-d are some of the digital images.



a b

c d

Figure 3.3a-d Dental images of Digital Radiographs

The dental radiographs collected were sorted and categorized based on;

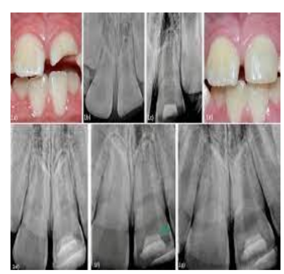
- **a.** Dental disease types
- **b.** Location of the dental disease
- **c.** The tooth /teeth affected.

3.6.1 Dental Disease Radiographs and Interpretation

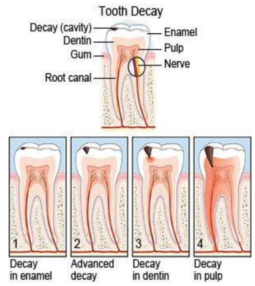
For this study, we concentrated on training the model with six common dental diseases. The reason for limiting the dental diseases to six is because each disease's type radiograph is needed in their thousands to train our system. The more dental disease radiographs we needed, the more time and dental practitioners' attention needed. All of these were a major bottleneck in our dental radiograph data acquisition process, hence the limitation to six dental disease type radiographs. The dental disease types in Figures 3.4, with a photo to depict them were chosen for the reason that they are X-ray visible dental diseases.

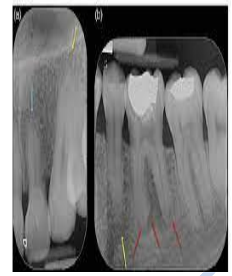
Dental caries

Dental apical cysts



Fractured tooth





Impacted tooth   Dental Cavities   Periodontitis.

Figure 3.4 Dental disease types

Source: https://www.drugs.com/cg/dental-cavities.html

3.6.2 Dental Periapical Radiograph Noise Removal

The dental radiographs collected had low contrast and so, there was an obvious need to sharpen them. This study aims at using enhanced medical images to train the system model. The model was provided with filtered images as training data to enhance the learning speed. This in turn improved the classification accuracy of the model.

3.7 Experimental Setup

The model is developed to classify six dental diseases through periapical dental radiographs. Each of these six dental diseases has its peculiar pattern and is different from the others. Some basic components make up a dental image; teeth and gum on the external. The diseased portion either the tooth or gum is the area of interest with which the model is trained to learn to give an accurate classification. To extract areas of interest from the images, the location of the diseased portion of the image, the size of the diseased portion, and the orientation of the diseased portion were key factors that were put into consideration.

Extracting the diseased portion of the dental radiograph helps also to reduce the dimension of the image**.** First, all the dental images were resized to 256 x 256 binary images. Every image passes through a denoising process with the application of MM operators for proper detection of areas of interest to be extracted.

The morphological feature extraction tool embedded in the CNN model was developed using dilation, erosion, and opening, and closing operators of mathematical morphology.

The objects of our images were represented as set points where each element of the set is a vector with x and y coordinates.

To remove the presence of internal noise from our images, we first applied dilation to the images. We started by defining a 3x3 mask (B), otherwise known as a structuring element with an origin t, with which we dilated the image X. The structuring element acted as a convolution mask.

Dilation operation was first applied to the images to expand some of the small areas thereby enlarging some noisy areas as shown in figure 3.5

Dilation is defined as;

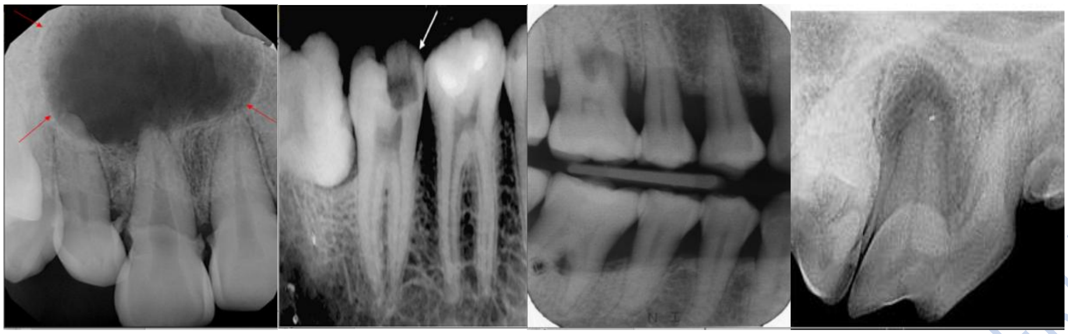
$$X \oplus B = \{P \in Z^2 \mid p = x + b, \\ x \in X, b \in B\}$$

Where;

X = set points of the image

B = set points of structuring element

P = summation of the Input image set points (X $\{x_1, x_2\}$) and the structuring element set points (B $\{b_1, b_2\}$) at particular points.



a b c d

Figure 3.5 Noisy dental images

a b c d

Figure 3.6 Dilated dental images

a b c d

Figure 3.7 Eroded dental images

The images used in this study are represented as sets of points in two a dimension space Z^2, hence every pixel point in both our images and structuring element is represented by an ordered pair of pixel values X $\{x_1, x_2\}$ for the images and B $\{b_1, b_2\}$ for the structuring element. Consequent upon this, the application of MM is based on set theory.

Here, vector addition of the image set points and the structuring element set points were carried out. All the locus of points that satisfied the dilation equation is the dilated pixel sets.

The dilation process takes care of all internal noises as well as expanded the boundary of the image depicted in Figure 3.6. After the dilation operation on the input image, dilated images were eroded as shown in Figure 3.7 to clean the background by eliminating some noisy areas at the same time filtering out some boundary pixels added to the image during dilation.

Erosion is defined as:

$$X \ominus B = \{P \in Z^2 | \, p + b \in X \quad \text{For every } b \in B\}$$

Where;

X = set points of image

B = set points of structure ng element

P = point set of X

b = point set of B

p + b = Vector addition of input image set points (X $\{x_1, x_2\}$) and the structuring element set points (B $\{b_1, b_2\}$) at particular points.

P = Result of $\boldsymbol{p + b}$

The erosion formula says that p + b must be within our image set points for every b $\in$**B**

Using the above formulae, the expanded boundaries of the dilated images eroded because those set points did not satisfy $\boldsymbol{p + b \in X}$.

For contour smoothing of the images, a combined operation of erosion and dilation was applied. First, combination of erosion followed by dilation with the same structuring element, a combination termed morphological opening.

Morphological opening operation is the opening of set X by a structuring element B which is defined as;

$$X \cdot B = (X \ominus B) \oplus B.$$

Above formula is interpreted as morphological opening equals the erosion of X by B, followed by the dilation of the result by the same structuring element B.

With the defined structuring element, images were first eroded which shrank the images but removed all unwanted elements from the images. The shrunk images were followed by a dilation operation with the same structuring element. The dilation operation compensated for the shrinking thereby expanding the shrank images. It restored the shapes to their original sizes.

Next, we applied dilation followed by erosion using the same structuring element, a situation known as morphological closing,

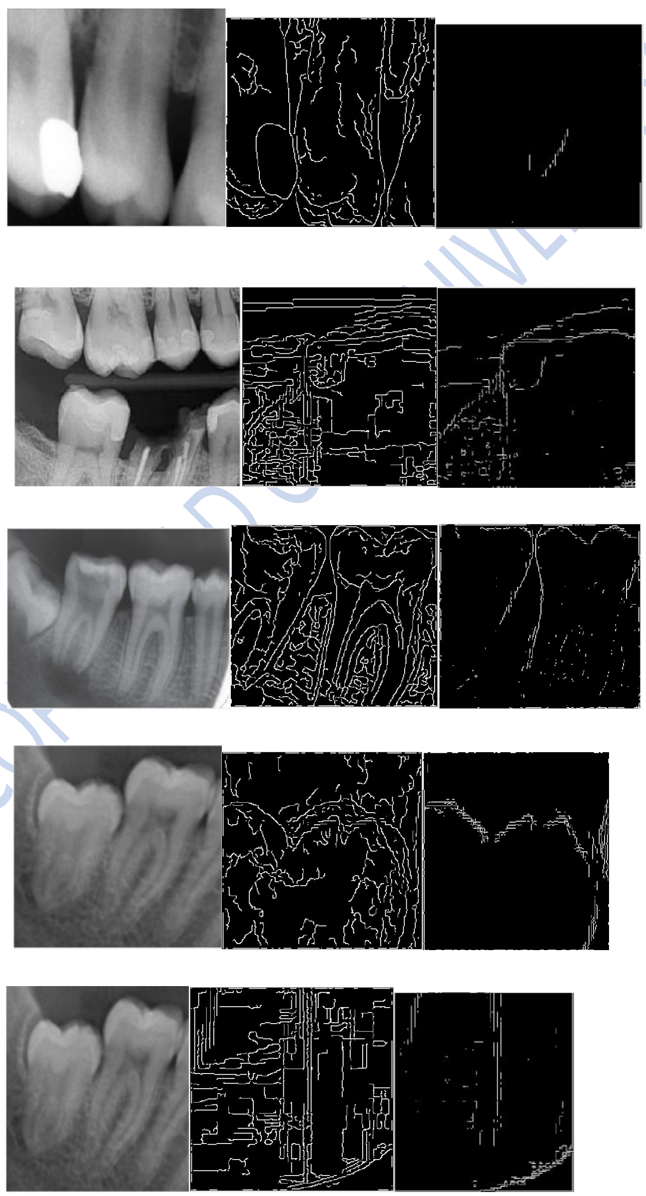
The closing operation is the closing of set X (set points of the image) by the structuring element B (set points of the structuring image), defined as;

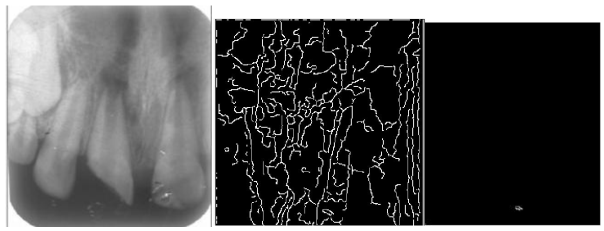
$$X \cdot B = (X \oplus B) \ominus B$$

This is interpreted as morphological closing equals the dilation of X by B, followed by the erosion of the result by the same structuring element B.

The morphological opening is useful for removing small objects and thin lines from an image while preserving the shape and size of larger objects in the image.

In a summary, the morphological opening got rid of all unwanted objects from the images while preserving the shape and size of the useful objects. The morphological closing operation takes care of any internal noise present in any of our training and testing images' object regions. Figures 3.8 and 3.9 below shows some dental images with morphological effects





Original images   Eroded/dilated images

Figure 3.8 Morphological operation effects of dental Radiographs.

3.7.1 Model Training

The model is developed with 3 MM convolution layers, 3 pooling layers, a fully connected layer and a softmax layer. Each of the MM convolution layers has 32 filters with dimensions 3 x 3 and a stride size of 3.

The conventional convolution layer which is the brain behind CNN does multiplicative process of its input values with corresponding linear weights and takes an aggregate of the weighted input as depicted by the gold colour portions of figure 3.9.

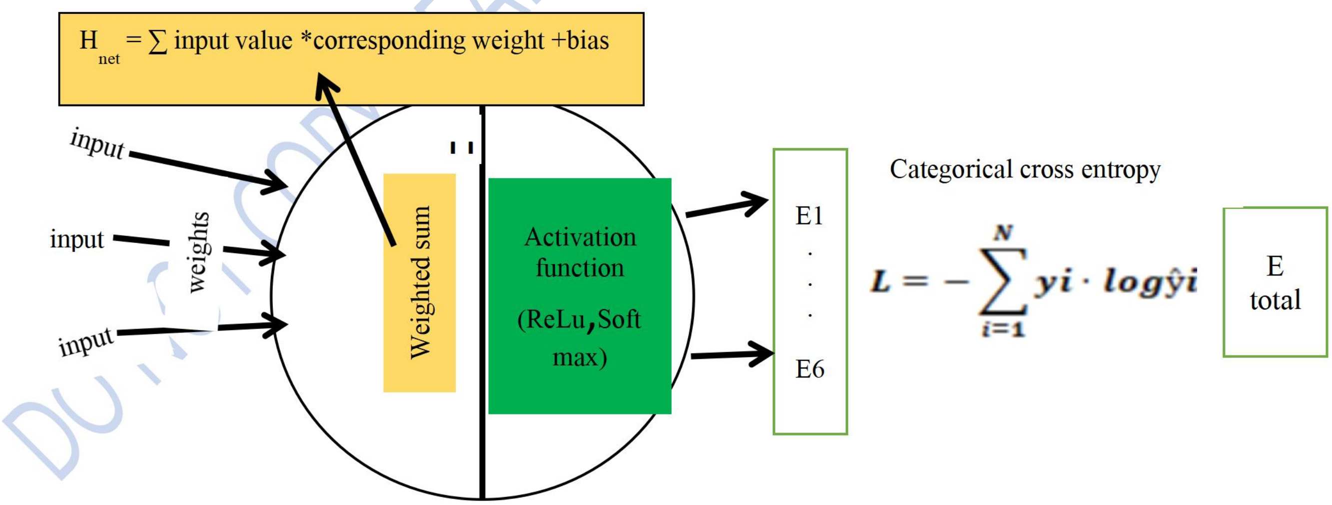


Figure 3.9 Graphical representation of CNN forward propagation

The weighted sum is passed through a non-linear activation layer depicted by the green coloured portion of Figure 3.9 to get an output of the node H. In this layer, an element-wise operation is performed in which all negative pixels are set to zero (0).

f(x) = max (0, x) is applied to every value in the summed up weighted input data. If the function receives any negative input, zero (0) is returned; but if it receives any positive value x, it returns that value. As a result, the output has a range of 0 to infinite.

ReLU introduces non-linearity to the model's network and generates a rectified feature map. For this study, we choose ReLU over other activation functions because of its advantage over the others like sigmoid and hyperbolic tangent activation functions which have a vanishing gradient problem.[187] This step is carried out on every node in the network using the output of a layer as input to the next layer. At the output layer, the individual output neuron errors are calculated by taking a difference between the ideal output and actual output through the application of optimization function. These output errors are summed $E_1+E_2+E_3+E_4+\ldots.E_n$ to give the total error of the model.

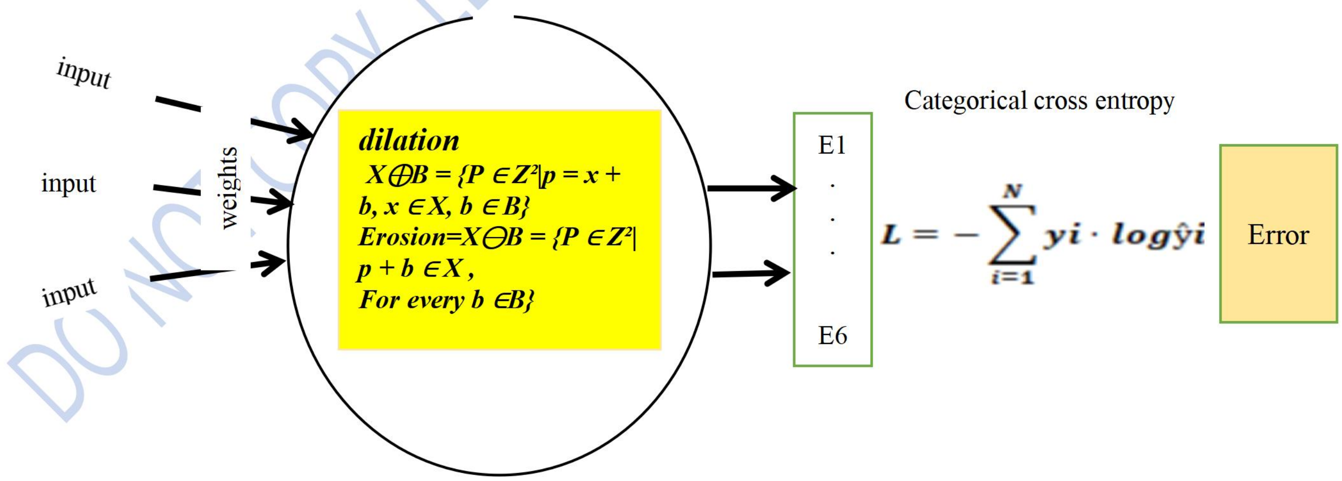


Figure 3.10 Graphical representation of MM-NN forward propagation

The convolution process of CNN as depicted in figure 3.9 is replaced with set-based MM operators; dilation, erosion and a combination of both (opening and closing) in Figure 3.10.

MM operators, dilation and erosion as defined in figure 3.10 depicts an image "X" under process being probed by a structuring element "B".

Where "X" and "B" are set points of the image and the structuring element respectively in Z^2 Cartesian grid as already explained. As depicted in figure 3.10, MM-NN filters are non-linear, therefore have no need to pass through an activation layer or process like a CNN model. Dilation and erosion were used at the initial layers to identify simple structures while the combination of both (opening and closing) was used to identify complex structures.

The model is designed to extract areas of interest from the dataset using MM operations. First, we set a learning rate of 0.001 for the model. The learning rate is set small so as not to have over- fitting and then an objective function known as the loss function for the model was defined also. The MM-NN layer inputs were probed with 32 filters of 3x3 dimensions with a stride of 3 and valid padding. To avoid partial processing of the image, valid padding was introduced. Valid padding makes every pixel of the image valid so that the input image can get fully covered by the filter. Each MM-NN layer is followed by a pooling layer. At the pooling phase, max-pooling was used in all the 3 layers. The feature maps obtained after the MM-NN convolution were max-pooled using a pooling stride of 2, 32 filters of 2x2 size to down-sample the MM-NN output. The down-sampling causes a drastic reduction in the image size thereby bringing about a reduction in spatial dimension.

The last pooling layer output is converted to a vector as input to a fully connected layer, then through a softmax activation layer to classify the images according to their classes in a one-hot-encoder.

3.7.2 Output Generation.

This model is trained to use one-hot encoding; hence categorical cross-entropy is used as loss function.

The fully connected layer of this model receives input volume from the output of the last pooling layer. The fully connected layer of this study is a combination of different stages;

1. The first stage receives the output of the last pooling layer as input and flattens it to a one-dimensional layer (1D).
2. The next stage or process is another layer that received the flattened data and passed it through a linear function (also known as affine function) with an added bias as a constant. Mathematically expressed as;

$$y = f(Wx + b),$$

where;

y = output,
x = input,
W = weights used in for the linear combination,
b = bias
f = activation function.

3. The final output was then passed through a softmax activation layer for classification.

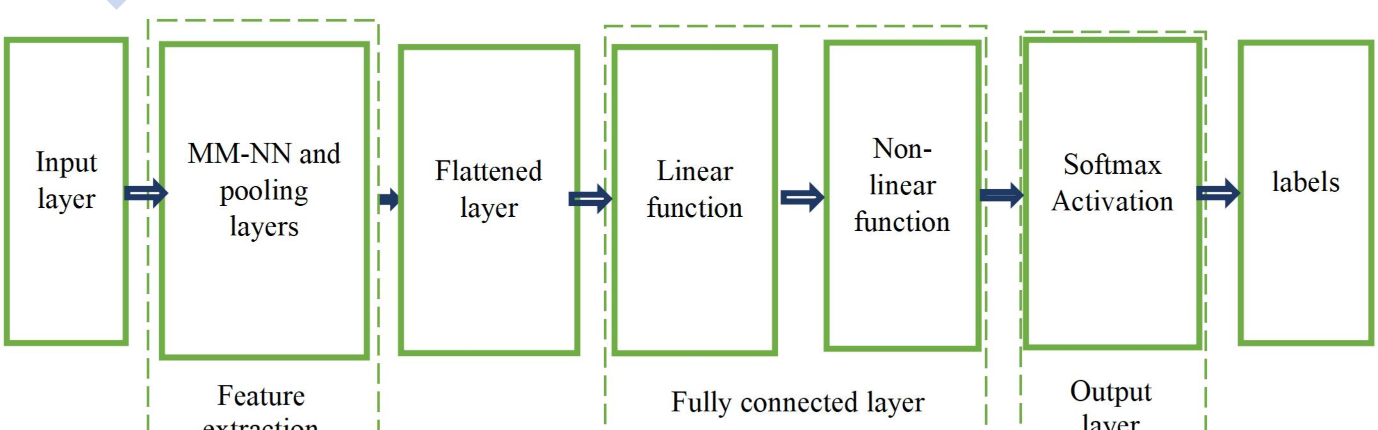


Figure 3.11 Data flow from input to output layer

As demonstrated graphically in figure 3.11, a summary of data flow from the input to the output and classification of the model. The model received dental images as input at the input layer. Areas of interest extracted for learning at the MM-NN layer. Extracted feature maps are spatially reduced at the pooling layer. Pooled feature maps flattened and passed through linear and non-linear functions at the fully connected layer. And finally a non-linear activation function, softmax was used for the classification.

3.7.3 Model Parameter Adjustment in Backward Propagation

1. **CNN back propagation**: During the forward propagation, data was propagated in a batch size of 16 and from the outcome, the lost function which is the distance between real value Y and the predicted value y-hat was calculated using *Categorical* cross-entropy.

$$L = -\sum_{i=1}^{N} y_i \cdot \log \hat{y}_i$$

Where;

L= Difference between system's predicted value, that is, outcome of softmax and expected value.

N= the number of classes; in this case, the number of classes is 6.

y = Expected value

$\hat{y}$ = predicted value which is the softmax outcome

i = *i*-th sample in a set

Categorical cross-entropy is used to calculate the loss in this study as it is a multi-class classification problem where a given sample is classified into one of multiple classes. The model predicts the likelihood of input data belonging to one of a defined number of classes and then cross-entropy takes the output probability and measures the distance from the true value and gives the loss function.

Having calculated the loss which is the error, the model is back-propagated by adjusting the key parameters, (the learnable weights and biases) of the model whose values were randomly initialized in the first layer of the model.

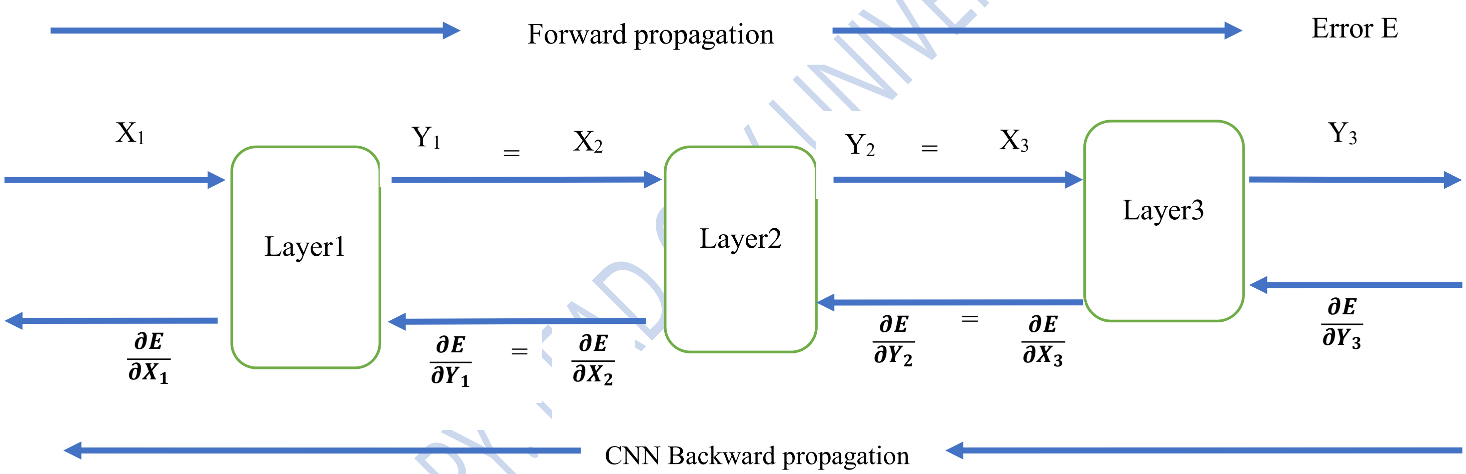


Figure 3.12 Categorical cross-entropy illustration

the gradient of the loss function is calculated with respect to the weights and biases of the model using a mini-batch gradient descent algorithm. The weights of the model are iteratively adjusted to reduce output error until the model reached a desired output. The relationship between the model's error and each of the learnable weights is a derivative $\frac{\partial E}{\partial W}$ that measures the extent or degree to which a slight difference in weight causes a change in the error as demonstrated in Figure 3.12. The learnable weights adjustment is done when a l layer is given the derivative of its layer's error E with respect to its output Y ($\frac{\partial E}{\partial Y}$), It gives back the derivative of error E with respect to its input X ($\frac{\partial E}{\partial X}$).

In order to update the parameters, the layers compute the derivative of the error E in respect to the weight ($\frac{\partial E}{\partial W}$) and the derivative of error E with respect to the input X ($\frac{\partial E}{\partial X}$).

Applying the chain rule, $\frac{\partial E}{\partial W}$ can be derived thus;

$$\frac{\partial E}{\partial W} = \frac{\partial E}{\partial Y} * \frac{\partial Y}{\partial W}$$

Where;

$\frac{\partial E}{\partial W}$ = derivative of error E with respect to weight W.

$\frac{\partial E}{\partial Y}$ = derivative of error E with respect to output Y

$\frac{\partial Y}{\partial W}$ =derivative of output Y with respect to weight W

And $\frac{\partial E}{\partial X}$ can also be derived thus;

$$\frac{\partial E}{\partial X} = \frac{\partial E}{\partial Y} * \frac{\partial Y}{\partial X}$$

Where;

$\frac{\partial E}{\partial X}$ = derivative of error E with respect to input X

$\frac{\partial E}{\partial Y}$ = derivative of error E with respect to output Y

$\frac{\partial Y}{\partial X}$ = derivative of output Y with respect to input X

After calculating $\frac{\partial E}{\partial W}$, the various learnable weights are updated with their new values thus;

New weight = old weight – step size

Where

step size =learning rate *$\frac{\partial E}{\partial W}$

learning rate in this study = 0.001.

The model is a sequential network, therefore, the output Y_1 of one layer (network) is the input X_2 of the next layer.

This also means that the derivative of error E with respect to the input $\frac{\partial E}{\partial X_2}$ of one layer is the same as the derivative of the error E with respect to the output $\frac{\partial E}{\partial Y_1}$ of the previous layer. So, when a layer is given the derivative of error E with respect to output Y $\frac{\partial E}{\partial Y}$ and returns the derivative of error E with respect to input $\frac{\partial E}{\partial X}$ to the previous layer, then the layer before it receives it as $\frac{\partial E}{\partial Y}$ and by so doing, every parameter in every layer is updated.

2. **MM-NN back propagation:** The back propagations of CNN and the MM-NN model are operated in the same fashion. As explained in the CNN back propagation, the MM-NN model's predicted outputs are compared with target output from which a loss function is calculated. The loss in MM-NN model is equally affected by the input "x" and structuring function "w" through its output "z".

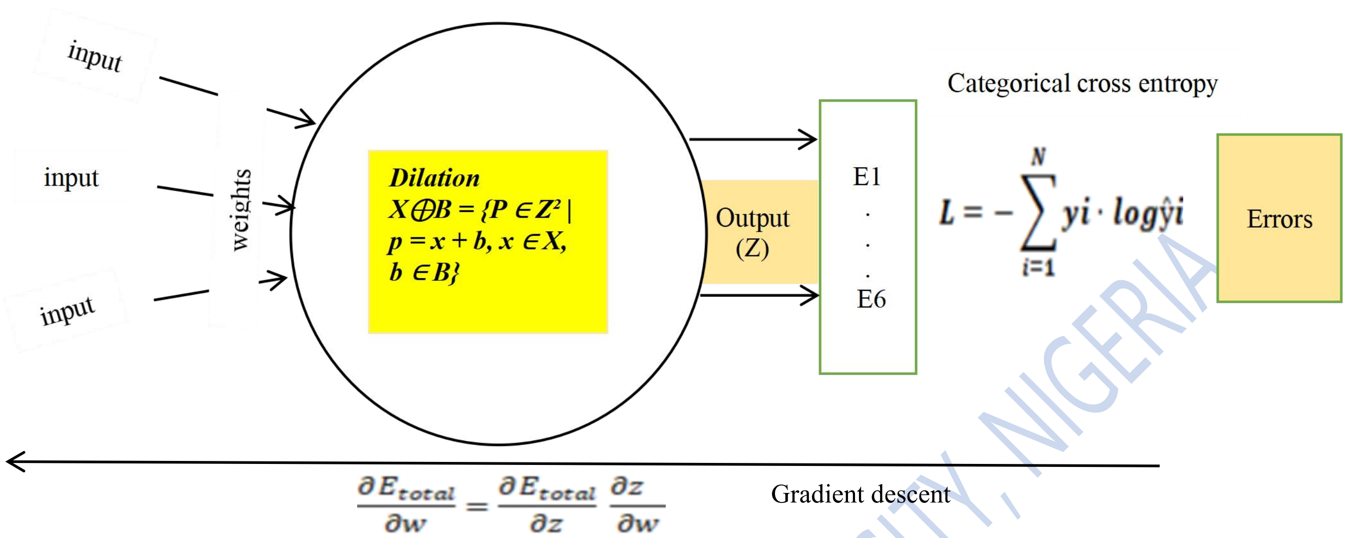


Figure 3.13 Graphical representation of dilation back propagation

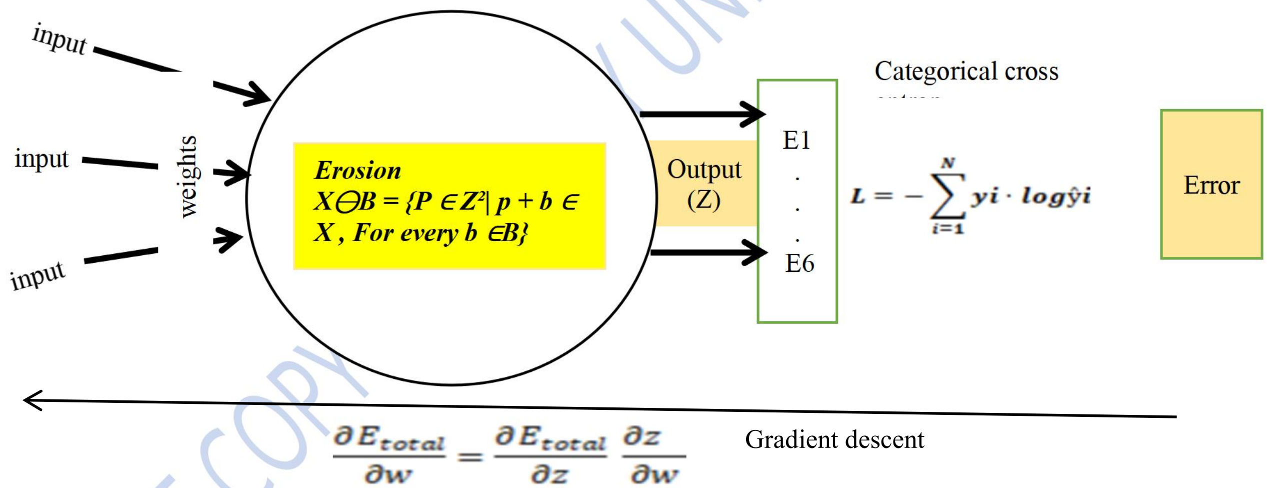


Figure 3.14 Graphical representation of erosion back propagation

In figures 3.13 and 3.14 above,

$\frac{\partial E_{total}}{\partial w}$ = Derivative of error with respect to structuring function w.

$\frac{\partial E_{total}}{\partial z}$ = Derivative of error with respect to output z.

It is the back propagated gradient from subsequent node that acts as input to the prior node.

$\frac{\partial z}{\partial w}$ = Derivative of output with respect to structuring function w.

It is also the computed dilation or erosion at the various nodes.

Using chain rule, $\frac{\partial z}{\partial w}$ is calculated first with which result $\frac{\partial E_{total}}{\partial z}$ is calculated and finally $\frac{\partial E_{total}}{\partial w}$ which is the loss with respect to structuring function w. The parameter adjustment and updating of weights reiterates until the loss converges.

3.7.4 CNN Algorithm

1. Get Training instance
2. Initialize training parameters
3. Compute: $y = \sum_{i=1}^{n} w_{ij} k_{ij} + b$
4. Compute: $\boldsymbol{Loss} = -\sum_{i=1}^{N} \boldsymbol{yi} \cdot \boldsymbol{log\hat{y}\ i}$
5. Compute: $Derivative = \frac{\partial Error}{\partial weight}$
6. Update weight: new weight = old weight – step size
7. Until Loss has converged, repeat steps 4-6

3.7.5 MM-NN algorithm

1. Get Training instance
2. Initialize training parameters
3. Compute: (F⊕h(s)=max{f(n)+h(s-x)})
   or minimum (FΘh(s)=min{f(s+n)-h(n)})
4. Compute: $\boldsymbol{Loss} = -\sum_{i=1}^{N} \boldsymbol{yi} \cdot \boldsymbol{log\hat{y}\ i}$
5. Compute Derivative: $\frac{\partial E_{total}}{\partial w} = \frac{\partial E_{total}}{\partial z} \frac{\partial z}{\partial w}$
6. Update weight: new weight = old weight – step size
7. Until Loss has converged, repeat steps 4-6

3.7.6 System Algorithm

1) Define the MM-NN model
2) Get dental images from source.
3) Load dental images dataset
4) Resize images; 256*256
5) Split (3) into 70% training dataset and 30% testing dataset
6) Label 70% training dataset into six dental diseases (caries, fractured tooth, dental cysts, dental cavities, periodontitis, and impacted tooth)
7) Input training dataset (256*256 pixel) into the MM-NN system input layer
8) Pass input matrix values to MM-N layer for preprocessing and feature extraction
9) Pass feature map obtained from step 9 to pooling layer for down-sampling
10) Pass down-sampled map to Fully connected layer.
11) Classify output through Softmax activation.
12) Compare predicted output with actual output.
13) Obtain loss function using categorical cross-entropy.
14) Adjust parameters using mini-batch gradient descent
15) Is output desirable?
    a) If no, repeat steps 12-14.
    b) If yes, end
16) Obtain doctor's prescription.

3.8 System Framework

Figure 3.15 is a summary of the frame work of the model. The system uses dental Periapical radiographs as its training data. The data is in the ratio of 70%:30 % where 70% is used to train the model and 30% for testing.

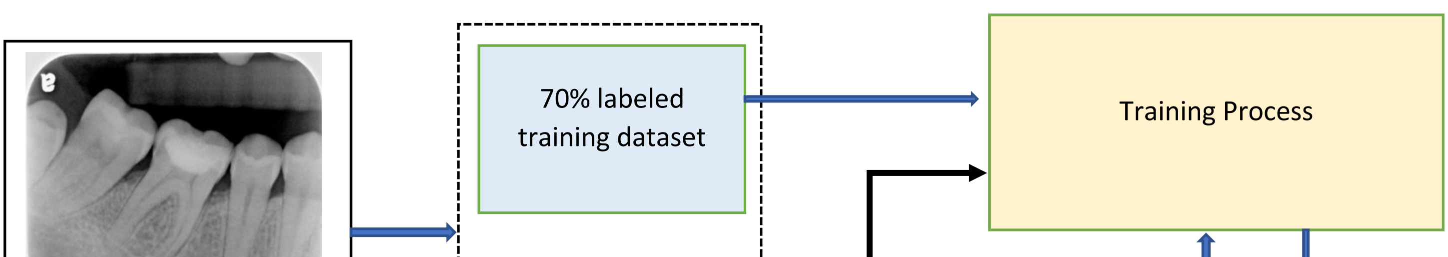


Figure 3.15 System framework

3.8.1 Training Process

Figure 3.16 is a graphical representation of the training process. The model is trained with 70% of collected data. A preprocessor is designed to receive the raw data to cleanse the data of any noise for easy training. Denoised data is passed on to a feature extractor known as MM-NN extractor to extract features of the various images for learning purpose. Extracted feature map is downsampled at the pooling layer. Downsampled feature map is flattened to a vector as input and fed to the fully connected layer through a softmax activation function for final output classification.

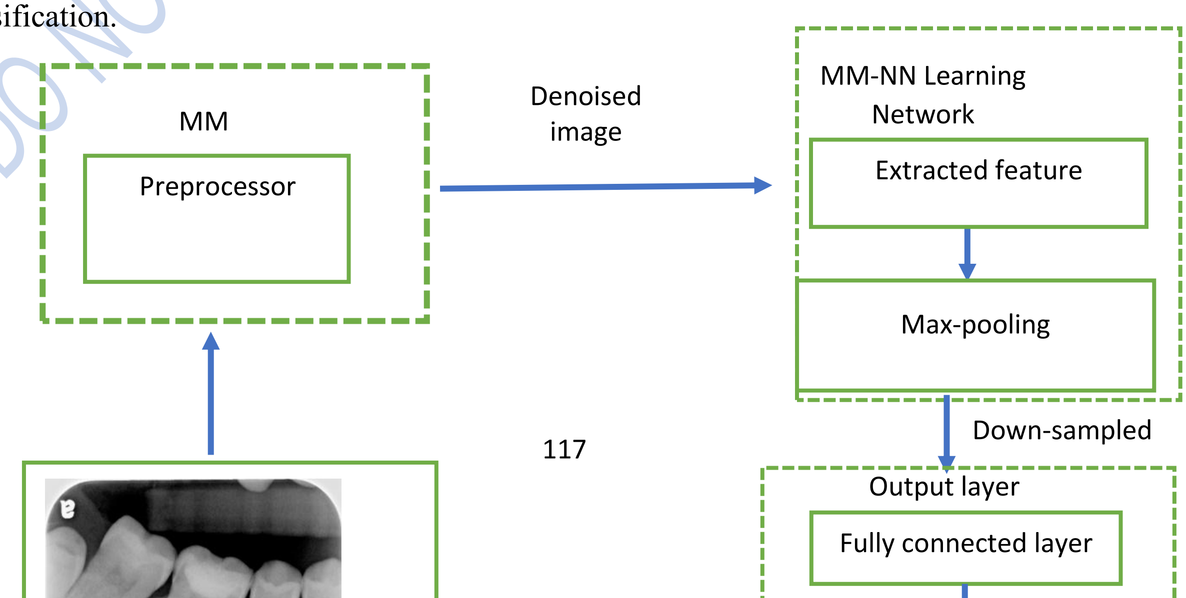


Figure 3.16 Training section of system framework

3.8.2 Testing Process

The Testing process as depicted in Figure 3.17 is a process to check how much the model has learned to identify and classify trained data. Unlike the training process where data are labeled, here unlabeled data is passed to the model. If the output is not desirable, output loss function is calculated and learnable parameters are adjusted and retraining continues until loss function is minimized drastically.

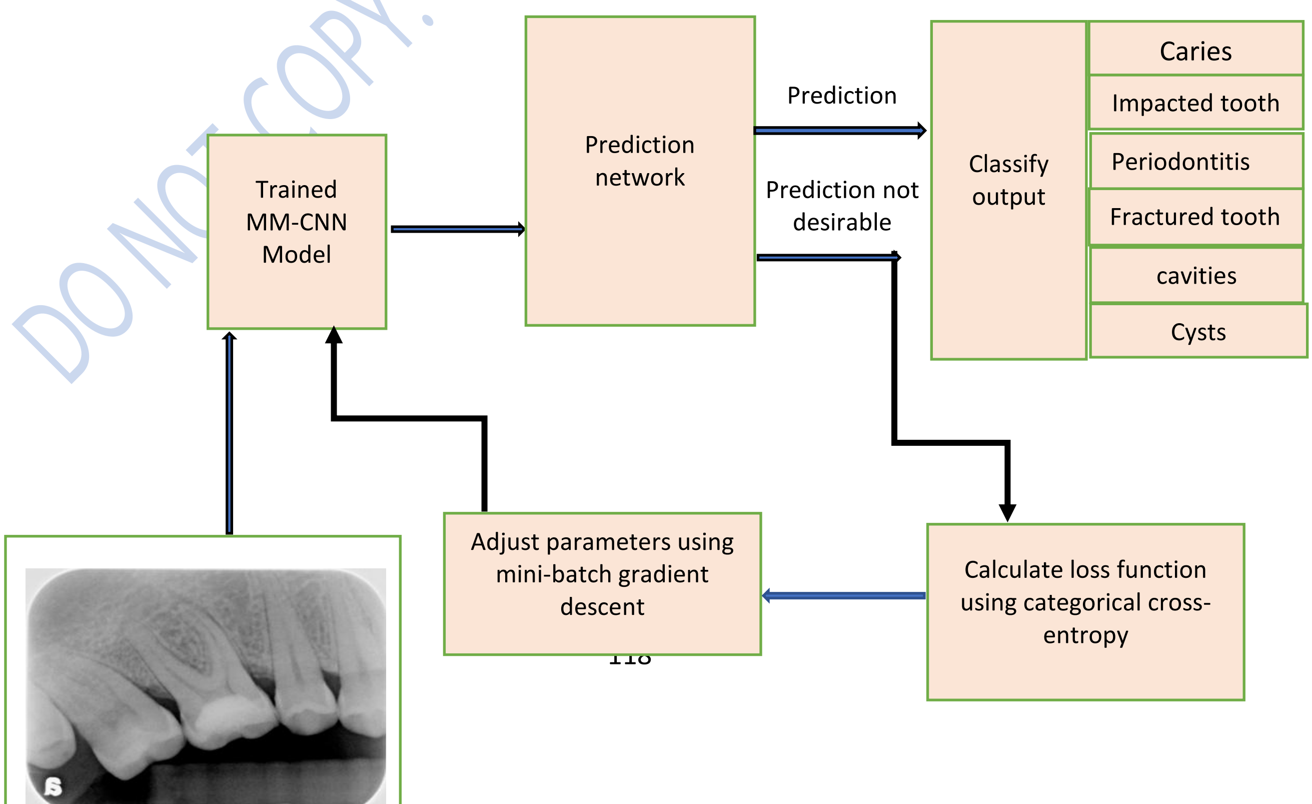
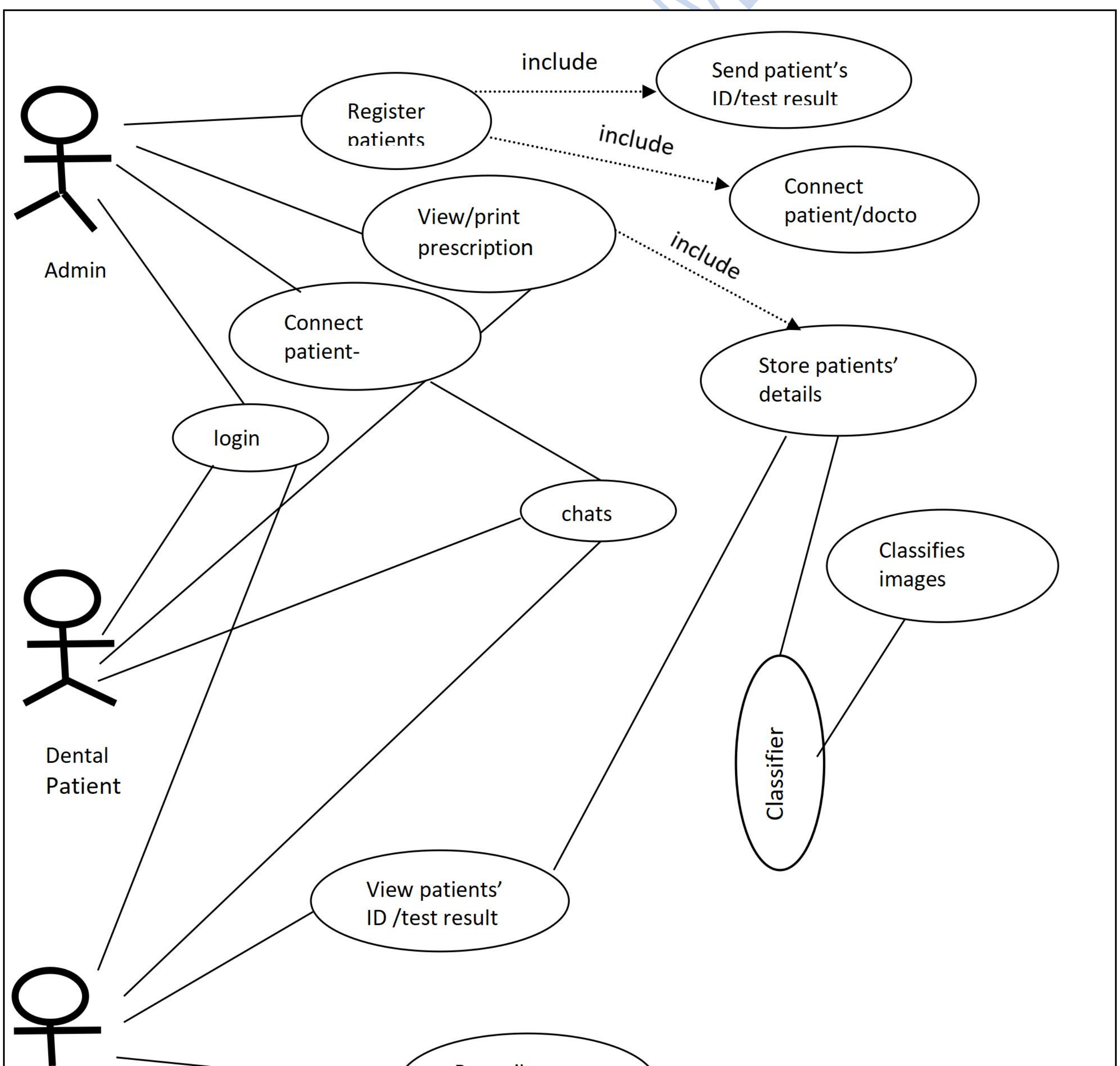


Figure 3.17 Test section of conceptual system framework

3.9 Treatment Planning

This study included a telemedicine section besides the dental image classification (otherwise dental disease diagnosis). One of the gaps to be filled in the previous study is inclusion of a treatment planning to diagnosed diseases. The telemedicine application as illustrated in a Use-Case-Diagram in Figure 3.18 is included to fill that gap. It is developed with a singular objective to provide patients an easy access to dental doctors irrespective of geographical location. The model can be deployed for use in dental clinics and training centres. A database was created to store patients' diagnostic and personal details. Dental doctors who are interested in rendering consultation services are registered with their personal and professional details. This application is developed to work in connection with the classification model. Results from the classifier are stored in a database and used as the basis for treatment planning. Patients are distributed among registered dental doctors for consultation. Listed and discussed are the outputs of the telemedicine application.


Admin
Dental
Patient
Register
patients
include
Send patient's
ID/test result
include
Connect
patient/docto
View/print
prescription
include
Connect
patient-
Store patients'
details
login
chats
Classifies
images
Classifier
View patients'
ID /test result

In this experimental study, a CNN model was developed alongside the MM-NN model with a total of 864 images. At the end of training the models, the models were tested with several random data including the 30% test data. Accuracy, precision, recall and error rate were the performance metrics used to evaluate the models. The outcomes are expressed in Figures 3.19, 3.20, 3.21 and 3.22.

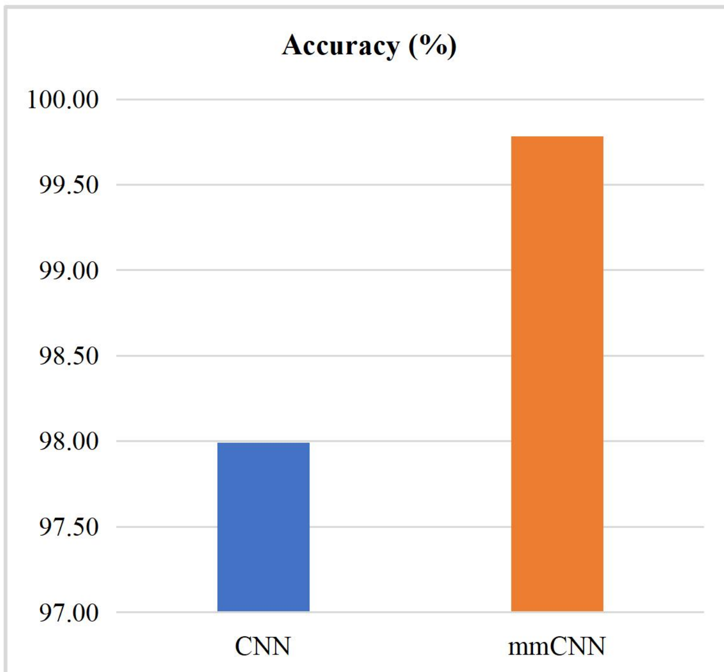


Figure 3.19 System's accuracy bar chart

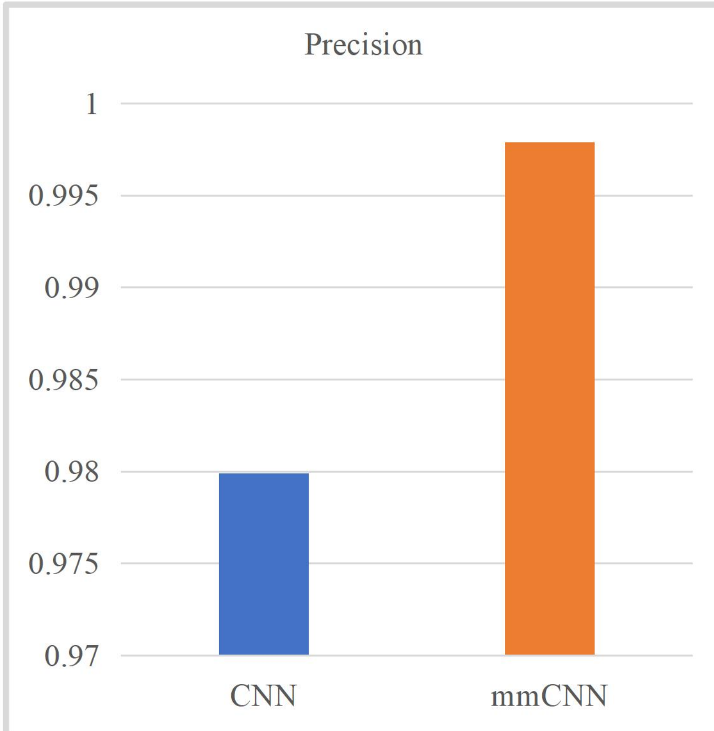


Figure 3.20 System's precision bar chart

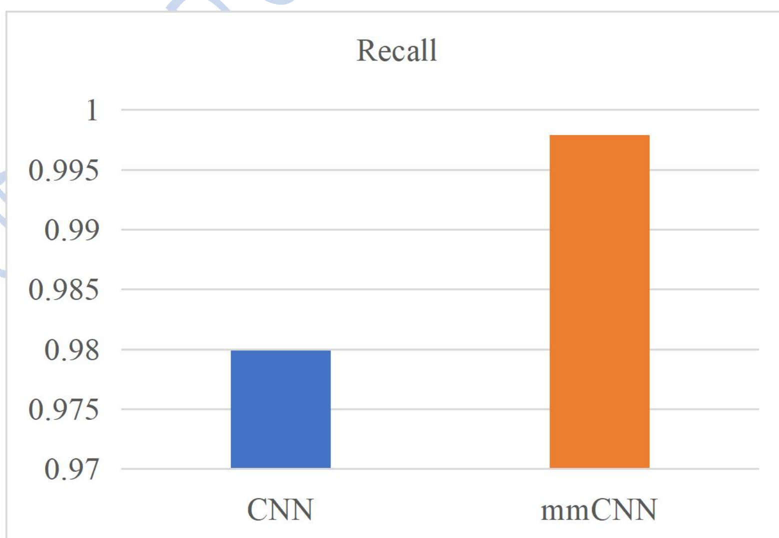


Figure 3.21 System's recall bar chart

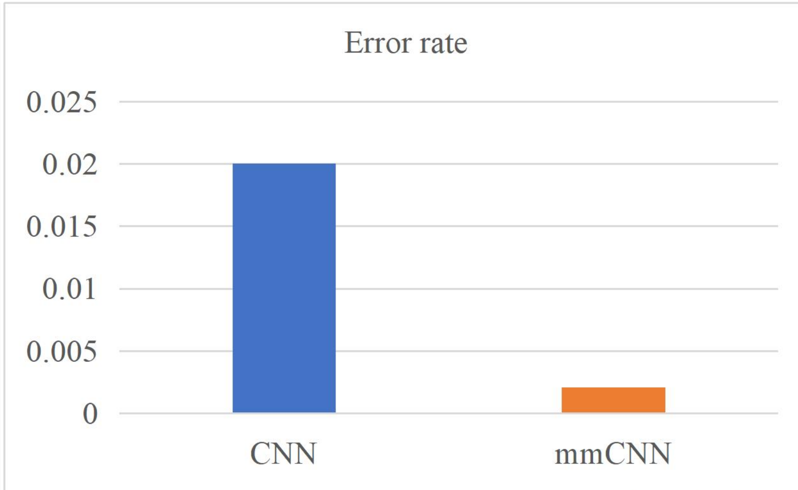


Figure 3.22 System's error rate bar chart

The metric results displayed in the above bar charts were calculated and achieved thus;

Accuracy: Accuracy tells us how often our model's classifier is correct.

It is calculated as the sum of all true values divided by total values as demonstrated in Equation 3.1 below.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (3.1)$$

Precision: How often is the model's predicted positive classification right? It is calculated as the true positives divided by total number of predicted positive values as seen in Equation 3.2.

$$Precision = \frac{TP}{TP+FP} \quad (3.2)$$

Recall/Sensitivity: The model's ability to predict the positive values correctly as shown in Equation 3.3. It is calculated as the true positives divided by total number of real positive values

$$Recall = \frac{TP}{TP+FN} \quad (3.3)$$

Specificity: Specificity as seen in Equation 3.4 corresponds to the true negative rate of the considered class. It is calculated as true negative divided by the total number of all the negative values

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (3.4)$$

Table 3.1 Metric Table of the Model

		Actual					
		dA	dB	dC	dD	dE	dF
	dA	TP_A	E_{AB}	E_{AC}	E_{AD}	E_{AE}	E_{AF}
	dB	E_{BA}	TP_B	E_{BC}	E_{BD}	E_{BE}	E_{BF}
Predicted	dC	E_{CA}	E_{CB}	TP_C	E_{CD}	E_{CE}	E_{CF}
	dD	E_{DA}	E_{DB}	E_{DC}	TP_D	E_{DE}	E_{DF}
	dE	E_{EA}	E_{EB}	E_{EC}	E_{ED}	TP_E	E_{EF}
	dF	E_{FA}	E_{FB}	E_{FC}	E_{FD}	E_{FE}	TP_F

Representing caries, fractured tooth, dental cavities, dental cyst, imparted tooth, and periodontitis with dA, dB, dC, dD, dE, and dF respectively in table 3.1, the rows of the matrix correspond to a predicted class while the column of the matrix correspond to an actual class as seen in table 3.2.

Table 3.2 Illustration of the Application of Accuracy metric

		Actual					
		dA	dB	dC	dD	dE	dF
	dA	TP_A	E_{AB}	E_{AC}	E_{AD}	E_{AE}	E_{AF}
	dB	E_{BA}	TP_B	E_{BC}	E_{BD}	E_{BE}	E_{BF}
Predicted	dC	E_{CA}	E_{CB}	TP_C	E_{CD}	E_{CE}	E_{CF}
	dD	E_{DA}	E_{DB}	E_{DC}	TP_D	E_{DE}	E_{DF}
	dE	E_{EA}	E_{EB}	E_{EC}	E_{ED}	TP_E	E_{EF}
	dF	E_{FA}	E_{FB}	E_{FC}	E_{FD}	E_{FE}	TP_F

FP (A)
Predicted as 'Positive A' but actually 'Negative A'

"TN (A)
Predicted as 'Negative A' and actually 'Negative A'

FN (A)
Predicted as 'Negative A' but actually 'Positive A'

The accuracy metric of the model as shown in table 3.2 can be interpreted thus;

- TP: Red texted diagonal values are TP values for all the classes of diseases dA-dF.
- FP: Blue coloured row 'A' apart from the red texted TP is FP for disease A. Likewise other rows, every row apart from the TP value is FP for the disease in that row.
- FN: Green coloured column apart from the TP on that column is FN for disease A. Likewise other columns for the other diseases.
- TN: Content of gold coloured broken lines is TN for disease A. TN values are the values of that disease apart from the row and coloumn that contain that disease.

Above explained metric parameters and their respective equations (1-4) were calculated thus;

$$Precision = \frac{TP}{TP + FP}$$

Where:

$$Total\ number\ of\ FP\ for\ a\ class = Sum\ of\ values\ in\ the\ corresponding\ row\ excluding\ the\ TP$$

Where FP for;

class A = $E_{BA}+E_{CA}+E_{DA}+E_{EA}+E_{FA}$

Class B = $E_{AB}+E_{CB}+E_{DB}+E_{EB}+E_{FB}$

Class C = $E_{AC}+E_{BC}+E_{DC}+E_{EC}+E_{FC}$

Class D = $E_{AD}+E_{BD}+E_{CD}+E_{ED}+E_{FD}$

Class E = $E_{AE}+E_{BE}+E_{CE}+E_{DE}+E_{FE}$

Class F = $E_{AF}+E_{BF}+E_{CF}+E_{DF}+E_{EF}$

$$Recall = \frac{TP}{TP + FN}$$

Where:

$$Total\ number\ of\ FN\ for\ a\ class = Sum\ of\ values\ in\ the\ corresponding\ column\ excluding\ the\ TP$$

Where FN for;

class A = $E_{AB}+E_{AC}+E_{AD}+E_{AE}+E_{AF}$

Class B = $E_{BA}+E_{BC}+E_{BD}+E_{BE}+E_{BF}$

Class C = $E_{CA}+E_{CB}+E_{CD}+E_{CE}+E_{CF}$

Class D = $E_{DA}+E_{DB}+E_{DC}+E_{DE}+E_{DF}$

Class E = $E_{EA}+E_{EB}+E_{EC}+E_{ED}+E_{EF}$

Class F = $E_{FA}+E_{FB}+{}_{CCF}+E_{FD}+E_{FE}$

$$Specificity = \frac{TN}{TN + FP}$$

Where:

$$Total\ number\ of\ TN\ for\ a\ class = Sum\ of\ all\ columns\ and\ rows\ excluding\ that\ class's\ column\ and\ row$$

FP for the various classes is defined already in precision

Where TN for;

class A = $TP_B+E_{BC}+E_{BD}+E_{BE}+E_{BF}+E_{CB}+TP_C+E_{CD}+E_{CE}+E_{CF}+E_{DB}+E_{DC}+TP_D+ED_E+E_{DF}+E_{EB}+E_{EC}+E_{ED}+TP_E+E_{EF}+E_{FB}+E_{FC}+E_{FD}+E_{FE}+TP_F.$

class B = $TP_A+E_{AC}+E_{AD}+E_{AE}+E_{AF}+E_{CA}+TP_C+E_{CD}+E_{CE}+E_{CF}+E_{DA}+E_{DC}+TP_D+ED_E+E_{DF}+E_{EA}+E_{EC}+E_{ED}+TP_E+E_{EF}+E_{FA}+E_{FC}+E_{FD}+E_{FE}+TP_F.$

class C = $TP_A+E_{AB}+E_{AD}+E_{AE}+E_{AF}+E_{BA}+TP_B+E_{BD}+E_{BE}+E_{BF}+E_{DA}+E_{DB}+TP_D+ED_E+E_{DF}+E_{EA}+E_{EB}+E_{ED}+TP_E+E_{EF}+E_{FA}+E_{FB}+E_{FD}+E_{FE}+TP_F.$

$$class\ D = TP_A+E_{AB}+E_{AC}+E_{AE}+E_{AF}+E_{BA}+TP_B+E_{BC}+E_{BE}+E_{BF}+E_{CA}+E_{CB}+TP_C+E_{CE}+E_{CF}+E_{EA}+E_{EB}+E_{EC}+TP_E+E_{EF}+E_{FA}+E_{FB}+E_{FC}+E_{FE}+TP_F.$$

$$class\ E = TP_A+E_{AB}+E_{AC}+E_{AD}+E_{AF}+E_{BA}+TP_B+E_{BC}+E_{BD}+E_{BF}+E_{CA}+E_{CB}+TP_C+E_{CD}+E_{CF}+E_{DA}+E_{DB}+E_{DC}+TP_D+E_{DF}+E_{FA}+E_{FB}+E_{FC}+E_{FD}+TP_F.$$

$$class\ F = TP_A+E_{AB}+E_{AC}+E_{AD}+E_{AE}+E_{BA}+TP_B+E_{BC}+E_{BD}+E_{BE}+E_{CA}+E_{CB}+TP_C+E_{CD}+E_{CE}+E_{DA}+E_{DB}+E_{DC}+TP_D+E_{DE}+E_{EA}+E_{EB}+E_{EC}+E_{ED}+TP_E.$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

3.11 Implementation Tools

Both hardware and software tools were employed in the design through implementation to evaluation of this dental disease diagnosis MM-CNN model. They both played their significant roles to make the work a success. Without speaking much, the software and hardware systems included:

Software Requirement

1. PHP: PHP is an abbreviation that initially stood for Personal Homepage. But now it is a recursive acronym for Hypertext Preprocessor. Recursive in the sense that the first word itself is a combination of two words coined by Ted Nelson[188], so the full meaning doesn't follow the abbreviation. PHP is both an open-source server-side scripting and general-purpose language that is employed by developers[189]. In this study, PHP was used as a server-side scripting language for the web development and as a general-purpose language for Graphical User Interfaces (GUIs). The popularity of PHP over the years is due to its advantages like its cross-platform nature where it can run on every OS platform be it Windows, Mac, or Linux. PHP's

original code is made available for people to build upon which also makes it an easy to learn programming language. PHP was also used in this study to connect all databases as it supports a variety of database management systems be it relational or non-relational.

2. CSS: CSS stands for Cascading Style Sheets. It is a language used to design markup languages like HTML elements. CSS was used in this study to give the appearance of the markup language document with some styles like the layout of the document, the colour, text alignment, font size, etc. The use of CSS solved the problem of the bulky, hard-to-comprehend, difficult-to-manage Hyper Text Markup Language (HTML) codes as well as the use of duplicate HTML tags.

3. JavaScript. JavaScript is one of the powerful tools for web design[190]. We used JavaScript both on the client-side and server-side of the web development to give interactive ability to the various web pages. We also used JavaScript to make forms in the telemedicine application interactive in such a way that users can response to follow-up-questions.

4. XAMPP: XAMPP is an abbreviation that stands for X (cross-platform; Windows,Linux,Mac OS X),Apache(HTTP Server), MYSQL(Database), PHP, and Perl (programming language). XAMPP is a local server that runs on a personal computer used to test clients or websites before publishing them to a remote web server. XAMPP was used to test the server software on our local computer to see how the MYSQL, PHP, Apache, and Perl projects interacted with one another. XAMPP is made up various components with each component with a unique function that makes it as a whole;

i. **Cross-Platform:** A feature that enables XAMPP to be installed on any operating system platform

ii. **Apache:** It is a cross-platform HTTP web server that is used to transport web material all over the globe. If someone requests files, photos, or documents using their browser, HTTP servers will serve such assets to clients.

iii. **MariaDB Database:** New version of XAMPP now includes MariaDB. It is a relational system database management system that provides data storage, manipulation, and retrieval, management, and deletion services via the internet.

iv. **PHP:** It is open-source server-side scripting and general-purpose language that is employed by developers.

v. **Perl:** Used for web development, graphic user interface (GUI).

vi. **phpMyAdmin:** is a database administration tool for MariaDB.

vii. **OpenSSL:** This is an open-source implementation of the Secure Sockets Layer (SSL) and the Transport Layer Security (TLP).

viii. **XAMPP Control Panel:** Assists in the operation and regulation of other XAMPP components.

ix. **Webalizer:** Keeps track of user logs and reports on usage.

x. **Mercury:** Mail server that facilitates in the management of emails across the internet.

xi. **Tomcat:**Provides JAVA functionality.

xii. **Filezilla:**Is a File Transfer Protocol Server that aids file transfer.

5. **Anaconda.** Anaconda is a free and open-source distribution of Python and R programming language. Anaconda contains the packages that are useful for data science and machine learning pre-installed with it

Anaconda also acts as environment managers. This means that with Anaconda you can create separate environments for different projects with the help of Anaconda Navigator. Anaconda Navigator is the GUI of Anaconda that enables users to create environment, launch IDE's like Jupyter notebook, Jupyter lab and Spyder.[191]

a) **Spyder**. Spyder is an open-source cross-platform integrated development environment (IDE) for scientific programming in the Python language.

The Python Spyder IDE is written completely in Python. It is designed by scientists and is exclusively for scientists, data analysts, and engineers. It is also known as the Scientific Python The Python Spyder IDE comes as a default implementation along with Anaconda Python distribution[192]

b) Tensorlow. TensorFlow is a Python-friendly open-source library for numerical computation and large-scale machine learning that makes machine learning and developing neural networks fast and easy. It was created by the Google Brain team, written in C++, Python, and CUDA and initially released in 2015to the public It uses either JavaScript or Python to provide a convenient front-end API for building applications while executing those applications in high-performance C++.[193]

TensorFlow can develop text-based applications, train and run deep neural networks for classification, perception, image recognition, voice search, discovering, word embeddings, understanding, prediction, and creation. Tensorflow is packed with so many applications such as make algorithms that can paint images, train a pc to recognize objects in an image, teach the computer to read and synthesize new phrases which are a part of Natural Language Processing and many more.[194]

a. **Hardware Requirement:** The basic hardware requirements are;

1. **Graphics Processing Unit (GPU)**

GPU is a computer chip that performs rapid mathematical calculations, primarily for the purpose of rendering images. A GPU is able to render images more quickly than a CPU because of its parallel processing architecture, which allows it to perform multiple calculations at the same time which a single CPU does not have. For the purpose of this work, we chose to use a computer system with a GPU that supports the CUDA® Deep Neural Network library (cuDNN) designed for Nvidia GPUs (Nvidia Corp. Santa Clara, CA).This will tremendously speed up training up to 75 times faster than a CPU.[195]

2 RAM: The RAM (Random-Access Memory) is a volatile Memory in the computer system that stores data and machine code currently being used. A random-access memory device allows data items to be read or written in almost the same amount of time irrespective of the physical location of data inside the memory. RAM is measured both in size and speed. RAM size determines how much temporary data the computer can store and how fast it runs. For the purpose of this study, a RAM size and speed less than 8gigabytes will result in a slow and tiresome performance. `

3 Hard disk drive (HDD). The hard disk drive is the main, and usually largest, data storage hardware device in a computer. The operating system, software titles, and most other files are stored in the hard disk drive.

The least expected size of external storage for this system to work effectively is 1tera.

Chapter Four

Results and Discussions of Findings

Having done justice to this study in previous chapters by defining and reviewing basic concepts which are fundamental, as well as the steps that were taken to implement the model, this chapter presents the output. The study in a bit to answering the research question, designed, developed and implemented a MM-NN model that replaced the summation of the product of outputs with corresponding weights ($\sum w*x +b$) with addition of outputs and corresponding weights and taking maximum ($F\oplus h(s)=\max\{f(n)+h(s-x)\}$) or minimum ($F\Theta h(s)=\min\{f(s+n)-h(n)\}$) as the case may be in the convolution layer of CNN. In filling the gaps of previous study, treatment planning was also included in the form of a telemedicine application. The telemedicine application is designed to serve the "medically underserved populace" of developing countries.

4.1 Results

One of the key purposes of this study is to develop an intelligent system to diagnose dental radiographs through the experimentation of shifting from the conventional CNN algorithm to MM-NN algorithm. This shifting is the change from the result of a "multiplicative process" of the strength of the electric potential of a signal traveling along an axon on which CNN is built, to an "additive process" from which the mechanism of postsynaptic membranes only accepts signals of certain maximum strength.

The system was successfully designed, developed and implemented from scratch through the employment of mathematical morphological tools to achieve the additive process of the postsynaptic membranes. This section outlined the various training results and demonstrated the steps on how the system is built.

4.1.1 Outcome of Varying Filter sizes

During the training phase of the model, the depth of each layer of both the CNN and the MM-NN were varied starting from 8, 16, 32 and 64. These depths represent the filter numbers applied to probe the training images. Table 4.1 is an outcome of the various depth outcomes. From the table 4.1, it is clear that layer depths 32 and 64 outputted similar accuracy results. Therefore, for reasons of training and computational time, depth 32 became an obvious depth to adopt; hence, 32 filters were used in all the layers of the model. Figure 4.1 is a graphical representation of table 4.1.

Table 4.1 Accuracy Using Different Filter Sizes

Diseases	64	32	16	8
Dental caries	0.9907985	0.9907984	0.9815465	0.9707984
Dental Cysts	0.9997654	0.9997654	0.9902356	0.9697654
Fractured Tooth	0.9989684	0.9989684	0.9757938	0.9489684
Periodontitis	0.9999688	0.9999687	0.9688943	0.93997679
Impacted tooth	0.9987994	0.9987994	0.9889999	0.95657903
Dental Cavities	0.9979998	0.9979998	0.9959534	0.9135799

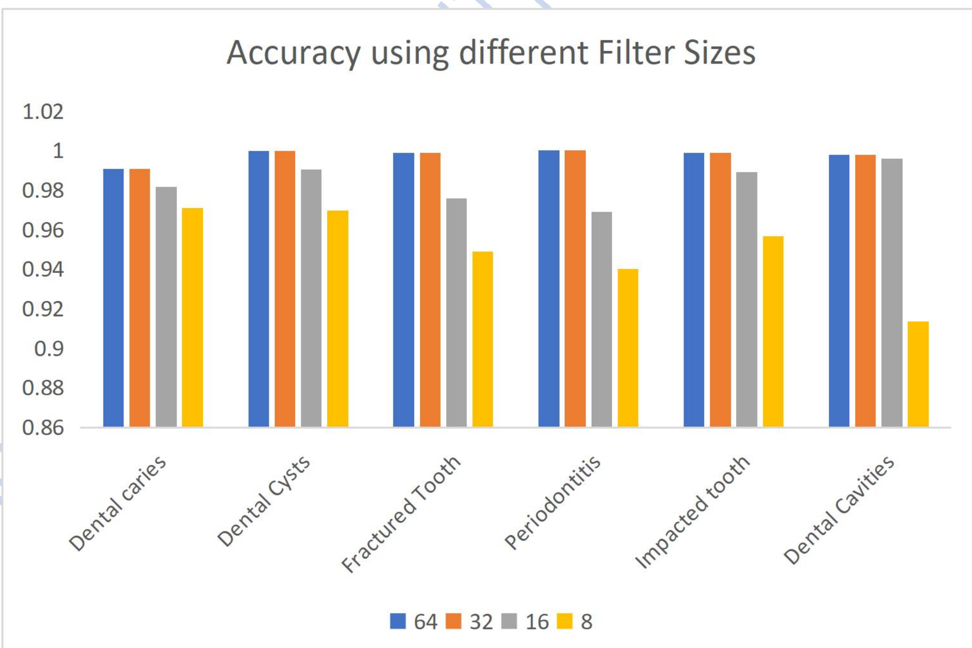


Figure 4.1 Graphical representation of filter sizes outcome

Table 4.2 and Figure 4.2 are the tabular and graphical representations of the error rates of different filter sizes respectively.

Table 4.2 Error rates of different filter sizes

	64	32	16	8
Dental caries	0.0092015	0.0092016	0.0184535	0.0292016
Dental Cysts	0.0002346	0.0002346	0.0097644	0.0302346
Fractured Tooth	0.0010316	0.0010316	0.0242062	0.0510316
Periodontitis	3.12E-05	3.13E-05	0.0311057	0.06002321
Impacted tooth	0.0012006	0.0012006	0.0110001	0.04342097
Dental Cavities	0.0020002	0.0020002	0.0040466	0.0864201

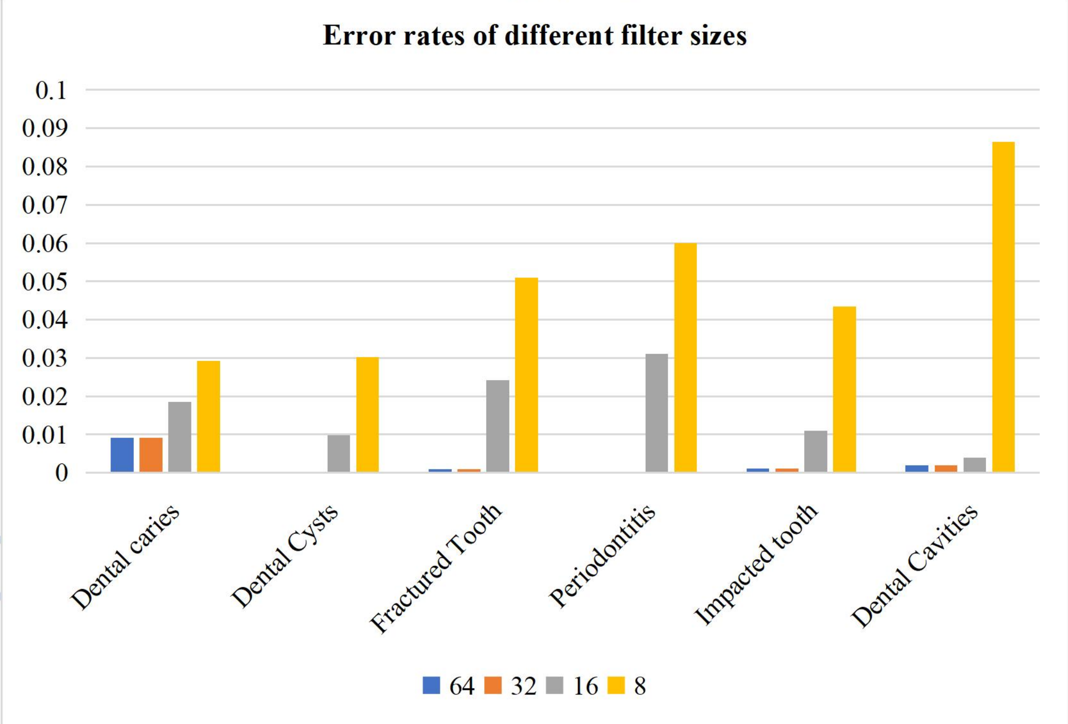


Figure 4.2 Graphical representation of error rates of different filter sizes

4.1.2 Training Time Difference between MM-NN and CNN

Table 4.3 illustrates a comparative difference between MM-NN and CNN training times in second. From the table, the MM-NN model and CNN model subjected under the same training data size shows an obvious difference time-wise. Table 4.3 is represented graphically in Figure 4.3

Table 4.3 Training Time Difference between MM-NN and CNN

	64 MM	64 CNN	32MM	32 CNN	16MM	16 CNN	8MM	8 CNN
Dental caries	274	337	263	218	250	298	239	287
Dental Cysts	231	284	227	275	211	251	190	228
Fractured Tooth	227	279	218	264	200	238	188	226
Periodontitis	259	319	248	300	231	275	213	256
Impacted tooth	240	295	237	287	223	265	204	245
Dental Cavities	267	328	250	303	243	289	228	274

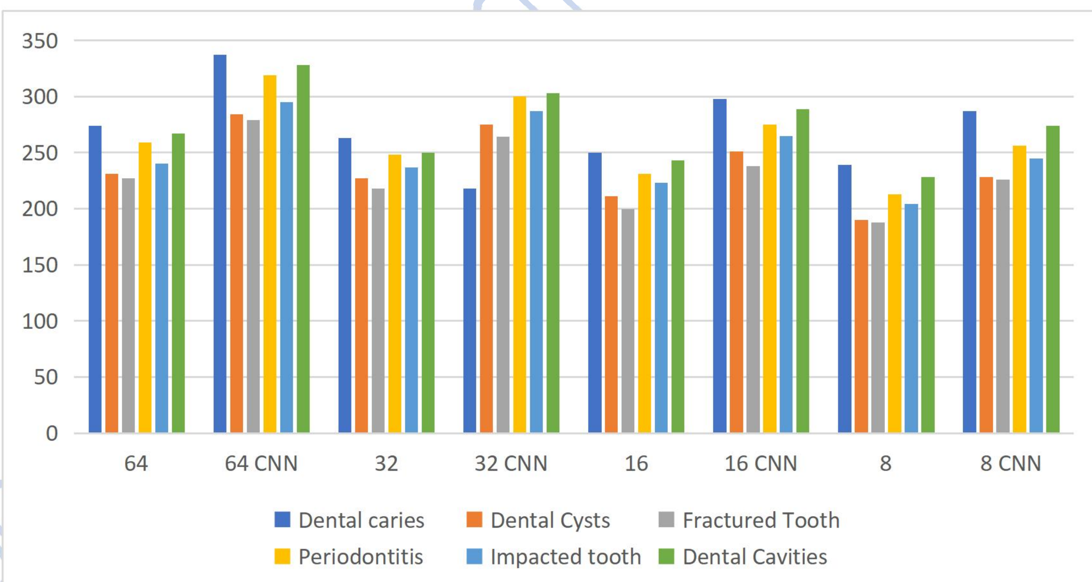


Figure 4.3 Graphical representation of table 4.3

4.1.3 Data size and Image Features

Table 4.3 contains the data size and image features that produced the discussed results. The models (MM-NN and CNN) were trained with six classes of dental periapical radiograph images as listed in table below. Each class of the images had its training time as they were of different sizes and dimensions.

Table 4.4 Data size and Image Features

Diseases	Data size	Image Dimension
Dental caries	120	748 by 512
Dental Cysts	131	685 by 627
Fractured Tooth	112	233 by 217
Periodontitis	159	235 by 215
Impacted tooth	152	413 by 402
Dental Cavities	174	692 by 587

4.1.4 Model Test Outcomes

On completion of the development of the system, the model was tested with several datasets from different sources. The model was tested with the 30% benchmark test dataset separated for testing as well as other dataset from the internet and hospitals.

4.1.5 Benchmark and Random Dataset Test

The Benchmark dataset gave perfect test results. The various diseased images all gave high percentages showing that the system is working perfectly. But when the model was tested with a random dataset, there was a deviation. Most of the times, the random dataset test gave high value to dental caries even though it was not given a caries image. To solve this problem, more dataset was added to the training dataset to improve the accuracy of the model. Table 4.5 is a display of the test results in some metric formats.

Table 4.5 Random Dataset Test Results

Images	Accuracy (%)	Precision	Recall	Specificity	Sensitivity	Error rate
Dental Cavities	78.81	0.9981461	0.9981461	0.000854	0.998146	0.21192010
Dental Cavities	71.89	0.9989461	0.9989461	0.0010539	0.998946	0.28102101
Dental Cavities	69.18	0.99175334	0.99175334	0.0082467	0.991753	0.30832034
Dental Caries	99.08	0.9907684	0.9907684	0.0092316	0.990768	0.00923162
Dental Caries	97.99	0.9798832	0.9798832	0.0201168	0.979883	0.02011681
Dental Caries	99.75	0.99754385	0.99754385	0.0024561	0.997544	0.00245615
Dental cysts	67.96	0.95963295	0.95963295	0.0403671	0.959633	0.32040306
Dental cysts	70.70	0.9569666	0.9569666	0.0430334	0.956967	0.29310120
Dental cysts	66.82	0.9681589	0.9681589	0.0318411	0.968159	0.33182345
Fractured Tooth	98.82	0.9881589	0.9881589	0.0118411	0.988159	0.01184101
Fractured Tooth	98.75	0.9874529	0.9874529	0.0125471	0.987453	0.01254701
Fractured Tooth	95.10	0.95096346	0.95096346	0.0490365	0.950963	0.04903654
Impacted Tooth	89.99	0.9599171	0.9599171	0.0400829	0.959917	0.10012302
Impacted Tooth	87.50	0.9849955	0.9849955	0.0150045	0.984996	0.12510451
Impacted Tooth	89.50	0.98499554	0.98499554	0.0150045	0.984996	0.10510446
Periodontitis	68.23	0.992281	0.992281	0.007719	0.992281	0.31770109
Periodontitis	62.90	0.9989913	0.9989913	0.0010087	0.998991	0.3710087
Periodontitis	56.88	0.9487613	0.9487613	0.0512387	0.948761	0.4312387

4.1.6 Subsequent Test Results

After more training dataset were added to the model for more training, it was tested again with random dataset. The model achieved tremendous improvement in terms of accuracy. Table 4.6 is a tabular representation of some of the results of the improved trained model while Figures 4.4, 4.5, 4.6, 4.7, 4.8, and 4.9 are the model predicted output results.

Table 4.6 Improved Test Results

Images	Accuracy	Precision	Recall	Specificity	Sensitivity	Error rate
Dental Cavities	100.00	0.999989	0.999989	1.11E-05	0.999989	1.11E-05
Dental Cavities	99.99	0.999943	0.999943	5.72E-05	0.999943	5.72E-05
Dental Cavities	99.91	0.999146	0.999146	0.000854	0.999146	0.000854
Dental Caries	100.00	0.99998	0.99998	1.95E-05	0.99998	1.95E-05

Dental Caries	99.88	0.999883	0.999883	0.000117	0.999883	0.000117
Dental Caries	100.00	0.999991	0.999991	8.94E-06	0.999991	8.94E-06
Dental cysts	99.58	0.995752	0.995752	0.004248	0.995752	0.004248
Dental cysts	99.99	0.999892	0.999892	0.000108	0.999892	0.000108
Dental cysts	99.99	0.999902	0.999902	9.8E-05	0.999902	9.8E-05
Fractured Tooth	99.82	0.998152	0.998152	0.001848	0.998152	0.001848
Fractured Tooth	99.99	0.999893	0.999893	0.000107	0.999893	0.000107
Fractured Tooth	100.00	0.999999	0.999999	1.2E-06	0.999999	1.2E-06
Impacted Tooth	99.99	0.999917	0.999917	8.28E-05	0.999917	8.28E-05
Impacted Tooth	98.50	0.984996	0.984996	0.015004	0.984996	0.015004
Impacted Tooth	98.50	0.984996	0.984996	0.015004	0.984996	0.015004
Periodontitis	100.00	0.999981	0.999981	1.86E-05	0.999981	1.86E-05
Periodontitis	99.99	0.999785	0.999785	0.000215	0.999785	0.000215
Periodontitis	100.00	0.999993	0.999993	6.7E-06	0.999993	6.7E-06
	99.78	**0.997899**	**0.997899**	**0.002101**	**0.997899**	**0.002201**

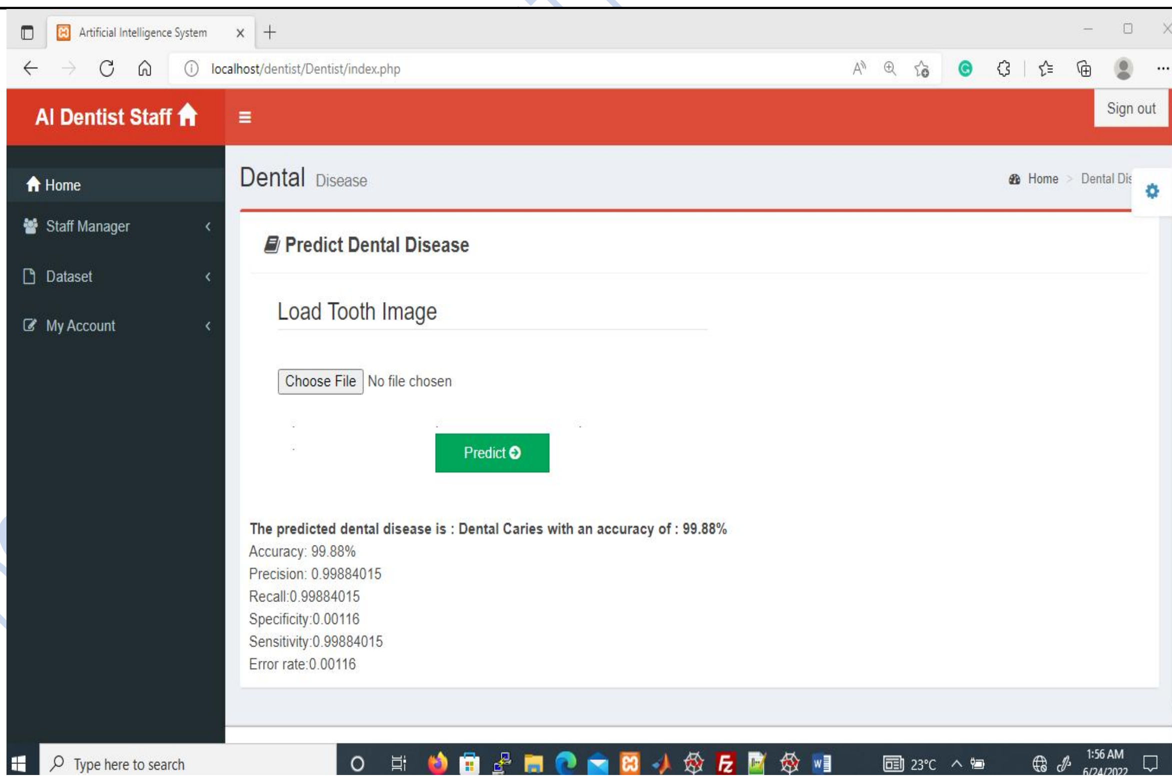


Figure 4.4 Predicted dental caries result

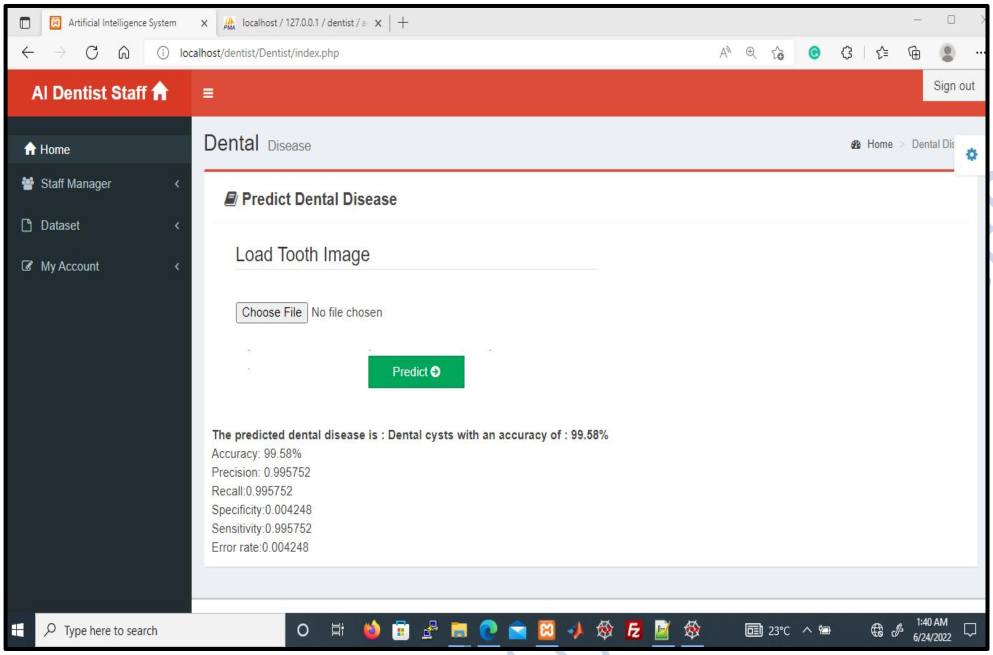


Figure 4.5 Predicted dental cysts result

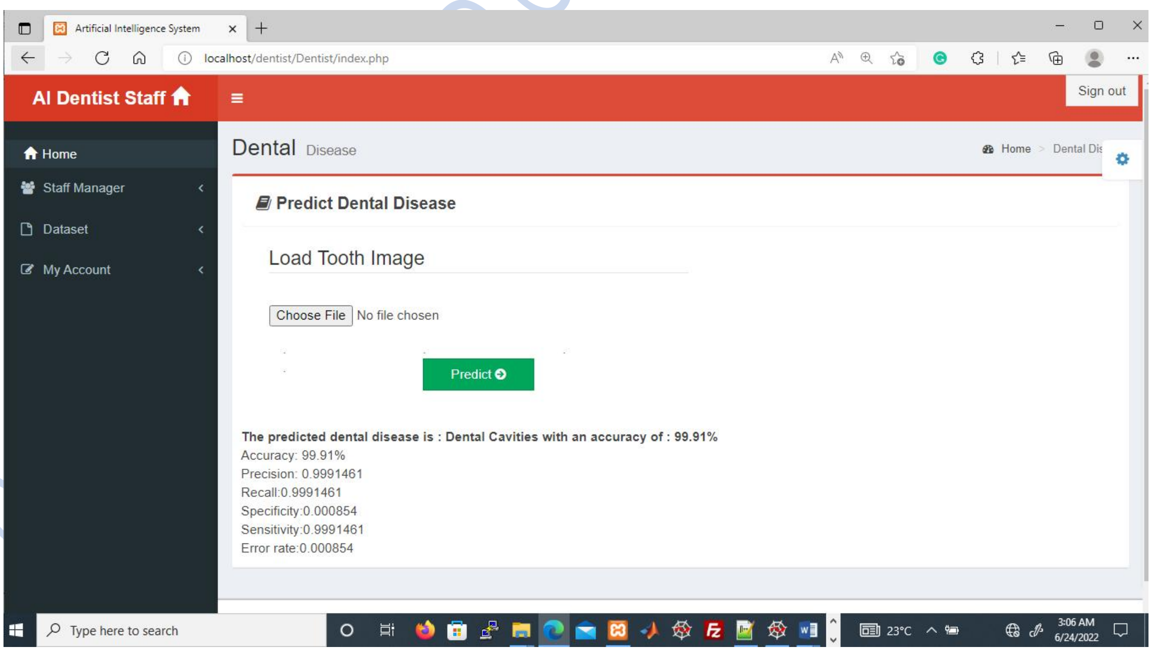


Figure 4.6 Predicted dental cavities result

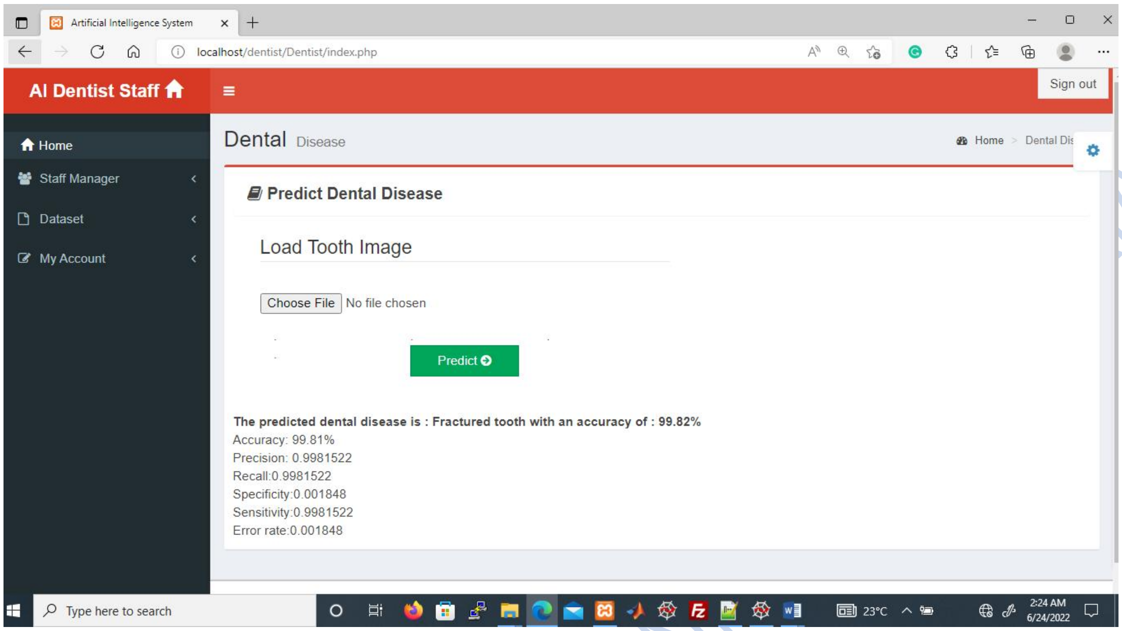


Figure 4.7 Predicted fractured tooth result

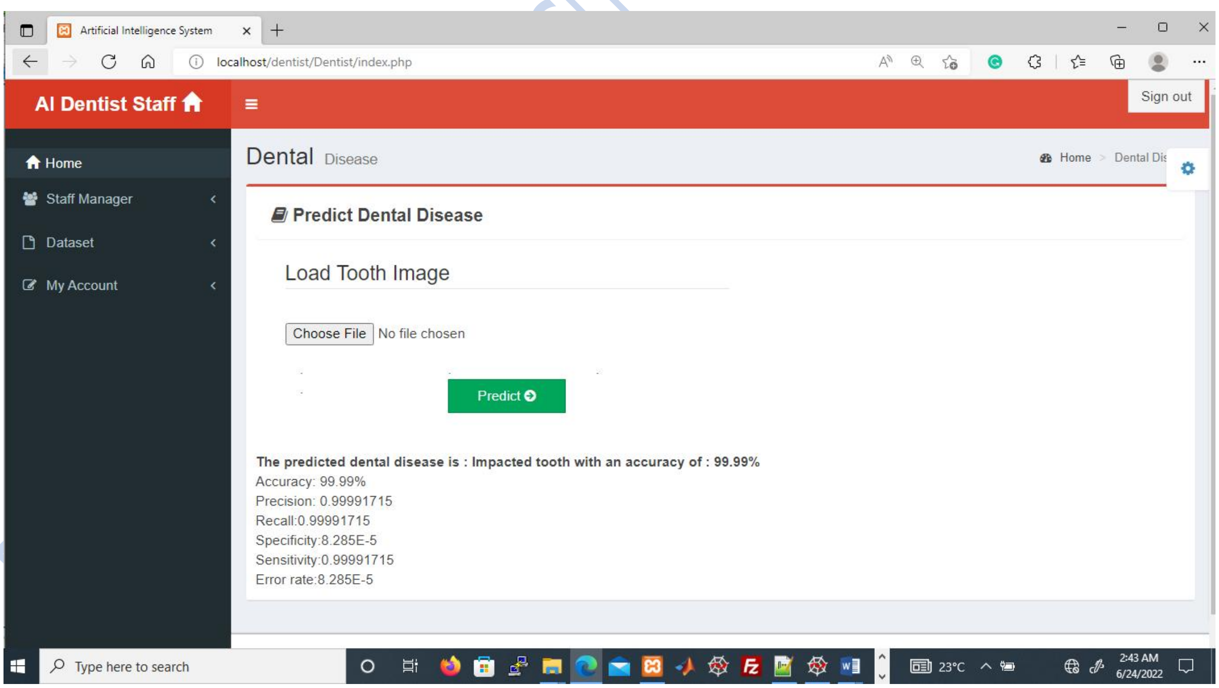


Figure 4.8 Predicted impacted tooth result

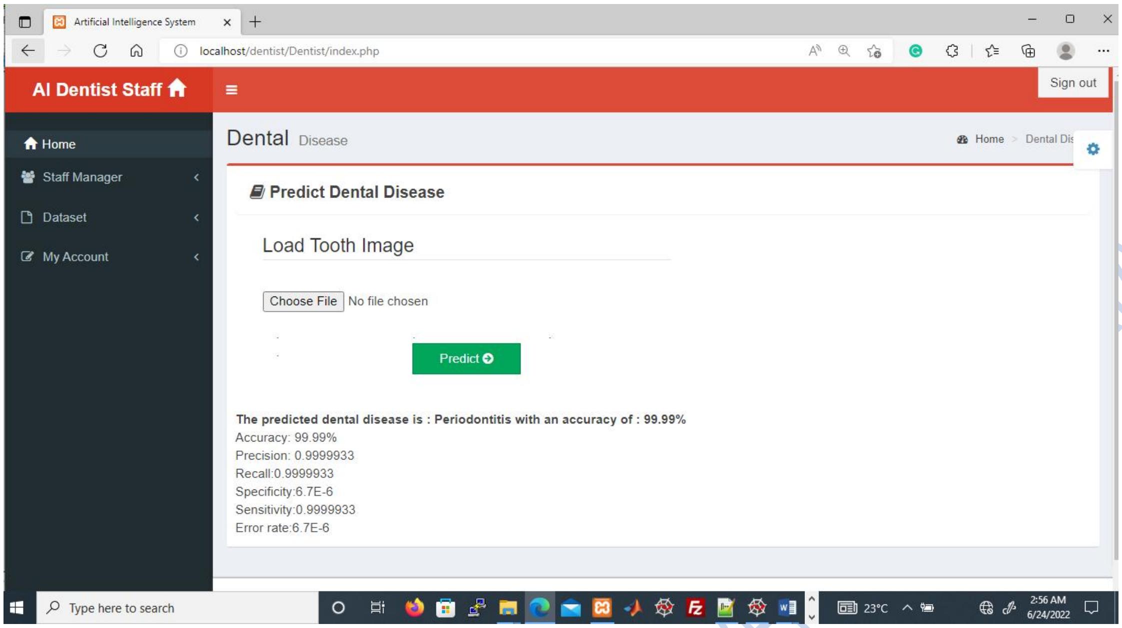


Figure 4.9 Predicted periodontitis tooth result

4.2 Analytical Comparism Between Existing Systems And Improved System

Upon completion of the development of this model, random periapical dental radiographs were used to test the accuracy and the effectiveness of the model wether there is appreciable correlation between the models output and a dentist's clinical judgment. With the accuracy the model gave, there was a remarkable correlation.

Table 4.8 Analytical comparism between existing systems and improved system

	Author	Title	Year	Problem	Method and number of disease	Precision	Accuracy
Existing systems	Abdullah S. AL-Malaise AL-Ghamdi et al	Detection of Dental Diseases through X-Ray Images Using Neural Search Architecture Network	2022	Dental disease classification	CNN 3 diseases		96.51%

	Lee *et al*	Deep learning for early dental caries detection in bitewing radiographs	2021	Dental caries	CNN 1 disease		
	Bidgoli*et al*	Automatic diagnosis of dental diseases using convolutional neural network and panoramic radiographic images	2021	classify teeth as healthy, decayed, root-canaled, and .	CNN 4 classifications	92%	
Improved system		A Deep mathematical morphological neural network to classify dental periapical radiograph for the diagnosis and treatment of dental diseases	2022	Dental disease classification	MM-NN 6		99.78%

The model was also compared with three state-of-the-art classification models to validate its effectiveness. The comparism was based on accuracy/precision, the type of dental problem solved, the method and number of dental diseases the model classified.

Table 4.8 is an analytical comparism between improved system and three existing systems. Existing system evaluation was based upon the accuracy of the classifier on a given test set that were correctly classified by the system. The system was termed positive when it classified set test in their correct classes and negative when it classified set test in a wrong class.

The true positives (TP) were the positive set test that were correctly predicted, that is, predicted value and actual value is positive.True negatives (TN) were the set test that were correctly predicted as negative. A situation where predicted value and actual value is negative. The false negative (FN) values were those that the system predicted as negative but actually positive while the false positive (FP) are values the system predicted as positive but actually negative.

4.3 Accessing the System

The system can be accessed locally from your computer system (laptop, desktop) and from your browser.

From browser: To access the system (Dentist) through a browser is simply typing ***localhost/dentist*** on the browser's Url as shown in Figure 4.10. Upon clicking the enter key on keyboard brings up the splash/login screen page of the system as seen in figure 4.11.

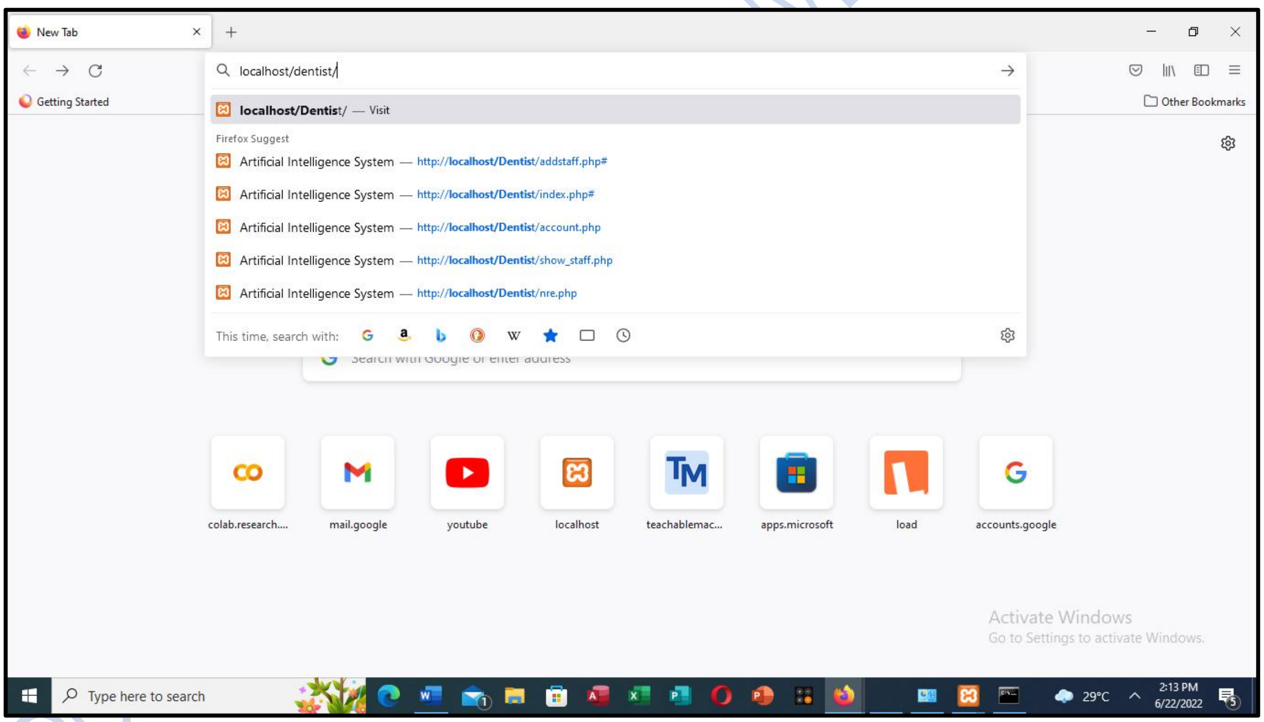


Figure 4.10 Google url

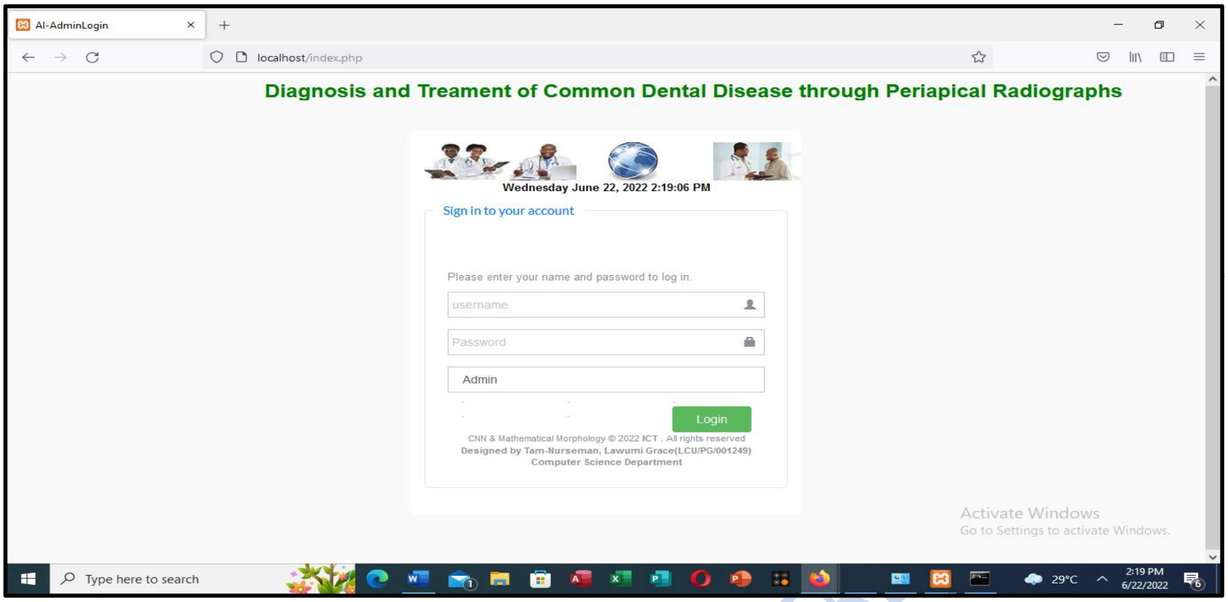


Figure 4.11 Splash/System Login

Accessing locally: to access it locally from a local computer system, go to the drive where XAMPP is installed. In most cases it is installed in `C` drive, `C:\xampp\` and with few steps, the system is accessed.

Step1. Double click on XAMPP control panel as displayed in figure 4.13. A submenu comes on. Click on Open on the submenu that pops up.

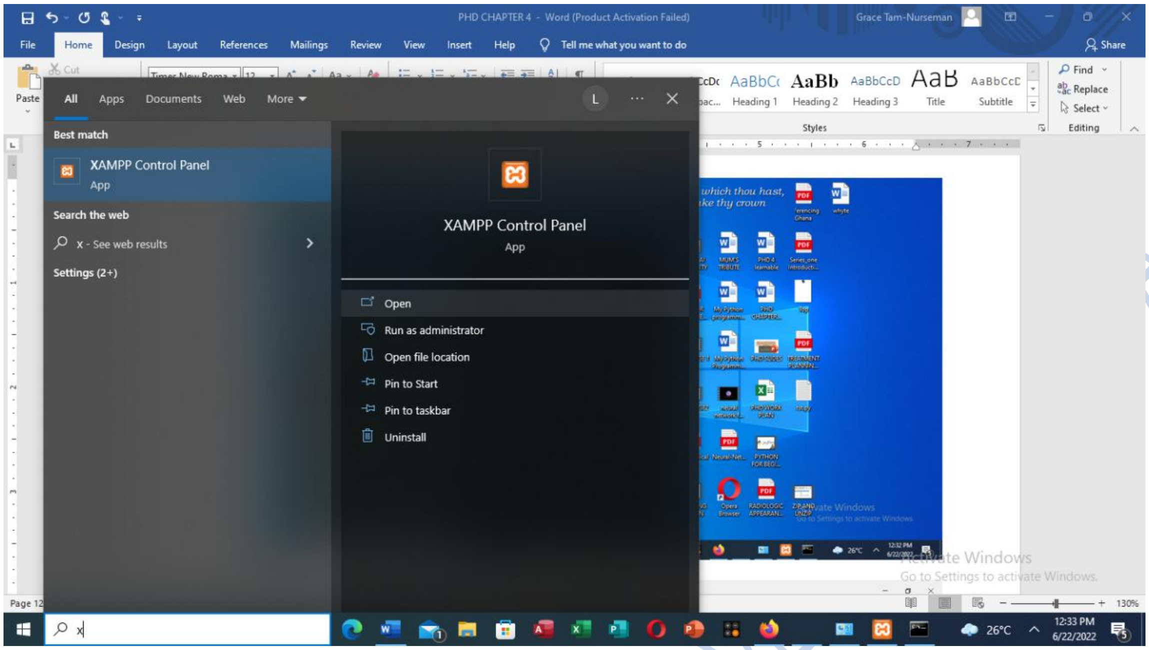


Figure 4.12 XAMPP at start-ups menu of local system

When the controller opens, it takes you to another environment as seen in figure 4.12. The items under ‘Module’ in figure 4.13 (Apache, MySql, FileZila, Mercury and Tomcat) can be started and stopped.

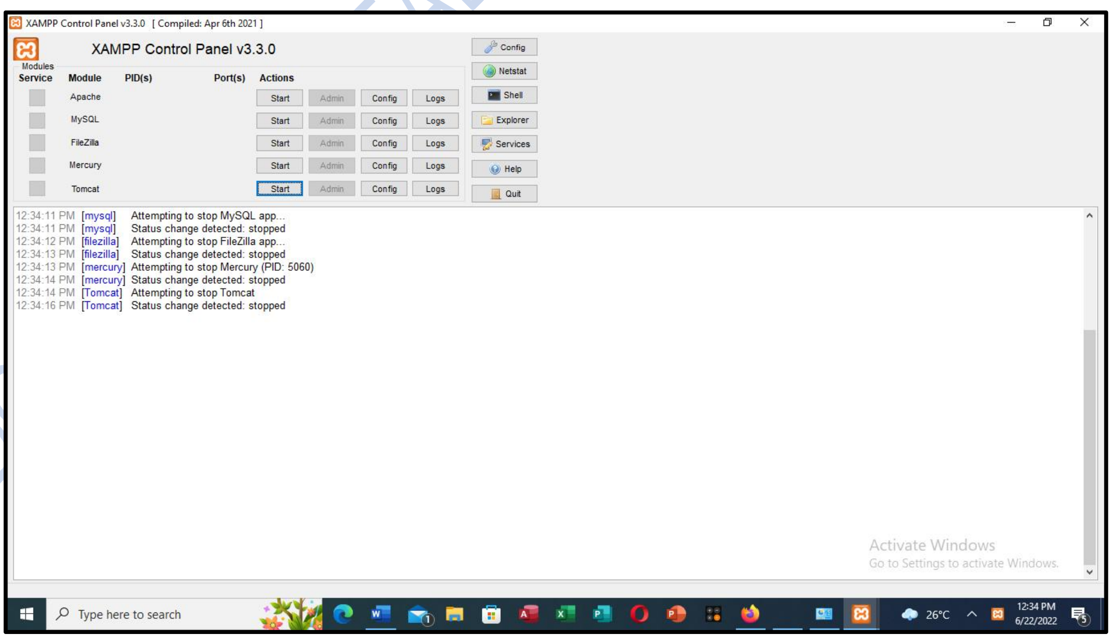


Figure 4.13 Inactivated XAMPP Control Panel

Step 2.Click on the Start actions of the modules and they all turn lemon green when started as showned in Figure 4.14. At this point, the 'start' under Actions turns to 'Stop' which means that the modules are started or running.

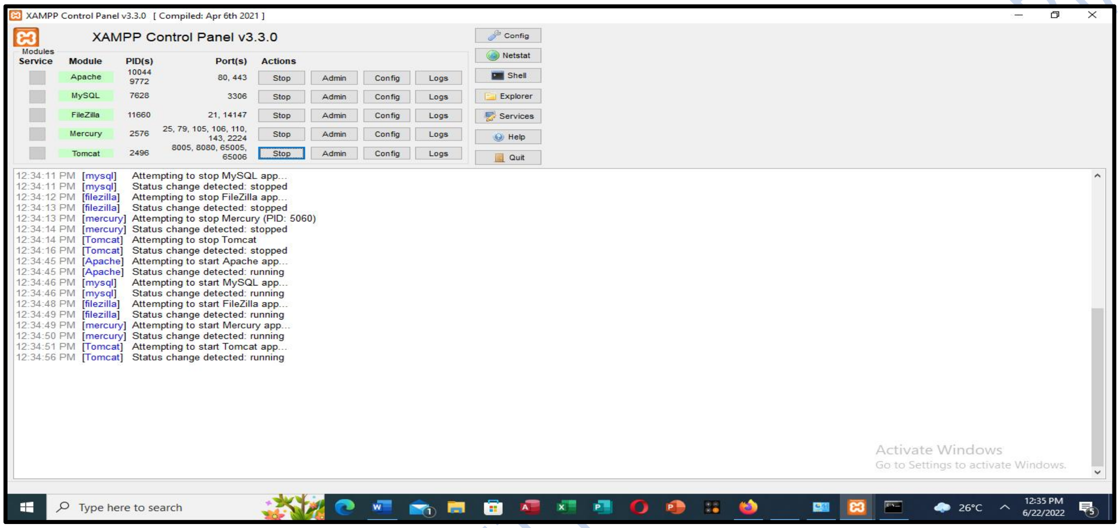


Figure 4.14 Activated XAMPP control panel

Step 3. Click on Apache's Admin as seen infigure 4.15 and that takes you to the splash screen of the model.

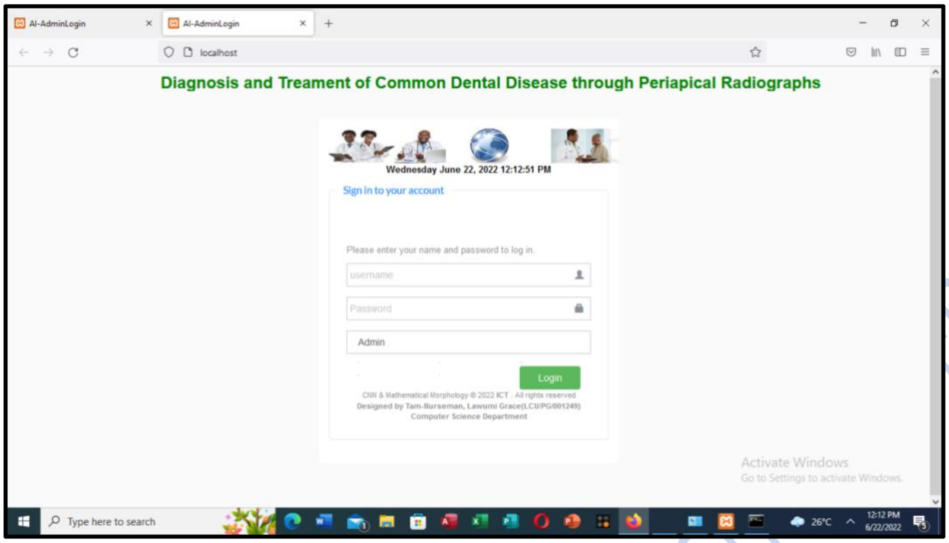


Figure 4.15 System login

4.3.1 System Login Security Measures

The startup screen as shown in Figure 4.15 is a combination of a splash screen and a login page. It comes up with the title of the software scrolling leftward from the right upper corner of the screen. An inbuilt calendar with date-time displays the day, month, date, year, and time whenever the system is logged into. A current version of the software is displayed at the bottom left corner of the screen. As a login page, this is where security measures are applied to prevent unauthorized users from accessing the system. It is a measure to ensure that only authorized users are allowed entry into the system.

Two classes of users are defined who can access this system; admin and non admin user who are expected to be staff of any organization where the system will be used. There are two key information needed from either the admin or staff; user name and password. The username is the name of the administrator or any user authorized or allowed to gain access to the application while the password is a string of characters used to verify the identity of the user during the process.

4.3.2 System Main Menu Page

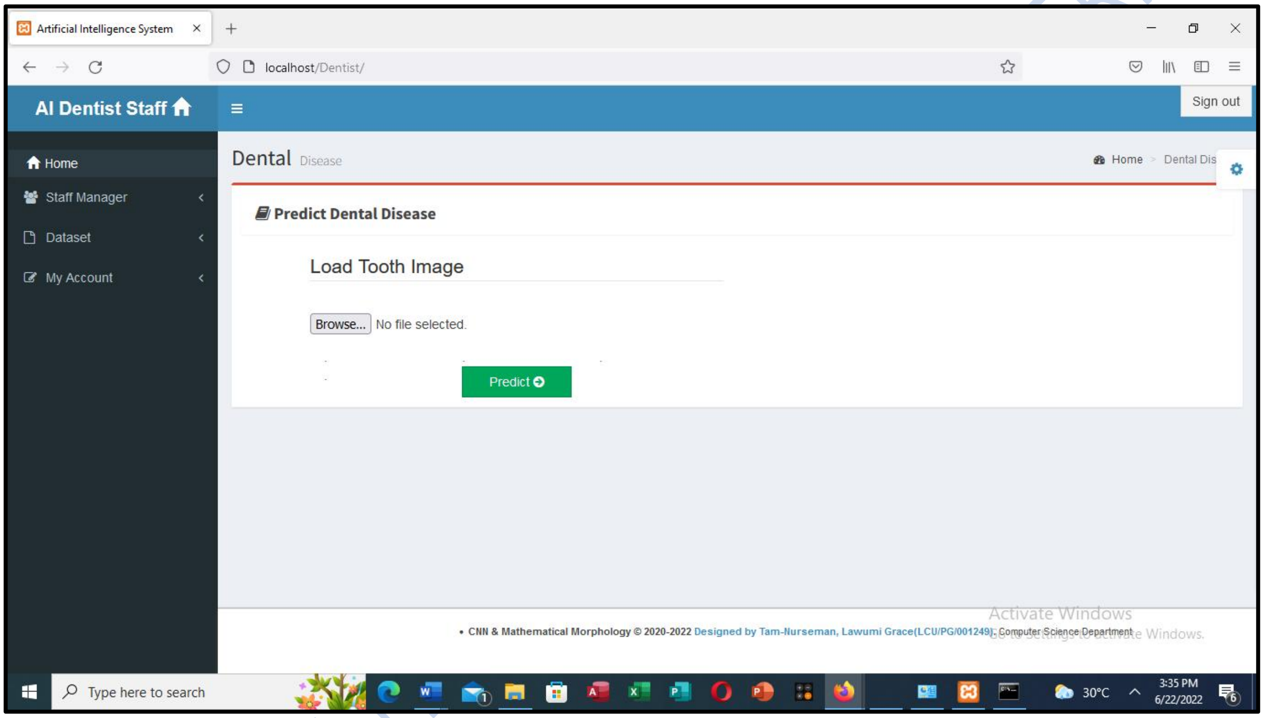


Figure 4.16 System main menu

The system main menu is ushered in from the login page. The page at the upper left corner contains a menu made up Home, Staff Manager, Dataset and My Account.

i. **Home** takes you to the home page of the system. The home page is same with system main menu in figure 4.10.

ii. **Staff Manager:** Figure 4.17 displays a menu where a staff can be added or removed. Add staff with a + sign registers a new user where staff name, contact number, email address and user's category are registered for future verification. The impending user is registered either as an admin or a staff using the select category. A staff who was registered to access the system can also be removed with the Remove Staff label.

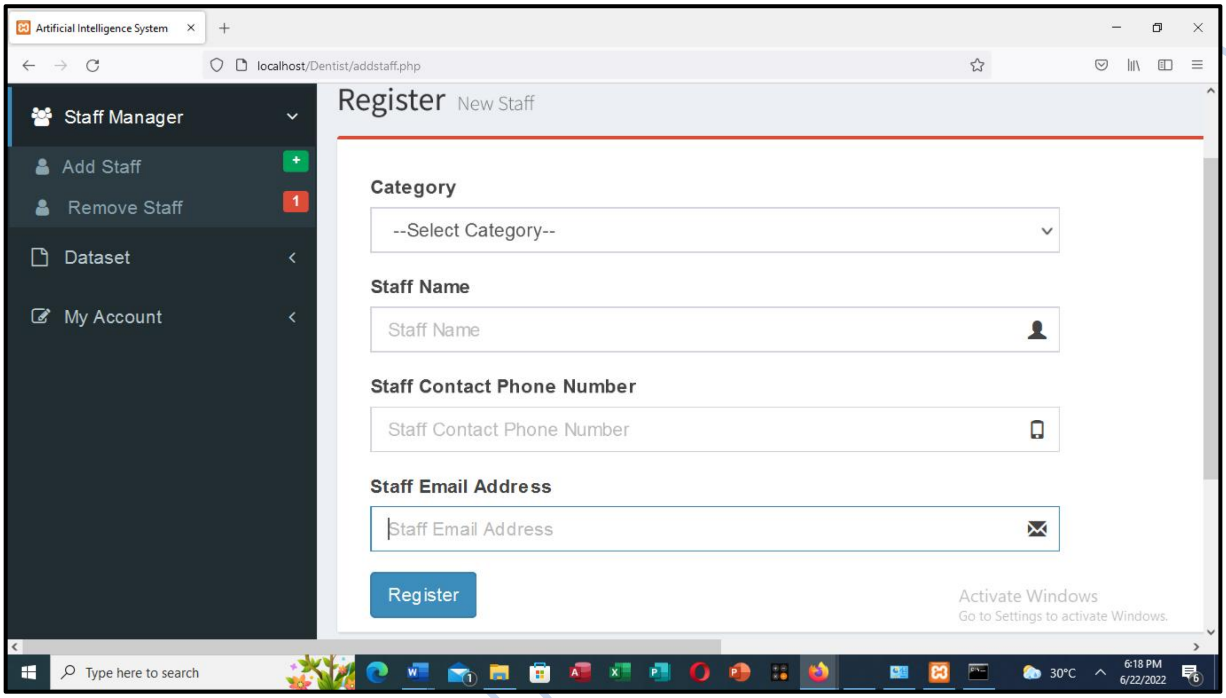


Figure 4.17 Staff registration page

iii. **Dataset:** The system is built to be scalable. It therefore has room for more dataset to be added as seen in Figure 4.18. Dataset to be added are placed in their right category by selecting disease category as displayed in Figure 4.19

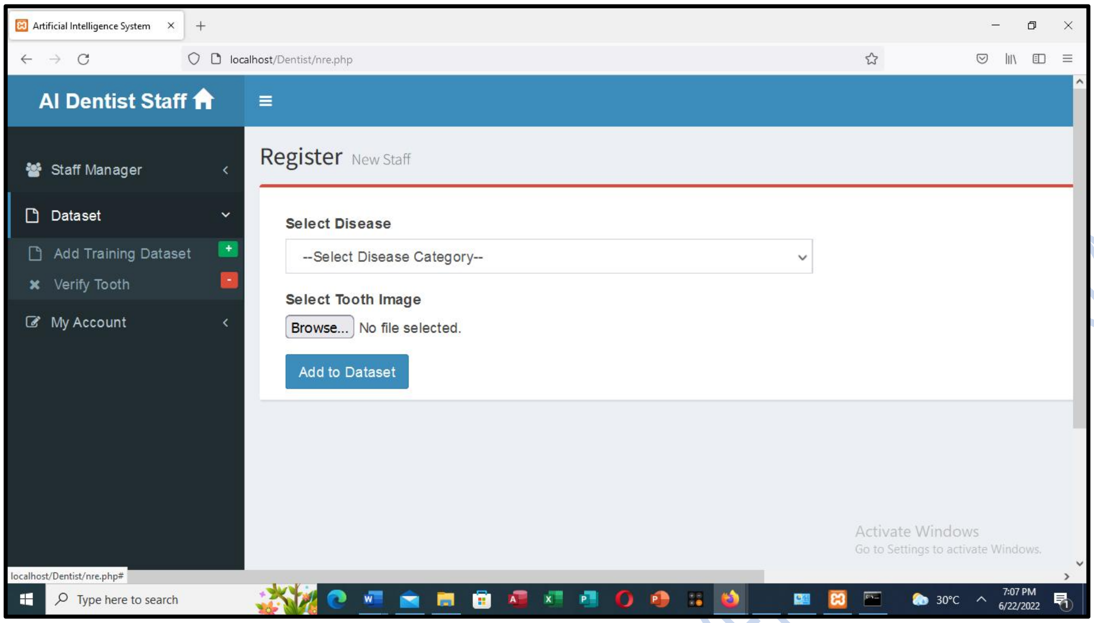


Figure 4.18 Dataset add menu

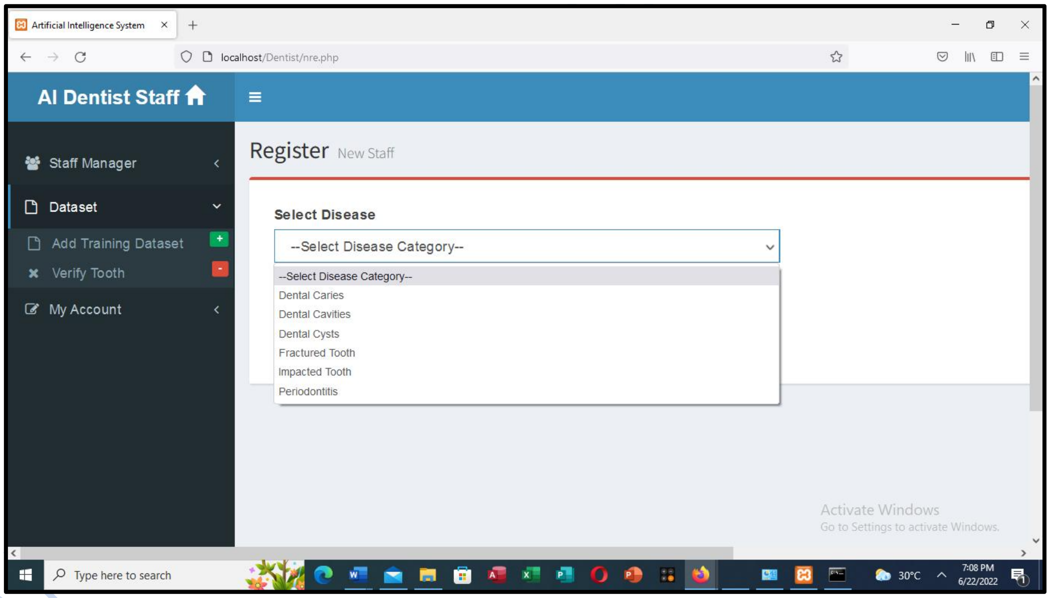


Figure 4.19 Disease selection menu

iv. **My Account**: This is created for the purpose of updating admin or staff profile.

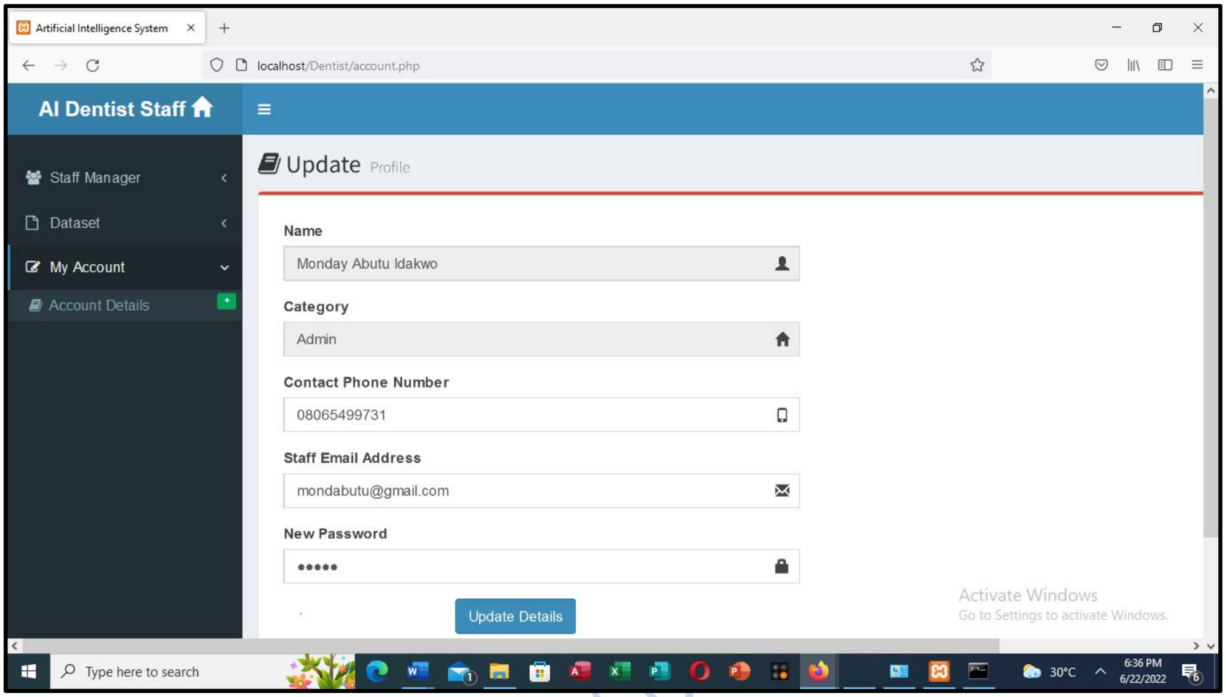


Figure 4.20 Admin/Staff account menu

Name and category are not updateable as they are details that can only be altered at the registration point. The contact number, staff email address and new password are the key details required or affected in this page.

4.3.3 Dental Disease Diagnosis

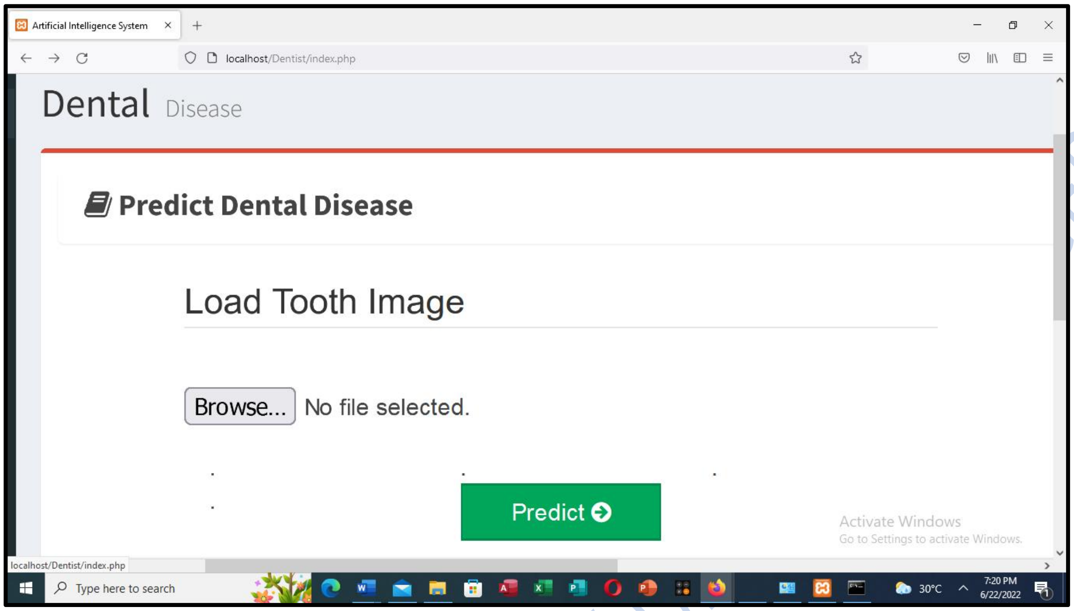


Figure 4.21 Disease diagnosis menu

This is the part of the main menu where the six categories of dental diseases limited to this study are diagnosed. ‘Load Tooth Image’ reminds us that the system is meant to diagnose dental diseases through periapical radiographs. Dental images are expected to be saved in files from which they will be fed to the system for diagnosis. Clicking on the ‘Browse’ takes you to a storage environment where you load a dental radiograph dataset from its repository to be fed to the system for diagnosis.

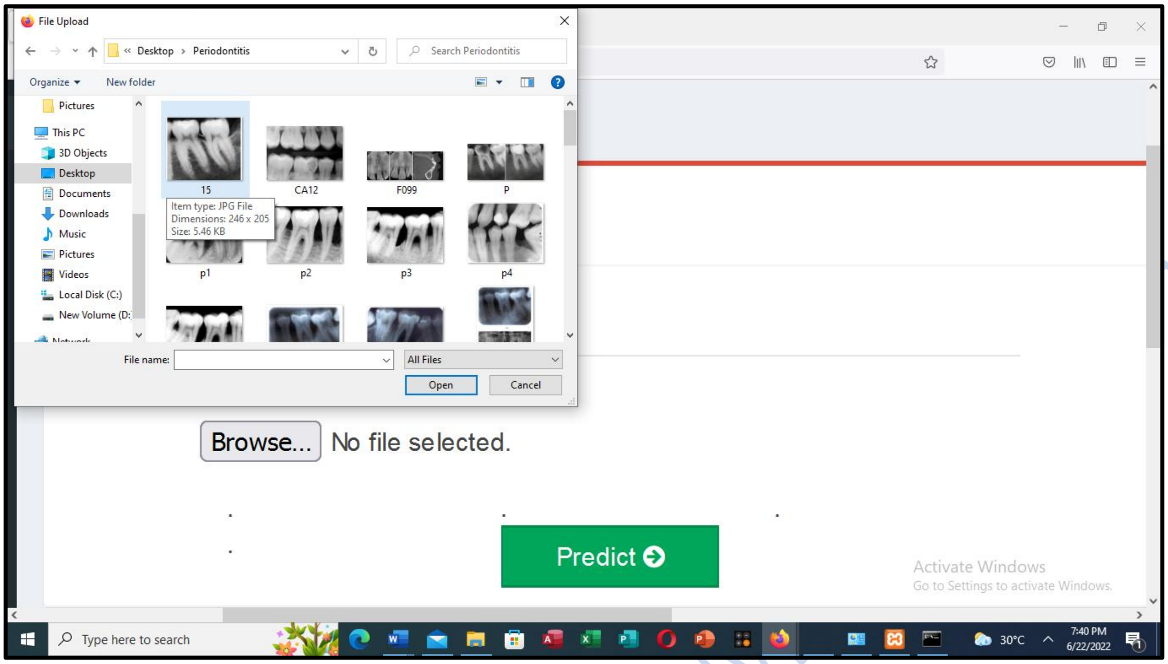


Figure 4.22 Data input for Diagnosis

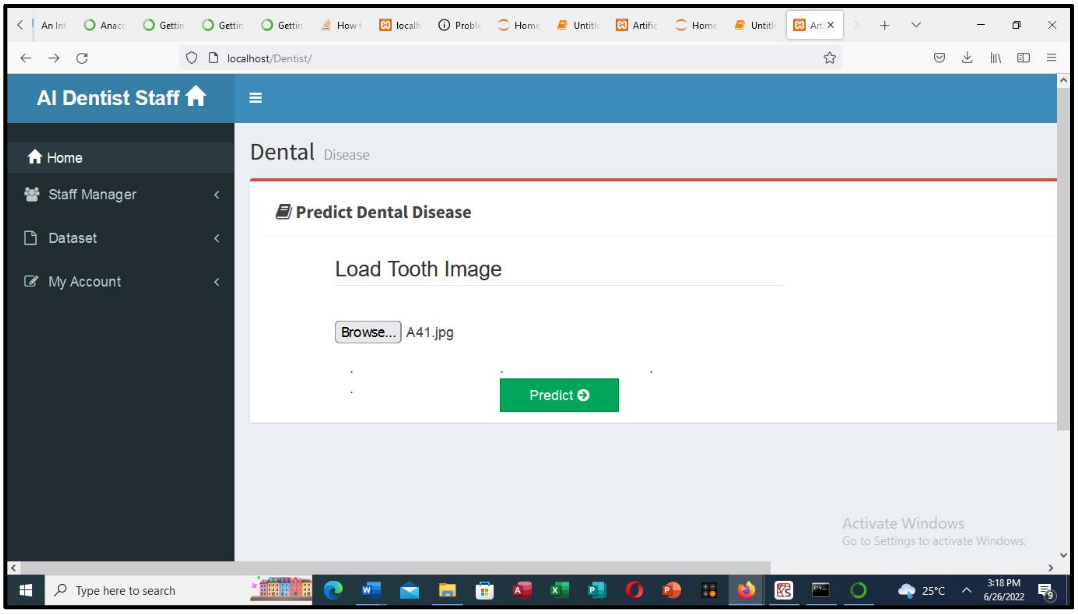


Figure 4.23 Disease prediction menu

On selecting and loading a dental radiograph dataset as shown in Figure 4.23 and with a click on ‘Predict’, the system predicts the disease associated with the loaded image alongside its accuracy, precision, specificity, recall, sensitivity and error rate as shown in Figure 4.24

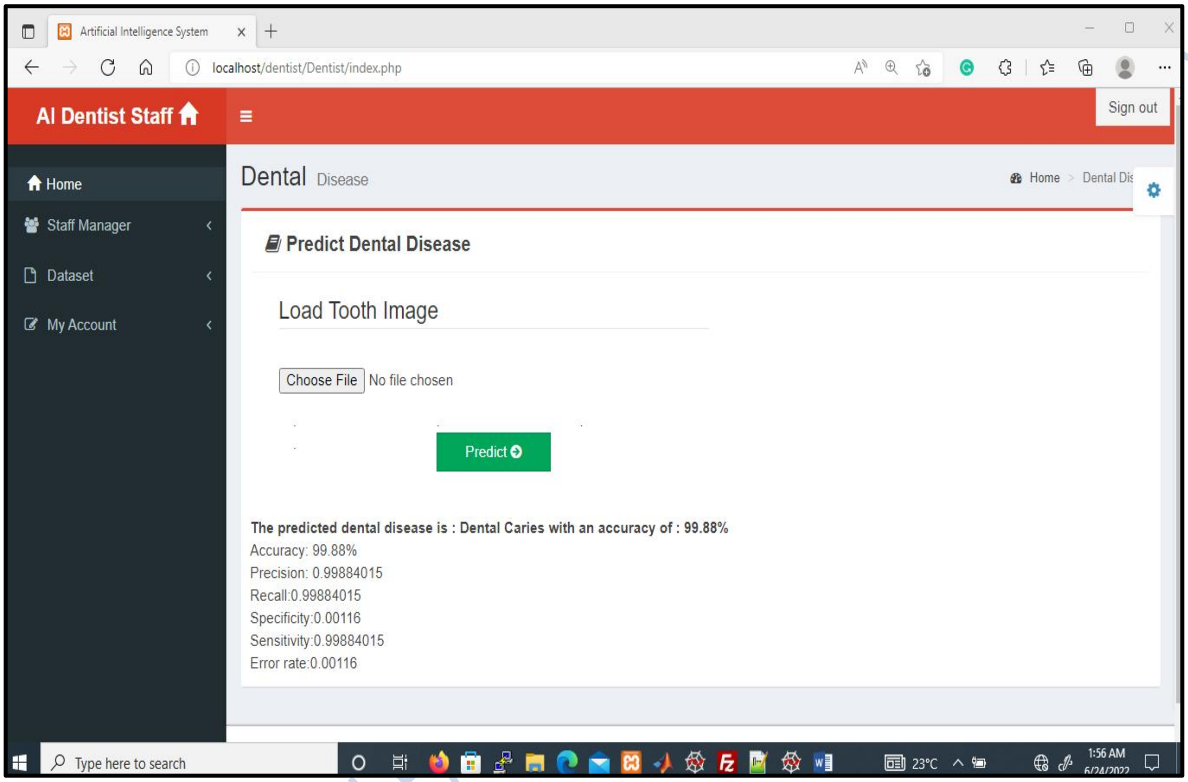


Figure 4.24 Predicted dental caries result.

4.4 Results of Telemedicine Application

a. **Staff Manager Menu**. Enlisted dental doctors and staff are registered here. Registration is one of the processes by which dental doctors and patients’ interaction is made viable. Qualified dental doctor’s personal data is captured and registered both for legal and professional record keeping. Data captured for this system’s use are doctor’s full name, contact number, and email address. These data undoubtedly are the key information with which a user of this system can contact a doctor. Information such as the email address is as it is used to transfer patient's personal and diagnostic details to doctors.

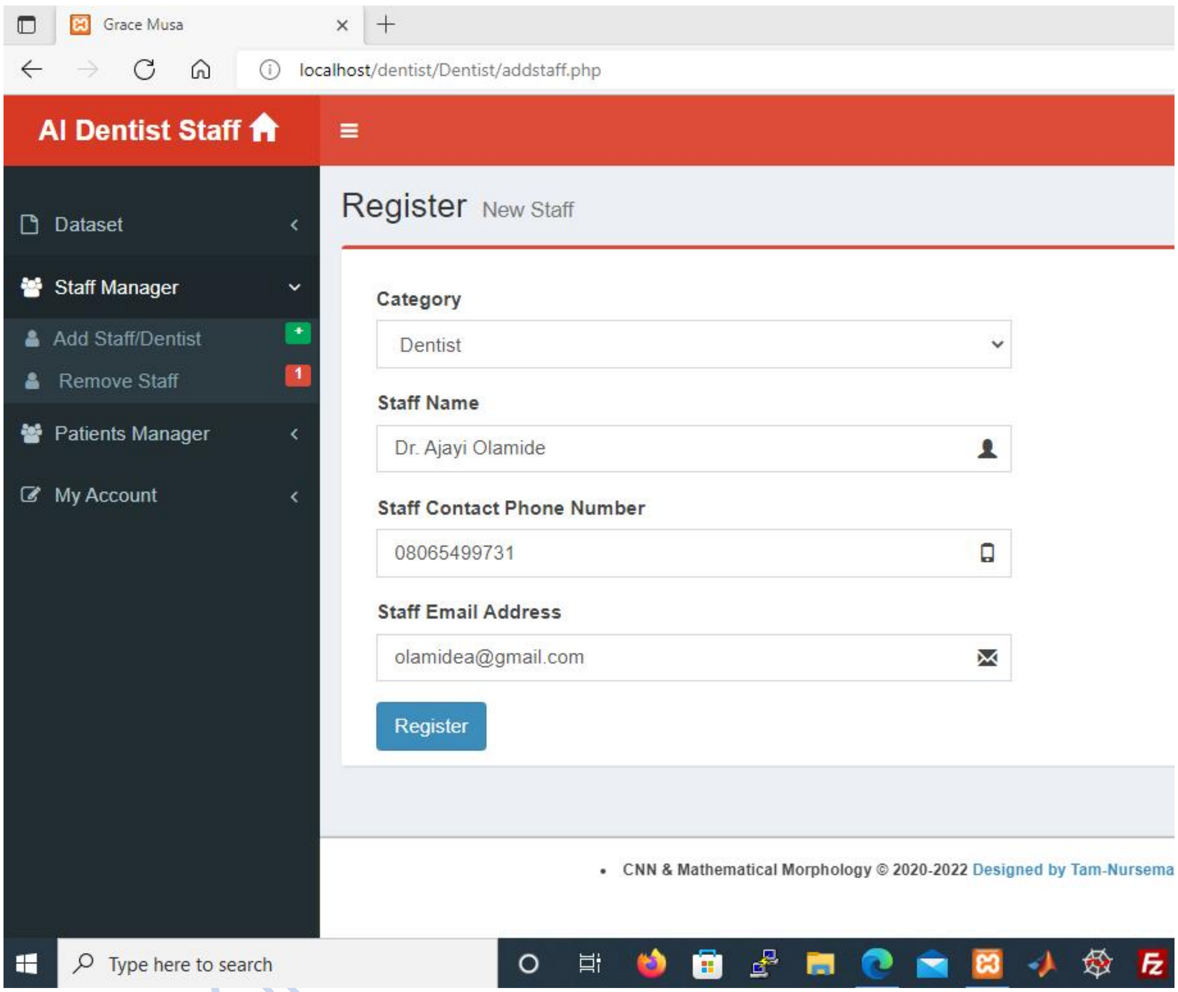


Figure 4.25 Dental doctor registration

As seen in Figure 4.25, the staff manager menu is where, besides registering staff/dental doctor removes staff/dental doctor. A user no longer in the organization is removed and therefore has no access to the system.

b. Figure 4.26 displays a page with a list of registered prospective end users of the telemedicine application. Users account can also be removed in this page

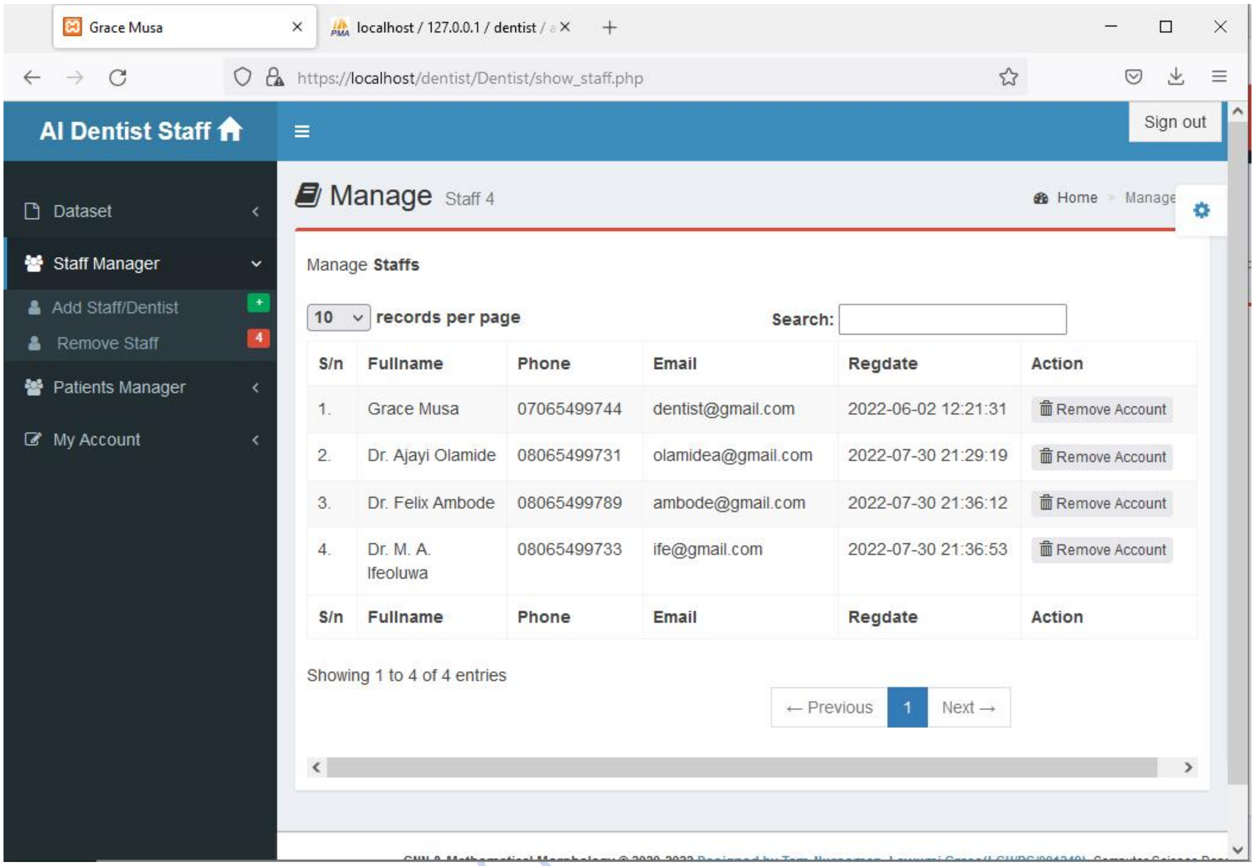


Figure 4.26 Staff/doctor's list

c. **Patients Manager Menu.** This page is where an avenue for consultation is created. Here, the doctor of preference is chosen from a dropdown menu that contains the list of doctors available for consultation. Patient's personal and diagnostic details including patient Identification Number (ID) are captured and sent across to the preferred doctor.

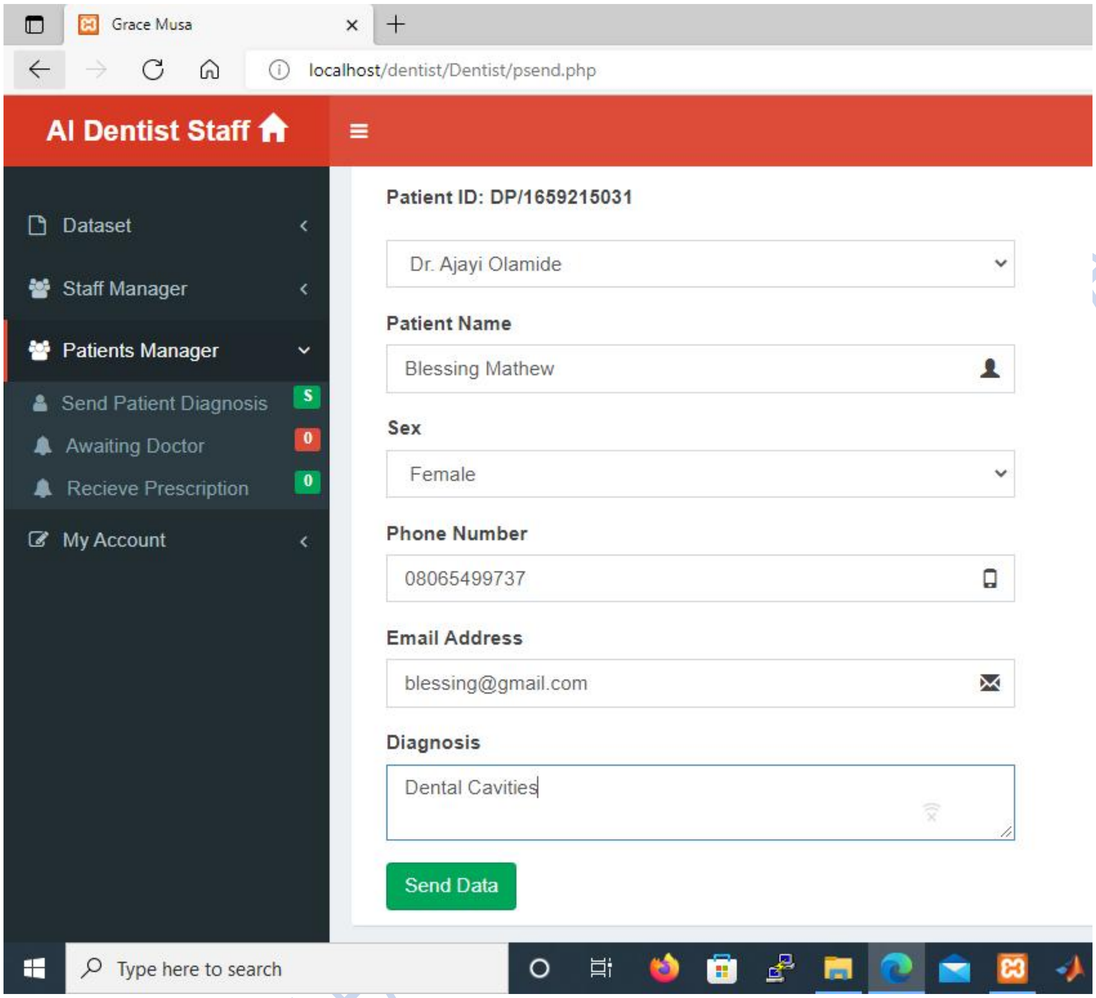


Figure 4.26 Sending Patient personal and diagnostic details to registered Doctor

d. A good number of doctors can be accessed by different patients. This makes the system robust. Patients are assigned to the number of doctors registered for consultation.

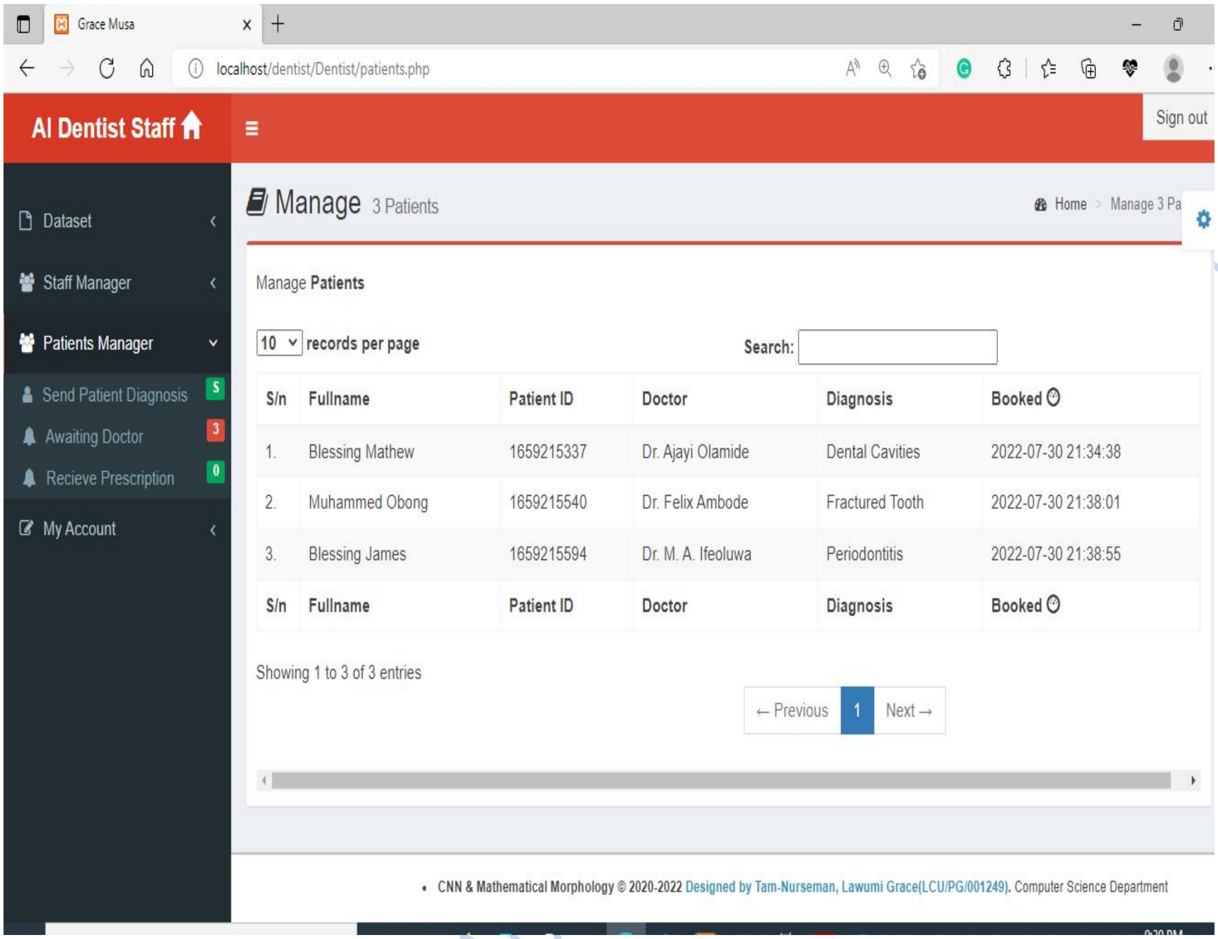


Figure 4.28 Patients' diagnostic list sent to different doctors

e. **Doctor's Dashboard.** Figure 4.28 displays a doctor's patient(s) list on queue awaiting to be atteneded to. The number of patients on treatment is indicated. If no patient is on treatment and awaiting queue tends to increas, the admin checks for possible problem and find solution.

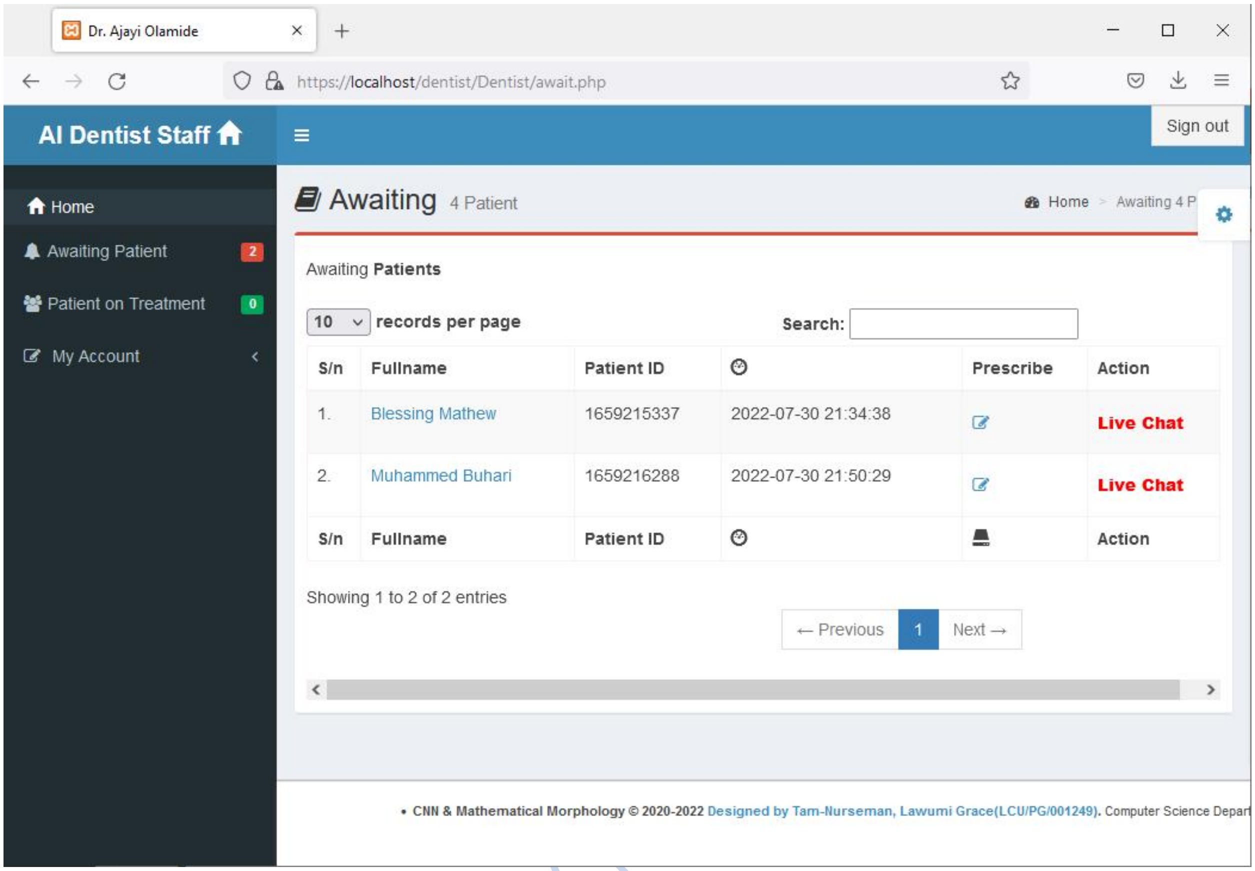


Figure 4.29 Doctor's dashboard

f. Patient's Dashboard. The patient's dashboard page as seen in figure 4.29 indicates whether or not a patient is on chat with a doctor. Whenever a patient is on with a doctor, the next patient to be attended to waits on a queue and as soon as the current chat is over, the awaiting patient is connected.

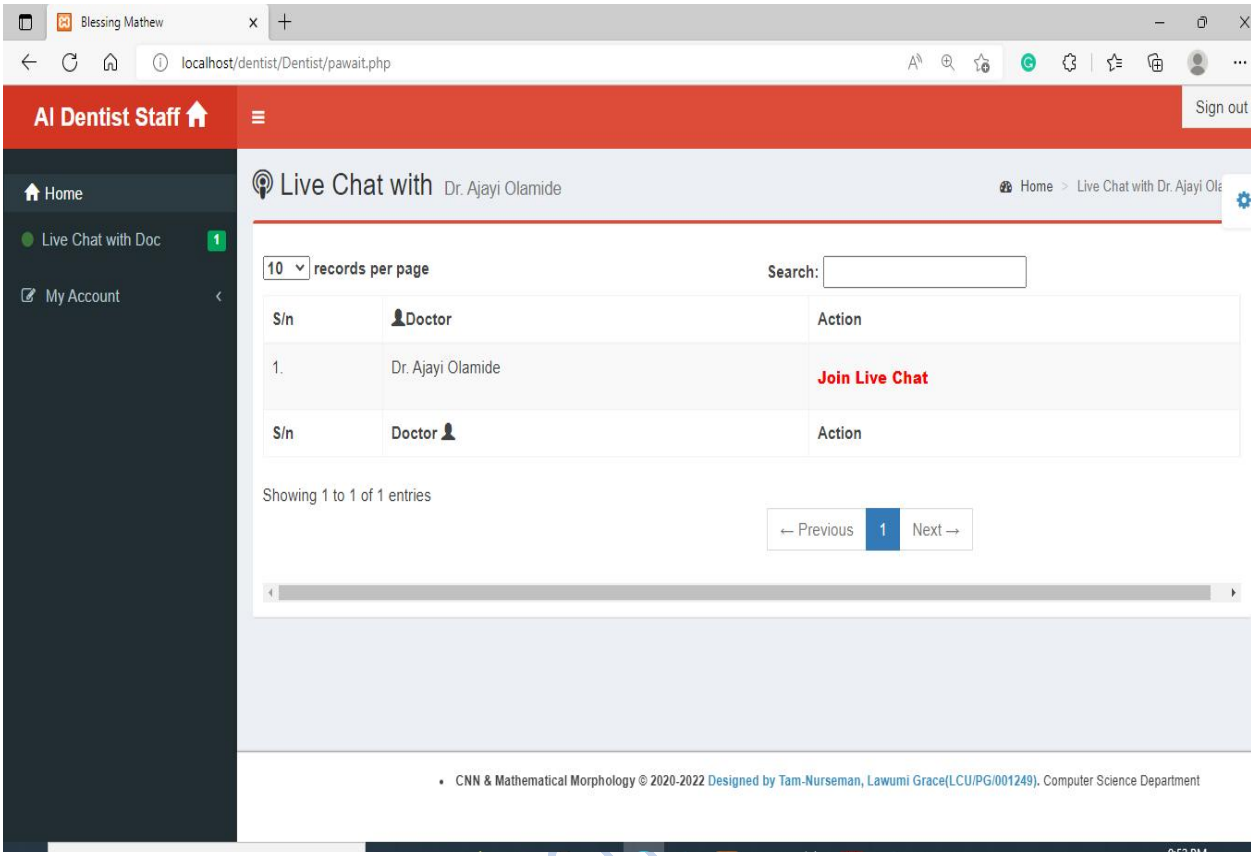


Figure 4.30 Patient's dashboard

g. Figure 4.31 is a view of a patient-doctor chat. This can be likened to a consulting room. Here the doctor exercises the three elements of diagnosis which are;[196]

1. History
2. Examination
3. Diagnostic test

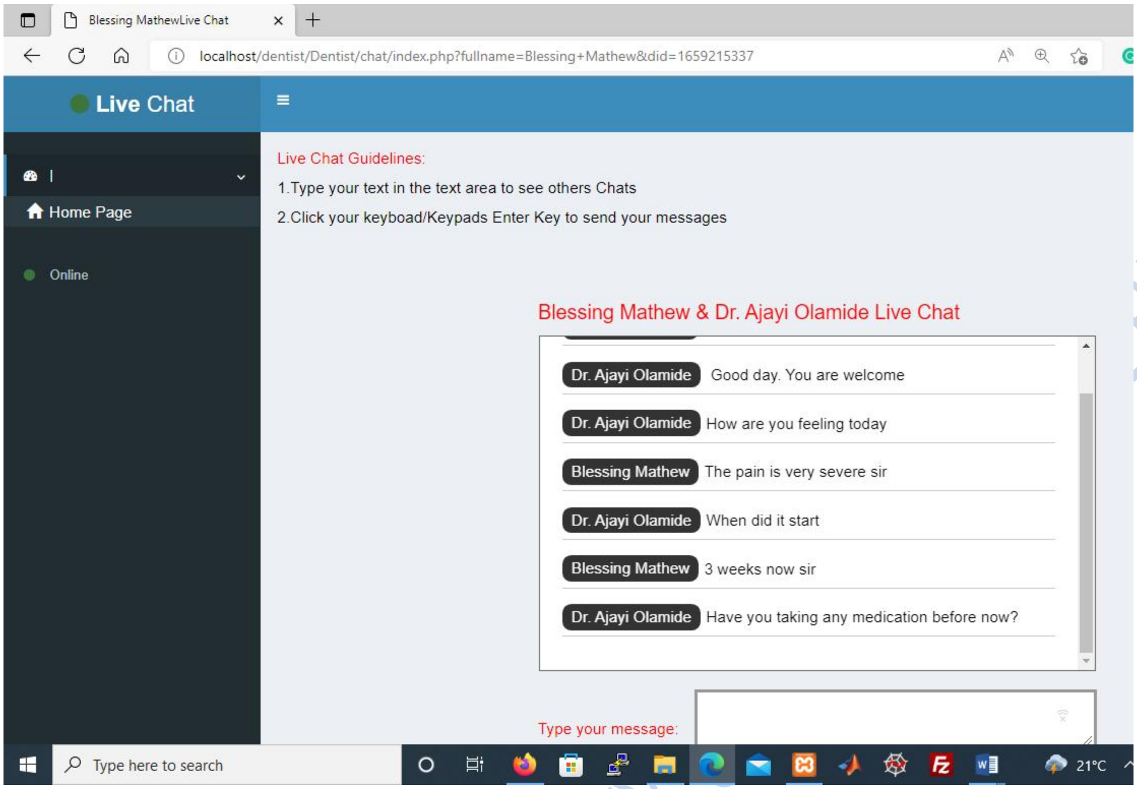


Figure 4.31 Patient-doctor live chat

Having received the patient's personal and diagnostic details, the doctor listens to the patients' complaints and ask some structured questions. At this point, the doctor establishes rapport with the patient to arrive at a provisional diagnosis through direct chat with the patient. Besides the diagnostic report sent from the diagnostic test, the doctor further makes inquiry from the patient to get more details about the history of the present complaint, previous dental history, family, and social history from the patient. Response to these structured questions will give the doctor an idea of the best possible treatment plan.

Figure 4.32 displays a sample page of doctor's prescription after doctor-patient chat. The patient's name, diagnostic reports alongside the doctor's report are seen displayed in the page.

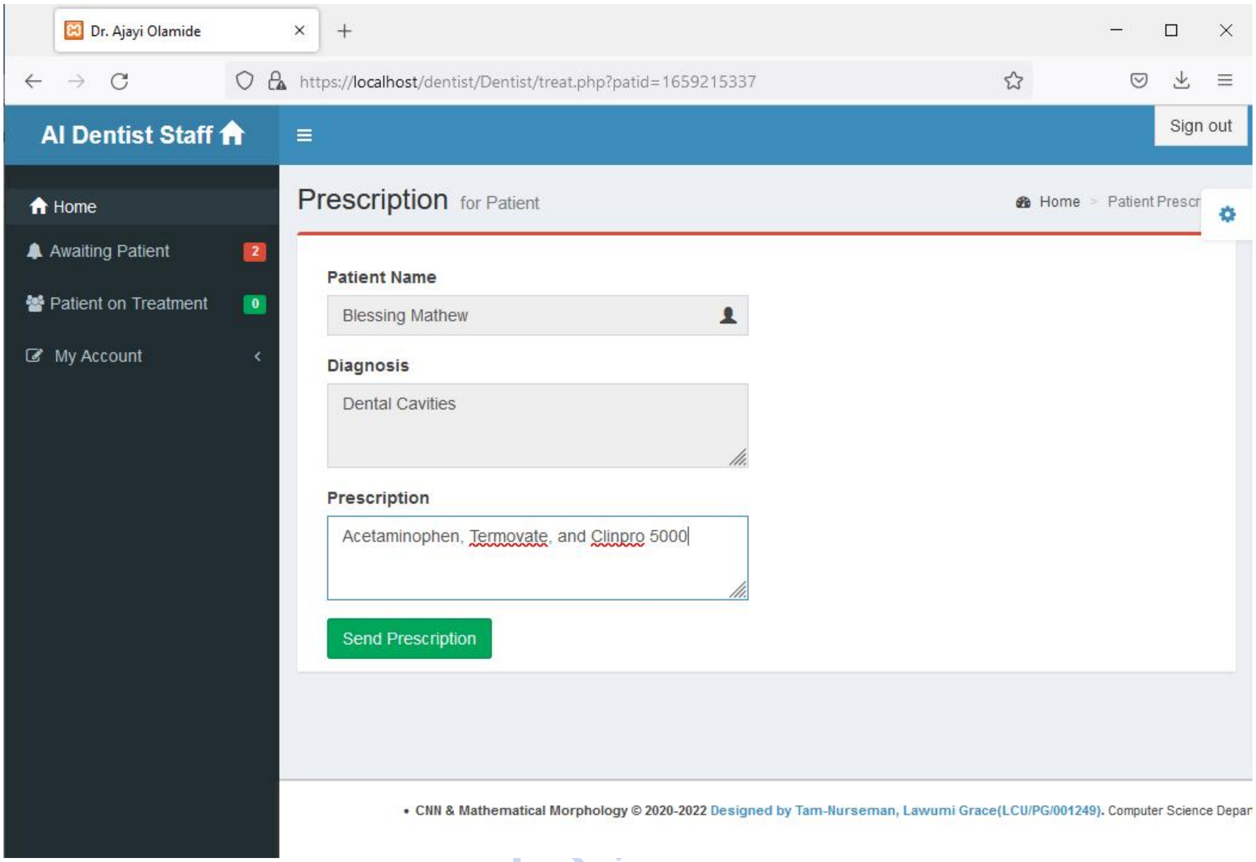


Figure 4.32 Doctor's prescription page

h. All the prescriptions of the various doctors to different patients are stored in a database for record and reference purposes. Figure 4.33 displays patients' details, consulted doctor's name, diagnostic detail, date of consultation, and prescription.

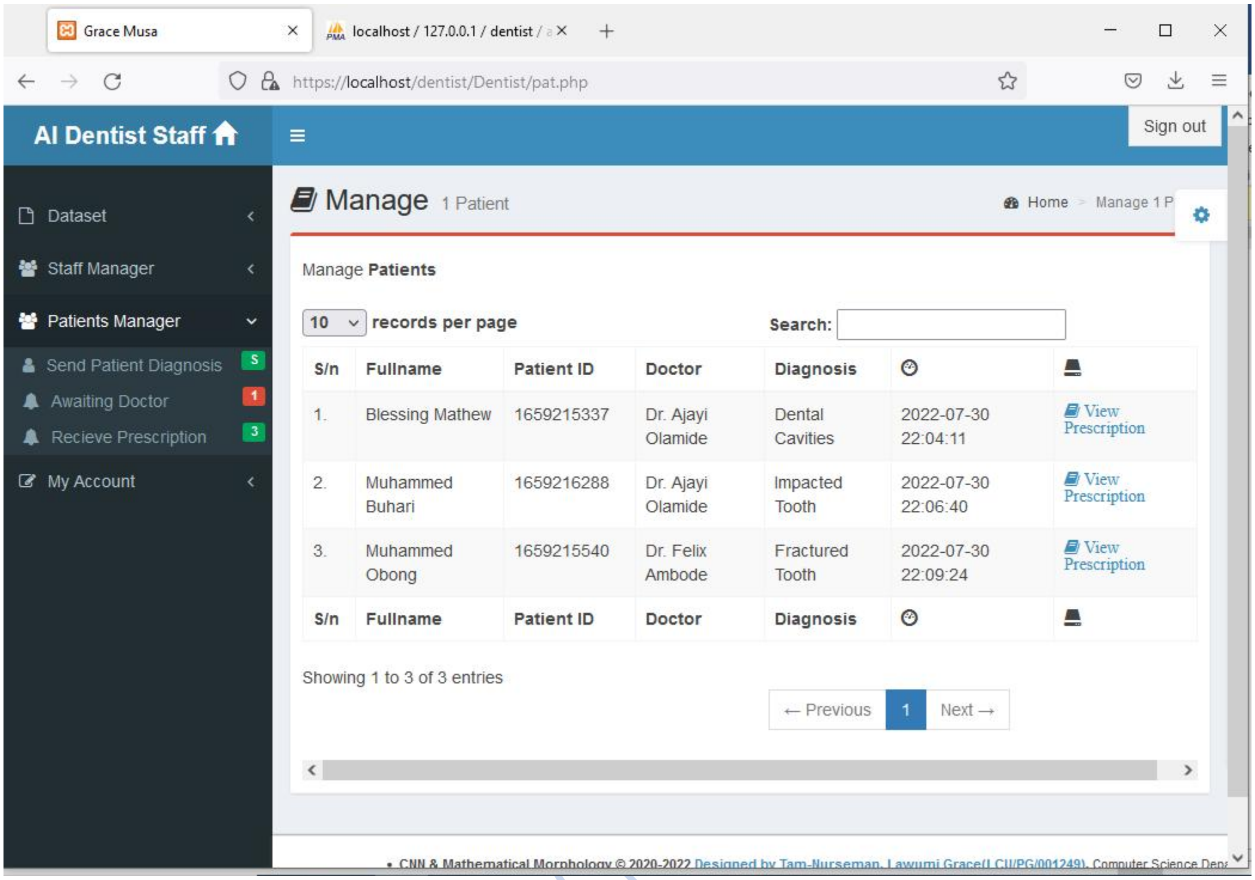


Figure 4.33 Received prescription lists

i. Every prescription is sent to the subscribing organization or hospital displayed in figure 4.34. Patients receive a printout copy or soft copy sent to their email address

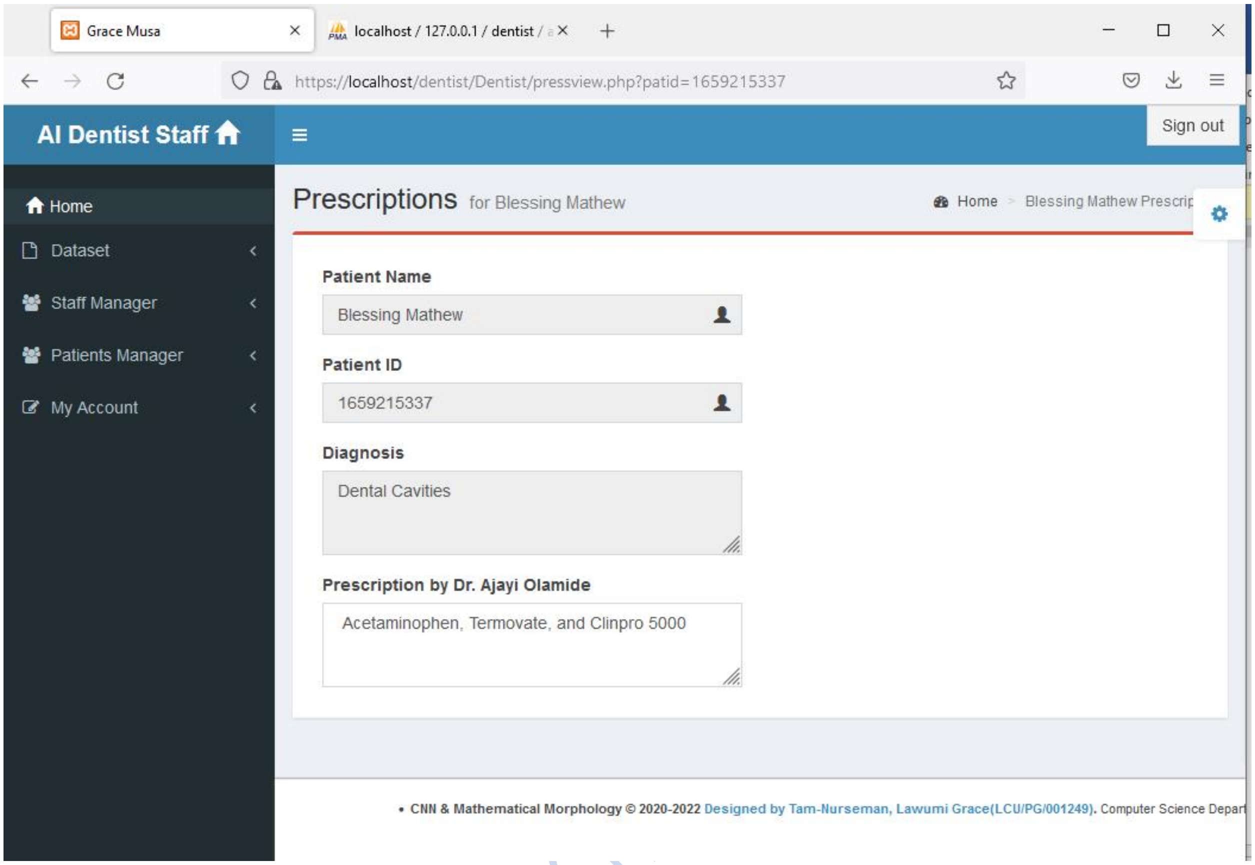


Figure 4.34 Prescription received in hospital

4.5 Discussions

Calculative steps and Mathematical algorithms were employed to the design and implementation of this model. The research questions; 'In what way can CNN be applied differently yet achieve great accuracy?' was critically analyzed and answered by integrating MM operations into the convolution layer of CNN. The model was trained with periapical dental radiographs. In this study, a CNN model was also developed sideways the MM-NN model with same quality and quantity of dataset. They were both tested with the same test set and the findings from this research hopefully will be beneficial to future researchers as well as dental practitioners.

The parameters used for the development of model are periapical dental radiographs, set theory base MM operators and some linear and non-linear functions. The model comprises dental radiograph classifier (that is able to classify dental radiographs into six classes according to the respective disease) and a telemedicine application. The classifier's output is proportional to disease diagnosis upon which an appropriate treatment plan is executed through a telemedicine application.

Chapter Five

Conclusion

5.1 Summary of Findings

This work has presented a framework through the design and development of a computer system with artificial intelligence to handle dental medical diagnostic processes through periapical radiographs while ensuring high precision and accuracy.

The work began with an introduction to the background which established the context of the study. AI, the big umbrella under which CNN is was briefly discussed alongside a brief discussion on how it evolved through ML, DL to CNN. An introduction to X-rays history and dental X-ray types came into the limelight of the study as the study has to do with dental radiographs.

In order to meet professional standards and to avoid duplicative research as evidenced by Maggio *et al,* several related pieces of literature were reviewed. The designs and limitations of each reviewed work were noted, from which the insights into the reasons for this work arose.

After identifying the limitations of existing works, an improved algorithm was proposed, implemented, and evaluated. The implementation phase employed the operations of MM for both preprocessing and extraction of relevant features from the dental images.

The research methodology engaged in this work was an experimental method. Secondary data was used to implement the system after which random data from hospitals was used to test the efficiency of the model.

The findings of this research revealed that;

i. MM operations can be conveniently integrated into the convolution layer of a CNN algorithm to effectively extract image features.

ii. The learning of the model was faster with the MM integrated convolution layer than the conventional CNN convolution layer.

iii. In terms of the Accuracy, precision, and recall metrics used, the MM-CNN model gave higher values which makes it better as demonstrated in below accuracy, precision and recall charts.

iv. MM-CNN recorded less errors as shown in figure 5.5c

iv. In the face of lack of big dataset, MM-CNN algorithm can be implemented with available dataset.

v. The research findings also revealed that digital dental images are not available in the quantity needed to develop a CNN based algorithm as dental departments/clinic lack digital imaging equipment.

5.2 Conclusion

This study adopted the fundamental question concerning the difference between biological neural network and artificial neural network which seeks to know whether the strength of the electric potential of a signal traveling along an axon is the result of multiplicative process and the mechanism of the postsynaptic membrane of a neuron adds the various potentials of the electric impulses or an additive process and the mechanism of postsynaptic membranes only accept signals of certain maximum strength? In a bit to answering this fundamental question, a research question was formulated as to how can CNN be applied differently yet with better accuracy. This research question guided the study to experiment on replacing multiplicative process in the convolution layer of CNN with additive process which employed the operations of MM. The study met all of its objectives by successfully answering the research question and came up with findings as outlined in Section 5.1.

In conclusion, this model is good and safe enough to be used in dental centres.

5.3 Contribution to Knowledge

1. The conventional convolution layer of CNN was replaced with MM and it functioned as a preprocessor and a perfect feature extractor.
2. The CNN learning Network learned faster with the presented extracted features from MM operations.
3. From Past works of literature, no study has developed a model that could diagnose up to the number of dental radiograph that this model di.
4. The model development process shifted from the usual CNN convolution feature extraction method.
5. Less data than expected was used to achieve great accuracy
6. Reduction of radiologist's increasing workload.
7. The system can be used with high confidence in dental hospitals and training institutions.
8. While dental consultants will find this system as a reliable tool to confirm the correctness of their subjective diagnosis, young dental doctors will find it as a pathway to gaining experience.
9. It will facilitate a quick and accurate radiograph-based diagnosis of dental diseases.

5.4 Recommendations

From the findings and problems encountered during the course of this research, it is highly recommended that;

1. This work be installed in the university dental department for use to reduce workload and a checkmate for correctness of subjective diagnosis.

2. Research scholars are provided with basic research facilities like research laboratories and access to relevant journals.

3. To carry out a complex and internationally acceptable research, access to basic information is key. One of such information is value data, most especially medical data. Researchers who need digital medical imaging especially in dentistry find themselves in helpless situations as reasonable number of hospitals in Nigeria are yet to go digital, and as a result find it difficult to get basic knowledge with which to continue with their research. For this reason, Nigeria Government should provide hospitals (public and private) with digital imaging equipment so as to enable researchers in medical imaging have data of value to work with.

4. Collaboration with international research communities should be strongly encouraged for intellectual and academic exposure.

5. In the face of absence of big data as required for the development of CNN model, future researchers should try out MM-CNN algorithm with available dataset.

6. The various heads of computer departments and the university at large should encourage the design, development, and implement of projects that can solve real life problems.

5.4.1 Suggestions for Further Studies

This work has been able to establish all of its objectives, thereby answering its research questions as well. However, it has its shortcomings. The work is limited to only 6 dental disease classes. It is therefore suggested that;

1) More dental disease classes be added to make the system more scalable.

2) Lattice theory, random function or topology based mathematical morphology other than set theory should be experimented in the convolution layer of CNN to compare findings in terms of dataset size, learning rate and accuracy with that of this study.

3) MM-NN depth and the layer depths should increase from 3 and 32 respectively.

4) MM-NN should be experimented with Non-flat morphological structuring elements

Endnotes

[1] Giarratano Joseph & Riley Gary,"*Expert Systems: principles and Programming,"* Second Edition, **PWS Publishing Company**, 1994. Page 2

[2] Bakator, Mihalj, & Dragica Radosav. "*Deep Learning and Medical Diagnosis: A Review of Literature* ." **ScienceGate**, 2018: 47.

[3]Ciara Mulrenan, Kawal Rhode, and Barbara Malene Fischer. "*A Literature Review on the Use of Artificial Intelligence for the Diagnosis of COVID-19 on CT and Chest X-ray* ." **Diagnostics**, March 2022: 1-22.

[4] Kumar, Yogesh, Koul Apeksha, Singla Ruchi, & Ijaz Muhammad Fazal. "*Artificial intelligence in disease diagnosis: a systematic literature review, synthesizing framework and future research agenda.*" **Journal of Ambient Intelligence and Humanized Computing**, January 2022.

[5] Gerhard, Ritter. "An introduction to morphological neural networks." *1996, Proceedings of 13th International Conference on Pattern Recognition.* Washington, DC; United States: **IEEE Computer Society**., 1996. 1-19.

[6] Shen Yucong, Xin Zhong, & Frank Y. Shih. "*Deep Morphological Neural Networks*." ***arXiv* (arXiv),** September 2019.

[7] Franchi Gianni, Amin Fehric, & AngelaYaob. *"Deep morphological networks."* **Pattern Recognition**, 2020: 107246.

[8]Deep, Paul. "*Screening for Common Oral Diseases.*" **J Can Dent Assoc 2000; 66:298-9**)2000.[Google Scholar]

[9] Mulrenan, Ciara, Kawal Rhode, and Barbara Malene Fischer. "*A Literature Review on the Use of Artificial Intelligence for the Diagnosis of COVID-19 on CT and Chest X-ray* ." ***Diagnostics***, March 2022: 1-22.

[10] Rogers, W, B.Ryack, & G.Moeller. "*Computer-aided medical diagnosis: Literature review*." **International Journal of Bio-Medical Computing** Volume 10, no. 4 August 1979: 267-289.

[11] Kumar, Yogesh, Koul Apeksha, Singla Ruchi, & Ijaz Muhammad Fazal. "*Artificial intelligence in disease diagnosis: a systematic literature review, synthesizing framework and future research agenda*." **Journal of Ambient Intelligence and Humanized Computing**, January 2022.

[12]Ojoma, Akor. "*Brain drain: Nigeria lost over 9,000 doctors in 2 years* – NMA." **Daily Trust,** April05 2022

[13] Grace Tam-Nurseman, Philip Achimugu, Oluwatolani Achimugu, Hilary Kelechi Anabi & Sseggujja Husssein. "*Expert System for the Diagnosis and Prognosis of Common Dental Diseases Using Bayes Network* ." **Journal of Biomedical Science and Engineering** 14, no. 11 2021: 361-370.

[14]Warren Birnbaum & Stephen Dunne, "*Diagnosis: The Clinician Guide*," **Reed Educational and Professional Publishing Ltd**, 2000. Page 72.

[15]Warren, Birnbaum & Stephen Dunne, "*Oral Diagnosis:the Clinician Guide*" **Reed Educational and Professional Publishing Ltd**, 2000.

[16]Hamid Hassan pour, Najmeh Samadiani & Mahdi Salehi1. "*Using morphological transforms to enhance the contrast of medical images.*" ***The Egyptian Journal of Radiology and Nuclear Medicine*** (Elsevier) 46, no. 2 June 2015: 481-489.

[17]Makkar, Hina, Mark A. Reynolds, Abhishek Wadhawan, Aline Dagdag, Anwar T Merchant, & Teodor T. Postolache. "*Periodontal, metabolic, and cardiovascular disease*: *Exploring the role of inflammation and mental health*." **PMC**, November 2018: 124-163.

[18]Nazir, Muhammad Ashraf. "*Prevalence of periodontal disease, its association with systemic diseases and prevention*." **International Journal of health sciences,** 2017: 72-80.

[19]D'souza, Durand. "*A Layman's Guide to Computer Vision.*" **Towards Data Science**. March 07, 2017. https://towardsdatascience.com/a-laymans-guide-to-computer-vision-39b9291e5278.

[20]Hamid Hassanpour, Najmeh Samadiani & Mahdi Salehi1. "*Using morphological transforms to enhance the contrast of medical images*." **The Egyptian Journal of Radiology and Nuclear Medicine** (Elsevier) 46, no. 2 June 2015: 481-489.

[21]Tutorials point. *Artificial Intelligence; Intellent Sytems*. n.d, http://www.tutorialspoint.com

[22] John, McCarthy. "*What Is Artificial Intelligence*." *Technical report, Stanford University.* November 12, 2007. http://jmc.stanford.edu/artificial-intelligence/what-is-ai/index.html.

[23] Myers, Andrew. "*Stanford's John Mccarthy, Seminal figure of artificial intelligence, dies at 84*." *Stanford News.* October 25, 2011. http://news.stanford.edu/news/2011/octtober/john-mccarthy-obit-102511.html

[24]Stefanie Chiou, Craig Music, Kara Sprague, & Rebekah Wahba. *A Marriage of Convenience:The Founding Of The Mit Artificial Intelligence L Aboratory.* Massachusetts, December 5, 2001.

[25]Peter Hajek, & Julio J.Valdes. "*An analysis of MYCIN-like expert systems*." *Mathware and Soft Computing*, 1994: 45-68.

[26] Mitchell, Tom M. *Machine Learning.* New york: McGraw-Hill Science/Engineering/Math, 1997.

[27] Kersting, Kristian. "*Machine Learning and Artificial Intelligence: Two Fellow Travelers on the Quest for Intelligent Behavior in Machines.*" **Frontiers**, November 2018: 1-6.

[28]Schunk, Dale H. *Learning TheoriesAn Educational Perspective.* Sixth. Greensboro: **Pearson**, 2012.

[29]Kavlakoglu, Eda. "*AI vs. Machine Learning vs. Deep Learning vs. Neural Networks: What's the Difference?*" *IBM Cloud.* May 27, 2020. https://www.ibm.com/cloud/blog/eda-kavlakoglu

[30]Palm, Gunther. *"Warren McCulloch & Walter Pitts: A Logical Calculus of the Ideas Immanent in Nervous Activity." Brain Theory.* Berlin: **Springer, Berlin, Heidelberg,** 1986. 229-230.

[31]Roy, Rupali. "AI, ML, and DL: *How not to get them mixed!*" *Towards Data Science.* April 29, 2020. https://towardsdatascience.com/understanding-the-difference-between-ai-ml-and-dl-cceb63252a6c

[32]Nguyen, Kelly. "*The History of Machine Learning: A Timeline.*" *experian.* January 31, 2020. https://www.experian.com/blogs/insights/2020/01/the-history-of-machine-learning-a-timeline

[33]Fradkov, L Alexander. "*Early History of Machine Learning*." ***IFAC-PapersOnLine* (Elsevier)** 53, no. 2 2020: 1385-1390.

[34]Myers, Andrew. "*Stanford's John Mccarthy, Seminal figure of artificial intelligence, dies at 84." Stanford News.* October 25, 2011. http://news.stanford.edu/news/2011/octtober/john-mccarthy-obit-102511.html

[35]Draelos, Rachel Lea Ballantyne. "*The History of Convolutional Neural Networks.*" *Toward DataScience.* April 13, 2019. https://towardsdatascience.com/a-short-history-of-convolutional-neural-networks-7032e241c483

[36] Anderson, James A., & Rosenfeld Edward. "*Talking Nets: An Oral History of Neural Networks."* In *Talking Nets: An Oral History of Neural Networks.*, by James A., & Edward, Rosenfeld Anderson, 54. Cambridge, Mass. : **MIT Press**, 2000.

[37]Fogg, Andrew. "A History of Machine Learning and Deep Learning." *Import.io.* May 30, 2018. https://www.import.io/post/history-of-deep-learning/

[38]Yann Lecun, Leon Bottou, Yoshua Bengio & Patrick Haffner. "*Gradient-based learning applied to document recognition*." *Proceedings of the IEEE* (IEEE) 86, no. 86 Novmber 1998: 2278-2324.

[39]Krizhevsky, Alex, Sutskever Ilya and Hinton Geoffrey E. "*ImageNet classification with deep* convolutional *neural networks.*" ***Communications of the ACM*** 60 (2012): 84-90.

[40] Goyal, Kechit. "Machine Learning vs Neural Networks: *What is the Difference?*" February 13, 2020. https://www.upgrad.com/blog/machine-learning-vs-neural-networks/

[41]Schmidhuber, Juergen. "*Deep Learning in Neural Networks: An Overview.*" ***arXiv:****1404.7828 [cs.NE]* 61 January 2015: 85-117.

[42]Zell, Andreas. *Simulation Neuronaler Netze [Simulation of Neural Networks] (in German).* **Addison-Wesley**, 1994.

[43] João Alexandre Lôbo Marques, Francisco Nauber Bernardo Gois, João Paulo do Vale Madeiro, Tengyue Li, & Tengyue Li. "*Chapter 4 - Artificial neural network-based approaches for computer-aided disease diagnosis and treatment.*" In *Cognitive and Soft Computing Techniques for the Analysis of Healthcare Data*, by Francisco Nauber Bernardo Gois, João Paulo do Vale Madeiro, Tengyue Li, & Simon James Fong João Alexandre Lôbo Marques, edited by & Victor Hugo C. Akash Kumar Bhoi, 79-99. Cambridge, Massachusetts: **Academic Press,** 2022.

[44]Singh, Ankita. *"Artificial Neural Networks."* *MSA Technosoft* . May 21, 2018. https://msatechnosoft.in/blog/category/tech-blogs/

[45]Saha, Sumit. "*A Comprehensive Guide to Convolutional Neural Networks* — the ELI5 way." *Towards Data Science.* December 15, 2018. https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way

[46]Manav m. "*Convolutional Neural Networks (CNN).*" *Analytics Vidhya.* May 01, 2021. https://www.analyticsvidhya.com/

[47]Saha, Sumit. "*A Comprehensive Guide to Convolutional Neural Networks* — the ELI5 way." *Towards Data Science.* December 15, 2018. https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-

[48]Saad Albawi, Tareq Abed Mohammed & Saad Albawi. "*Understanding of a Convolutional Neural Network*." **The International Conference on Engineering and Technology** *2017* . Antalya, Turkey: IEEE, 2017. 1-6.

[49]Draelos, Rachel Lea Ballantyne. "T*he History of Convolutional Neural Networks.*" *Toward DataScience.* April 13, 2019. https://towardsdatascience.com/a-short-history-of-convolutional-neural-networks-7032e241c483

[50]Saad Albawi, Tareq Abed Mohammed & Saad Albawi. "*Understanding of a Convolutional Neural Network*." **The International Conference on Engineering and Technology** 2017 . Antalya, Turkey: IEEE, 2017. 1-6.

[51]Walia, Anish Singh. *Activation functions and it's types-Which is better?* May 29, 2017. https://towardsdatascience.com/activation-functions-and-its-types-which-is-better .

[52]Bacanin,Timea & Bezdan Nebojsa. "*Convolutional Neural Network Layers & Architectures*." **Sinteza 2019 International Scientific Conference on Information Technology and Data Related Research**. Belgrade, 2019. 445- 45.

[53] Unzueta, Diego. "*Fully Connected Layer vs. Convolutional Layer: Explained*." *built in.* October 18, 2022. https://builtin.com/machine-learning/fully-connected-layer.

[54]Raven, H.George & Johnson B. Peter. ***BIOLOGY*. Texas: HOLT, RINEHART AND WINSTON, 2004.**

[55]Thomas, Andy. *An introduction to neural networks for beginners.* 2017.

[56]Smith, Steven W. *The Scientist and Engineer's Guide to Digital Signal Processing.* 2nd. California : **California Technical Publishing**, 1997.

[57]Eluyode, O.S. & Dipo Theophilus Akomolafe. "*Comparative study of biological and artificial neural networks*." **European Journal of Applied Engineering and Scientific Research,** 2013: 36-46.

[58]Smith, Steven W. *The Scientist and Engineer's Guide to Digital Signal Processing.* 2nd. California **California Technical Publishing,** 1997.

[59]Pulkit Sharma. "*A Comprehensive Tutorial to learn Convolutional Neural Networks from Scratch* (deeplearning.ai Course #4)."*Analytics Vidhya.* December 26, 2018. https://www.analyticsvidhya.com/blog/2018/12/guide-convolutional-neural-network-cnn/

[60]Shamsaldin S.Ahmed, Pola Fattah, Tarik A. Rashid & Nawzad K. Al-Salihi. "*The Study of the Convolutional Neural Networks Applications.*" ***UKH Journal of Science and Engineering*** 3, no. 2 December 2019: 31-39.

[61]Marr, Bernard. "Deep Learning Vs Neural Networks - What's The Difference?" *Bernard Marr.* 2020. https://bernardmarr.com/default.asp?contentID=1789

[62]Britz, Denny. "*Understanding Convolutional Neural Networks for NLP*." **WILDML**. November 7, 2015. http://www.wildml.com/2015/11/understanding-convolutional-neural-networks-for-nlp/.

[63]Electronic IDentification (eID). "*Face Recognition: how it works and its safety*." **Electronic IDentification (eID).** July 27, 2020. https://www.electronicid.eu/en/blog/post/face-recognition/en

[64]Yadav, Samir S & Jadhav Shivajirao M. "*Deep convolutional neural network based medical image classification for disease diagnosis*." **Journal of Big Data (Springer)** 6, no. 1 December 2019: 113.

[65]Mayank Mishra, Tanupriya Choudhury & Tanmay Sarkar. "*CNN based efficient image classification system for smartphonedevice*." **PPR313351 (Research Square**), 2021: 1-15.

[66]Jing Wang, Jiaohua Qin, Xuyu Xiang, Yun Tan & Nan Pan. "C*APTCHA recognition based on deep convolutional neural network*." **Mathematical Biosciences and Engineering** 16, no. 5 June 2019: 5851–5861.

[67]Yijun Xiao & Kyunghyun Cho. "*Efficient Character-level Document Classification by Combining Convolution and Recurrent Layers*." **arXiv preprint arXiv,** February 2016: . 1602-00367.

[68]Liang Yao, Chengsheng Mao & Yuan Luo. "*Graph Convolutional Networks for Text Classification*." **Proceedings of the AAAI Conference on Artificial Intelligence** 33, no. 1 (July 2019): 7370-7377.

[69]Hongping Wu, Yuling Liu & Jingwen Wang. "*Review of Text Classification Methods on Deep Learning.*" **Computers, Materials and Continua (CMC)** 63, no. 3 February 2020: 1309-1321.

[70]Arunnehru, J.,Chamundeeswari G. & Bharathi S. Prasanna. "*Human Action Recognition using 3D Convolutional Neural Networks with 3D Motion Cuboids in Surveillance Videos.*" **Procedia Computer Science (Elsevier)** 133 January 2018: 471-477.

[71]Bevilacqua, Antonio, MacDonald Kyle, Rangarej Aamina, Widjaya Venessa, Caulfield Brian & Kechadi Tahar. "*Human Activity Recognition with Convolutional Neural Networks.*" **European Conference***,* **ECML PKDD 2018***, Dublin, Ireland.* Dublin, Ireland: RearchGate, 2018. 1-14.

[72]Ankita, Rani Shalli, Babbar Himanshi, Coleman Sonya, Singh Aman & Aljahdali Hani Moaiteq. "*An Efficient and Lightweight Deep Learning Model for Human Activity Recognition Using Smartphones*." **Sensors** 21, no. 11 (June 2021): 1-17.

[73]Ming Zeng, Le T. Nguyen, Bo Yu, Ole J. Mengshoel, Jiang Zhu, Pang Wu, & Joy Zhang. "*Convolutional Neural Networks for Human Activity Recognition using Mobile Sensors.*" *2014 6th* **International Conference on Mobil Computing, Application and Services** *(MobiCase).* **Austin, TX, USA: IEEE**, 2014. 197-205.

[74]Isabelle Bloch, Henk Heijmans, Christian Ronse. *"Mathematical Morphology."* In *HANDBOOK OF SPATIAL LOGICS*, by Ian E. Pratt-Hartmann & Johan F.A.K. van Benthem Marco Aiello, 857–944. Groningen: Springer, 2007.

[75]Singh, Sukhvinder, & Grewal,Surender Kumar. "*Role of Mathematical Morphology in Digital Image Processing*: *A Review*." **International Journal of Scientific Engineering and Research (IJSER)** 2, no. 4 April 2014: 1-3.

[76]Ghoshal, Dibyendu & Acharjya, Pinaki Pratim. "***Image Segmentation by Mathematical** Morphology*: *An Approach through Linear, Bilinear and Conformal Transformation.*" *World Academy of Science, **Engineering and Technology International Journal of Mathematical and Computational** Sciences.* 8, no. 8 2014.

[77]Matheron, Georges & Jean Serra. "*The Birth of Mathematical Morphology*." **VI International Symposium-ISMM2002**. **Sydney: CSIRO publishing,** 2002. 1-50.

[78]Ledda, Alessandro. "*MathematicalMorphology in Image Processing.*" PhD Thesis, **Applied Engineering, University of Antwerp,, Antwerp, Belgium** , 2007.

[79]heumans, Henk J. A. M. "Mathematical Morphology: *A Modern Approach In Image Processing Based On Algebra And Geometry*." *centre for Mathematics and Computer Science* (centre for Mathematics and Computer Science) 37, no. 1 March 1995: 237-276.

[80]Kulathilake, Hemantha. *COM2304: Morphological Image Processing.* **Rajarata University Sri Lanka**, **Mihintale**, January 13, 2015.

[81]Ravi, Srisha & Am Khan. "*Morphological Operations for Image Processing : Understanding and its Applications*." **National Conference on VLSI, Signal processing and Communications**. Guntur: Research Gate, 2013. 17-19.

[82]Dougherty Edward R. *An introduction to morphological image processing.* ellingham, Wash., USA : : **BSPIE Optical Engineering Press,** 1992.

[83]Suryanarayana, C. & Grant Norton M. "*X-Rays and Diffraction*." *In X-Ray Diffraction*, by C. & Grant Norton M. C. Suryanarayana, 3-19. **Boston: Springer**, 1998.

[84]MedlinePlus. *X-Rays.* April 30, 2018. https://medlineplus.gov/xrays.htm. [Google Scholar]

[85]NDT. "*History of Radiography*." *NDT Resource Centre Web site.* n.d. https://www.nde-ed.org/EducationResources/.../Radiography/Introduction/history.htm.

[86]History.com Staff. "*German scientist discovers X-rays*." **A+E Networks** 2009.

[87]NDT. "*History of Radiography." NDT Resource Centre Web site.* n.d. https://www.nde-ed.org/EducationResources/.../Radiography/Introduction/history.htm (accessed May 11, 2021).

[88]Pauwels, Ruben. "*History Of Dental Radiography*: *Evolution of 2D and **3D*** ."**Medical Physics International Journal**, April 2020: 235-277.

[89]Dr Brazdo, Maryam. "*The History and Benefits of Dental X-ray Imaging*." *The History and Benefits of Dental X-ray Imaging.* December 18, 2017. https://www.artistictouchdentistry.com/general-dentistry/history-benefits-dental-x-ray-imaging/

[90]Riaud, Xavier. "First dental radiograph (1896)." ***J*ournal of Dental Health, Oral Disorders and Therapy** 9, no. 1 (2018): 33-34.

[91]Dr Brazdo, Maryam. "*The History and Benefits of Dental X-ray Imaging.*" *The History and Benefits of Dental X-ray Imaging.* December 18, 2017. https://www.artistictouchdentistry.com/general-dentistry/history-benefits-dental-x-ray-imaging/

[92]Raper, Howard Riley. *Elementary and dental radiography.* New York: New York, **Consolidated dental mfg**. co., 1913.

[93]Pauwels, Ruben. "*History Of Dental Radiography: Evolution of 2d And 3d* ." **Medical Physics International Journal**, April 2020: 235-277.

[94]Nakashima, Justyn & Hieu Duong. "Radiology, Image Production and Evaluation." *In Radiology, Image Production and Evaluation*, by Justyn and Hieu Duong Nakashima, 1-12. **Treasure Island (FL): StatPearls**, 2021.

[95]National Institute of Biomedical Imaging and Bioengineering (NIBIB). "*X-rays*." *National Institute of Biomedical Imaging and Bioengineering (NIBIB).* October 2017. https://www.nibib.nih.gov/science-education/science-topics/x-rays

[96]Gupta, Anuj, Devi Parvathi, Srivastava Rahul, & Bhuvan Jyoti. "*Intra oral periapical radiography - basics yet intrigue: A review.*" **Bangladesh Journal of Dental Research & Education** 04, no. 02 (July 2 2014): 83-87.

[97]Allen, Bryana. "*5 Types of Dental X-rays*." **Delta Dental of Washington**. June 8, 2018. http://www.deltadentalwa.com.

[98]Bhagyashree V. Shivpuje, and Dr G.S. Sable. "*A Review on Digital Dental Radiographic Images for Disease Identification and Classification*." **Int. Journal of Engineering Research and Application** 6, no. 7 July 2016: 38-42

[99]Deep, Paul. "Screening for Common Oral Diseases." **J Can Dent Assoc 2000;** 66:298-9) 2000.[Google Scholar]

[100]Mar, Bernard. *What Are Artificial Neural Networks - A Simple Explanation For Absolutely Anyone.* September 24, 2018. https://www.bernardmarr.com/

[101]Moolayil, Jojo John. *A Layman's Guide to Deep Neural Networks.* July 24, 2019. https://towardsdatascience.com

[102]Gupta, Dishashree. *Fundamentals of Deep Learning – Activation Functions and When to Use Them?* Octobeer 23, 2017. https://www.analyticsvidhya.com.

[103]Shekhar Amit. *What is Bias in Artificial Neural Networks?* August 2, 2019. https://afteracademy.com/blog/what- is-bias-in-artificial-neural-network

[104]American Dental Association,"*Glossary of Dental Clinical and Administrative Terms*," **American Dental Association**. n.d.

[105]Maan Al-Abbasi,*"Anatomy of Oral Cavity,"*February 2, 2016. https://uomustansiriyah.edu.

[106]Tinuke Oladele O, Sanni Yetunde,"*Dental Expert System*." **International Journal of applied Information Systems,** Vol. 8, no. 2 January 2015.

[107]Spielman Andrew, "*The birth of the most important 18th century dental text*: *Pierre Fauchard's Le chirurgien dentis*," **Journal of Dental Research**, Vol.86, no.10 (2007),922-926.

[108]Moore Wendy, "The Knife Man. Transworld," (September 2010), 223-224.

[109]Helen Dingwall, "*A pioneering history: dentistry and the Royal College of Surgeons of Edinburgh,*" April 2004.

[110]A.J.Solanki. " *A Review on Dental Radiographic Images*." **Int. Journal of Engineering Research and Application** 7, no. 7 July 2017: 49-53.

[111]Norman Tinanoff. "*Dental Caries." In Pediatric Dentistry: Infancy through Adolescence Expert Consult,* by John Christensen Tad Mabry, Janice Townsend, & Martha Wells Arthur Nowak, 169-179. **Elsevier**, 2019.

[112]Manu Rathee, & Amit Sapra. *Dental Caries.* Treasure Island (FL): **StatPearls Publishing**, 2022.

[113]Robert H Selwitz, Amid I Ismail, & Nigel B Pitts. "*Dental caries.*" **Lancet,** January 2007: 51-59.

[114]Neha Mehrotra, & Saurabh Singh. *Periodontitis.* Treasure Island (FL): **StatPearls Publishing,** 2022.

[115]Stuart C. White, & Michael J. Pharoah. *Oral radiology : principles and interpretation.* 7th. Amsterdam: **Elsevier**, 2014.

[116]Hausmann, E. "Radiographic & digital imaging in periodontal practice." **Journal of periodontology** 71, no. 3 March 2000: 497-503.

[117]Arun K. Patnana, & Tanuj Kanchan. *Periodontitis.* Treasure Island (FL): **StatPearls Publishing,** 2022.

[118]Zaleckiene, Vaida, Peciuliene Vytaute, Brukiene Vilma, & Drukteinis Sauliu. "raumatic dental injuries: etiology, prevalence and possible outcomes." **Stomatologija, Baltic Dental and Maxillofacial Journal** 16 (2014): 7-14.

[119]Preferred Dental Care. "***Dental cyst and infection***: Causes, symptoms and treatment." *Preferred Dental Care.* 2021. https://www.preferreddentalcaresanrafael.com/dental-cyst-and-infection-causes-symptoms-and-treatment/

[120]Dental, MGA. "*What Are Dental Cysts and How to Treat Each Type.*" *MGA Dental .* May 31, 2021. https://www.mgadental.com.au/dental-cysts/

[121]Evans, Julie Ryan. "*Identifying and Treating Impacted Teeth." healthline.* may 22, 2018. https://www.healthline.com/health/dental-and-oral-health/impacted-teeth

[122]HASSAN A. AZIZ, & HIBA ABOCHAR. "*Telemedicine.*" **journal of the American Society for Medical Technology** , October 2015: 256-259.

[123]American Telemedicine Association. "*What is Telemedicine?*" *American Telemedicine Association.*2012.http://www.americantelemed.org/about-telemedicine/what-is-telemedicine#.U3u3x0KKDIU.

[124]Sood, Sanjay, Mbarika Victor, Jugoo Shakhina, Dookhy Reena, Doarn Charles R, Prakash Nupur, and Merrell, Ronald C. "*What is telemedicine? A collection of 104 peer-reviewed perspectives and ." Telemedicine journal and e-health :* **the official journal of the American Telemedicine Association** 13, no. 5 (October 2007): 573-590.

[125]Thelma, Ideozu. "*Everything You Need To Know About Telemedicine In Nigeria*." *Culture Custodian.* April 13, 2022. https://culturecustodian.com/everything-you-need-to-know-about-telemedicine-in-nigeria/

[126]*Alliance for Affordable Internet (A4AI). Advancing Meaningful Connectivity: Towards Active & Participatory Digital Societies. Survey* , Washington DC: **Alliance for Affordable Internet**, 22022.

[127]Sani, Nasiru, Adamu Abdullahi Muhammed, & Lawal Shuaibu. "*Factors affecting the adoption of telemedicine in Nigeria*: *A case of Rasheed Shekoni Specialist Hospital Dutse Jigawa State*." **Information Technologist**. 17, no. 1 (July 2020).

[128]Obikunkle, Femi. "*Successes, Challenges of Telemedicine adoption in Nigeria Clinical Settings*." **The Guardian**, May 14 2020

[129]Ojoma, Akor. "*Brain drain: Nigeria lost over 9,000 doctors in 2 years – NMA*." **Daily Trust**, April05 2022

[130]Williams, Aaron M, Bhatti, Umar F, Alam, Hasan B, & Nikolian, Vahagn C. "*The role of telemedicine in postoperative care.*" **mHealth** 4 (2018): 11.

[131]Boxer, Richard J,& Ellimoottil Chad. "*Advantages and utilization of telemedicine*." **Mhealth** 5 May 2019: 12.

[132]Young, Katherine, Gupta, Amar, Palacios, Rafael,. "*Impact of Telemedicine in Pediatric Postoperative Care*." Telemedicine journal and e-health *:* **The official journal of the American Telemedicine Association** 25, no. 11 November 2019: 1083-1089.

[133]Finkelstein, Julia B, Cahill Dylan, Young Katherine, Humphrey Kate, Campbell Julie, Schumann Caitlin, Nelson Caleb P, Gupta Amar, and Estrada Carlos R Jr. "*Telemedicine for Pediatric Urological Postoperative Care is Safe, Convenient and Economical ."* **The Journal of urology** 204, no. 1 (July 2020): 144-148.

[134]Yann Lecun, Leon Bottou, Yoshua Bengio & Patrick Haffner. *"Gradient-based learning applied to document recognition."* **Proceedings of the IEEE (IEEE)** 86, no. 86 (Novmber 1998): 2278-2324.

[135]Krizhevsky, Alex, Sutskever Ilya & Hinton Geoffrey E. "ImageNet classification with deep convolutional neural networks." **Communications of the ACM** 60 (2012): 84-90.

[136]Patel, Khush. "*Architecture comparison of AlexNet, VGGNet, ResNet, Inception, DenseNet." Towards Data Science.* March 08, 2020. https://towardsdatascience.com/architecture-comparison-of-alexnet-vggnet-resnet-inception-densenet-beb8b116866d.

[137]Verma, Abhishek. "ZFNet: *An Explanation of Paper with Code.*" *Towards Data Scince.* September 20, 2020. https://towardsdatascience.com/zfnet-an-explanation-of-paper-with-code-f1bd6752121d.

[138]Krizhevsky, Alex, Sutskever Ilya & Hinton Geoffrey E. "*ImageNet classification with deep convolutional neural networks."* **Communications of the ACM** 60 (2012): 84-90.

[139]Abdullah S. AL-Malaise AL-Ghamdi, Mahmoud Ragab, Saad Abdulla AlGhamdi, Amer H. Asseri, Romany Fouad Mansour, & Deepika Koundal. "*Detection of Dental Diseases through X-Ray Images Using Neural Search Architecture Network*." **Computational Intelligence and Neuroscience** , April 2022: 1-7.

[140]Aslan, Muhammet Fatih , Unlersen Muhammed Fahri , Sabanci Kadir & Durdu Akif. "CNN-based transfer learning–BiLSTM network: *A novel approach for COVID-19 infection detection*." **Applied Soft Computing** (Elsevier) 98 January 2021: 106912.

[141]Cha, Jun-Young,Hyung-In Yoon, In-Sung Yeo, Kyung-Hoe Huh & Jung-Suk Han. " *Bone Loss Measurement Using a Region-Based Convolutional Neural Network on Dental Periapical Radiographs.*" **Journal of Clinica*l Medicine*** 10, no. 5 (March 2021): 1-12.

[142] Lee, Ki-Sun, Jung Seok-Ki, Ryu Jae-Jun, Shin Sang-Wan, & Choin Jinwook. "*Evaluation of Transfer Learning with Deep Convolutional Neural Networks for Screening Osteoporosis in Dental Panoramic Radiographs.*" **Clin Med** 9, no. 2 2020: 1-13.

[143]Muhamad Yani, Budhi Irawan S, & Casi Setiningsih. "*Application of Transfer Learning Using Convolutional Neural Network."* **J. Phys.: Conf. Ser**. *1201 012052.* IOP Publishing, 2019. 1-9.

[144]Khan, Irfan U., Aslam, Nida. "*A Deep-Learning-Based Framework for Automated Diagnosis of COVID-19 Using X-ray Images*." **Information** 11, no. 9 2020: 419.

[145]Yabo Fu, Bangjun Guo, Yang Lei, Tonghe Wang, Tian Liu, Walter Curran, Longjiang Zhang, & Xiaofeng Yang. "*Mask R-CNN based coronary artery segmentation in coronary*

computed tomography angiography",." Edited by Horst K. Hahn and Maciej A. Mazurowski. **International Society for Optics and Photonics**. Houston, Texas, United States: SPIE, 2020. 1047 -- 1052.

[146]Muramatsu, Chisako, Morishita Takumi,Takahashi Ryo,Hayashi Tatsuro, Nishiyama Wataru, Ariji Yoshiko ,Zhou Xiangrong, Hara Takeshi, Katsumata Akitoshi, Ariji Eiichiro & Fujita Hiroshi. "*Tooth detection and classification on panoramic radiographs for automatic dental chart filing: improved classification by multi-sized input data*." **Oral Radiology** (Springer) 37, no. 1 January 2021: 13-19.

[147]Lakhani P, Sundaram B. "*Deep learning at chest radiography: automated classification of pulmonary tuberculosis by using convolutional neural networks.*" **Radiology**. 284, no. 2 (August 2017): 574-582.

[148]Khan, Irfan U., Aslam, Nida. "*A Deep-Learning-Based Framework for Automated Diagnosis of COVID-19 Using X-ray Images.*" **Information** 11, no. 9 (2020): 419.

[149]Yadav, Samir S.& Jadhav, Shivajirao M. "*Deep convolutional neural network based medical image classification for disease diagnosis."* **Journal of Big Data** 6, no. 1 (December 2019): 1-18.

[150]Singh Prerna & Sehgal, Priti. "*Numbering and Classification of Panoramic Dental Images Using 6-Layer Convolutional Neural Network.*" **Pattern Recognition and Image Analysis** 30, no. 1 2020: 125-133.

[151]Lakhani Paras, Gray, Daniel L., Pett, Carl R.,Nagy, Paul & Shih, George. *"Hello World Deep Learning in Medical Imaging*." **Journal of Digital Imaging** 31, no. 3 June 2018: 283-289.

[152]Yamashita Rikiya, Nishio Mizuho, Do Richard Kinh Gian & Togashi Kaori. "*Convolutional neural networks: an overview and application in radiology."* **Insights into Imaging** *9, no. 4 (September 2018): 611-629.*

[153]Ravi Kaushik, & Shailender Kumar. "*Image Segmentation Using Convolutional Neural Network.*" **International Journal Of Scientific & Technology Research** *Volume 8, Issue 11, November 2019 Issn 2277-8616* (Ijstr©2019) 8, No. 11 (November 2019): 667-675.

[154]Hu Chen, Kailai Zhang, Peijun Lyu, Hong Li, Ludan Zhang, Ji Wu & Chin-Hui Lee. "*A deep learning approach to automatic teeth detection and numbering based on object detection in dental periapical films."* **Scientific Reports** *9, no. 1 (March 2019): 3840.*

[155]Oualid, Benkarim, Gemma Piella, Nadine Hahnerb, Elisenda Eixarch, Miguel Angel, González Balleste & Gerard Sanroma. "*Patch spaces and fusion strategies in patch-based label fusion*." **Computerized medical imaging and graphics: the official journal of the Computerized Medical Imaging Society.** 71 January 2019: 79-89.

[156]Ozaki, Masao & Wataru MOTOKAWA. *"Dental Age Estimation by Two Computer Methods : Fuzzy Logic and Neural Network."* **International Journal of Biomedical Soft Computing and Human Sciences: the official journal of the Biomedical Fuzzy Systems Association**, 2000: 13-17.

[157]Zhang, Kailai, Wu Ji, Chen Hu &. "*An effective teeth recognition method using label tree with cascade network structure*." **Computerized medical imaging and graphics: the official journal of the Computerized Medical Imaging Society** (PubMed) 68 September 2018: 61-70.

[158] Mellouli, Doura, Hamdani M.Tarek,Sanchez-Medina J Javier, Ben Ayed Mounir, & Alimi M Adel. "*Morphological convolutional Neural Network architecture for digit recognition*." **IEEE Transactions on Neural Networks and Learning Systems**, September 2019: 2876-2885.

[159]Ramesh, C. A. & Rishikeshan H. "*A novel mathematical morphology based algorithm for shoreline extraction from satellite images*." **Geo-spatial Information Science (Taylor & Francis)** 20, no. 4 January 2017: 345-352.

[160]Pedro H. M. Lira, Gilson A. Giraldi, & Luiz A. P. Neves. "*Using the Mathematical Morphology and Shape Matching for Automatic Data Extraction in Dental X-Ray Images*." **IX Workshop de Visao Computacional**. 2013.

[161]Mumtaz Ali, Le Hoang Son , Mohsin Khan & Nguyen Thanh Tung. "*Segmentation of dental X-ray images in medical imaging using neutrosophic orthogonal matrices."* **Expert Systems With Applications (Elsevier Ltd.),** 2017: 431-441.

[162]Yusra Y. Amer, & Musbah J. Aqel. "*An Efficient Segmentation Algorithm for Panoramic Dengtal Images."* **International Conference on Communication, Management and Information Technology(ICCMIT). Elsevier**, 2015. 718-725.

[163]Oladele Tinuke O,& Sanni Yetunde. "*Dental Expert System*." **International Journal of applied Information Systems(IJAIS)** 8, no. 2 January 2015.

[164]Mehdi Khosravi, Mohammad Yazdanshenas & Mohammad Reza Vatandost. " *Design of an Expert System for Diagnosis of Oral Cancer*." **Journal of Applied Environmental and Biological Sciences** 5, no. 8S May 2015: 98-101.

[165]Sorana-Maria Buur, Manuela Chibelean,Adrian Gligor,& Mariana Pacurar. *"Expert System for Determining the Level of Stress befor Pediatric dental Treatment."* **The 7th International Conference Interdisciplinarity in Engineering** *INTER-ENGR @2013*. 2012.

[166]Eyad Haj Said, Diaa Eldin M. Nassar, Gamal Fahmy, Hany H. Ammar,". "*Teeth Segmentation in Digitized Dental X-ray Films using Mathematical Morphology*." ***IEEE*, n.d.**

[167]Raju, Jincy & Modi, Chintan. "*A Proposed Feature Extraction Technique for Dental X-Ray Images Based on Multiple Features."* **2011 International Conference on Communication Systems and Network Technologies**. **IEEE Xplore,** 2011. 545-549.

[168]Krithigaa, R.Rani & Lakshmia C. *A Survey:* Segmentation in Dental X-ray Images for s Diagnosis of Dental Caries. Vol. 09. I**nternational Science Press**, 2016.

[169]Krithiga, R.Rani C.Lakshmi,& A.Alice Nithya. Segmentation of dental caries from dental X-ray images using wavelet and watershed transforms. Vol. 9. © **Research India Publications.**, 2014.

[170]Reddy, M.V.Bramhananda , Varadala.Sridhar, & Nagendra M. "*Dental X-Ray Image Analysis by Using Image Processing Techniques*." **International Journal of Advanced Research in Computer Science and Software Engineering** 2, no. 6 June 2012.

[171]Rad, Abdolvahab Ehsani , Rahim Mohd Shafry Mohd , & Norouzi Alireza. *"Digital Dental X-Ray Image Segmentation and Feature Extraction*." **TELKOMNIKA** 11, no. 6 June 2013: 3109- 3114

[172]Na`am, Jufriadif, Harlan, Johan & Wibowo, Eri Prasetyo. "*Image Processing of Panoramic Dental X-Ray for Identifying Proximal Caries*." **TELKOMNIKA** 15, no. 2 June 2017: 702-708.

[173]Krizhevsky, Alex, Sutskever Ilya & Hinton Geoffrey E. "*ImageNet classification with deep convolutional neural networks."* **Communications of the ACM** *60 2012: 84-90.*

[174]Fukushima, Kunihiko. "Neocognitron:*A self-organizing neural network model for a mechanism of pattern recognition unaffected by shift in position*." **Fukushima, Kunihiko Springer** 36, no. 4 April 1980: 193-204.

[175] Ayyar, Tejas Mohan. "LeNet." *A practical experiment for comparing LeNet, AlexNet, VGG and ResNet models with their advantages and disadvantages.* November 6, 2020. https://tejasmohanayyar.medium.com/a-practical-experiment-for-comparing-lenet-alexnet-vgg-and-resnet-models-with-their-advantages-d932fb7c7d17

[176]Lakhani Paras, Gray, Daniel L., Pett, Carl R.,Nagy, Paul & Shih, George. *"Hello World Deep Learning in Medical Imaging*." **Journal of Digital Imaging** 31, no. 3 June 2018: 283-289.

[177] Howard G. Andrew, Menglong Zhu, Bo Chen , Dmitry Kalenichenko, Weijun Wang, Tobias Weyand, Marco Andreetto, & Hartwig Adam. "*MobileNets*: *Efficient Convolutional* Neural *Networks for Mobile Vision*." ***arXiv***, 2017: 1-9.

[178] Keiller Nogueira, Jocelyn Chanussot, Mauro Dalla Mura & Jefersson A. Dos Santos. . "*An Introduction to Deep Morphological Networks.* ." **IEEE Access 9** , 2021: 114308-114324.

[179]Krizhevsky, Alex, Sutskever Ilya & Hinton Geoffrey E. "ImageNet classification with deep convolutional neural networks." **Communications of the ACM** 60 (2012): 84-90.

[180] Dawson, Catherine. "*Advantages and Disadvantages of Open and Close questiions*." In *Practical Research Methods: A User-friendly Guide to Mastering Research Techniques and Projects*, by Catherine Dawson, 88. Oxford, United Kingdom: **How To Books,** 2002.

[181] Hajic, E. J & Simonett, D. S. "Comparisons of qualitative and quantitative image analysis." In *Remote sensing of environment.*, by E. J, & Simonett, D. S Hajic, 374-411. California: Addison-Wesley Publishing Co., Inc., 1976.

[182]Colgate-Palmolive. "*Types of X-rays*." *Colgate-Palmolive.* February 4, 2022. https://www.colgate.com/en-us/oral-health/x-rays/types-of-x-rays#

[183]Rubin, Herbert J., and Irene Rubin. *Qualitative Interviewing: The Art of Hearing Data.* Third Edition. Thousand Oaks,, California: **Sage Publications,** 2012.

[184]Sharon M. Ravitch, and Sharon M. Ravitch. *Qualitative Research:Bridging the Conceptual, Theoretical, and Methodological.* 2nd. **Thousand Oaks,** California: SAGE, 2016.

[185]Nigerianscholars.com. "*List of Courses Offered at Federal School Of Dental Technology And Therapy, Enugu* (FEDSDTTEN)." *nigerianscholars.com.* May 30, 2020. https://nigerianscholars.com

[186]Rubin, Herbert J., and Irene Rubin. *Qualitative Interviewing: The Art of Hearing Data.* Third Edition. Thousand Oaks,, California: **Sage Publications,** 2012.

[187]Jason Brownslee on January 9, 2019. "*A Gentle Introduction to the Rectified Linear Unit (ReLU)." Machine Learning Mastery. January 9, 2019. https://machinelearningmastery.com*

[188]Nielsen, Jakob. "*The History of Hypertext.*" *NN/g Nielsen Norman Group.* February 1, 1995. https://www.nngroup.com/articles/hypertext-history/

[189]Chris, Kolade. "*What is PHP? The PHP Programming Language Meaning Explained*." *freeCodeCamp.* August 30, 2021. https://www.freecodecamp.org/news/what-is-php-the-php-programming-language-meaning-explained/

[190]Reactor, Hack. "*What is JavaScript used for?*" *Hack Reactor.* August 26, 2021. https://www.hackreactor.com/blog/what-is-javascript-used-for

[191]Kathirkamar, Vignesh. "A brief overview of "*Python and Anaconda*"—*for starters."* **Analytics Vidhya**. September 6, 2020.

[192]Urooj, Wajiha. "*What is Python Spyder IDE and How to use it?*" *Edureka.* September 11, 2019. https://medium.com/edureka/spyder-ide-2a91caac4e46

[193]Yegulalp, Serdar. "*What is TensorFlow*? *The machine learning library explained.*" *nfoWorld.* June 3, 2022. https://www.infoworld.com/article/3278008/what-is-tensorflow-the-machine-learning-library-explained.html

[194]Gour, Rinu. "*Various Uses of TensorFlow." DZone.* January 8, 2019. https://dzone.com/articles/learn-various-uses-of-tensorflow

[195]Lakhani, Paras, Gray, Daniel L., Pett, Carl R.,Nagy, Paul, and Shih, George. *"Hello World Deep Learning in Medical Imaging."* **Journal of Digital Imaging** *31, no. 3 (June 2018): 283-289.*

[196]Warren Birnbaum, and Stephen M. Dunne. *Oral Diagnosis: the Clinician's Guide.* London: Reed Educational and Professional Publishing Ltd, 2000.

Bibliography

Book

Dougherty, Edward R. *An introduction to morphological image processing.* ellingham, Wash., USA : : **BSPIE Optical Engineering Press,** 1992.

Giarratano, Joseph & Riley Gary,"*Expert Systems: principles and Programming,"* Second Edition, **PWS Publishing Company**, 1994. Page 2

Krithigaa, R.Rani & Lakshmia C. "*A Survey: Segmentation in Dental X-ray Images for Diagnosis of Dental Caries".* Vol. 09. **International Science Press**, 2016.

Krithiga, R.Rani C.Lakshmi,& A.Alice Nithya. *Segmentation of dental caries from dental X-ray images using wavelet and watershed transforms.* Vol. 9. © **Research India Publications**., 2014.

Manu, Rathee, & Amit Sapra. *Dental Caries.* Treasure Island (FL): **StatPearls Publishing**, 2022.

Mitchell, Tom M. "*Machine Learning".* New york: **McGraw-Hill** Science/Engineering/Math, 1997

Muhamad, Yani, Budhi Irawan S, & Casi Setiningsih. "Application of Transfer Learning Using Convolutional Neural Network." *J. Phys.: Conf. Ser. 1201 012052.* **IOP Publishing,** 2019. 1-9.

Neha, Mehrotra, & Saurabh Singh. "*Periodontitis".* **Treasure Island (FL): StatPearls Publishing,** 2022.

Raven, H., George B.Johnson & Peter. BIOLOGY. Texas: **HOLT, RINEHART AND WINSTON, 2004.**

Rubin, Herbert J., & Irene Rubin. *Qualitative Interviewing: The Art of Hearing Data.* Third Edition. Thousand Oaks,, California: **Sage Publications**, 2012

Warren, Birnbaum, & Stephen M. Dunne. *Oral Diagnosis: the Clinician's Guide.* London: **Reed Educational and Professional Publishing Ltd**, 2000.

Zell, Andreas. *Simulation Neuronaler Netze "Simulation of Neural Networks" (in German).* **Addison-Wesley**, 1994.

Book Chapter

Anderson, James A., & Rosenfeld Edward. "*Talking Nets: An Oral History of Neural Networks."* In *Talking Nets: An Oral History of Neural Networks.*, by James A., & Edward, Rosenfeld Anderson, 54. Cambridge, Mass. : **MIT Press,** 2000.

Dawson, Catherine. "*Advantages and Disadvantages of Open and Close questiions*." In *Practical Research Methods: A User-friendly Guide to Mastering Research Techniques and Projects*, by Catherine Dawson, 88. Oxford, United Kingdom: **How To Books**, 2002.

Isabelle, Bloch, Henk Heijmans, Christian Ronse. "*MATHEMATICAL MORPHOLOGY*." In *HANDBOOK OF SPATIAL LOGICS*, by Ian E. Pratt-Hartmann & Johan F.A.K. van Benthem Marco Aiello, 857–944. **Groningen: Springer**, 2007.

[196] João Alexandre Lôbo Marques, Francisco Nauber Bernardo Gois, João Paulo do Vale Madeiro, Tengyue Li, & Tengyue Li. "*Chapter 4 - Artificial neural network-based approaches*

for computer-aided disease diagnosis and treatment." In *Cognitive and Soft Computing Techniques for the Analysis of Healthcare Data*, by Francisco Nauber Bernardo Gois, João Paulo do Vale Madeiro, Tengyue Li, & Simon James Fong João Alexandre Lôbo Marques, edited by & Victor Hugo C. Akash Kumar Bhoi, 79-99. Cambridge, Massachusetts: **Academic Press,** 2022.

Nakashima, Justyn & Hieu Duong. "*Radiology, Image Production and Evaluation." In Radiology, Image Production and Evaluation*, by Justyn & Hieu Duong Nakashima, 1-12. **Treasure Island (FL): StatPearls,** 2021.

Norman, Tinanoff. "*Dental Caries." In Pediatric Dentistry: Infancy through Adolescence Expert Consult,* by John Christensen, Tad Mabry, Janice Townsend, & Martha Wells Arthur Nowak, 169-179. **Elsevier**, 2019.

Smith, Steven W. *The Scientist and Engineer's Guide to Digital Signal Processing.* 2nd. California : **California Technical Publishing**, 1997.

Yabo, Fu, Bangjun Guo, Yang Lei, Tonghe Wang, Tian Liu, Walter Curran, Longjiang Zhang, & Xiaofeng Yang. "*Mask R-CNN based coronary artery segmentation in coronary computed tomography angiography",*." Edited by Horst K. Hahn & Maciej A. Mazurowski. International Society for Optics and Photonics. Houston, Texas, United States: **SPIE**, 2020. 1047 - 1052.

Conference Proceeding

Bacanin, Timea Bezdan & Nebojsa. *"Convolutional Neural Network Layers and Architectures."* *Sinteza 2019* **INTERNATIONAL SCIENTIFIC CONFERENCE ON INFORMATION TECHNOLOGY AND DATA RELATED RESEARCH**. **Belgrade**, 2019. 445- 451.

Bevilacqua, Antonio, MacDonald Kyle, Rangarej Aamina, Widjaya Venessa, Caulfield Brian & Kechadi Tahar. "*Human Activity Recognition with Convolutional Neural Networks."* **European Conference***,* **ECML PKDD 2018***,* **Dublin, Ireland**. Dublin, Ireland: RearchGate**,** 2018. 1-14.

Gerhard, Ritter. *"An introduction to morphological neural networks."* **1996, Proceedings of 13th International Conference on Pattern Recognition.** Washington, DC; United States: IEEE Computer Society., 1996. 1-19.

Liang, Yao, Chengsheng Mao & Yuan Luo. "*Graph Convolutional Networks for Text Classification."* **Proceedings of the AAAI Conference on Artificial Intelligence** 33, no. 1 July 2019: 7370-7377.

Matheron, Georges & Jean Serra. "*The Birth Of Mathematical Morphology*." **VI International Symposium-ISMM2002. Sydney**: **CSIRO publishing**, 2002. 1-50

Palm, Gunther. " " *Brain Theory.* **Proceedings of the First Trieste Meeting on Brain Theory, October 1–4, 1984: Springer,** Berlin, Heidelberg, 1986. 229-230.

Pedro, H. M. Lira, Gilson A. Giraldi, & Luiz A. P. Neves. *"Using the Mathematical Morphology and Shape Matching for Automatic Data Extraction in Dental X-Ray Images."* **IX Workshop de Visao Computacional**. 2013

Saad, Albawi, Tareq Abed Mohammed & Saad Albawi. "*Understanding of a Convolutional Neural Network."* **The International Conference on Engineering and Technology 2017**. Antalya, Turkey: **IEEE**, 2017. 1-6.

Sorana-Maria, Buur, Manuela Chibelean,Adrian Gligor,& Mariana Pacurar. *"Expert System for Determining the Level of Stress befor Pediatric dental Treatment*." **The 7th International Conference Interdisciplinarity in Engineering** *(**INTER-ENGR** @2013* 2012

Stuart, C. White, & Michael J. Pharoah. *Oral radiology : principles and interpretation.* **7th. Amsterdam:** Elsevier, 2014.

Yann, Lecun, Leon Bottou, Yoshua Bengio & Patrick Haffner. "*Gradient-based learning applied to document recognition*." **Proceedings of the IEEE** (IEEE) 86, no. 86 Novmber 1998: 2278-2324.

Yusra, Y. Amer, & Musbah J. Aqel. "*An Efficient Segmentation Algorithm for Panoramic Dengtal Images."* **International Conference on Communication, Management and Information Technology(ICCMIT). Elsevier**, 2015. 718-725.

Journal

Abdullah, S. AL-Malaise AL-Ghamdi, Mahmoud Ragab, Saad Abdulla AlGhamdi, Amer H. Asseri, Romany Fouad Mansour, & Deepika Koundal. "*Detection of Dental Diseases through X-Ray Images Using Neural Search Architecture Network."* **Computational Intelligence and Neuroscience** , April 2022: 1-7.

Ankita, Rani Shalli, Babbar Himanshi, Coleman Sonya, Singh Aman & Aljahdali Hani Moaiteq. *"An Efficient and Lightweight Deep Learning Model for Human Activity Recognition Using Smartphones.*" **Sensors 21**, no. 11 June 2021: 1-17.

Arunnehru, J.,Chamundeeswari G. & Bharathi S. Prasanna. "*Human Action Recognition using 3D Convolutional Neural Networks with 3D Motion Cuboids in Surveillance Videos*." **Procedia Computer Science** (**Elsevier**) 133 January 2018: 471-477.

Aslan, Muhammet Fatih , Unlersen Muhammed Fahri , Sabanci Kadir & Durdu Akif. "*CNN-based transfer learning–BiLSTM network: A novel approach for COVID-19 infection detection.*" **Applied Soft Computing (Elsevier)** 98 January 2021: 106912.

Bakator, Mihalj, & Dragica Radosav. "*Deep Learning and Medical Diagnosis: A Review of Literature"* **ScienceGate,** 2018: 47.

Bhagyashree, V. Shivpuje, & Dr G.S. Sable. "*A Review on Digital Dental Radiographic Images for Disease Identification and Classification.*" ***Int. Journal of Engineering Research and*** **Application** 6, no. 7 July 2016: 38-42

Ciara Mulrenan, Kawal Rhode, & Barbara Malene Fischer. "*A Literature Review on the Use of Artificial Intelligence for the Diagnosis of COVID-19 on CT and Chest X-ray* ." ***Diagnostics***, March 2022: 1-22.

Deep, Paul. "S*creening for Common Oral Diseases.*" **J Can Dent Assoc 2000**; 66:298-9 2000.[Google Scholar]

Eluyode, O.S. & Dipo Theophilus Akomolafe. "*Comparative study of biological and artificial neural networks."* **European Journal of Applied Engineering and Scientific Research,** 2013: 36-46.

Finkelstein, Julia B, Cahill Dylan, Young Katherine, Humphrey Kate, Campbell Julie, Schumann Caitlin, Nelson Caleb P, Gupta Amar, & Estrada Carlos R Jr. "*Telemedicine for Pediatric Urological Postoperative Care is Safe, Convenient and Economical* ." **The Journal of urology** 204, no. 1 July 2020: 144-148.

Eyad Haj Said, Diaa Eldin M. Nassar, Gamal Fahmy, Hany H. Ammar,". "*Teeth Segmentation in Digitized Dental X-ray Films using Mathematical Morphology."* **IEEE Transactions on Information Forensics and Security** 1, no 2 5 June 2006:178-189**.**

Fradkov, L Alexander. "*Early History of Machine Learning*." *IFAC-PapersOnLine* (**Elsevier)** 53, no. 2 2020: 1385-1390.

Franchi Gianni, Amin Fehric, & AngelaYaob. "*Deep morphological networks.*" **Pattern Recognition**, 2020: 107246.

Fukushima, Kunihiko. "*Neocognitron:A self-organizing neural network model for a mechanism of pattern recognition unaffected by shift in position.*" *Fukushima, Kunihiko* (**Springer**) 36, no. 4 April 1980: 193-204

Grace Tam-Nurseman, Philip Achimugu, Oluwatolani Achimugu, Hilary Kelechi Anabi & Sseggujja Husssein. "*Expert System for the Diagnosis and Prognosis of Common Dental Diseases Using Bayes Network* ." ***Journal of Biomedical Science and Engineering*** 14, no. 11 2021: 361-370.

Hausmann, E. "*Radiographic and digital imaging in periodontal practice.*"   71, no. 3 (March 2000): 497-503.

Hamid, Hassan pour, Najmeh Samadiani & Mahdi Salehi1. "*Using morphological transforms to enhance the contrast of medical images*." **The Egyptian Journal of Radiology and Nuclear Medicine** (Elsevier) 46, no. 2 June 2015: 481-489

Hongping, Wu, Yuling Liu & Jingwen Wang. "*Review of Text Classification Methods on Deep Learning.*" ***Computers, Materials & Continua*** *(CMC)* 63, no. 3 February 2020: 1309-1321.

Howard G. Andrew, Menglong Zhu, Bo Chen , Dmitry Kalenichenko, Weijun Wang, Tobias Weyand, Marco Andreetto, & Hartwig Adam. "*MobileNets*: *Efficient Convolutional* Neural *Networks for Mobile Vision*." ***arXiv***, 2017: 1-9.

Hu, Chen, Kailai Zhang, Peijun Lyu, Hong Li, Ludan Zhang, Ji Wu & Chin-Hui Lee. "*A deep learning approach to automatic teeth detection and numbering based on object detection in dental periapical films."* **Scientific Reports** 9, no. 1 March 2019: 3840.

Jing, Wang, Jiaohua Qin, Xuyu Xiang, Yun Tan & Nan Pan. "*CAPTCHA recognition based on deep convolutional neural network*." **Mathematical Biosciences and Engineering** 16, no. 5 June 2019: 5851–5861.

Keiller Nogueira, Jocelyn Chanussot, Mauro Dalla Mura & Jefersson A. Dos Santos. . "*An Introduction to Deep Morphological Networks.* ." **IEEE Access 9** , 2021: 114308-114324.

Kersting, Kristian. "Machine Learning and Artificial Intelligence: Two Fellow Travelers on the Quest for Intelligent Behavior in Machines." ***Frontiers***, November 2018: 1-6.

Khan, Irfan U., Aslam, Nida. "*A Deep-Learning-Based Framework for Automated Diagnosis of COVID-19 Using X-ray Images.*" *I***nformation** 11, no. 9 2020: 419.

Krizhevsky, Alex, Sutskever Ilya & Hinton Geoffrey E. "*ImageNet classification with deep convolutional neural networks."* **Communications of the ACM** 60 2012: 84-90.

Kulathilake, Hemantha. *COM2304: "Morphological Image Processing".* **Rajarata University Sri Lanka, Mihintale,** January 13, 2015.

Kumar, Yogesh, Koul Apeksha, Singla Ruchi, & Ijaz Muhammad Fazal. "*Artificial intelligence in disease diagnosis: a systematic literature review, synthesizing framework and future research agenda."* **Journal of Ambient Intelligence and Humanized Computing, January** 2022.

Lakhani, Paras, Gray, Daniel L., Pett, Carl R.,Nagy, Paul & Shih, George. "*Hello World Deep Learning in Medical Imaging*." **Journal of Digital Imaging** 31, no. 3 June 2018: 283-289.

Maggio, Lauren A, Sewell Justin L, & Artino, Anthony R Jr. "*The Literature Review: A Foundation for High-Quality Medical Education Research.*" **Journal of graduate medical education** 8, no. 3 July 2016): 297-303.

Makkar, Hina, Mark A. Reynolds, Abhishek Wadhawan, Aline Dagdag, Anwar T Merchant, & Teodor T. Postolache. "*Periodontal, metabolic, and cardiovascular disease: Exploring the role of inflammation and mental health.*" **PMC,** November 2018: 124-163.

Mayank, Mishra, Tanupriya Choudhury & Tanmay Sarkar. "*CNN based efficient image classification system for smartphonedevice."* **PPR313351 (Research Square)**, 2021: 1-15.

Mehdi, Khosravi, Mohammad Yazdanshenas & Mohammad Reza Vatandost. " *Design of an Expert System for Diagnosis of Oral Cancer."* **Journal of Applied Environmental and Biological Sciences** 5, no. 8S May 2015: 98-101.

Mellouli, Doura, Hamdani M.Tarek,Sanchez-Medina J Javier, Ben Ayed Mounir, & Alimi M Adel. "Morphological convolutional Neural Network architecture for digit recognition." ***IEEE Transactions on Neural Networks and Learning Systems,*** September 2019: **2876-2885.**

Moore, Wendy, "*The Knife Man.*" **Transworld,** September 2010, 223-224.

Mulrenan, Ciara, Kawal Rhode, & Barbara Malene Fischer. "*A Literature Review on the Use of Artificial Intelligence for the."* **Diagnostics** , March 2022: 1-22.

Mumtaz, Ali, Le Hoang Son , Mohsin Khan & Nguyen Thanh Tung. *"Segmentation of dental X-ray images in medical imaging using neutrosophic orthogonal matrices*." **Expert Systems With Applications (Elsevier Ltd.),** 2017: 431-441.

Muramatsu, Chisako, Morishita Takumi,Takahashi Ryo,Hayashi Tatsuro, Nishiyama Wataru, Ariji Yoshiko ,Zhou Xiangrong, Hara Takeshi, Katsumata Akitoshi, Ariji Eiichiro and Fujita Hiroshi. "*Tooth detection and classification on panoramic radiographs for* *automatic dental chart filing: improved classification by multi-sized input data.*" **Oral Radiology (Springer)** 37, no. 1 (January 2021: 13-19.

Na`am, Jufriadif, Harlan, Johan & Wibowo, Eri Prasetyo. "*Image Processing of Panoramic Dental X-Ray for Identifying Proximal Caries."* **TELKOMNIKA** 15, no. 2 June 2017: 702-708.

Nazir, Muhammad Ashraf. *"Prevalence of periodontal disease, its association with systemic diseases and prevention*." **International Journal of health sciences**, 2017: 72-80.

Oladele, Tinuke O, & Sanni Yetunde. "*Dental Expert System*." **International Journal of applied Information Systems(IJAIS)** 8, no. 2 January 2015

Oualid, Benkarim, Gemma Piella, Nadine Hahnerb, Elisenda Eixarch, Miguel Angel, González Balleste & Gerard Sanroma. "*Patch spaces and fusion strategies in patch-based label fusion.*" **Computerized Medical Imaging and Graphics** 71 January 2019: 79-89.

OZAKI, Masao & Wataru MOTOKAWA. "*Dental Age Estimation by Two Computer Methods : Fuzzy Logic and Neural Network."* **International Journal of Biomedical Soft Computing and Human Sciences: the official journal of the Biomedical Fuzzy Systems Association,** 2000: 13-17.

Pauwels, Ruben. "*History Of Dental Radiography: Evolution Of 2d And 3d* ." **Medical Physics International Journal,** April 2020: 235-277.

Peter, Hajek, & Julio J.Valdes. "*An analysis of MYCIN-like expert systems."* **Mathware and Soft Computing, 1994: 45-68.**

Ravi, Kaushik, & Shailender Kumar. "*Image Segmentation Using Convolutional Neural Network."* **International Journal Of Scientific & Technology Research** *Volume 8, Issue 11, November 2019 Issn 2277-8616* (Ijstr©2019) 8, No. 11 November 2019: 667-675.

Reddy, M.V.Bramhananda , Varadala.Sridhar, & Nagendra M. "*Dental X-Ray Image Analysis by Using Image Processing Techniques."* **International Journal of Advanced Research in Computer Science and Software Engineering** 2, no. 6 June 2012

Riaud, Xavier. *"First dental radiograph 1896.*" **Journal of Dental Health, Oral Disorders & Therapy** 9, no. 1 2018: 33-34.

Robert, H Selwitz, Amid I Ismail, & Nigel B Pitts. *"Dental caries."* **Lancet**, January 2007: 51-59.

Rogers, W, B.Ryack, & G.Moeller. "*Computer-aided medical diagnosis: Literature review*." **International Journal of Bio-Medical Computing** Volume 10, no. 4 August 1979: 267-289

Shen, Yucong, Xin Zhong, & Frank Y. Shih. *"Deep Morphological Neural Networks."* **arXiv (arXiv),** September 2019.

Singh, Prerna & Sehgal, Priti. "*Numbering and Classification of Panoramic Dental Images Using 6-Layer Convolutional Neural Network."* **Pattern Recognition and Image Analysis** 30, no. 1 2020: 125-133.

Singh, Sukhvinder, & Grewal,Surender Kumar. "*Role of Mathematical Morphology in Digital Image Processing: A Review.*" **International Journal of Scientific Engineering and Research (***IJSER)* 2, no. 4 April 2014: 1-3.

Solanki, A.J. " *A Review on Dental Radiographic Images."* **Int. Journal of Engineering Research and Application** 7, no. 7 July 2017: 49-53.

Sood, Sanjay, Mbarika Victor, Jugoo Shakhina, Dookhy Reena, Doarn Charles R, Prakash Nupur, & Merrell, Ronald C. "*What is telemedicine? A collection of 104 peer-reviewed perspectives and." T***elemedicine journal and e-health : the official journal of the American Telemedicine Association** 13, no. 5 October 2007: 573-590

Spielman, Andrew, "*The birth of the most important 18th century dental text: Pierre Fauchard's Le chirurgien dentis,*" **Journal of Dental Research**, Vol.86, no.10 2007,922-926.

Stefanie, Chiou, Craig Music, Kara Sprague, & Rebekah Wahba. "*A Marriage of Convenience:The Founding Of The MIT Artificial Intelligence Laboratory."* **Massachusetts,** December 5, 2001.

Teshome, Amare & Muche, Abebe and Girma, Biruk. "Prevalence of Dental Caries and Associated Factors in East Africa, 2000–2020: Systematic Review and Meta-Analysis." **Frontiers in Public Health** 9(April 2021.

Thomas, Andy. *An introduction to neural networks for beginners.* 2017.

Williams, Aaron M, Bhatti, Umar F, Alam, Hasan B, & Nikolian, Vahagn C. "The role of telemedicine in postoperative care." **mHealth** 4 2018: 11.

Yadav, Samir S.& Jadhav, Shivajirao M. "*Deep convolutional neural network based medical image classification for disease diagnosis.*" **Journal of Big Data** 6, no. 1 De cember 2019: 1-18.

Yamashita, Rikiya, Nishio Mizuho, Do Richard Kinh Gian & Togashi Kaori. *"Convolutional neural networks: an overview and application in radiology.*" **Insights into Imaging** 9, no. 4 September 2018: 611-629.

Young, Katherine, Gupta Amar, & Palacios Rafael,. "I*mpact of Telemedicine in Pediatric Postoperative Care."* **Telemedicine journal and e-health : the official journal of the American Telemedicine Association** 25, no. 11 November 2019: 1083-1089.

Zaleckiene, Vaida, Peciuliene Vytaute, Brukiene Vilma, & Drukteinis Sauliu. "*Traumatic dental injuries: etiology, prevalence and possible outcomes." S***tomatologija, Baltic Dental and Maxillofacial Journal** 16 2014: 7-14.

Zhang, Kailai, Wu Ji, & Chen Hu. "*An effective teeth recognition method using label tree with cascade network structure." Computerized medical imaging and graphics :* **the official journal of the Computerized Medical Imaging Society** (PubMed) 68 September 2018: 61-70.

Electronic Source

Addison Dental. "Dealing with Decay." *Addison Dental.* July 11, 2019. https://addisondentalil.com/2019/07/11/dealing-with-decay/

Allen, Bryana. "5 Types of Dental X-rays." *Delta Dental of Washington.* June 8, 2018. http://www.deltadentalwa.com

Alliance for Affordable Internet (A4AI). *Advancing Meaningful Connectivity: Towards Active & Participatory Digital Societies. Survey* , Washington DC: Alliance for Affordable Internet, 2022.

American Dental Association,"*Glossary of Dental Clinical and Administrative Terms,*" American Dental Association. n.d.,

American Telemedicine Association. "*What is Telemedicine?*" *American Telemedicine Association.* 2012. http://www.americantelemed.org/about-telemedicine/what-is-telemedicine#.U3u3x0KKDIU.

Arun, K. Patnana, & Tanuj Kanchan. *Periodontitis.* Treasure Island (FL): StatPearls Publishing, 2022.

Ayyar, Tejas Mohan. "LeNet." *A practical experiment for comparing LeNet, AlexNet, VGG and ResNet models with their advantages and disadvantages.* November 6, 2020. https://tejasmohanayyar.medium.com/a-practical-experiment-for-comparing-lenet-alexnet-vgg-and-resnet-models-with-their-advantages-d932fb7c7d17

Britz, Denny. "*Understanding Convolutional Neural Networks for NLP*." *WILDML.* November 7, 2015. http://www.wildml.com/2015/11/understanding-convolutional-neural-networks-for-nlp/

Chris, Kolade. "*What is PHP? The PHP Programming Language Meaning Explained*." *freeCodeCamp.* August 30, 2021. https://www.freecodecamp.org/news/what-is-php-the-php-programming-language-meaning-explained/

Colgate-Palmolive. "*Types of X-rays." Colgate-Palmolive.* February 4, 2022. https://www.colgate.com/en-us/oral-health/x-rays/types-of-x-rays#

Dental MGA. "*What Are Dental Cysts and How to Treat Each Type.*" *MGA Dental* . May 31, 2021. https://www.mgadental.com.au/dental-cysts/ (accessed July 29, 2022).

Draelos, Rachel & Lea Ballantyne. "*The History of Convolutional Neural Networks.*" *Toward DataScience.* April 13, 2019. https://towardsdatascience.com/a-short-history-of-convolutional-neural-networks-7032e241c483

Dr Brazdo, Maryam. "*The History and Benefits of Dental X-ray Imaging*." *The History and Benefits of Dental X-ray Imaging.* December 18, 2017. https://www.artistictouchdentistry.com/general-dentistry/history-benefits-dental-x-ray-imaging/

D'souza, Durand. "*A Layman's Guide to Computer Vision.*" *Towards Data Science.* March 07, 2017.https://towardsdatascience.com/a-laymans-guide-to-computer-vision-39b9291e5278

Electronic IDentification (eID). "*Face Recognition: how it works and its safety*." *Electronic IDentification (eID).* July 27, 2020. https://www.electronicid.eu/en/blog/post/face-recognition/en

Evans, Julie Ryan. "*Identifying and Treating Impacted Teeth*." *healthline.* may 22, 2018. https://www.healthline.com/health/dental-and-oral-health/impacted-teeth

Fogg, Andrew. "A History of Machine Learning and Deep Learning." *Import.io.* May 30, 2018. https://www.import.io/post/history-of-deep-learning/

Gour, Rinu. "*Various Uses of TensorFlow." DZone.* January 8, 2019. https://dzone.com/articles/learn-various-uses-of-tensorflow

Goyal, Kechit. "*Machine Learning vs Neural Networks: What is the Difference?"* February 13, 2020. https://www.upgrad.com/blog/machine-learning-vs-neural-networks/

Helen Dingwall, "*A pioneering history: dentistry and the Royal College of Surgeons of Edinburgh*," April 2004.

History.com Staff. "*German scientist discovers X-rays." (*A+E Networks) 2009.

Jason Brownslee on January 9, 2019. "*A Gentle Introduction to the Rectified Linear Unit* (*ReLU*)." *Machine Learning Mastery.* January 9, 2019.https://machinelearningmastery.com

John, McCarthy. "*WHAT IS ARTIFICIAL INTELLIGENCE." Technical report, Stanford University.* November 12, 2007. http://jmc.stanford.edu/artificial-intelligence/what-is-ai/index.html

Kathirkamar, Vignesh. "A brief overview of "Python and Anaconda" — for starters." *Analytics Vidhya.* September 6, 2020.

Kavlakoglu, Eda. "*AI vs. Machine Learning vs. Deep Learning vs. Neural Networks: What's the Difference*?" *IBM Cloud.* May 27, 2020. https://www.ibm.com/cloud/blog/eda-kavlakoglu

Maan, Al-Abbasi,*"Anatomy of Oral Cavity,"*February 2, 2016. https://uomustansiriyah.edu

Manav, m. *"Convolutional Neural Networks (CNN)." Analytics Vidhya.* May 01, 2021. https://www.analyticsvidhya.com/

Marr, Bernard. "*Deep Learning Vs Neural Networks - What's The Difference?" Bernard Marr.* 2020. https://bernardmarr.com/default.asp?contentID=1789

Mar, Bernard. *What Are Artificial Neural Networks - A Simple Explanation For Absolutely Anyone.* September 24, 2018. https://www.bernardmarr.com/[Google Scholar]

Moolayil, Jojo John. A Layman's Guide to Deep Neural Networks. July 24, 2019. https://towardsdatascience.com

Myers, Andrew. "*Stanford's John Mccarthy,* Seminal figure of artificial intelligence, dies at 84." *Stanford News.* October 25, 2011. http://news.stanford.edu/news/2011/octtober/john-mccarthy-obit-102511.html

National Institute of Biomedical Imaging and Bioengineering (NIBIB). "*X-rays.*" *National Institute of Biomedical Imaging and Bioengineering (NIBIB).* October 2017. https://www.nibib.nih.gov/science-education/science-topics/x-rays

NDT. "*History of Radiography*." *NDT Resource Centre Web site.* n.d. https://www.nde-ed.org/EducationResources/.../Radiography/Introduction/history.htm

Nguyen, Kelly. "*The History of Machine Learning*: A Timeline." *experian.* January 31, 2020. https://www.experian.com/blogs/insights/2020/01/the-history-of-machine-learning-a-timeline

Nielsen, Jakob. "*The History of Hypertext*." *NN/g Nielsen Norman Group.* February 1, 1995. https://www.nngroup.com/articles/hypertext-history/

Nigerianscholars.com. "*List of Courses Offered at Federal School of Dental* Technology And *Therapy*, Enugu (FEDSDTTEN)." *nigerianscholars.com.* May 30, 2020. https://nigerianscholars.com

Patel, Khush. "*Architecture comparison of AlexNet*, *VGGNet*, *ResNet*, *Inception*, *DenseNet*." *Towards Data Science.* March 08, 2020. https://towardsdatascience.com/architecture-comparison-of-alexnet-vggnet-resnet-inception-densenet-beb8b116866d

Preferred Dental Care. "*Dental cyst and infection: Causes, symptoms and treatment." Preferred Dental Care.* 2021. https://www.preferreddentalcaresanrafael.com/dental-cyst-and-infection-causes-symptoms-and-treatment/

Pulkit, Sharma. "*A Comprehensive Tutorial to learn Convolutional Neural Networks from Scratch* (deeplearning.ai Course #4)." *Analytics Vidhya.* December 26, 2018. https://www.analyticsvidhya.com/blog/2018/12/guide-convolutional-neural-network-cnn/

Reactor, Hack. "*What is JavaScript used for?" Hack Reactor.* August 26, 2021. https://www.hackreactor.com/blog/what-is-javascript-used-for

Roy, Rupali. *"AI, ML, and DL: How not to get them mixed!*" *Towards Data Science.* April 29, 2020. https://towardsdatascience.com/understanding-the-difference-between-ai-ml-and-dl-cceb63252a6c

Saha, Sumit. "*A Comprehensive Guide to Convolutional Neural Networks* — the ELI5 way." *Towards Data Science.* December 15, 2018. https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-

Shekhar, Amit. *What is Bias in Artificial Neural Networks?* August 2, 2019. https://afteracademy.com/blog/what- is-bias-in-artificial-neural-network

Singh, Ankita. "*Artificial Neural Networks*." *MSA Technosoft* . May 21, 2018. https://msatechnosoft.in/blog/category/tech-blogs/

Thelma, Ideozu. "*Everything You Need To Know About Telemedicine In Nigeria*." *Culture Custodian.* April 13, 2022. https://culturecustodian.com/everything-you-need-to-know-about-telemedicine-in-nigeria/

Tutorials point. *Artificial Intelligence; Intellent Sytems.* n.d, http://www.tutorialspoint.com

Unzueta, Diego. "*Fully Connected Layer vs. Convolutional Layer: Explained*." *built in.* October 18, 2022. https://builtin.com/machine-learning/fully-connected-layer.

Urooj, Wajiha. "What is Python Spyder IDE and How to use it?" *Edureka.* September 11, 2019. https://medium.com/edureka/spyder-ide-2a91caac4e46

Verma, Abhishek. "*ZFNet: An Explanation of Paper with Code." Towards Data Scince.* September 20, 2020. https://towardsdatascience.com/zfnet-an-explanation-of-paper-with-code-f1bd6752121d

Walia, Anish Singh. *Activation functions and it's types-Which is better?* May 29, 2017. https://towardsdatascience.com/activation-functions-and-its-types-which-is-better

News Papers

Obikunkle, Femi. "*Successes, Challenges of Telemedicine adoption in Nigeria Clinical Settings."* **The Guardian**, May 14 2020

Ojoma, Akor. *"Brain drain: Nigeria lost over 9,000 doctors in 2 years* – NMA." **Daily Trust**, April05 2022

PhD Thesis

Ledda, Alessandro. "*MathematicalMorphology in ImageProcessing." PhD Thesis*, **Applied Engineering,** University of Antwerp,, Antwerp, Belgium , 2007

Apendices

Apendix A: System codes

```
import tensorflow.keras
from PIL import Image, Image Ops
import numpy as np
import mmlib
import cv2
import time

# Disable scientific notation for clarity
np.set_print options (suppress=True)

# Load the model
model = tensorflow.keras.models.load_model ('keras_model.h5')
model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy',
'val_accuracy'])
print(model.summary())

# Create the array of the right shape to feed into the keras model
# The 'length' or number of images you can put into the array is
# determined by the first position in the shape tuple, in this case 1.
data = np.ndarray(shape=(1, 224, 224, 3), dtype=np.float32)

# test image path from the UI


image = Image.open('test.jpg')
#resize the image to a 224x224 to fit in bencmark dataset:
#resizing the image to be at least 224x224 and then cropping from the center
size = (224, 224)
image = ImageOps.fit(image, size, Image.ANTIALIAS)

#turn the image into a numpy array
image_array = np.asarray(image)

# display the resized image


# Normalize the image
normalized_image_array = (image_array.astype(np.float32) / 127.0) - 1

# Load the image into the array
data[0] = normalized_image_array

# run the inference
prediction = model.predict(data)
```

```
labels=['Dental Caries','Dental cysts','Fractured tooth','Periodontitis','Impacted tooth',' Dental
Cavities']
print(labels)
print(max(prediction))

a=max(prediction)

L=max(a)

b= max(prediction);

c = b.tolist();
q=max(c);
index = c.index(q);
print('The predicted dental disease is :',labels[index],', with an accuracy of :',L)
g=(1-L)
h=round(g,6)
print('Error rate :',h)

image = cv2.imread('test.jpg')
initial_time = time.time()
kernel=np.ones((5,5),np.uint8)
img_erosion=cv2.erode(image, kernel, iterations=1)

img_dilation=cv2.dilate(image,kernel,iterations=1)
cv2.imshow('Input',image)

cv2.imshow('Erosion',img_erosion)

cv2.imshow('Dilation',img_dilation)

cv2.waitKey(0)
final_time= time.time()
print('Time Elapse',(final_time-initial_time))
```


Apendix B: Questionnaire

Lead City University (LCU)

Department of Computer Science,

Off Lagos-Ibadan Expressway, Toll

Gate Area, Ibadan

15/10/2021

Dear Correspondents

I am Tam-Nurseman Grace Lawumi, a Doctoral degree (PhD) student of the above named department and university.

I would want you to please use your experience to fill the questionnaire on the prevalence of dental diseases on the next page.

Please note that your response is strictly for research purpose and as such, there is no known risk for participating in this research.

Please answer all questions as honestly as possible and return the completed questionnaires promptly to the researcher.

Thank you for taking the time to assist in this research.

Sincerely,

Tam-Nurseman Grace Lawumi

LCU/PG/0001249

08068021278

Signed…………………

SectionA: Personal Details

1. NAME (optional)…………………………………………
2. SEX…………………..
3. DENTAL SPECIALITY
    a. Surgeon
    b. Technologist
    c. Therapist
    d. Surgery Assistant

4. List of dental diseases

- Dental caries
- Toothache
- Dental cysts
- Cavities
- Periodontitis
- pulpitis Impacted tooth
- Fractured tooth
- Cracked Tooth
- Bad breath (halitosis)
- Oral ulcer
- Pericoronitis
- Dental fluorosis
- Dry socket.
- Candidiasis
- Salivary gland stones
- Ludwig angina
- gingivitis

- Denture Stomatitis
- Anodontia
- Osteomyelitis of jaws
- dental abscess
- Pregnancy Epulis

5. From your experience, tick the 6 most prevalent dental diseases listed above
6. Which 6 among listed dental diseases can be diagnosed by periapical x-rays

Apendix C: Letters of Introduction for Data Collection

Lead City University, Ibadan

Beside Methodist High School, Oba Otudeko Avenue, Toll gate, P.O. Box 30678 Secretariat Ibadan
Tel: 02-7510681; 7510682; fax: 02-2001248
leadcity@lcu.edu.ng, www.lcu.edu.ng

November 02, 2020

TO WHOM IT MAY CONCERN

Dear Sir/Madam,

Letter of Introduction: TAM-NURSEMAN LAWUMI GRACE

I wish to introduce above named as a PhD student of Computer Science under my supervision in Lead City University Ibadan.

She is currently undergoing her research work on a topic titled "Diagnosis and Treatment of Common Dental Diseases through Dental X-ray Images using Convolutional Neural Network and Mathematical Morphology".

She needs to acquire some datasets in designated dental clinics in order to assist in model development and testing.

I shall be grateful if she is given the required cooperation to actualize her goal.

Yours faithfully,

Dr. P.O. Achimugu, FIPMD, MNCS, MCPN, MITSSP, CITP
B.Sc. Comp. Sc. (Anyigba); M.Sc. Comp. Sc. & Engr. (Ife); Ph.D. Comp. Sc. (Malaysia)
Head of Department, Computer Science
check4philo@gmail.com, philip.achimugu@lcu.edu.ng, Mobile: 234809348228

Lead City University (LCU)

Department of Computer Science

Off Lagos-Ibadan Expressway, Toll Gate Area, Ibadan
www.lcu.edu.ng

Dr Wilson Sakpere
PhD, MNSE, MIEEE, MSAIEE, MIITPSA

E-mail: sakpere.wilson@lcu.edu.ng
Phone: +234 913 779 2962

27th September, 2021

TO WHOM IT MAY CONCERN

Dear Sir/Madam,

INTRODUCTION: TAM-NURSEMAN GRACE LAWUMI (MRS)

I am writing to you concerning the above named Doctoral student of the Department of Computer Science, Lead City University Ibadan. She is currently undergoing her Doctoral research work under my supervision on the topic, "Diagnosis and Treatment of Common Dental Diseases through Periapical Radiographs Using Convolutional Neural Network and Mathematical Morphology".

She has gotten to the stage where she needs to acquire dataset in designated dental clinics to assist in the model development and testing of her research innovation.

I shall be grateful if she is given the required cooperation to actualise her goal. We remain at your disposal for more information.

Sincerely,

Wilson Sakpere, *PhD*
Head of Department

Bio Data

Personal Data:

Surname: TAM-NURSEMAN

Other Names: **GRACE LAWUMI**

Date of Birth: 5th December 1974

Gender: Female

Local Government Area: Burutu

State of Origin: Delta

Nationality: Nigerian

Marital Status: Married

Religion: Christianity

Next of Kin: Colonel Tamaraubrakaemi Samson Nurseman

Contact:

Residential Address: House Number 2, Tam-Nurseman Close, off Messi-Ogor, Akobo, Ibadan.

Postal Address: Same as above.

Email Address: lawumigrace@gmail.com

Mobile Number: 08068021278

Educational Background:

Institutions attended with dates and Qualifications:

Lead City University, Toll Gate, Ibadan, Oyo State: 2019 till date (PhD Computer science)

Lead City University, Toll Gate, Ibadan, Oyo State: 2016-2019 (MSc. Computer science)

Lead City University, Toll Gate, Ibadan, Oyo State: 2015-2016 (PGD Computer science)

Enugu State University of Science and Technology, Enugu: 1997-2010 (B.Eng. Computer Engineering)

Our Lady's High School, Effurun, Delta State: 1986-1992(WAEC)

Work Experiences with Date:

Industrial Training Department, High Mega Technology Enugu.2001 (6months) SIWES Trainee

High Mega Technology Enugu 2004-2009

Alpha Speedlink Computers 2010-2016

Unpublished Journal Articles:

Grace Tam-Nurseman, and Wilson Sakpere "Learning in Artificial Neural Networks" 2022

Grace Tam-Nurseman, and Wilson Sakpere "Design and Development of a Telemedicine System" 2022

A Mathematical Morphological Deep Neural Network for the Classification of Periapical Radiographs in the Diagnosis and Treatment of Dental Diseases. PhD Dissertation

Published Journal Articles:

Philip Achimugu, Oluwatolani Achimugu, Mohammed Ahmed Taiye, Sseggujja Husssein, Grace Tam-Nurseman, and Saheed Adekeye "How to Support Communication among Stakeholders during Software Requirements Prioritization" Journal of Software Engineering and Applications Volume 14, Issue 7 (July 2021) ISSN Print: 1945-3116 ISSN Online: 1945-3124 Google-based Impact Factor: 1 Citations h5-index & Ranking

Grace Tam-Nurseman, Philip Achimugu, Oluwatolani Achimugu, Hilary Kelechi Anabi and Sseggujja Husssein "Expert System for the Diagnosis and Prognosis of Common Dental Diseases Using Bayes Network" Journal of Biomedical Science and Engineering, Volume 14, Issue 11 (November 2021) ISSN Print: 1937-6871 ISSN Online: 1937-688X Google-based Impact Factor: 0.86 Citations h5-index & Ranking

Skills:

Programming in Python

Machine Learning Programming

Computer hardware repairs and maintenance

Computer system networking

Referee:

1. Colonel TS Nurseman

   2 Div Legal Service

   Adekunle Fajuyi Cantonment,Ojoo, Ibadan, Oyo State

   08037187480

2. Dr B.A Adebo

   Lead City University, Ibadan, Oyo State

   08035022462

3. Barr F.T Okorotie

   Abeokuta Chambers, Yenagoa, Bayelsa State

   08033398525

---------------------------------- ------------------------------------

Signature Date

University Compliance Certification

This is to certify that this thesis by Grace Lawumi Tam-Nurseman with Matriculation Number LCU/PG/001249 in the Department of Computer Science, Faculty of Natural and Applied Sciences, Lead City University, Ibadan, Oyo State, Nigeria, is in full compliance with the approved University's Format and Style.

…………………………………………………… …………………………………

Signature Date

NURSEMAN_GRACE_LAWUMI._PhD LCU LIBRARY

ORIGINALITY REPORT

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