Improved Sentimental Response System for Classifying Emergency Incidence Through Hybridized Minning Techniques

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Being a PhD Thesis Submitted to the Department of Computer Science, Faculty of Natural and Applied Sciences, Lead City University, Ibadan, Oyo State, Nigeria

In Partial Fulfillment of the Requirements for the Award of Doctor of Philosophy Degree (PhD) in Computer Science

2024

Certification

This is to certify that Oluwatobi Akanbi JOHNSON with matriculation number LCU/PG/000135 carried out this research work titled "Improved Sentimental Response System for Emergency Incidence" in the Department of Computer Science, Faculty of Natural and Applied Sciences, Lead City University, Ibadan, Oyo State, for the award of Doctor of Philosophy Degree (PhD) in Computer Science and that this has not been previously submitted.

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Dedication

This research work is dedicated to God Almighty for His sufficient grace, provision, mercy, favour and for the sustenance of my life throughout my programme in this institution.

Acknowledgement

Special thanks to Lead City University, Ibadan, the great citadel of learning for given me the opportunity to carried out my research in the institution, also the institution library for availing me to access online resources, articles and journal publications during this reseach work and I want to thank management of Facebook for giving me access to get relevant data from their site to carry out my research.

Special thanks goes to my supervisor, Prof. S.O. Akinola, for his attention, motivation and moral support throughout this research. May God bless you sir. To all lecturers in Computer Science Department, Lead City University, Ibadan, Prof. M.O. Agbaje, Dr. A.A. Waheed, Dr. Wumi Ajayi, and Dr. Wilson Sakpere (H.O.D), with a humble heart, I say thank you very much for impacting in me knowledge.

My profound gratitude goes to Dr. Adeola Lukmon Kiadese, Dr. A.G. Ayeni, my wife Mrs. Esther Opeyemi Johnson, my mum Mrs. G.O. Johnson, Mr. O. A. Johnson, Mrs. O.A. Afolabi and Mrs. O.O. Adefowoba for their numerous support.

“Even 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

Emergency occurrences can be caused by both natural disasters and human error. This study addresses the classification of emergency incidence, stemming from both natural disasters and human errors, emphasizing the critical need for swift response and effective mitigation. Governments typically implement measures to mitigate negative effects, with outcomes dependent on their responsiveness. The research aims to enhance sentiment analysis for emergency incidence through a hybridized mining technique. The system combines Natural Language Processing and Bayesian belief learning, focusing on data mining, machine learning, and NLP for effective classification and sentiment analysis. Social media data from Facebook is gathered using the Facebook API and Graph function 'Requests' for training. Pre-processing involves eliminating unwanted characters and transforming text into lowercase. Experimental analysis involves 450 data samples with four characteristics, creating a multivariate time series dataset for classification tasks. Python with the requests library and Graph API is used for live data capture, while MySQL manages the backend database, and XML and PHP handle the frontend for sentimental response. The study unveils a linear dimension in the classification algorithm, transforming non-linear textual data during pre-processing. Probability computations for incidence parameters and input intervals rely on frequency distribution from emergency observations. Experimental scenarios instill confidence in the improved framework, incorporating supervised learning into NLP for improved precision. The system achieves over 90.93% efficiency in signal precision, a substantial enhancement compared to existing models. Performance evaluation involves using emergency datasets for training (75%) and testing (25%), demonstrating the system's high precision through a confusion matrix. The improved sentimental response system represents a significant advancement, leveraging social media data for proactive emergency management. With a precision rate exceeding 90.93%, the system adeptly identifies and categorizes emergency signals, enabling timely and targeted response strategies.

Keywords: Emergency, Hybrid, Incidences, Minning ,Response, Sentiment, Socialmedia

Word Counts: 297

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List of Acronyms

Abbreviation	Meaning
AI	Artificial Intelligence
ACID	Atomicity, Consistency, Isolation and Durability
ACK	Acknowledged
AE	An Auto-encoder
4IR	Fourth Industrial Revolution
ANN	Artificial Neural network
BBL	Bayesian Belief Learning
CNN or ConvNet	Convolutional Neural Network
CN	Cognitive networks
DOM	Document Object Model
DRAT	Domains, Resources, Activities, and Tasks
DRC	Disaster Research Center
DTD	Document Type Definition
DT	Decision Tree
DTL	Deep Transfer Learning
DRL	Deep Reinforcement learning
DDL	Data Definition Language
DML	Data Manipulation Language
DL	Deep Learning
EM	Emergency Management
GUIs	Graphical User Interfaces
JSON	JavaScript Object Notation
KNN	K Nearest Neighbor

NLP	Natural language processing
NB	Naive Bayes
NBC	Naïve Bayes Classification
LDA	Linear Discriminant Analysis
OM	Opinion Mining
PHP	Personal Home Page
PIP	Python Package Index
RDF	Resource Description Framework
SA	Sentiment Analysis
SQL	Structured Query Language
SVM	Support Vector Machine
SYN	Sychronization
TCP	Tramission Control Protocol
UNIX	UNiplexed Information Computing System
W3C	Wide Web Consortium
XML	eXtensible Markup Language

Chapter One

Introduction

1.1 Background to the Study

A condition that poses an urgent threat to public health, lives, property or the environment is referred to as an emergency. When a significant, unexpected, and frequently severe threat interferes with daily living, an emergency occurs. Emergency occurrences can be caused by both natural disasters (like earthquakes, cyclones, and floods) and human error (such fires, explosions, and moving vehicle accidents)[21]. Most emergencies require immediate action to avoid a worsening of the condition, while mitigating may not be able to provide palliative care in the aftermath in some cases yet it is an important aspect. Emergency incidence relating to disaster response and control system need urgent attention for detecting any outbreak; as quick as possible to speed up recovery process or allow escape. In disaster situation, information and prompt interactions with first responders in any learned society or community is quite germane[6].

When an emergency occurs in a country, the government usually adopt measures to curtail the negative effects of the phenomenon. The severity or otherwise of the effects of national emergencies, most times depends on how the government and people react or respond to[22]. In multinational organizations and other large scale environment, critical infrastructure needs continuous monitoring for emergency and preventive measures. During emergencies, positive psychological suggestions will generate positive emotions, counteracting the influence of negative emotions, which is of great help in controlling disease and restoring healthy life, in addition, the existing sentiment classification focuses more on the three polarities (positive, negative and neutral) of sentiments, which are not fine-grained enough to fully characterize the overall evolution of short text sentiments[3].

Intelligent system or supportive agents should be devised and installed to complement security agents' efforts in ensuring proper safety during emergencies[16]. Preventive emergency measures help in line with universal best practices for hazard management and control when timely information is provided for rescue. Event-awareness mechanism provides fast information for broadcast and data transmission through control panel when signal processing is not obstructed[7].

Ever since the development of wireless communication, when virtually everyone from all walks of life is hooked on information technology, their postings, messages, and chats are full of untapped knowledge[23].The importance of this technology along with the way popular algorithms operate in combination with it help the Naive Bayes algorithm perform better. A simple probabilistic classifier simplifying (naive) assumption based on applying Bayes' theorem with strong independence assumptions is known as the Bayesian classifier[24].The Bayesian prediction requires complete approximation or estimation, including joint possibilities, so as to ascertain its conclusions and correctness of principles to draw inference. More so, explicit data gathering and testing process is time consuming[17].

Sentiment analysis is the machine learning technicality used to determine if the weighted volume of textual content is high for specified entities, phrase, theme within a given category or topic. In sentiment classification, grouping of text data that share homogenous attributes by similarity normally inculcate predefined polarity to determine if written content belongs to positive, negative or neutral category. An artificial entity that will control and send notification about any outbreak is quite germane in order to ensure timely escalation and to avert its consequences[10].

Language processor translates a single statement from a source program into machine code, executes it, and then moves on to the next line. If the statement contains a mistake, the

interpreter stops translating at that point and outputs an error notice. Natural language processing (NLP) actually embed translating element for pattern or text recognition. Instructions written in a computer or scripting language are executed immediately by an interpreter without being first converted to machine code or object code of the underlying machine[9].

Bayesian Belief learning is an aspect of deep learning techniques. Deep learning is an improved variation of machine learning technique which is especially helpful to data scientists because it streamlines and expedites the process of collecting, analysing, and interpreting huge amounts of data. Deep learning can be thought of as an automated kind of predictive analytics in the most basic form. Unlike most machine learning algorithms, which are linear, deep learning algorithms are stacked in a hierarchy of increasing complexity and abstraction[18].Deep learning isregarded as a crucial technology of the Fourth Industrial Revolution (4IR or Industry 4.0) due to its learning capabilities from data technology originated from artificial neural network (ANN). However, several application fields, including healthcare, image identification, text analytics, cyber security, and others, make extensive use of it[4].

Precautionary safety and security is the key to healthy and peaceful co-existence in our neighbourhood. Emergency incidence is relatively unpredictable, and as such it could bring about untimely death and damage of critical infrastructure resources[17].

Meanwhile, sentimental response system can leverage on big data analytics and multi-agents network to detect and escalate unplanned incidence relating to emergency[13]; using sensorial notification and visual surveillance in surroundings and around the residents when augmented reality is being leveraged upon. Robotic technology is usually implored to inculcate fire

control and safety measure in accordance with wireless specification, network configuration, and intelligent reasoning[14].

As a primary means of communication, texts are used to implicitly or explicitly reflect emotions. Emotion or sentiment detection from text has emerged as an important and expanding research area to more clearly understand the actual feelings of humans[2].

Hybridizing a mining technique involves combining two or more data mining approaches or algorithms to leverage their individual strengths and overcome their limitations. The goal of hybridization is to enhance the performance, accuracy, or efficiency of data mining tasks such as classification, clustering, regression, or anomaly detection[23].

1.2 Statement of the Problem

Emergency incidence pose significant challenges at local and national levels, yet existing frameworks for addressing these incidence often lack effective implementation and testing[18]. The non-implementation of solution frameworks hampers the ability to experimentally validate approaches tailored to specific emergency that are not categorized. Additionally, current methodologies in text classification suffer from a lack of multi-class precision, resulting in lower type-matching rates that could enhance the understanding and response to these events[11]. Furthermore, there is insufficient exploration of data mining techniques that could optimize system performance, thereby limiting the capacity to extract actionable insights from data related to emergency incidence[18]. Addressing these gaps is crucial for improving emergency preparedness, response, and recovery efforts, hence this study.

1.3 Aim and Objectives of the Study

The aim of this study is to provide an improved sentimental system for classifying emergency incidence using hybridized mining technique. The specific objectives are:

i. Design an enhanced classification framework for emergency incidence using Natural Language Processing (NLP) and Bayesian Belief Learning (BBL).

ii. Implement the design (i) using Request Library of Python with Graph API for big data technology through XML and PHP MySQL.

iii. Collection of emergency incidence data via facebook graph application program interface (API) for experimental analysis.

iv. Evaluate the experimental functionality of improved system using Confusion Matrix and Precision as performance metrics.

1.4 Significance of the Study

The significance of this study lies in its technological innovation, practical relevance, global applicability, and academic contribution. It motivates efforts to advance emergency management systems and provides a framework for future research and development in emergency response technologies.

1.5 Scope of the Study

In this study, hybridized mining technique was used as an improved sentimental system for classifying emergency incidence. Facebook data was also used for sentiment analysis to identify public sentiments and investigate the increased fear associated with emergency incidence. Facebook effectively conveys real-time information about ongoing events and captures people's feelings and views, just like twitter[8]. Since people rely on social media for educational content, social media users are growing with time, and the volume of data is growing as well. This study focused on the use of Natural Language Processing (NLP) with data mining approach like Bayesian Belief Learning (BBL) to effectively extract useful data.

Traditionally, emergency incidence impact assessments have been made via fieldwork by non-governmental organisations (NGO's) sponsored data collection; however, this approach

is time-consuming, expensive and often limited. Recently, social media (SM) has become a valuable tool for quickly collecting large amounts of first-hand data after an emergency and it shows great potential for decision-making. The social media platform Fcebook is a well-known online media outlet. In a short time, tweets or posts about the epidemic have grown exponentially on social media networks like Twitter[7]. Positive, negative, and neutral sentiment categories were used to group Facebook posts and comments.

1.6 Limitation of the Study

The study is limited by the selected cases of emergency incidence based on localized peculiarity choice of emergency incidence included in the research. To improve the generalizability and robustness of the model, future studies should consider incorporating a wider range of emergency cases to measure variability and dispersion among different incident types. This would provide better insight into the model's specificity.

The study focuses on a localized dataset, which may limit the broader applicability of the findings. Experimentation with a more diverse dataset could help harmonize emergency incidences control systems in different regions, improving the adaptability of the model across varied contexts. Finally, The model's specificity in its current form may not be fully optimized due to the limited scope of cases

1.7 Operational Definition of Terms

Some of the terminologies are defined as used in this study below:

Data: Data is the raw material to produce information.

Bayesian Classifier: A Bayesian Belief or Learning classifier is a simple probabilistic classifier based on applying Bayes' theorem with strong (naive) independence assumptions.

Deep Learning:may be viewed of as an Artificial Intelligence function that imitates the way the human brain processes data, representing learning techniques from data and computation using multi-layer neural networks.

Convolutional Neural Network (CNN or ConvNet): is a well-known discriminative deep learning architecture that learns straight from the input without the use of human feature extraction.

An Auto-encoder (AE):is a well-known technique for learning representations unsupervised using neural networks.

Big Data::is the data whose dynamics such as volume, velocity, veracity, and variety are extended massively and unable to be handled by traditional data management system.

Cognitive Networks (CN): are intelligent wireless networks, which analyze communication channels and tell which communication channel is free or occupied.

Sentiment Analysis (SA) or Opinion Mining (OM): is the computational study of people's opinions, attitudes, and emotions toward an entity.

Cloud Computing: This is the provisioning of resources, including computation, memory, storage, network, and applications/services, over the Internet.

XML: stands for eXtensible Markup Language, it is adata exchange format used for distributing data over the Internet or web.

SQL: stands for Structured Query Language (SQL), a language mostly used with relational databases to create and modify databases.

Confusion Matrix: is a summary of prediction results on a classification problem.

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Chapter Two

Literature Review

2.1 Conceptual Review

2.1.1 Emergency

Emergency is any unplanned event that can cause death or significant injury to anyone. It can disrupt, cause physical or environmental damage and financial threat to lives and the economy can be greatly affected. Emergencies are phenomena that occur globally at various times whether severe or mild, they need proper management to minimize their effects on human existence. When a significant, unexpected, and frequently severe threat interferes with daily living, an emergency occurs.There have been emergencies such as, plane crashes, road traffic accidents, industrial accidents, ship wrecks, terrorism, war, floods, earthquakes, disease outbreaks, explosions, civil disturbances[69].

2.1.2 Types of Emergency

An emergency can happen at any time and in any place.Emergency occurrences can be caused by both natural disasters (like earthquakes, cyclones, and floods) and human error (such fires, explosions, and moving vehicle accidents). Emergency can be classified into:

1. Biological Emergencies: These include diseases as well as biological agents that may be used for terrorism.
2. Chemical Emergencies: These include harmful chemical spills and chemicals that are used in acts of terrorism.
3. Radiological Emergencies: These are emergencies involving the release of radiation that could harm people's health.
4. Weather and Home Emergencies: These are emergencies involving potential hazards such as winter weather, extreme heat, flooding, or carbon monoxide.

There have been emergencies such as, plane crashes, road traffic accidents, industrial accidents, ship wrecks, terrorism, war, floods, earthquakes, disease outbreaks, explosions, civil disturbances, etc. Emergency can be interchangeable represented with the word 'disaster'[69].

2.1.3 Emergency Incidence

Emergency incidence/events require early detection, quick response, and accurate recovery[24].Emergency can be divided into 4 major area: natural disasters, man-made accidents, public health events, and social security events. Emergency recovery encompasses awareness and rescue with adequate collaboration involving human, machine, volunteer or eye witness to initialize necessary notification by technological aid. Nevertheless, when an area is prone to two or more disasters like earthquakes, floods, tsunamis, or cyclones and/ or thunderstorms then proper recovery techniques or combinations must be in place[74].

Table 2.1 Correlation between Intensity and Impact Factors of Disaster Incidence

Disaster	Existing Scale	Fatalities	Injuries	Damage	House Destroyed	House Damaged	Missing
Volcano	VEI scale	0.33	0.39	0.09	0.33	–	0.45
Earthquake	Richter Scale	0.13	0.285	0.488	0.23	0.237	–
Tsunami	Intensity Scale	0.248	0.134	0.168	0.043	–	–
Tornado	EF Scale	0.339	0.366	0.32	–	–	–

Source: [56]

This table shows the correlation between the intensity and impact factors of a disaster incidence.

2.1.4 Emergency Detection

Emergency Detection System is a system capable of detecting an emergency condition such as fire, security, gas, explosives and then initiating an emergency warning. One of the most

crucial stages of an emergency management system is the emergency detection phase. The detection phase consists of constant monitoring of the environment via vision, sound or any other sensor-based system and reporting any abnormal findings immediately. Emergency notice targets giving a trustworthy notice to the inhabitants and firemen, just as other fiasco the executives faculty. A lot of inhabitants in metropolitan settings reflect intricacy in their regular daily existence; accordingly yielding uniqueness between human undertakings and lifestyle in enormous scope premises[85] .

Figure 2.1 shows the detector activating elevator control and process involved when there is an emergency.

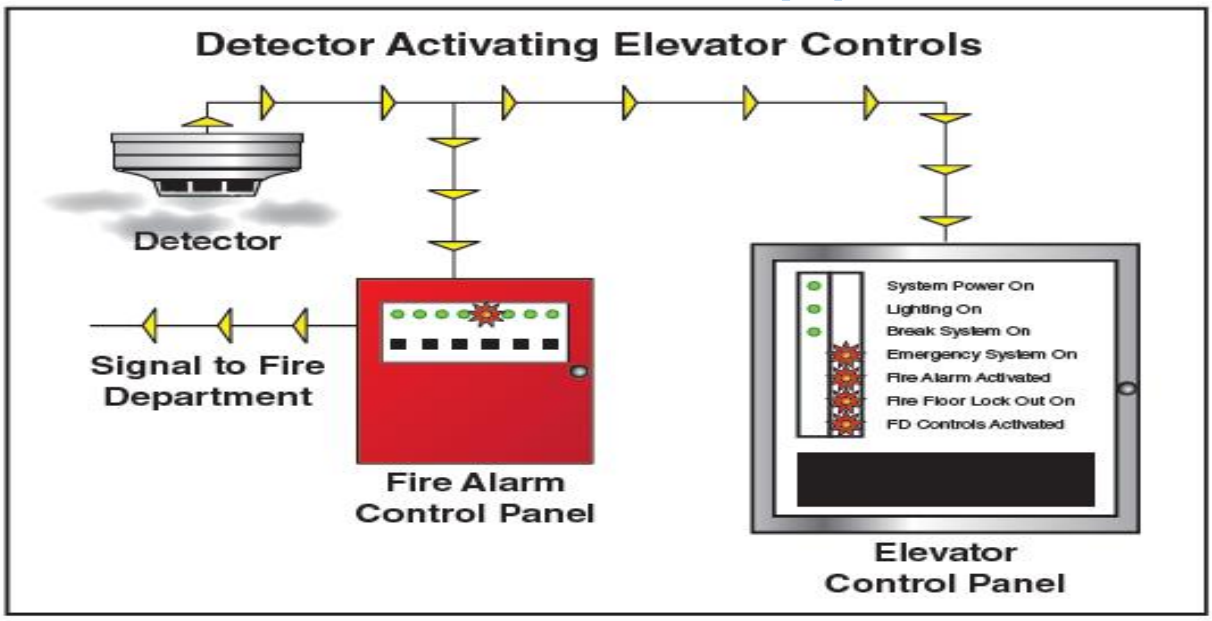

Figure 2.1:Fire Alarm Control Panel Source: [88]

2.1.5 Emergency Management

Emergency Management is a process which is undertaken by a person or their staff representing dozens of agencies or organizations. Emergency activities are divided into phases that form a cycle this includes Mitigation, preparedness, response, and recovery[34].This process functions as a full life cycle of any disaster. Emergency management envelops

mindfulness, salvage, or recuperation with sufficient coordinated effort including human, machine, volunteer or observer to introduce vital notice by innovative guide[36]. Emergency Management has become more professionalized and has transformed due to the rapid growth in research which are being designed to provide knowledge essential for emergency managers[71]. Emergency management, also called emergency response or disaster management, is the organization and management of the resources and responsibilities for dealing with all humanitarian aspects of emergencies (prevention, preparedness, response, mitigation, and recovery).Operations in emergency management, is the combining of actors and assets to help plan, prepare, respond, recover and mitigate an event. Teams are formed and structured according to the Incident Commander and task are assigned and played out accordingly. Driven by doctrine such as the National Response Framework, and the National incident Management System, qualified incident commanders are given guidelines to help with the management of an event[70].There are four phases of emergency actions, which are organized into a cycle. Mitigation, readiness, reaction, and recovery are the cycle's phases[34].

Figure 2.2: Emergency Management cycle Source: [102]

In figure 2.2 emergency management cycle comprises four key stages: mitigation, readiness, response, and recovery. Prior to a crisis, mitigation entails foreseeing and reducing risks. In

order to aid authorities and the public in responding to a crisis correctly, preparation entails a connected series of planning, organizing, and analyzing actions. Prior to a crisis occurs, both preparedness and mitigation take place. The next two phases start after a crisis. Reaction involves steps made before, during, and after an occurrence to safeguard lives, lessen financial losses, and ease suffering. The Emergency Operations Center (EOC) may be activated, at-risk citizens may be evacuated, shelters may be opened, and medical assistance, firefighting, and search and rescue efforts may be provided. The rehabilitation period also includes the procedures required to resume regular activities. Efforts were done to return a community to normal, including the restoration of essential services and the repair of social and physical harm. Debris removal, financial aid to people and communities, road reconstruction, and power line maintenance are typical recovery operations[105]. The management of emergency also involves proactive measures to prepare so as to minimize the effects of the negative consequences of disasters[69].

2.1.6 Emergency Recovery

Emergency recovery encompasses awareness and rescue with adequate collaboration involving human, machine, volunteer or eye witness to initialize necessary notification by technological aid. Nevertheless, when an area is prone to two or more disasters like earthquakes, floods, tsunamis, or cyclones and/ or thunderstorms, then proper recovery techniques or combinations must be chosen[13].

2.1.7 Sentiment or Emotion Analysis

Emotion analysis is also known as opinion mining. Sentiment Analysis (SA) or Opinion Mining (OM) is the computational study of people's opinions, attitudes and emotions toward an entity. The entity can represent individuals, events or topics[29]. Sentiment analysis or opinion mining is one method for obtaining an overall picture of the public's impressions of service quality in the form of services or goods that tend to be positive, negative, or

neutral[100].Sentiment analysis is the process of examining a text written in natural language to identify whether it has a positive or negative emotional tendency. Sentiment Analysis aims to detect positive, neutral, or negative feelings from a text; whereas, Emotion Analysis aims to detect and recognize types of feelings through the expression of texts, such as anger, disgust, fear, happiness, sadness, and surprise. Emotion detection may have useful applications, such as gauging the happiness of citizens or understanding the perceptions of consumers[23]. In analyzing sentiments, several steps need to be taken to get the best results[81]. This step is presented in the figure 2.3.

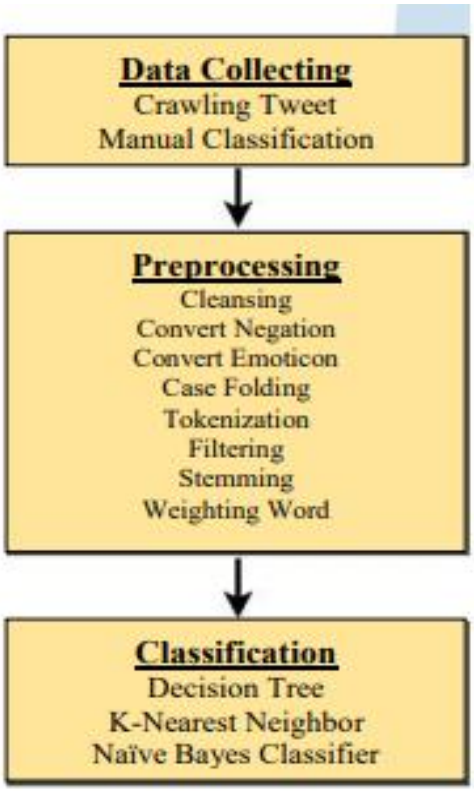

Figure2.3: Sentiment Analysis flowchart Source: [81]

Figure 2.3 shows sentiment analysis flowchart. A sentiment analysis is a subset of natural language processing used in association with text mining techniques for the extraction of subjective information from social media sources[50]. Emotion analysis can be divided into two categories; based on emotion lexicons and based on machine learning. Emotion analysis

based on emotion lexicons uses the existing knowledge to construct specific emotion lexicons by marking emotion words and calculating the weight. With the increasing popularity of emotion analysis based on machine learning and the emergence of various deep learning models, language models based on neural networks was constructed[18]. Due to the long training time of the model, in 2013, Google Company modified the model to build word2vec model, which has become the main vector representation model in natural language field[19]. There are three (3) main classification levels in Sentimental Analysis: document level, Sentence level, and Aspect level. The Document-level SA aims to classify an opinion document as expressing a positive or negative opinion or sentiment. It considers the whole document a basic information unit (talking about one topic). Sentence-level SA aims to classify sentiment expressed in each sentence. The Aspect-level SA aims to classify the sentiment with respect to the specific aspects of entities.

Sentiment analysis is a computational measurement of attitude, opinion and emotions (like positive/ negative) with the help of text mining and natural language processing of words and phrases. Sentiment analysis plays a greater role in gaining the overview of wider public opinion and social media interactive dataset is the best source for it[50]. Recently, sentiment analysis has been employed with Twitter analytics via different methodologies such as lexicon-base, machine learning based, emotion based and deep learning based[22].

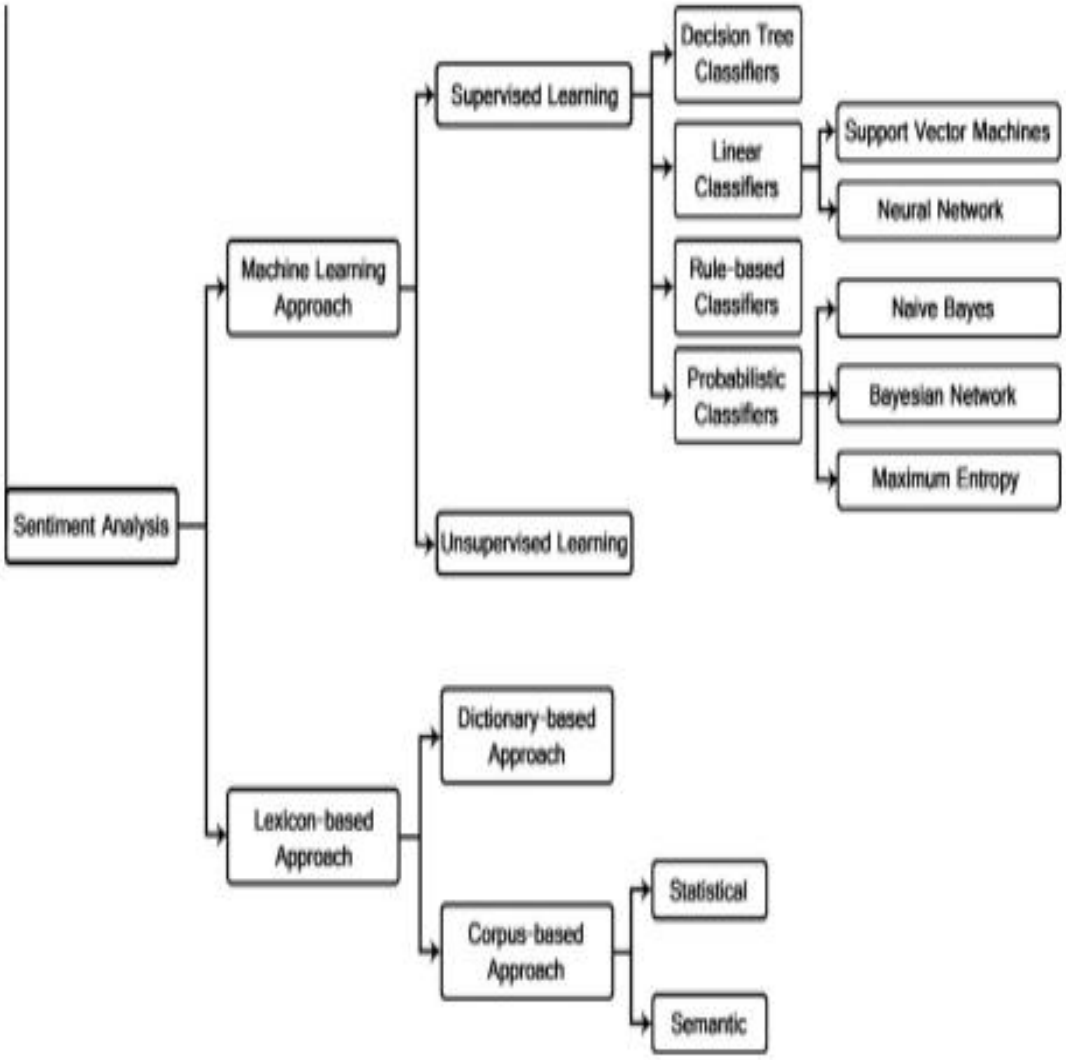

Figure 2.4: Sentiment classification techniques Source: [29]

Figure 2.4 shows the sentiment classification techniques employed with Twitter analytics via different methodologies.

2.1.8 Social Media

Social media has increasingly been used as a route for emergency response in recent years. The fundamental concept of social media is two-way communication.In the era of big data, social media users can be seen as social sensors to monitor real-time emergency events [24]. One of the key sources from which emergency responders and social media content analyzers may extract useful information to assist categorize and rank new concerns or provide

additional context regarding observed issues is information gathered from social media. When a crisis strikes, eyewitnesses use social media to convey alerts and updates, solicit assistance, or report on the situation around them. By doing so, they add to the information streams that both communities and emergency responders rely on[102]. The rapid popularity of smart phones and the 5G network enables every citizen to report what is happening around him or her at any time. Several countries have implemented online portals to provide users with access to the financial management information systems (FMIS) database and for reports to be run and data analysis to be conducted[31]. Social media is used for emotional expression, but it also has crucial real-time information. Social media communicates a lot about the current state of mind, attitude, and character of a sizable human population. Due to their reliance on social media for educational content, social media users are growing with time, and the volume of data is also growing as more attention is paid to employing Natural Language Processing (NLP) and various AI algorithms to effectively extract useful information[32].Social network information rates surge during emergencies, necessitating quick data processing to deal with the situation. Big data processing techniques are necessary because the content on social media platforms during emergencies creates enormous amounts of data that cannot be managed by conventional data processing techniques[75].

Identifying useful material from huge and noisy data is a difficult undertaking since online social media platforms like Twitter and Facebook record human sentiments and emotions, expressions, and thoughts. Social media is crucial for managing crises like environmental disasters, and it may also be used to raise environmental awareness and enhance health.

Social media channels are being adopted by emergency management professionals in order to reach more people. Community members provide information about the condition on social media during catastrophes. This data may be regarded as a crucial element that influences the Emergency Operations Centers (EOCs) unit's situational awareness and influences the quality

of their decisions103. During a crisis, emergency managers utilize social media to communicate, respond to information, and participate in the discourse. They respond to questions and concerns from the impacted public and provide information and guidance. They also make use of social media to debunk the propagation of false information. From the emergency services' point of view, this social media usage brings various complexity and difficulties[104].

Social media may be used as the main form of real-time communication. It offers a number of ways to disseminate information quickly, cheaply, and effectively, allowing victims, volunteer organizations, and authorities to post their problems and solutions on the same platform in real time. Via time-sensitive events, this real-time connection supports the decision-making requirements of impacted individuals and crisis management officials. Additionally, it can help with coordinating and managing response and recovery efforts, finding specialists for on-the-spot consulting, and training up-and-coming emergency managers[102].

2.1.9 Sentiment Analyses of Social Media Data in Disaster Relief

Social media has pervasively played an important role in providing individuals and communities with warnings about evacuations, volunteering services, humanitarian aid and fund-raising during disaster events. It is a common practice for people to post their experiences, ideas, needs and opinions regarding an event (incident) in the form of text, images, videos etc. to generate situational awareness, request and present donation needs, locate, help and support those in need[120]. Sentiment analysis of disaster related tweets is reflective of the emotional states, feelings, panics and concerns of the affected population and of those concerned to improve decision making of humanitarian organizations during mass emergencies. Current social media visualizations at the time of disasters focus only on spatial and temporal aspects of the geographical phenomena with no consideration to include

sentiments[117]. Sentiment information when combined with visual analytic methods could communicate real-time situation during hazards in a more readable and interpretable way[117]. Most common methods to analyze sentiments during a disaster event employ machine learning techniques using SVM, Naive Bayes, Maximum Entropy, Random Forest, Swarm Intelligence etc. Both polarity and subjectivity of tweets can be extracted as linguistic features to analyze the evolution of a social sentiment. SentiWordNet and AFINN packages have been extensively used on datasets gathered from social media posts to perform such an analysis[118]. The different packages and tools can process emotions into different categories. For instance, Senti-Strength can classify tweets into positive and negative on the basis of calculated sentiment scores while Sentiment Treebank provides a five class classification of sentiments into Very Negative, Negative, Neutral, Positive and Very Positive[119].

2.1.10 Twitter

Twitter is a rapidly developing social media platform that allows users to share thoughts, disseminate information, and facilitate contact with one another to better understand the situation during major emergencies. One of the most popular social media sites, Twitter, has seen a sharp rise in tweets about local topics, including both favorable and negative as well as neutral ones33. Twitter is a rapidly developing social media platform that allows users to share thoughts, disseminate information, and facilitate contact with one another to better understand the situation during major emergencies. Positive, negative, and neutral sentiment classifications are used to categorize tweets[10]. Tweets can also be grouped as follows; First-hand information, Second-hand information, Emotive, Comments, Irony, Useful information and Media[34].

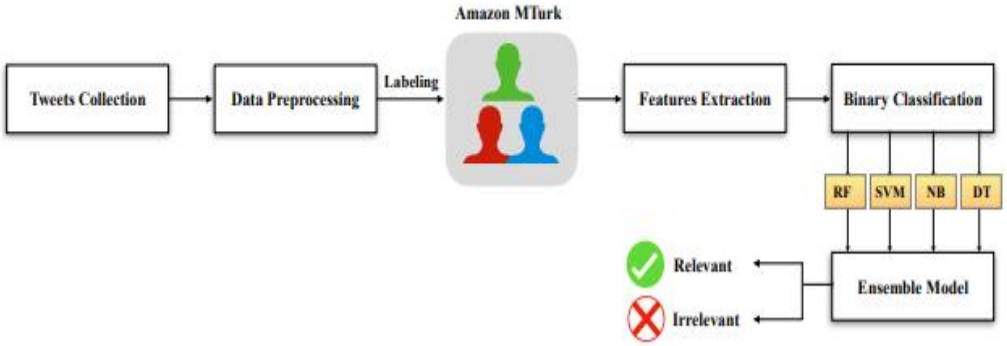

Figure2.5: Twitter situational awareness detection framework. Source:[102]

In figure 2.5, a small portion of Twitter's data (about 1% of all tweets) is made freely accessible to the public. There are, however, two different types of data: historical data and streaming real-time data. There are two methods to get this information:

(1) Create a Twitter developer account and finish the authentication procedure.

(2) Spend money with businesses (Twitter partners) like Crimson Hexagon.

Each Tweet has a multitude of characteristics, including:

Retweet: A retweet is just a tweet that has been shared by another Twitter user so that their followers may see it. Retweets are identified by the abbreviation RT.

Favorite: People mark tweets as favorites if they like them.Users may let the proprietors of tweets know that they like them by giving them a favorite. All Twitter users may see how many times a tweet has been favorited.

Followers: Different accounts that subscribe to a Twitter user's postings and updates are considered the user's followers. When someone follows an account, their name will show up

in the list of followers for that account. Twitter users can signal that they desire to follow someone else's posts by following them. Everyone may see how many followers a user has.

Following: The action of getting and reading a user's real-time posts on Twitter is known as "following;"on that person's profile, the follow button is selected. Also, when you subscribe to (follow) someone on Twitter, it is implied that you have given them permission to send you a direct message on the social media platform. The amount of accounts a person follows is visible to others.

Mention: By attracting attention from several users by employing the symbol (@) followed by a username, Mention allows interchangeable communications.

Reply: A reply is a direct, private communication (or tweet), sent from one user to another receiver; it is not displayed in the user's Twitter stream.

Hashtag (#): Any phrase that has the symbol (#) in front of it is a hashtag. In essence, hashtags were developed to speed up online discussions by categorizing tweets about a certain subject.[107].

Figure 2.6: Twitter data and methods of collecting tweets. Source:[2]

Figure 2.6 shows different types of data that can be collected in Twitter and two major types of tweets available.

2.1.11 Natural Language Processing

Sentiment analysis was first developed using Natural Language Processing (NLP), one of the disciplines of artificial intelligence technology. The use of NLP in sentiment analysis include text pre-processing using tokenization and featured selection[100]. Several connectionist natural language processing systems often employ recurrent architectures instead of feedforward networks. These systems with "reentrancy" are expected to be more adequate to deal with the temporal extension of natural language sentences, and, at the same time, they seem to be physiologically more realistic[101]. Natural language processing (NLP) is a theory-motivated range of computational techniques for the automatic analysis and representation of human language. NLP research has evolved from the era of punch cards and batch processing (in which the analysis of a sentence could take up to 7 minutes) to the era of Google and the likes of it (in which millions of webpages can be processed in less than a second[108].

Natural language processing (NLP), in fact, requires highlevel symbolic capabilities (Dyer, 1994), including:

1. Creation and propagation of dynamic bindings
2. manipulation of recursive, constituent structures;
3. acquisition and access of lexical, semantic, and episodic memories;
4. control of multiple learning/processing modules and routing of information among such modules;
5. grounding of basic-level language constructs (e.g., objects and actions) in perceptual/motor experiences;
6. representation of abstract concepts.

All such capabilities are required to shift from mere NLP to what is usually referred to as natural language understanding.

2.1.12 Machine Learning

Machine learning is the discipline of teaching computers to predict outcomes or classify objects without being explicitly programmed for such tasks[35]. Machine Learning deals with the design of programs that can learn rules from data, adapt to changes, and improve performance with experience. In addition to being one of the initial dreams of Computer Science, Machine Learning has become crucial as computers are expected to solve increasingly complex problems and become more integrated into our daily lives. Machine learning has been highly successful in areas like self-driving cars, speech recognition, effective web search, marketing and purchase recommendations[36].

In 2002, text emotion categorization was the first area in which machine learning was used. A comparison study was conducted using the Naive Bayes, Maximum Entropy, and Support Vector Machine algorithms for text emotion identification[17].Machine learning is any sort of computer program that can learn by their own without having specially programmed by the programmer[50].Machine learning based approaches needs extra effort of machine translation. Machine learning algorithms can be classified into two main groups: supervised and nonsupervised algorithms. Supervised learning refers to building models given a collection of training predictors X1,X2, . . . ,Xp and the corresponding response variable Y, whereas in unsupervised learning there exist only predictors, hence the algorithms have to learn the structure of the training data (clustering). Machine learning can be used also for inference tasks, i.e., in order to understand how the response variable is affected when the predictors change[35]. The Naïve Bayes (Bayesian network) is a subset of the supervised learning classification of the machine learning techniques as shown in the figure 2.7.

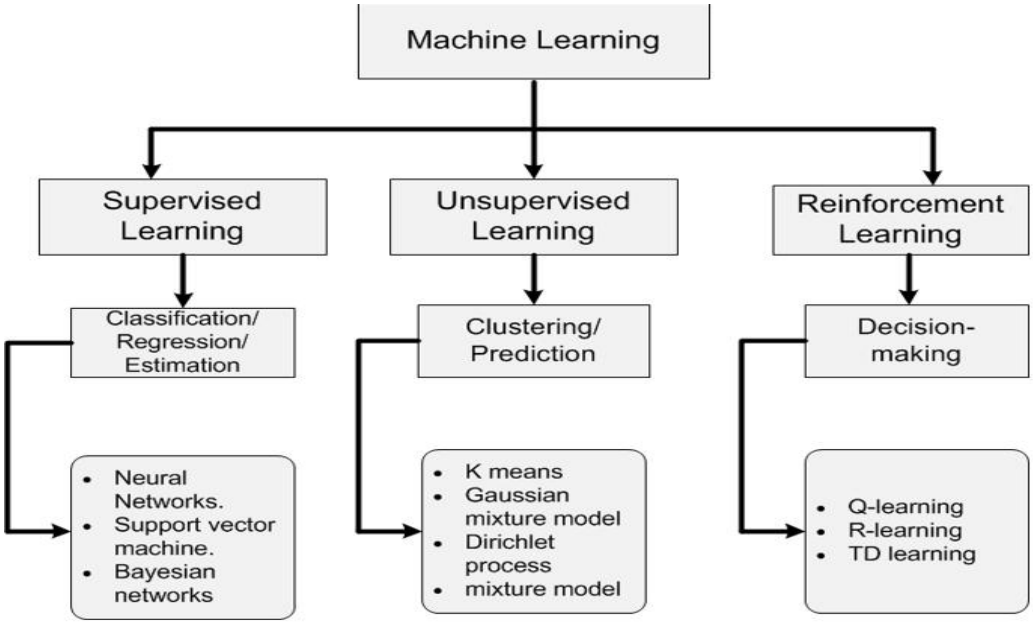

Figure 2.7: Types of Machine Learning Source:[44]

Figure 2.7 shows the comparison of differerent types of machine learning that are widely used.

Machine learning is defined as the stages in which provided data is learned in order to gather sufficient knowledge and afterwards produce the desired conclusion. Supervised, unsupervised, or semi-supervised machine learning are all possible. In our method, the following algorithms are applied: LSTM (long short-term memory), DT (Decision Tree), SVM (Support Vector Machine), KNN (K Nearest Neighbor), and NB (Naive Bayes)[109].

Recurrent Neural Networks (RNN) frequently use the Long Short-Term Memory (LSTM) layer of neural networks to solve the vanishing gradient problem. A typical LSTM unit consists of a cell, an input gate, an output gate, and a forget gate. The three gates keep track of data flow to and from the cell, and the cell keeps data for indefinite periods of time.

Decision tree (DT): Is a type of supervised classifier approach used for classification and regression. It became a typical tool for machine learning and big data issues because of its

power and efficacy. There are three different kinds of nodes in it: end nodes, chance nodes, and decision nodes.

Support Vector Machine (SVM): Both classification and regression issues are addressed by SVM. The best suitable hyperplane should be created in order to divide the dataset into two groups using SVM. SVM is a reliable machine learning algorithm that may be used in many different areas, including regression and nonlinear classification. It is one of the most used machine learning methods.

K Nearest Neighbor (KNN): A machine learning technique called K Nearest Neighbor (KNN) compares unclassified input to data that has previously been categorized using a predetermined training data class. This comparison is evaluated using the discrepancy between the trained data and the raw data. The data set with the lowest distance estimations is used to identify the closest neighbors.

Naive Bayes (NB): Because it works rapidly and is simple to implement, NB is useful for defining data sets containing a considerable amount of information. As a Bayesian classification method, the NB algorithm is based on the Bayes probability idea and builds probability tables for each variable separately[110].

2.1.13 Machine Learning Theory

Machine Learning Theory also known as Computational Learning Theory is a theory that impact knowledge to understand the fundamental principles of learning as a computational process. Machine Learning Theory seeks to understand at a precise mathematical level what capabilities and information are fundamentally needed to learn different kinds of tasks successfully, and to understand the basic algorithmic principles involved in getting computers to learn from data and to improve performance with feedback. It aids in the design of better automated learning methods and to understand fundamental issues in the learning process.

Machine Learning Theory draws elements from both the Theory of Computation and Statistics and involves tasks such as: Creating mathematical models that capture key aspects of machine learning, in which one can analyze the inherent ease or difficulty of different types of learning problems, proving guarantees for algorithms (under what conditions will they succeed, how much data and computation time is needed) and developing machine learning algorithms that provably meet desired criteria, mathematically analyzing general issues.Another highlight of Computational Learning Theory is the development of algorithms that are able to quickly learn even in the presence of large amounts of distracting information[82].

2.1.14 Artificial Intelligence

Synthetic intelligence is synonymous with artificial intelligence, which is a man-made intelligence that may be instilled in and displayed by an artificial entity[36]. Synthetic intelligence is synonymous with artificial intelligence, which is a man-made intelligence that may be instilled in and displayed by an artificial entity. An Artificial intelligent is a piece of software, hardware, or both that senses and exhibits cognitive behavior based on prior experience Humans can only discern the attribute trait of smoke that comes from a fire that is visible to the naked eye, but there are a variety of technological mechanisms that can be used to perceive smoke even from a distance, such as combining a light transmitter and receiver to create a beam that may be obscured by the presence of smoke flames[88].

2.1.15 Deep Learning

Deep learning provides an approach to utilizing large volumes of calculation and data using little manual engineering[6]. It is the recently emerged area of machine learning which has widely become popular for knowledge extraction and representation learning tasks particularly when huge raw data are available[8]. Deep learning is a set of algorithms that processes large set of data and imitates the thinking process. The history of deep leaning is

started from 1943, when Warren McCulloch and Walter Pitts created a neural network-based computer model. Deep Learning (DL) was officially introduced by Hinton, which was based on the concept of artificial neural network[3, 4].

Deep learning approaches can be applied according to the requirements of the tasks. To retain high attack detection accurately, while enabling a significant reduction in the complexity of deep neural classifiers involved in the process which simplifies the task of deep model training is very important[7]

The Rina Dechter introduced the word of deep learning in 1986, the main motivation behind the advent of field deep learning was making an intelligent machine that mimics the human brain. Deep learning is used everywhere, that is, bio-informatics, computer vision, IoT security, health care, e-commerce, digital marketing, natural language processing, and many more[41]. Deep learning is also called differential programming or structure learning. It is a member of a large family of machine learning class, which is used in automatic speech recognition, Image recognition, Natural language processing, Games and robotics, Financial fraud detection, Military, Cyber-security amongst others [40].

2.1.16 Deep Learning Techniques

Deep Learning Techniques is very important in predicting new attacks, which are often mutations of previous attacks because they can intelligently predict future unknown attacks by learning from existing examples. Deep learning models can detect threats more accurately than any other technology[40]. Deep learning techniques are data hungry and therefore they work best in case of big data analytics[50]. Consequently, the Internet of Things systems must have a transition from merely facilitating secure communication amongst devices to security-based intelligence enabled by Deep learning techniques for effective and secure systems.

2.1.17 Category of Deep Learning Technique

Deep Learning techniques is broadly divided into three major categories:

i. Deep networks for supervised or discriminative learning : This category of DL techniques is utilized to provide a discriminative function in supervised or classification applications. Discriminative deep architectures are typically designed to give discriminative power for classification by describing the posterior distributions of classes conditioned on visible data[3].

ii. Deep networks for unsupervised or generative learning: This category of DL techniques is typically used to characterize the high-order correlation properties or features for pattern analysis or synthesis, as well as the joint statistical distributions of the visible data and their associated classes. The key idea of generative deep architectures is that during the learning process, precise supervisory information such as target class labels is not of concern.

iii. Deep networks for hybrid learning and other approaches: this is the capacity to learn from both labeled and unlabeled data. Thus, an integration of diferent generative or discriminative models to extract more meaningful and robust features. other approaches such as deep transfer learning (DTL) and deep reinforcement learning (DRL) are popular[5].

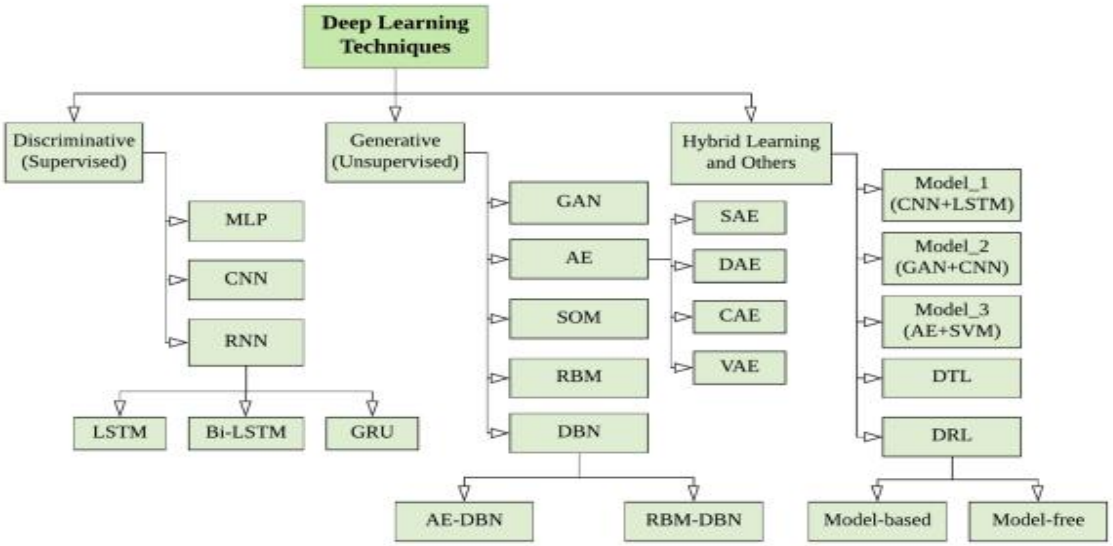

Figure 2.8: A Taxonomy of DL Techniques Source:[29]

Figure 2.8 shows the taxonomy of deep learning techniques, it is broadly divided into three major categories (i) deep networks for supervised or discriminative learning, (ii) deep networks for unsupervised or generative learning, and (ii) deep networks for hybrid learning and relevant others.

2.1.18 Comparison of Deep Learning, Artificial Intelligence and Machine Learning

These are three popular terms that are sometimes used interchangeably to describe systems or software that behaves intelligently; Deep learning, machine learning and Artificial Intelligence.Deep learning is a sub branch of machine learning, and machine learning is a sub branch of artificial intelligence. [1]Artificial Intelligence incorporates human behavior and intelligence into machines or systems, while Machine Learning is the techniques used to learn from data or experience, which automates analytical model building[2]. With the advent of deep learning model traditional approaches become invisible while they also have good computational powers. Deep learning also refers to data-driven learning techniques that use multi-layer neural networks for computing and processing. In the deep learning approach, the word "Deep" alludes to the idea of several levels or stages of data processing for the creation of data-driven technologies.

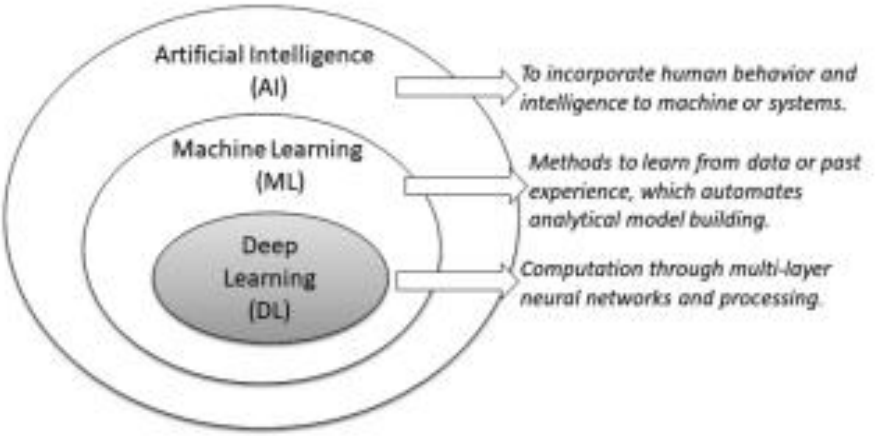

Figure 2.9: An illustration of the position of deep learning (DL), Machine Learning (ML) and Artificial Intelligence (AI) Source: [44]

2.1.19 Big Data Technology

Big data can be used in improving network service qualities as well as generate new mobile applications. For big data handling there should be novel big data analytics and advanced machine learning techniques such as Naïve Bayes learning, deep learning, neural networks, representation learning, transfer learning, active learningand online learning[75].

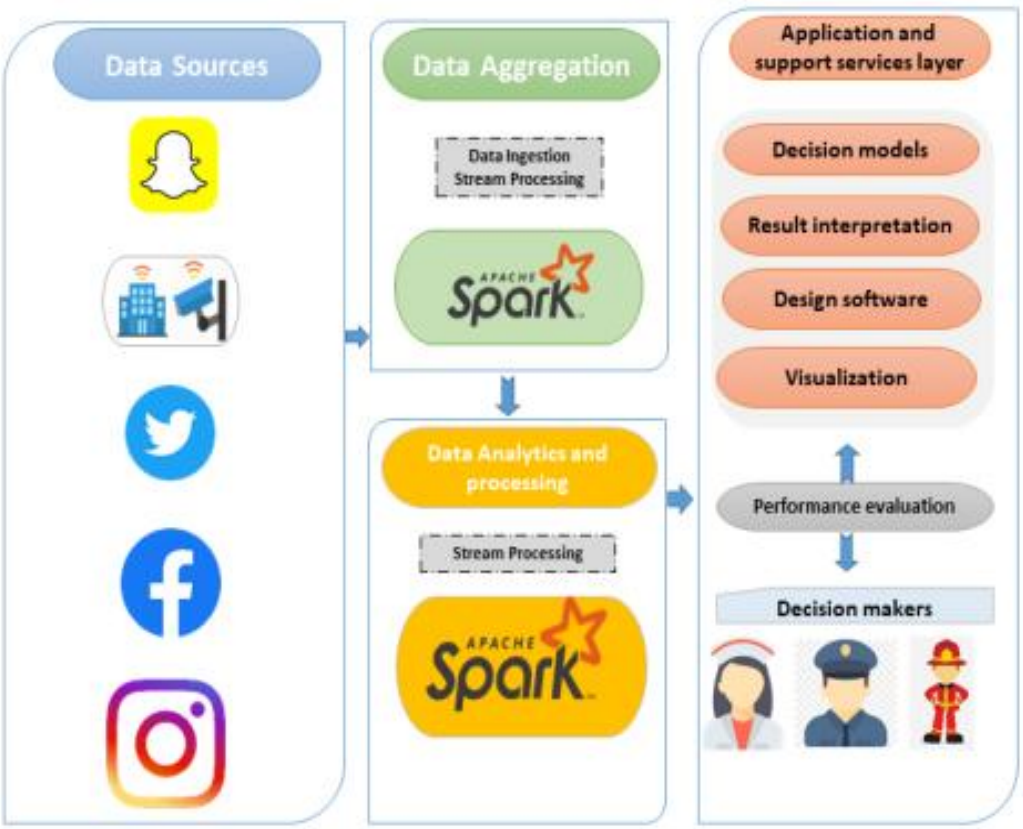

Figure 2.10: Overall of big data Technology Source: [75]

Due to the implementation of varioustechniques mentioned in figure 2.10, big data can be efficiently processedand decisions made accordingly. Raw data can be converted into right actionable data with the help of analytics techniques. Recently, some frameworks have been proposed which shows the significance of big data and big data analytics in next generation networks. Big data sources are of different types with different data rate, mobility and packet loss[8]. Big data is an extremely large or complex set of data that's why it is difficult to manage with the help of traditional databases or traditional tools/applications. Due to the diversities of data, there are several challenges related to it and complexity arises in the case of big data. According to the current state of the art about 80% of the data generated in the world is the unstructured type of data[39].

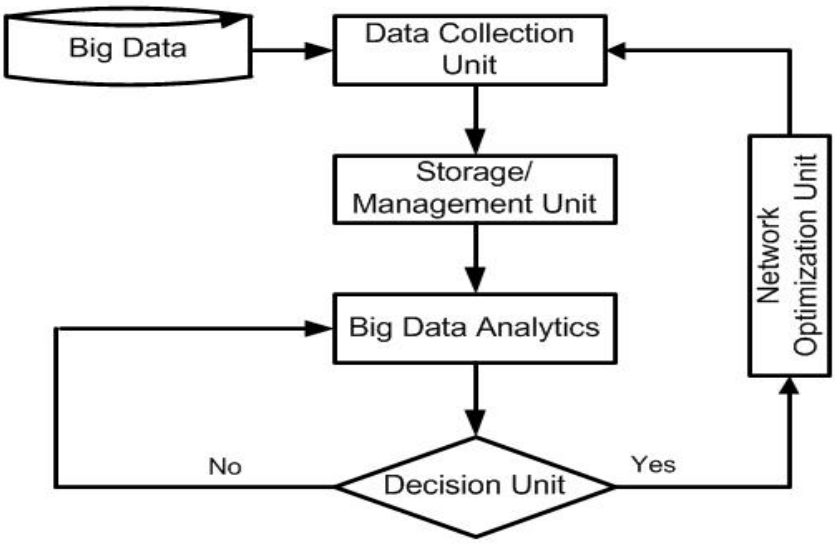

Figure 2.11: Big data flow diagram Source: [44]

Figure 2.11 shows how data flows and processes involved in big data technology.

2.1.20 Big Data Technology tools

1. Hadoop: Although it does not offer in-memory storage or real-time analytics, this platform is utilized to store, manage, and retrieve big datasets in a distributed setting for batch processing.
2. Data Lakes: These are places to store preprocessed data so that it may be used later. It is capable of doing quite difficult tasks. Traditional data storage and analysis methods do not integrate well with this technology.
3. Blockchain: A distributed database system that records information about transactions made between two nodes. It is extremely dependable, effective, and long-lasting. It is very safe and a great option for big data applications in delicate sectors since it is more failure resistant.. A major disadvantage is difficulty in updating and eliminating errors, difficulty of development, cannot redesign without loss of benefits.
4. Edge computing: This technique allows you to process data close to the edge of your network, where it is being generated, as opposed to centralizing data processing. Network

traffic and associated expenditures are reduced. Edge computing makes it possible to accelerate data streams and instantly process real-time data. It can expand attack surfaces, demand more local hardware, process, and only evaluate a portion of the data.

5. MapReduce: This program offers a method for parallel processing in a distributed setting. In-memory and real-time processing have drawbacks (stream processing).
6. Apache Spark: It offers a user interface for a parallel computing platform that is largely used for data engineering and analytics. Processing in memory and in real-time (stream processing), but at a high cost and with a lot of memory use.
7. ApacheStorm: is a framework for processing the infinite data stream in real-time. Excellent horizontal scalability, real-time processing, and auto restart on failure. Processing in batches is an issue.
8. Neo4G: is a graph database that uses the key-value pair method to store data and has node connection data that are interconnected. The various dimensions may be represented using the ACID property, encryption graph query language, high availability, and flexibility. It is not appropriate for a transactional database since it is more difficult to perform maximum and summing queries effectively.
9. Apache SAMOA: This scalable advanced mass online analysis is one of the tools used for mining large data and distributed stream processing, and it can be programmed once and utilized everywhere without the need for backup or labor-intensive updates. The disadvantage is system issues like load balancing and communication in a multi-target learning[57].

2.1.21 Data Mining Technology

Data Mining Technology provides a platform for information extraction from unstructured information to solicit useful data. Mining information from natural languages sent through

text message using mobile devices could be of significance during a disaster and crisis management[59].

2.1.22 Bayesian network

Using algorithms based on the Naive Bayes theorem, naive assumptions of conditional independence among predictors are used in the Nave Bayes technique to predict the category of unknown data sets. It is a classification that incorporates a number of data mining models. Several real-world applications, including text categorization, medical diagnosis, and system performance management, have shown that naive Bayes works well. Naive Bayes (NB) is easy to construct but surprisingly effective, and it is one of the top ten classification algorithms in data mining[76].Naive Bayes is the simplest and fastest classification algorithm for a large chunk of data. In various applications such as spam filtering, text classification, sentiment analysis, and recommendation systems, Naive Bayes is used successfully. It uses the Bayes probability theorem for unknown class prediction[111]. Naive Bayes is often used as a baseline in text classification because it is fast and easy to implement[115].

2.1.23 Bayesian belief classification

Bayesian Belief Learning (BBL) is a collection of classification algorithms, being an enhanced variation of the Bayes Theorem. The Bayesian classifier is surprisingly effective in practice since its classification decision may often be correct even if its probability estimates are inaccurate.The classification performance of Bayesian learning method is comparable to well-known classifiers[77]. The Bayesian Classification represents a supervised learning method as well as a statisticalmethod for classification. Assumes an underlying probabilistic model and it allows us to capture uncertainty about the model in a principled way by determining probabilities of the outcomes. It can solve diagnostic and predictive problems.A classifier is a rule that assigns to an observation a guess or estimate of what the unobserved label actually was. In theoretical terms, a classifier is a measurable function, with the

interpretation that C classifies the point x to the class C(x). The probability of misclassification, or risk[114].

The Bayesian classification technique is a simple and powerful classification task in machine learning. The use of Bayes' theorem with a strong independence assumption between the features is the basis for Bayesian classification. When used for textual data analysis, such as Natural Language Processing, the Bayesian classification yields good results[111].However, the conditional independent assumption of Bayesian learning ignores the dependencies between attributes in real-world applications, so its probability estimates are often suboptimal[78]. The idea behind Nave Bayes classification, which is that, each pair of characteristics categorized independently of one another, is shared by a number of different algorithms rather than a single one. The following are stages in creating the Bayesian Classification model:

1. Cross-Validating: The dataset will first be split into two sections, the Data Train and Data Test, for this step.

a. Data Train: The Data Train is made up of 80% of the data that has been randomly divided and utilized as learning material for the next Naive Bayes Classification model. Using the provided setseed function, this data has been randomly generated.

b. Test Data: When the Naive Bayes Classification model has been trained using the prior data train model, the test data will be used to evaluate the model's performance. In order to assess the correctness of the model that has been developed, the test data utilized at the conclusion of the modeling process will be used once again to compare the findings obtained with the results of the model acquired.

2. Bernoulli Convolution: To construct a data train label and test data label that the computer can recognize, the Bernoulli Convolution function must be created next.

This label will indicate whether a news item has positive or negative sarcasm, which are represented by the symbols 0 and 1, respectively.

3. Bayesian Classification Modeling: When the data has been collected, cross-validate the model and use Bernoulli convolution. The data train is then prepared for use in modeling using the Bayesian Classification technique. The categorization of vectors created earlier through text preprocessing allows us to determine which sentences in the data have a positive or negative sarcastic meaning through this modeling approach[66]. The BBL model will be able to determine news that has the meaning of sarcasm both positive and negative. This model is entered into the test data that has previously been cross-validated to see the comparison of accuracy with the original test data. This test is performed using the "predict" function [98].

2.1.24 Bayesian Classifier

The Bayesian classifier is used for the purpose of identifying the positive and the negative sentiments. That was a visual intuition for a simple case of the Bayes classifier, also called: Idiot Bayes , Naïve Bayes or Simple Bayes. A straight forward method with precise semantics is offered by the Bayesian classifier to express the learning of probabilistic knowledge of the Bayes theorem. Because it is based on two crucial simplifying assumptions, many people see the classifier as a type of Bayesian network that is referred to as naïve[68]. Bayesian classifiers assume attributes and have independent distributions.

The Bayesian classifier can be expressed as:

$$\arg \max_{1 \le k \le m} P(C_k \backslash X) = \arg \max_{1 \le k \le m} \frac{P(C_k) P(X \backslash C_k}{P(X)} \quad (1)$$

This rule is called Bayes rule. For each class, the denominator of equation (1) is the same and it will not interfere in classification. So, the Bayesian classifier can be rewritten as:

$$\arg \overset{max}{1 \leq k \leq m} P(C_k \backslash X) \propto \arg \overset{max}{1 \leq k \leq m} P(C_k) P(X \backslash C_k) \quad (2)$$

Naïve Bayes Classification (NBC) is a collection of classification algorithms based on the Bayes Theorem.

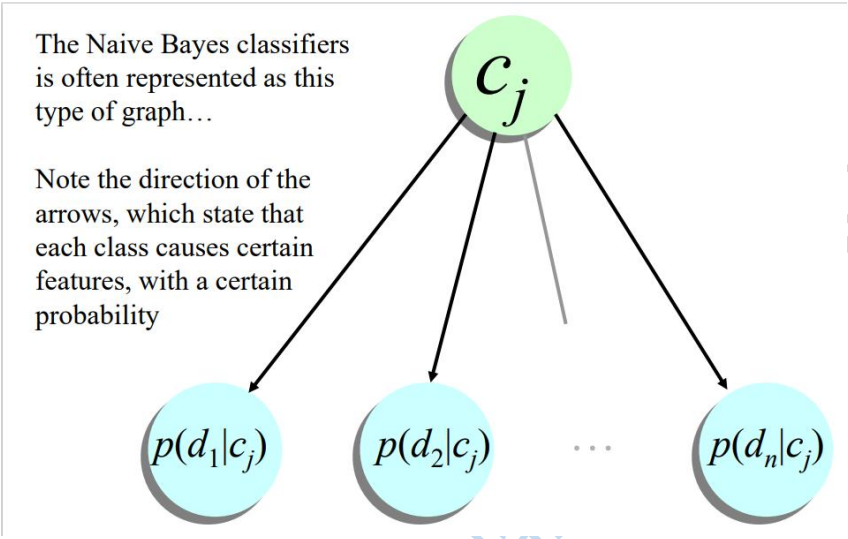

Figure 2.12: Bayesian Classifier Source: [116]

Figure 2.12 shows Bayesian Classifier, it is not a single algorithm but a collection of several algorithms where they all have the same principle, that is, each pair of features classified does not depend on each other. The naïve Bayes classifiers are based on the conditional probability of the features belonging to one class after features selection using auxiliary feature method[116].

2.1.25 Bayesian Techniques

Bayesian technique is quite dynamic for deducing statistical conclusion; its diversification goes through several dimensions like Bayesian Belief Learning, Bayesian Probability Algorithm, Bayesian Classification Netweork and others. It is usually useful in prediction as data mining method which operates based on Bayes principle that uses an assumption of independent elements. In other words, a Bayesian model presumes that the availability of particular trait in a cluster is not related to the appearance of other elements[79].

Bayesian approach can be quickly adopted and particularly helpful for very large amount data. Apart from the simplicity, Bayesian is commonly recognized for optimal result in classification accuracy even beyond some complex and famous classification methods[80]. Traditional machine-learning algorithms assume that data are precise, but for uncertain data the Bayesian classifier is favorable to use. Naïve Bayes models are very popular and effective in many complex problems despite its simplicity[65].

Figure 2.3 shows Naïve Bayes classification method, this technique is dependent on the training method conducted in the system. After the process, messages m1 to mn will become classes of c1 to cn of the learned classifier.

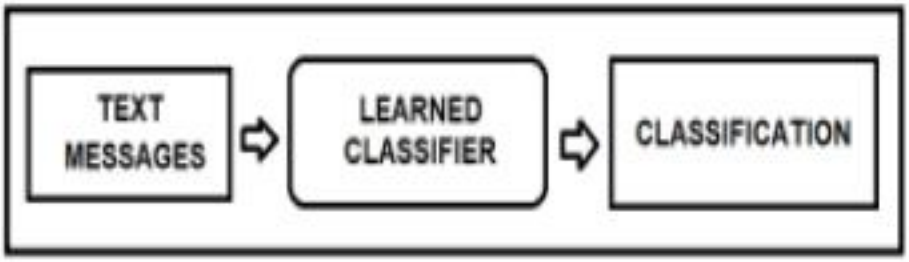

Figure 2.13: Bayesian Classification Method Source: [23]

2.1.26 Bayesian Probability Algorithm

Bayesian is one of the data classification algorithms. The Bayes theorem is used by the Bayesian Classifier to forecast membership probabilities for each class, such as the likelihood that a given record or data point belongs to that class. The most likely class is defined as the one having the highest probability. The Maximum A Posteriori is another name for this (MAP)[111]. As Bayesian classification method, the Bayesian algorithm creates probability tables for each variable separately and is based on the Bayes probability notion. The procedures used by the Naive Bayes Text Classification Algorithm are as follows:

1) Using NLP, create a Bag of Words (Corpus) for each item;

2) Create a Bayesian Classifier (Training Set); and

3) Perform a Bayesian Belief Classification Procedure.

Natural Language Processing is a technology used in the process to remove grammatical errors (language faults), noise (unnecessary words), stop words (words with minimal semantic importance), and repetitive words and letters in the message. The remainder of the objects are regarded as tokens that make up the Bag of Words (Corpus) y (message) = c.A portion of the message free of grammatical errors, noise, stop words, and repeats is known as the "bag of words" (c). Natural Language Processing must be applied to raw communications in order to remove superfluous words. The trained classifier required for the actual classification process will subsequently be created using the produced bag of words to produce training set y. The text messages will be classified using the Bayesian Classifier on the basis of the trained classifier. As a machine learning algorithm, Bayesian belief learning, the reliability and validity of the training set would be crucial for the accomplishment of its subsequent operations[59].

Advantages of working with Bayesian algorithm are; it requires a small amount of training data to learn the parameters; it can be trained relatively fast compared to sophisticated models. The main disadvantage of Bayesian Algorithm is; it is a decent classifier but a bad estimator, it works well with discrete values but not with continuous values (cannot be used in a regression). Bayesian classification uses a zero-one loss function. In this function error means number of incorrect classifications.

Here accuracy of probability estimation is not taken into account by error function given that class with the highest probability is predicted right. Matlab provides Bayesian classification facility for data processing[63].

Bayesian algorithm is an algorithm based on Bayes theory (invented by Thomas Bayes). Bayesian is a straightforward probabilistic classification technique. Using the frequency and combinations of values in a certain data collection, this technique determines a set of

probabilities[94]. By computing the frequency of each feature value in the class from the training data set, it is possible to determine the likelihood that certain characteristics in the data will appear as members in a probability sequence. A portion of the training data set is utilized to hone classification algorithms. In order to forecast unknown values, the training process employs known values[93]. Bayes' theorem was named after the Reverend Thomas Bayes (1702–1761), who studied how to compute a distribution for the probability parameter of a binomial distribution. After Bayes' death, his friend Richard Price edited and presented the work in 1763, as an Essay towards solving a Problem in the Doctrine of Chances.

The Bayes Theorem formula is as follows:

$$P(A \mid B) = \frac{P(B \mid A)\, P(A)}{P(B)}$$

Where:

P (A | B): the posterior probability

P (B | A): the likelihood

P (A): prior probability P (B): predictor prior probability

Bayesian algorithm is a supervised algorithm, the data used is not large and reliable. It is also used for machine learning[91].

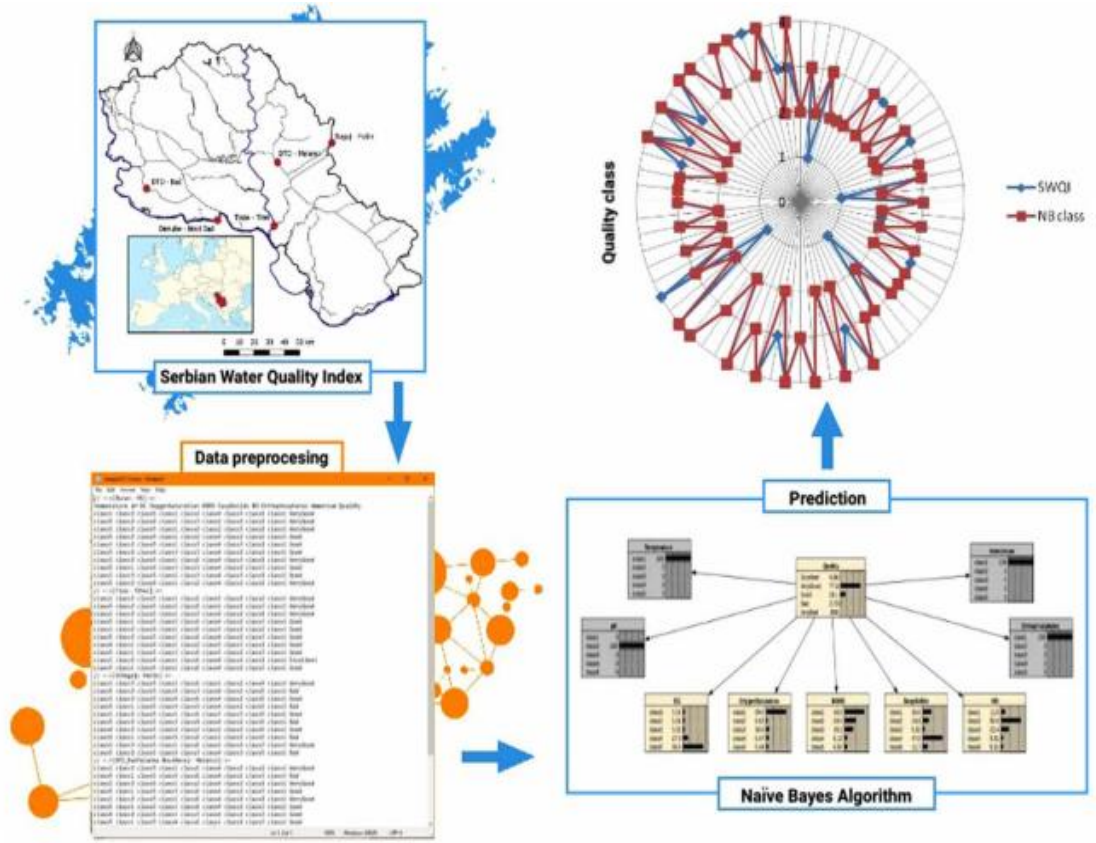

Figure 2.14: Bayesian Algorithm Source: [97]

2.1.27 Types of Bayesian Algorithm

Bayesian learning is one of the most straightforward and fast classification algorithms. It is very well suited for large volumes of data. It is successfully used in various applications such as; Spam filtering, Text classification, Sentiment analysis, Recommender systems, It uses the Bayes theorem of probability for the prediction of unknown classes.

There are 3 types of Naïve Bayes algorithm. The 3 types are listed below:-

1. Gaussian Naïve Bayes
2. Multinomial Naïve Bayes
3. Bernoulli Naïve Bayes

2.1.28 Multinomial Naive Bayes Classifier

One of the two traditional Naive Bayes variations used in text categorization is the Multinomial Naive Bayes method, which implements the Naive Bayes algorithm for multinomial distributed data. Multinomial Naive Bayes models the distribution of words in a document as a multinomial. A document is treated as a sequence of words and it is assumed that each word position is generated independently of every other[115]. With a multinomial event model, samples (feature vectors) represent the frequencies with which certain events have been generated by a multinomia. The data are typically represented as word vector counts. The distribution of word vector count is parametrized by vectors θy = (θy1, … , θyn) for each class y, where n is the number of features (in text classification, the size of the vocabulary) and θyi is the probability P(xi | y) of feature i appearing in a sample belonging to class y. The parameter θy is estimated by a smoothed version of maximum likelihood, i.e. relative frequency counting:

$$\hat{\theta}_{yi} = \frac{N_{yi} + \alpha}{N_y + \alpha n}$$

Where Nyi = ∑ i x∈T xi is the number of times feature appear in a sample of class y in the training set, and Ny = ∑ n i=1 Nyi is the total count of all features for class y. The smoothing priors α ≥ 0 account for features not present in the learning samples and prevent zero probabilities in further computations. Setting α = 1 is called Laplace smoothing, while α < 1 is called Lidstone smoothing[96].

2.1.29 Bernoulli Naive Bayes Classifier

In the multivariate Bernoulli Naïve Bayes Classifier algorithm, features are independent binary variables, which represents that whether a term is present in the document under consideration. The decision rule for Bernoulli Naive Bayes is based on:

$$P(A \mid B) = \frac{P(B \mid A) \cdot P(A)}{P(B)}$$

where:-

A: event 1

B: event 2

P(A|B): Probability of A being true given B is true - posterior probability

P(B|A): Probability of B being true given A is true - the likelihood

P(A): Probability of A being true - prior

P(B): Probability of B being true - marginalization

Multi-variate Bernoulli performs well with small vocabulary but that the multinomial performs usually performs even better at larger vocabulary sizes--providing on average a 27% reduction in error over the multi-variate Bernoulli model at any vocabulary size. Bernoulli Naive Bayes might perform better on some datasets, especially those with shorter documents.

2.1.30 Gussian Naïve Bayes

Numerical data input are processed by Gaussian Naive Bayes Classifier which give decision result in the form of normal access or attack. When dealing with continuous data, a typical assumption is that the continuous values associated with each class are distributed according to a normal (or Gaussian) distribution.

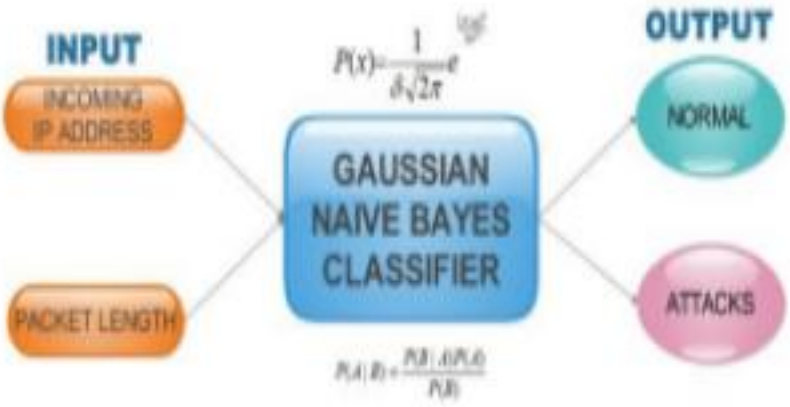

Figure 2.15: Classification process using the Gaussian Naive Bayes method Source: [63]

The Gaussian Naive Bayes is a variant of Naive Bayes that implements the Gaussian normal distribution and supports continuous data for classification. The likelihood of the features used is assumed to be using Gaussian:

$$P(x_i \mid y) = \frac{1}{\sqrt{2\pi\sigma_y^2}} \exp\left(-\frac{(x_i - \mu_y)^2}{2\sigma_y^2}\right)$$

By using this formula, we can calculate the probability of the classification data to fall within the normal distribution of the Gaussian algorithm[95].

2.1.31 Bayesian network

The Bayesian network is constructed of 10 nodes: one parent node (class node) named 'Quality' and nine child nodes that represent nine water quality parameters (Figure 3). The parameters are defined within the SWQI methodology.

2.1.32 Assumptions of Naïve Bayes

Naive Bayes is based on Bayes' theorem and an attribute independence assumption. Its competitive performance in classification is surprising, because the conditional independence assumption on which it is based, is rarely true in real world applications[116].Naive Bayes is a

conditional probability model. Naïve Bayes assumes independence of feature. The naive Bayes classifier greatly simplify learning by assuming that features are independent given class. Although independence is generally a poor assumption, in practice naive Bayes often competes well with more sophisticated classifiers. Despite its unrealistic independence assumption, the naive Bayes classifier is surprisingly effective in practice since its classification decision may often be correct even if its probability estimates are inaccurate. Although some optimality conditions of naive Bayes have been already identified in the past, a deeper understanding of data characteristics that affect the performance of naive Bayes[112].Naive Bayes can be optimal in situations just opposite to the class-conditional feature independence (when mutual information is at minimum) in cases of completely deterministic dependence among the features (when mutual information achieves its maximum[113].

2.1.33 Systematic Error

Naive Bayes has many systemic errors. Systemic errors are byproducts of the algorithm that cause an inappropriate favoring of one class over the other. In this section, we discuss two under-studied systemic errors that cause Naive Bayes to perform poorly. We highlight how they cause misclassifications and propose solutions to mitigate or eliminate them[115].

2.2 Theoretical Review

There are so many theories on emergency. The four principles of emergency Management theory are Preparedness, Response, Recovery and Mitigation. Some of the loopholes inherent in the Emergency Management Theory are the exclusion of the concept of sustainability, exclusion of the concept of vulnerability and resilience, exclusion of improvisation alongside preparedness[69]. Some of the emergency management theories are; normative theory, Prospect theory, three way handshake among others.

2.2.1 Normative Theory

Normative theory is a framework that has been designed to specify actions that emergency managers ought to take. It is assumed that their effectiveness will be enhanced if they abide by these prescriptive lessons. Most important among these is the collection of ideas commonly referred to as "comprehensive emergency management" (National Governor's Association 1978). Through a series of common managerial functions, i.e., mitigation, preparedness, response, and recovery, emergency managers can organize their programs for an all-hazard approach through implementing a series of broad strategies and specific tactics[72].

Emergency managers can benefit from a variety of normative ideas. These ideas aim to outline the steps that emergency managers should follow. It is anticipated that if they are followed, efficacy will increase. The most significant of them is the group of concepts often known as comprehensive EM[9]. by performing a number of standard managerial tasks, including mitigation, preparation, reaction, and recovery. By employing a number of broad ideas and targeted methods, emergency managers may structure their programs into an all hazard strategy. The "integrated EM" framework described by McLoughlin and countless other guidance materials created by the Federal Emergency Management Agency (FEMA) throughout the years might serve as a reference for multiyear preparation.. Each of these normative theories is relevant to EM and provides emergency managers with important theoretical foundations.

2.2.2 Prospect Theory

Prospect theory suggests that people put subjective weights on values and probabilities and that people weight values and probabilities associated with positive outcomes (i.e., gains) differently from those associated with negative outcomes (i.e., losses). Prospect theory successfully accounts for a number of systematic deviations from expected utility, such as the

finding that people are risk-averse for gains of high probability but risk-seeking for gains of low probability, and that people are riskseeking for losses of high probability but risk-averse for losses of low probability[73].

2.2.3 Three-way Handshake Theory

A three-way handshake is a required standard procedure for computer communication. A protocol exchange between the server and the attacker is present in the communication. By sending SYN to the server during the three-way handshake of a regular TCP connection, an attacker can start transmission. The server will then give the user a buffer and respond with SYN and ACK packets. The connection is now in a half-open state as it awaits the attacker's ACK response to complete the connection setup. The three-way handshake is used to seal the connection[63].

2.2.4 Broad Theories

There are several broad viewpoints in the social sciences that contribute to substantive theory, or theory developed to explain and predict human behavior. The theories of academics like Stallings (who used social constructionism to understand the "manufacturing" of seismic dangers) and Jenkins (who used social constructionism to interpret the "manufacturing" of terrorist threats) are among those that emergency managers find most helpful. There are several broad theoretical approaches that can help academics frame their study questions, connect elements of other disciplines, and give emergency managers crucial and practical insights into human behavior. Selected aspects ofthese broad perspectives may provide the basis for “true” theories of Emergency Management and disaster response. Collectively, they offer a foundation; but the house, so to speak, is yet to be built.

2.2.5 MicroTheories

Research from the past has produced helpful micro theories in a few domains, organizing a number of distinct ideas into multivariate theoretical models that seem to have a fair amount

of prediction value for very particular behavioral ranges. Despite the fact that many instances might be given, the two most well-developed ones are risk communication and catastrophe warning responses. Hence, we have a strong understanding of the variety of social variables that influence different public sectors in predictable ways when they confront risk information. Similar to this, during storms, floods, and a number of other sorts of calamities, the social elements that lead some individuals to react in a certain manner while others behave differently have been meticulously studied.Any of these micro theories can be valuable to emergency managers. Ultimately, they may be merged together to offer a holistic perspective of human response to tragedy within its whole life cycle. Nevertheless, none of these include a particular theory of emergency management.

2.2.6 Embryonic Theories

Early comparisons of catastrophes highlighted the crucial part that emergency systems play in disaster response. Drabek and McEntire reviewed other research that were finished over the previous ten years, underlining the importance of significant results for emergency management. They mentioned that one set of findings had led to the creation of a rough catastrophe response model. The combinations of these four elements—domains, resources, activities, and tasks (DRAT)—could be used to successfully identify various kinds of emergency systems, with a focus on the typology of groups responding to disasters developed by the Disaster Research Center (DRC) at the University of Delaware. A strong research agenda is clearly indicated by the fundamental assumptions of this strategy and the kind of goal envisioned.

2.3 Conceptual Framework (Model)

2.3.1 Extensible Markup Language (XML)

XML is a computer programming language designed to transmit both data and the meaning of the data. XML is a metalanguage (literally a language about languages) defined by the

World Wide Web Consortium (W3C), one of the main organizations driving the push to open Web standards. XML accomplishes this by being a markup language, a mechanism that identifies different structures within a document. Structured information contains both content (such as words, pictures, or video) and an indication of what role content plays, or its meaning. XML identifies different structures by assigning data "tags" to define both the name of a data element and the format of the data within that element. Elements are combined to form objects[43].

XML is not just a technology for defining data vocabularies. Surrounding XML is a wide variety of XML standards and initiatives that act in combination with XML to address many of the issues associated with bringing XML into mainstream computing, namely presentation, structure, and transformation. The XML family of technologies also includes initiatives for working with metainformation, which is literally information about the information contained in an XML document. Technologies in this space include RDF and InfoSet[84].

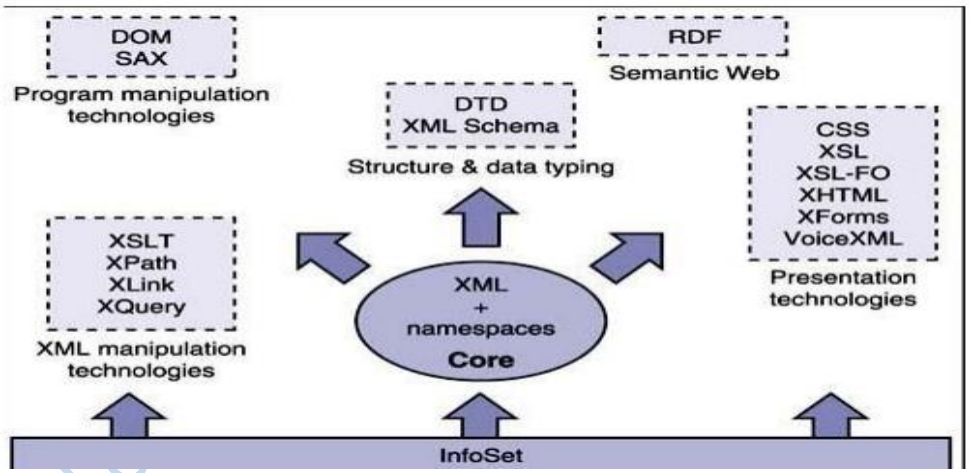

Figure2.16: The XML technology family Source: [84]

Figure 2.16 shows the XML technology family, this technology is compatible with major Internet transmission protocols, and is also highly compressible for faster transmission. When XML arrives at a server, it is typically validated against a DTD or XML Schema and then

stored, transformed, or processed in some way depending on the application. Both validation and processing can be performed by XML parsers. In the XML parsing and processing world there are two major alternatives: the Document Object Model (DOM) and the Simple API for XML (SAX)[53].

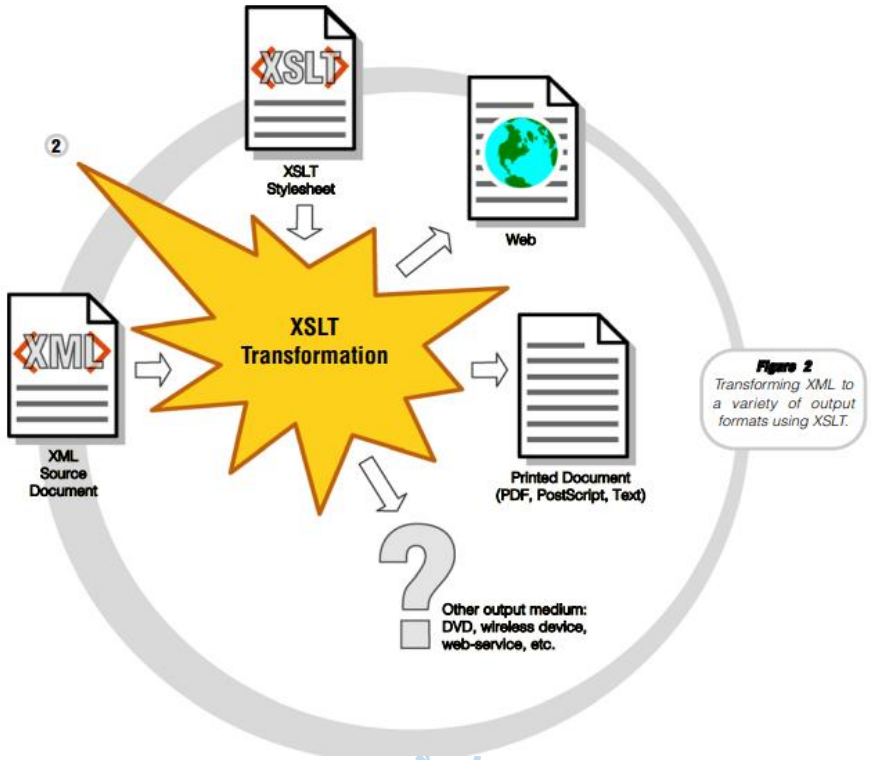

Figure 2.17: Transformation of XML to Output Source: [45]

2.3.2 Python

Python is the perfect programming language for Big Data because of its easy readability and statistical analysis capacity[44].Python is a general-purpose and open-source programming language used by big names such as Reddit, Instagramand Venmo[56]. Python provides a huge number of libraries to work on Big Data in terms of developing code. Research has showed that using Python for Big Data is much faster than any other programming language.Python has rapidly gained popularity in the IT community as a simple yet feature-rich language powering anything from simple web applications to the IoT, game development, and even

artificial intelligence. Python language consists of more readable code, which in turn helps users easily understand codebases. Python can also act as the gateway for big data and data science fields without having to learn a new language[55].

Python is an open-source language managed by the non-profit Python Software Foundation. This open-source nature allows Python to be used in any project without fearing any interference from a third party. Python comes with the Python Package Index (PIP), the open-source repository that contains all the third-party packages available for Python. This library consists of packages to help users in various tasks, from simple tasks like JSON parsing to complete data transformation, analytics, and visualizations packages. All major machine learning algorithms—including TensorFlow, Microsoft Cognitive Toolkit, scikit-learn, and Spark ML—are written in Python[55]. According to Stack Overflow Developers' Survey 2019, Python is the second "most loved" language with 73% of the developers choosing it above other languages prevailing in the market. Python programming supports prototyping ideas which help in making the code run fast.Python helps in supporting scientific computing operations such as matrix operations, data frames, etc. Python has an inbuilt feature of supporting data processing[56].

Python is a general-purpose and open-source programming language used by big names such as Reddit, Instagram, and Venmo says a press release. Making an application using the Python programming language is because it is easy to learn, having many libraries to support data analysis and growing rapidly[92].

2.3.3 Confusion Matrix and Precision

A confusion matrix is a summary of prediction results on a classification problem. The number of correct and incorrect predictions are summarized with count values and broken down by each class. This is the key to the confusion matrix. The confusion matrix shows the ways in which your classification model is confused when it makes predictions. It gives us

insight not only into the errors being made by a classifier but more importantly the types of errors that are being made[83].To evaluate any system for detecting things, confusion matrix will be built . In the field of machine learning and specifically the problem of statistical classification, a confusion matrix, also known as an error matrix. A confusion matrix is a table that is often used to describe the performance of a classification model (or "classifier") on a set of test data for which the true values are known. It allows the visualization of the performance of an algorithm. It allows easy identification of confusion between classes. A confusion matrix is a table for visualizing how an algorithm performs with respect to the human gold labels, using two dimensions (system output and gold labels), and each cell labeling a set of possible outcomes[64]. In the spam detection case, for example, true positives are documents that are indeed spam (indicated by human-created gold labels) that our system correctly said were spam. False negatives are documents that are indeed spam but our system incorrectly labeled as non-spam. Confusion matrix is a summerized table of the number of correct and incorrect predictions yielded by a classifier (or a classification model) for binary classification tasks[48]. A confusion matrix of size n x n associated with a classifier shows the predicted and actual classification, where n is the number of different classes[47].

The confusion matrix shows the ways in which your classification model is confused when it makes predictions. It gives us insight not only into the errors being made by a classifier but more importantly the types of errors that are being made.

	Class 1 Predicted	Class 2 Predicted
Class 1 Actual	TP	FN
Class 2 Actual	FP	TN

Figure:2.18: Confusion Matrix Source: [83]

Where:

Class 1 : Positive

Class 2 : Negative

The confusion matrix is in the form of a square matrix where the column represents the actual values and the row depicts the predicted value of the model has shown in the figure above. A confusion matrix contains information about actual and predicted classifications done by a classification system. Performance of such systems is commonly evaluated using the data in the matrix.

The prediction accuracy and classification error can be obtained from this matrix as follows:

Recall or Sensitivity=TP/(TP+FN)=TP/AllPositives

Specificity=TN/(TN+FP)=TN/AllNegatives

Precision=TP/(TP+FP)=TP/PredictedPositives

Prevalence=TP+FN/Total=AllPositives/Total

Accuracy=(TP+TN)/Total

Error Rate=(FP+FN)/Total

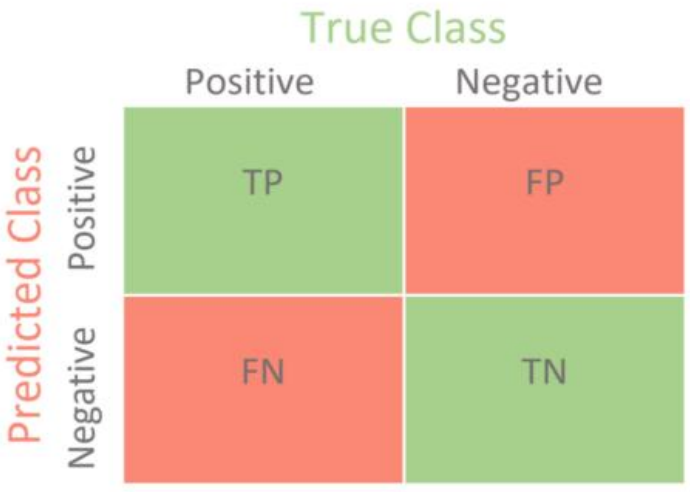

Figure 2.19: Confusion Matrix Predicted Class Source: [48]

Alternatively it can be represented as shown on the table diagram where:

TP means **True Positive**: The actual value was positive and the model predicted a positive value

FP means **False Positive**: Your prediction is positive, and it is false. (Also known as the Type 1 error)

FN means **False Negative**: Your prediction is negative, and result it is also false. (Also known as the Type 2 error)

TN means **True Negative**: The actual value was negative and the model predicted a negative value

Precision

Precison tells us how many of the correctly predicted case actually turned out to be positive. This would determine whether our model is reliable or not. Precision is a useful metric in case where False Positive is a higher concern than False Negative.

False Positives / Negatives = FP / (FP+TN)

2.3.4 SQL

Structural Query Language, or SQL, is primarily used for relational databases to design databases and perform database manipulations. A database's data can be created, dropped, inserted, deleted, or updated (modified)[57]. Structured Query Language (SQL) is a standardized programming language that is used to manage relational databases and perform various operations on the data in them. Initially created in the 1970s, SQL is regularly used not only by database administrators, but also by developers writing data integration scripts and data analysts looking to set up and run analytical queries. SQL became the de facto standard programming language for relational databases after they emerged in the late 1970s and early 1980s[49].

The Analytic SQL allows users to write a single line query with analytic functions rather than a complex self- join query . SQL statements start with a SQL command and end with a

semicolon (;). SQL commands are divided into several different types, including the following:

1. Data Definition Language (DDL) commands are also called data definition commands because they are used to define data tables.
2. Data Manipulation Language (DML) commands are used to manipulate data in existing tables by adding, changing or removing data. Unlike DDL commands that define how data is stored, DML commands operate in the tables defined with DDL commands.
3. Data Query Language consists of just one command, SELECT, used to get specific data from tables. This command is sometimes grouped with the DML commands.
4. Data Control Language commands are used to grant or revoke user access privileges.
5. Transaction Control Language commands are used to change the state of some data, for example, to COMMIT transaction changes or to ROLLBACK transaction changes.

2.3.5 PHP

The abbreviation PHP initially stood for Personal Homepage, but now it is a recursive acronym for Hypertext Preprocessor . PHP is an open-source server-side scripting language that many devs use for web development. It is also a general-purpose language that you can use to make lots of projects, including Graphical User Interfaces (GUIs). PHP is a server-side, cross-platform and HTML embedded scripting language. PHP is platform-independent. PHP is mostly used for making web servers. It runs on the browser and is also capable of running in the command line. So, if you don't feel like showing your code output in the browser, you can show it in the terminal[52].You don't have to have a particular OS to use it because it runs on every platform, whether it's Mac, Windows, or Linux. Facebook uses PHP to power its site while Wikipedia is built in PHP. PHP remains a relevant and widely-used language in web development. PHP is strong tool for create dynamic and interactive Web pages. PHP is

the widely-used, free, and efficient for rich applications/website development. This is open source technology, runs on Apache web server which in turn runs seamlessly on Windows, Linux, Solaris, and various other UNIX platforms. Suncore Microsystem's PHP development services offers unique, dynamic and highly functional web applications for across the world[54].

2.4 Review of Related Works

Numerous researchers have carried out investigations on emergency incidence and response system using Naïve Bayes learning techniques. Few among recent publications on this subject are discussed below:

The study carried out by Nico Nathanael Wilim and Raymond Sunardi Oetama[81],applied a sentiment analysis approach to examine public opinion on Twitter about Mata Najwa and Indonesia Lawyers Club (ILC) in 2018 and 2019. The study applied K-Nearest Neighbor, Naïve Bayes Classifier, and Decision Tree classification algorithm to validate the result. The analysis was performed using algorithms and operators in Rapidminer. Confusion matrix was used to check thenumber of positive and negative sentiments of ILC in 2018 and 2019 using the three algorithms (Bayesian, K-NN, Decision Tree). Findings revealed that Naïve Bayes was the best algorithm in 2018 while in 2019, K-NN was the best algorithm. This means that no algorithm is always at the top.The contribution of the study showed that public opinion on Twitter can be examined to figure out community sentiment on a TV talk show as well as to confirm the Award winner of TV Talkshow[81].

It was challenging for the Rapid Response Team and Rescue Agencies to group replies according to priorities due to the volume of SMS they received during catastrophes. The approach described in this paper divides SMS received by the organization into five categories: spam, invalid, alerts 1, 2, and 3. According to the current demands, this strategy enables a correct answer to be given to those who need it. This gives the opportunity to dismiss unnecessary communications and save wasting valuable time that could be required

to respond to them. In this study, a self-learning system called the Naive Bayes Algorithm was implemented together with natural language processing. Nevertheless, an extension of the approach is developed to account for the irregularity of the data to be processed.The test utilized a dataset containing pre-processed information (stop-words removed and normalized). In the work of Aris J. Ordoñez etal,[59]Dataset is composed of two (2) columns. The first column reflects the classification of the SMS where it is associated with, and the second column is the actual SMS. The expected system has the capability to classify SMS messages as Spam, Invalid, Alert 1 (does not need immediate attention), Alert 2 (requires attention within the day) and Alert 3 (requires immediate attention ASAP). The dataset contained 2,280 messages which are classified per category (578 of which are spam, 629 are invalid, 372 belongs to Alert 1 category, 295 to Alert 2 category, and 406 to Alert 3 category). This study demonstrated the expanded Naive Bayes Formula's capacity to categorize SMS texts into five separate groups using a database of previously categorized data that served as the trained classifier. According to particular categories, the study typically properly assigned test results with up to 89% accuracy. The number of items in the dataset that were used as the trained classifier by the Naive Bayes Algorithm is responsible for the 11% of the dataset that falls under the False-Negative outcome. The categorization approach was successfully implemented according to test findings, and as it is a self-learning process, it improves and becomes more accurate over time[59].

Based on network traffic patterns a research carried out by I. Marzuki etal, [68]the research created a novel method to identify Distributed Denial of Service (DDoS) assaults. The Gaussian Naive Bayes approach was used to statistically assess the data. Data was taken from the training and testing of network traffic in a core router at the Ahmad Dahlan University of Yogyakarta's Master of Information Technology Research Laboratory. In order to forecast the existence of DDoS assaults based on the average and standard deviation of network packets

in line with the Gaussian technique, the new way to detecting DDoS attacks was expected to have a relation with Intrusion Detection System (IDS). The Gaussian Naive Bayes approach was used to build a set of classes using the average and standard deviation as a reference. The results showed that the attack scenario was carried out in line with the topology, and that the victim, IP address 172.10.64.250, was the target of DDoS assaults by IP addresses 172.10.64.199, 172.10.85.151, 172.10.71.29, 172.10.71.49, 172.10.201.5, and 172.10.201.19. Attacks are carried out in three minutes, and packet capture software is used to record them. The categorization method was carried out using Matlab software. The research showed that the Gaussian Naive Bayes approach can precisely and reliably anticipate an assault[63].

The comparative examination of the performance and kind of modifications of the Naive Bayes classification was the main focus of the comparative analysis of Naive Bayesian techniques in the health-related classification task. Real-time prediction, multiclass prediction, text classification, and recommendation systems are the four main uses of Nave Bayes. The research used three Naive Bayes models—the Gaussian, Multinomial, and Bernoulli models—to address the shortcomings of these problems. These models fall under the same category of Bayesian-based categorization methodology. The goal of the study is to compare several versions of the Nave Bayes model to the original Nave Bayes model in order to determine which variation has the greatest classification accuracy.From the classification confusion matrix, the primary performance metric is assessed in terms of accuracy, precision, and recall. Two benchmark datasets were used to examine the three classification models' accuracy. These datasets, which were collected from the UCI machine learning library, include those for breast cancer and heart disease. Using the same dataset and settings as the other two algorithms, the simulation results demonstrate that the Multinomial Naive Bayes has greater mean accuracy[68].

To identify the DDoS attack, the study used an artificial neural network and a Naive Bayes classifier. Two components made up the proposed system. Create a database for later usage using the Initial Training Set Generation. Every incoming packets are passing through each stage of training set creation and build dynamic data set and designate the incoming packet as "OK packet" or "Attack". The second module is Real-Time Layered Intrusion Detection System, which classifies attacks as SYN flood, PING flood, and UDP flood by using K-means clustering and the Naive Bayes method for data mining[61].

The study developed a multiclass sentimental classifier which used skip-gram to embed support vector machine (SVM) algorithm with stochastic gradients descent (SGD). Findings from this research proved the efficacy of combined techniques for machine learning[20].

The study provided a framework for disaster response using sentiment analysis, to address the challenges of decision makers and emergency agency; for quick action and recovery process. The framework in this work is a good benchmark for the proposed system[18].

The study also designed an augmented agent model for disaster response in academic environment and educational setting, which could ensure smart community with coordinating mechanism for multi agent in order to detect and escalate any looming danger. Accuracy of a pre-trained sentiment analysis (SA) model was tested for the classification of tweets related to emergency response and early recovery assessment[15].

In the study, naïve Bayes algorithm was used as a method to detect DDoS attacks on the Software Defined Network network architecture. This research begins by designing a software architecture network defined networking using Mininet software as supporting software. The next stage is to configure the Mininet Software. The next step is testing the Software Defined Networking network architecture by carrying out a Distributed Denial of Service (DDoS) attack. The next stage is to classify the attack data class using the Naïve

Bayes Classifier Algorithm and an analysis of the classification results to obtain knowledge. The system can increase the detection rate and reduce the occurrence of false-positive alarms in the system to detect DDoS attacks using the Naïve Bayes classification. The system can detect DDoS attacks that occur on Software Define Network (SDN). In existing systems, false-positive rates decrease with increasing threshold and detection rates increase with an increasing threshold. The study concluded that the use of SDN networks is only in a simple topology with one type of DDoS attack. Prevention of DDoS in SDN using the naïve Bayes algorithm looks more accurate than DDoS prevention relying on the OpenFlow standard. But the naïve Bayes algorithm requires training data for the accuracy of packets received as attack packets or normal packets. For further research, it can use a more complex topology with many types of DDoS attacks and the application of the naïve Bayes algorithm uses more training data so that the detection accuracy is higher[90].

A detection of presentation on attacks against unsupervised remote biometric speaker verificationused a well-known challenge–response scheme. The novel approach used as convolutional phoneme classifier training, which ensures high phoneme recognition accuracy for significantly simplified network architectures, thus enabling efficient utterance verification on resource-limited hardware, such as mobile phones or embedded devices. The study considered Deep Convolutional Neural Networks operating on windows of speech Mel-Spectrograms as a means for phoneme recognition which showed that one can boost the performance of highly simplified neural architectures by modifying the principle underlying training set construction[7].

Gerardo Una etal,[30] carried out a research on an analysis of tweets by Indian netizens during the COVID-19 lockdown. The data included tweets collected on the dates between 23 March 2020 and 15 July 2020 and the text was labelled as fear, sad, anger, and joy. Data analysis was conducted by Bidirectional Encoder Representations from Transformers (BERT) model,

which is a new deep-learning model for text analysis and performance and was compared with three other models such as logistic regression (LR), support vector machines (SVM), and long-short term memory (LSTM). Accuracy for every sentiment was separately calculated. The result showed that each sentiment classification has accuracy ranging from 75.88–87.33% with a median accuracy of 79.34%, which is a relatively considerable value in text mining algorithms[30].

Three distinct government media outlets—Police China's Online, the Central Committee of the Communist Youth League, and China's Fire Control—were chosen for comparison in a study on government media in the context of public health emergencies. The emotion classification model of long-term memory network was built using the deep learning technique to analyze the emotion of users' comments on various government media. Comparative analysis of cross-platform government media was done using the number of contents, the number of retweets, the number of praises, and the number of comments as evaluating indicators. The study discovered that there are significant disparities between the emotional experiences of consumers of various government media types and platforms[11].

Findings revealed that in the standard normal distribution N (0,1), 1000 samples are randomly selected, assuming that the number of categories is C = 2, and the number of values of each attribute is q = 5. Based on the random sampling of traffic violation cases in a city from January 2019 to December 2019, a total of 115,482 samples were selected. Through numerical simulation, we found that, when the sample size is small, the accuracy rate of discrimination analysis of improved naive Bayesian classification algorithm fluctuates greatly, but with the increase of the sample size, the fluctuation gradually becomes smaller, and the overall trend tends to be stable, with the accuracy reaching more than 99%; when the sample attribute is less than 400, the accuracy is above 95%, which remains at a high level, and the trend is stable; when the sample attribute is between 400 and 600, the accuracy drops

precipitously; when the sample attribute is more than 600, the accuracy drops to about 50%, and the overall trend is stable; when the number of categories is small (< 24), the accuracy remains above 95%, and the trend is stable; when the number of categories is large (24–60), the accuracy fluctuates greatly, and the stability is poor; when the number of categories further increases (> 60), the accuracy rate quickly drops to zero[67].

T.R. Patil,developed and worked on a research titled Emergency Alert Management System (EAMS)[58], the system can broadcast warning notifications to multiple devices simultaneously to the targeted personnel, student and the entire academic community. The study addressed the need for improved emergency alert systems. The system was designed to function in the Federal College of Animal Health and Production Technology, Ibadan Nigeria in the event of emergencies such as fire outbreak, medical problems, accidents, cultism, and kidnapping amongst others. In this study, the Emergency Alert Management System (EAMS) broadcasts emergencies to several devices at the same time, and only registered response teams within the College are contacted when an emergency occurs. This is a web-based system designed from the scratch and developed with HTML (Hypertext markup language) for the UI framework, PHP (Hypertext Preprocessor) for the backend, XAMPP for the web server, phpMyadmin for the database, and Sublime Text for scripting the environment[58].

Michal Toman, et.al[60].,Investigatethe influence of word normalization on text classification using normalization of text as a pre-processing strategy, particularly in data cleaning and preparation before to the text classification process. Prior to normalization, which reduces words to their most basic forms, stop words are first deleted. The mobile SMS used as the operation's input is put through a procedure that rids it of extraneous words and vague terminology. Stop words are eliminated from the data, and it is then normalized. The cleaned data will be used as the input for the actual classification process, which is the following step. The outcome is the secret text message. The test utilized a dataset containing pre-processed

information (stop-words removed and normalized). The dataset is composed of two (2) columns. The first column reflects the classification of the SMS where it is associated with, and the second column is the actual SMS. The dataset contained 2,280 messages which are classified per category. 578 of which are spam, 629 are invalid, 372 belongs to Alert 1 category, 295 to Alert 2 category, and 406 to Alert 3 category[60].

The research explores ubiquitous technologies or solutions provided through intelligent information systems, and also depict their conceptual comparativeness through model which determines the preference for suitability, adequacy, efficiency, usability, rationality and functionality to support campus security and emergency notification. In this paper, use-cases model was proposed for functional exploration of web-agent system using Unified Modelling Language (UML). UML was used to describe the functional behaviour and operational scenarios of the selected systems which extend relationship in use-cases. The result shows that agent-based systems and/or web-based systems are often integrated as automaton mechanism in the design and implementation of campus security and emergency communication systems[74].

This study determined the interests and talents of children aged 10-18 years with data testing consisting of 100 records using the K-Nearest Neighbor and Naive Bayes algorithms with references from training data that is pre-existing data and obtained accurate algorithms. The algorithm used for analysis is the K-Nearest Neigbor and Naive Bayes algorithm. The training data used in this study were taken from 350 existing data and testing data were taken from the results of questionnaires given to children aged 10-18 as many as 148 children. Training data and data testing have the same number of attributes obtained from questioner psychology. All datasets will be selected to get the 17 relevant attributes. From 17 attributes, 8 attributes are used as data input to the classification. The analysis results are performance of accuracy results of both algorithms of classification. In knowing the accurate algorithm in

determining children's interests and talents, it can be seen from the accuracy of the data with the confusion matrix using the RapidMiner software for training data, testing data, and combined training and testing data.In knowing the algorithm that is accurate in determining the interests and talents of children, it can be seen from the accuracy of the data with the confusion matrix using RapidMiner software on training data, testing data, and a combination of training data & data testing. This study concluded that the K-Nearest Neighbor algorithm is better than Naive Bayes in terms of classification accuracy[89].

In 2021, a research was conducted at Matana University[91], on the use of machine learning based on the Naive Bayes Classifier to anticipate and categorize potential new students. Data mining, the Naive Bayes Classifier method, machine learning, marketing, and Python programming are all topics covered in the literature. The information utilized is that of potential students who have signed up for classes at Matana University. Python is a computer language that is used to create machine learning. The application's output has an accuracy of 0.73 (73%) and is highly useful to the marketing director in developing marketing strategy. The student data utilized for selection is that from the classes of 2018 and 2019.Data smoothing is accomplished by reducing data from various formats in each Excel sheet, eliminating data where duplicate data exists, and adding missing properties. removing errors from certain data. Data transformation is done so that the Naive Bayes Classifier algorithm can handle it. The Python programming language, 3.7.3, was used to create the software. Sklearn, Pandas, and Numpy make up the library (scikit-learn). The random function in the Python library is used to select the dataset for testing. The tests' findings indicate a tight connection between data reliability and process dependability, or the capacity to create accurate information. These findings can aid Matana University's marketing division in decision-making, particularly in regards to reaching out to new students in order to meet marketing objectives.The marketing department's ability to effectively and efficiently recruit

new students may be further improved with the help of the information provided by this application. Knowing these potential students' standing enables the marketing staff to instantly develop the best approach to reach them[91].

A study was carried out on the Naive Bayes Classifier's capacity to categorize the caliber of a journal known as Quartile[93]. The data was obtained on November 5, 2018, from the Journal Rangkings in the Scimago Journal and Country Rank. The dataset only utilizes instances with journal types and has computer science as its topic area. The dataset has 10 characteristics and 1491 occurrences. The accuracy, error rate, precision, and recall values of the data were examined using the confusion matrix. The Nave Bayes Classifier produces the greatest accuracy when used in Cross Validation with k-fold=5, which is 71.60%. The data are divided into different labels, including Q1, Q2, Q3, Q4 and NQ, based on the findings of the discussion in this study.H index, SJR, Total Docs. (2017), Total Docs. (3years), Total Refs, Total Cites, Citable Docs. (3years), Cites / Doc. (2years), and Ref. / Doc. are the variables employed in this study. The grouping of quality journals may make it simpler for individuals to select them. The researchers in this study also came to the conclusion that the Naive Bayes Classifier method, albeit having a less than ideal accuracy value, was able to categorize the quality of journals. Journals' quartile categorization using the Naive Bayes Classifier method needs to be improved with additional algorithms for greater accuracy[93].

The comparative investigation of the performance and kind of modifications of the Naive Bayes classification was the main focus of the study. Real-time prediction, multiclass prediction, text classification, and recommendation systems are the four main uses of Nave Bayes. The research used three Naive Bayes models—the Gaussian, Multinomial, and Bernoulli models—to address the shortcomings of these problems. These models fall under the same category of Bayesian-based categorization methodology. The Gaussian model assumes that a dataset's characteristics have a normal distribution and is used in basic

classification. Nevertheless, the multinomial model is employed for discrete counts, such as calculating the frequency with which the outcome of x is seen across a n number of interval.The Bernoulli model largely concentrates on looking for binary vector properties. The goal is to adapt and execute the original Naive Bayes model with several other models already in existence, such as the Multinomial Naive Bayes, the Gaussian, and the Bernoulli Naive Bayes. The study's findings will concentrate on the variations, capacities, and effectiveness of the probabilistic classifier of the Naive Bayes algorithms[95].

The study presented the results of the application of the Naïve Bayes, a widely used Machine Learning method, in creating the prediction model. The proposed model is based on nine water quality parameters: temperature, pH value, electrical conductivity, oxygen saturation, biological oxygen demand, suspended solids, nitrogen oxides, orthophosphates, and ammonium. It is created in Netica software and tested and verified using data covering the period 2013–2019 from five locations in Vojvodina Province, Serbia. Forty-eight samples were used to train the modelThe Bayesian network is constructed of 10 nodes: one parent node (class node) named ‘Quality’ and nine child nodes that represent nine water quality parameters (Figure 3). The parameters are defined within the SWQI methodology To train the network, parameters for 48 samples from the period 2015–2019 were selected, classified into five classes. The classifier correctly predicted 64 out of 68 cases. Thirteen of these 64 cases were selected in a different class but actually it is not wrong because it is the threshold value of the previous or the next class or very close to it. This is the case for 10 samples. Further, three samples are allocated to the real one and contiguous class by almost 50 percent of chances for both. In this case, index values are also almost on the border of the classes (samples No. 20, 31, and 46). Each class assessed as ‘Excellent’ is misclassified as the class below (‘Very good’). The reason lies in a small number of learning cases for ‘excellent’ quality class. However, just one out of four ‘Excellent’ quality samples is actually

misclassified, the rest are very close to the threshold of the predicted one. NB classifier can thus be recommended as a trustful tool in the transition from traditional to digital water management [97].

The author's quantitative method was employed in the study to describe the precision of the news text categorization machine learning. To determine the success of the strategy utilized, the study compared the accuracy values acquired using the Naive Bayes method with those obtained using other methods. Although the resultant accuracy number has not reached its maximum, it is still possible to reorganize and reevaluate the model to create a more accurate one. In this instance, the author attempted to boost the accuracy value generated by altering the established threshold value in order to make this machine capable of predicting news that contains sarcasm.The accuracy value dropped to 61% but the precision value rose to 77%, and the error value in the prediction of false positive headlines also dramatically increased. Just 89 mistakes were created in the prediction of sarcasm when the threshold value was lowered to 0.3. The ROC Curve test revealed that this machine learning model could still be enhanced by experimenting with additional text preprocessing techniques, such as bigrams, tidytext, and lemmatization techniques, to help the computer become more adept at predicting the resulting vectors and raise the value of precision and accuracy attained[98].

The categorization of text materials, including news and academic publications, performed quite well in a study on text documents and academic documents using the NBC approach to categorize the texts. Compared to academic publications, which had an accuracy rating of 82%, news documents had a better accuracy score of 91%. Without filters, the usage of unique terms in the collection of training papers could not produce the best results. The use of document frequency was attempted using a word filter. When compared to other filters, it was discovered that a minimum filter of words that appeared in four or five documents produced the best accuracy results.When there are more papers, it is impossible to establish

the minimum value limit to be utilized as a guide. It was discovered that using a large number of words that included all of the unique words in the collection of documents did not produce the best classification results, so researchers suggest that Hamzah suggested looking for a better technique for selecting word features to be used as a basis for classification[99].

Natural Language Processing (NLP) is a subfield of artificial intelligence research that serves as the foundation for sentiment analysis, as explained in the paper on the Implementation of Naive Bayes Algorithm on Sentiment Analysis Application. Three methods—Naive Bayes, Weighted Instance, and Zero-R—have been selected to see which produces the greatest accuracy results. With the value of K = 10, Cross-Validation is used five times in the tests. With an accuracy value of 99.62% in the training data and 94% in the testing data, and an average classification failure of 0.13%, the testing analysis findings demonstrated that Naive Bayes had a steady accuracy after being tested.Applications for sentiment-level sentence analysis are constructed using the word acquisition outcomes as a corpus. The PHP programming language and literature library were used to build the Naive Bayes algorithm application. The analysis process leads to the application implementation in the waterfall approach of application development. The algorithm generates an accuracy value of 86.66% after scrutinizing the correctness of 30 comments that it has categorised. Nevertheless, Weka's machine learning algorithm was used to retest the accuracy of comments that had been labeled as applications, and the accuracy result was 93.33%. The Naive Bayes method uses the appearance of words to construct a sentiment categorization, which accounts for the variation in accuracy.Based on the research, it can be said that the pre-processing of text is the first step in doing sentiment categorization analysis at the sentence level. The two types of data that must be prepared at the time of preparation are training data and testing data. Up to 457 sentences from which the sentiment class 100 was determined were used as the training material in this study.

Another study has looked into how individuals use mobile phones to communicate during disasters. From the past to the present, three different time periods may be used to rank these communication technologies. The use of social media tools, which may be classified as Disasters 2.0 and that are produced with the effect of Web 2.0, contrasts with the use of phone calls and text messages, which we can refer to as Disasters 1.0. Finally, it may be categorized as the current development of Disasters 3.0, which can be described as the utilization of sharing economy technologies. The study's introduction of the idea known as Disasters 3.0—a wide notion that also encompasses its predecessor, Disasters 2.0—came about as a result of research into how communication behavior is evolving in the modern world.The study's goal is to look at online and mobile methods that facilitate sending relief to the affected area during natural disasters. Moreover, there are actual instances of how social media technologies are used in the sharing economy as well as as communication tools. The study's scope included an analysis and categorization of the tweets sent on "Twitter" from Turkey during the week that followed the 2011 Van earthquake. It also looked at instances when well-known sharing economy businesses have helped during natural disasters. Thus, in the event of a disaster, the use of communication tools was revealed, and predictions were made about how they could be interpreted by the authorities in case of a possible disaster[34].

In the year 2020, a Landscape of XML Data from an Analytics Perspective was studied. The study compared the processing times of analytics queries written in Analytic SQL and XQuery. It shown that when running analytical queries, Analytic SQL outperformed XQuery. The experiment, which used XML-formatted health care data from openEHR, demonstrated that XML data's performance is not necessarily subpar. Nonetheless, BaseX outperforms eXist-DB in the present dataset[38].

The study of python script which demonstrates how to create a confusion matrix on a predicted model, confusion matrix module was imported from sklearn library which

generated the confusion matrix, the accuracy score was 0.7. The number of correct and incorrect predictions are summarized with count values and broken down byeach class[46].

The study developed a multiclass sentimental classifier which used skip-gram to embed support vector machine (SVM) algorithm with stochastic gradients descent (SGD). Findings from this research proved the efficacy of combined techniques for machine learning. An adapted model from machine learning repository was trained specifically to analyse and examine the intensity of major earthquakes that struck Albania by text polarity on twitter [14].

The study provided a framework for disaster response using sentiment analysis, to address the challenges of decision makers and emergency agency; for quick action and recovery process. The framework in this work is a good benchmark for the proposed system[13].

The study designed an augmented agent model for disaster response in academic environment and educational setting, which could ensure smart community with coordinating mechanism for multi agent in order to detect and escalate any looming danger.Accuracy of a pre-trained sentiment analysis (SA) model was tested for the classification of tweets related to emergency response and early recovery assessment[15].

The study of Kubicki e tal (2021)on detection ofpresentation onattacks against unsupervised remote biometric speaker verificationusing a well-known challenge–response scheme. The novel approach used as convolutional phoneme classifier training, which ensures high phoneme recognition accuracy for significantly simplified network architectures, thus enabling efficient utterance verification on resource-limited hardware, such as mobile phones or embedded devices. The study consider Deep Convolutional Neural Networks operating on windows of speech Mel-Spectrograms as a means for phoneme recognition which showed that one can boost the performance of highly simplified neural architectures by modifying the principle underlying training set construction[7].

The study of Chintalapudi (2021) analysed tweets by Indian netizens during the COVID-19 lockdown. The data included tweets collected on the dates between 23 March 2020 and 15 July 2020 and the text was labelled as fear, sad, anger, and joy. Data analysis was conducted by Bidirectional Encoder Representations from Transformers (BERT) model, which is a new deep-learning model for text analysis and performance and was compared with three other models such as logistic regression (LR), support vector machines (SVM), and long-short term memory (LSTM). Accuracy for every sentiment was separately calculated. The result showed that each sentiment classification has accuracy ranging from 75.88–87.33% with a median accuracy of 79.34%, which is a relatively considerable value in text mining algorithms[30].

In the context of public health emergencies, a comparative study on government media chose three distinct forms of official media, including China's Police Online, the Central Committee of the Communist Youth League, and China's Fire Control. The emotion classification model of long-term memory network was built using the deep learning technique to analyze the emotion of users' comments on various government media. Comparative analysis of cross-platform government media was done using the number of contents, the number of retweets, the number of praises, and the number of comments as evaluating indicators. The study discovered that there are significant disparities between the emotional experiences of consumers of various government media types and platforms[11].

The study identified and exploredtheglobalemotions expressed during the earlier months of the pandemic COVID 19 by utilizing Deep Learning and Natural language Processing (NLP). Over 2 million tweets during February–June 2020 were collected and analyzed using an advanced deep learning technique of Transfer Learning and Robustly Optimized BERT Pretraining Approach (RoBERTa). A Reddit-based standard Emotion Dataset by Crowdflower was utilized for transfer learning. Using RoBERTa and the collated Twitter dataset, a multi-class emotion classifier system was formed and a tweet classification

accuracy of 80.33% and an average MCC score of 0.78 was achieved, improving the existing AI-based emotion classification methods[20].

2.5 Summary of Gaps in Literature Reviewed

This gap is presented based on the review of related studies above. More recently, recurrent neural networks, Gussian Naïve Bayes specialized for sequential modelling have been used more frequently in text classifcation. RNNs with gating mechanisms like long short-term memory (LSTM) and bidirectional long short-term memory (BiLSTM) have been widely used, as they can capture longterm dependencies. Existing classifers and event but detection pipelines do not provide the capability to answer where and when emergency events occur. Fine-grained location and time information plays an important role in emergency response activities, that is, to coordinate territorial rescue forces according to the degree of urgency. Although location and time extraction techniques can estimate where and when a post came from based on geotags and the post content.

Although there have been several studies on the subject, emergency response seldom employs machine learning based on the natural language processing (NLP) and Bayesian belief learning (BBL). Also, some researchers have focused on emergency incidence using deep learning techniques or machine learning techniques but this study use hybridized mining technique. Bayesian learning is the simplest and fastest classification algorithm for a large chunk of data. In various applications such as spam filtering, text classification, sentiment analysis, and recommendation systems, Bayesian classifier is used successfully in creating prompt response for emergency incidence. It uses the Bayesian Belief Learning being an enhanced variation of Bayes probability theorem for unknown class prediction.

Also some researchers used social media platforms like twitter, facebook, instagram, Snapchat heat maps as a reliable source of precise emergency event location detection to

gather information and emergency response. The volume of data is increasing with focus on the use of Natural Language Processing. This study leveraged on big data technologies for application programming interface (API) of Facebook through Python Request library which were used for streaming the tweets or posts and comments of users on social media.

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Chapter Three

Materials and Methods

3.1 Methodology

In this study, developmental and experimental design was adopted by incorporating web scrapper being integrated as application programming interface (API) for streaming data from social media; with further grouping of weighted phrases through supervisory trained BBL model with NLP for quantitative reasoning and possibility approximation analysis. Bayesian Belief Learning was adopted as quantitative learning technique for opinion mining; simply called incidence classifier that filters public opinions, being exchanged on emergency related issues or sentiments via social media for credible reports that leads to responsive actions.

Developmental and experimental process of the classification model involves real time captured social media data, which had been pre-processed as localized sentiment dataset. Multi-class predictors of hybridized mining technique were used to define the classifier's target or input/output variables, as well as the cause and effect relationship between them.

3.1.1 Justification of Methodology

The replica of improved system provided in this study was developed in order to carry out functional experiment, by measuring and converting the text data obtained from web repository via social media. The target is to subject incidence likelihood to production of conditional probabilities in every sentiment data or Facebook post with assumption of independence among the predictors, because Bayesian learning technique is quite effective for text classification with big data. Rapid prototyping and exploratory approach was adopted as development process model because it is iterative in nature; while development product model was also made available for structural and abstract representation through architecture, algorithm, data flow diagram and mathematical formulation for the improved system.

3.2 Analysis of the Existing System

The existing system which has been benchmarked in this study is a framework for analyzing disaster related sentiments. The focus of existing system yielded information technology based model as solution framework to address disaster management with decision problem.

Extraction of tweets to generate training data from famous social media called twitter was made possible with Python library of function called Tweepy. Data cleaning was considered to allow elimination of special characters, hyperlink and symbols. Text data emanating from captured tweets were converted to small letters. The tweets being captured and compiled as text data were further tokenized as the segmented text into some predefined phrases.

Regular expression in natural language processing (NLP) was utilized to check the most occurring keywords. Frequently used phrases are removed using terminal words, major words are extracted from distribution count of given words. To discover the sentiments' subjectivity and polarity, TextBlob function for natural language processing in Python library was employed while positive, neutral and negative were the segments of tweets.

Geographical grouping for text manipulation was used to determine the location of twitter user where the escalation by tweet comes from; the geo-location of sentiment was based on the location on user's profile location with interactive data visualization for actionable reports. Experimental development of application to use Twitter API for operational testing and review was not embraced for the proposed solution as it is to model/ method of other systems. Meanwhile, implementation is quite germane to the integration of entire components of the designed architecture as shown in figure 3.1; to make a reproducible finding that is beneficial to decision makers and government agencies in preventing loss of lives and infrastructure.

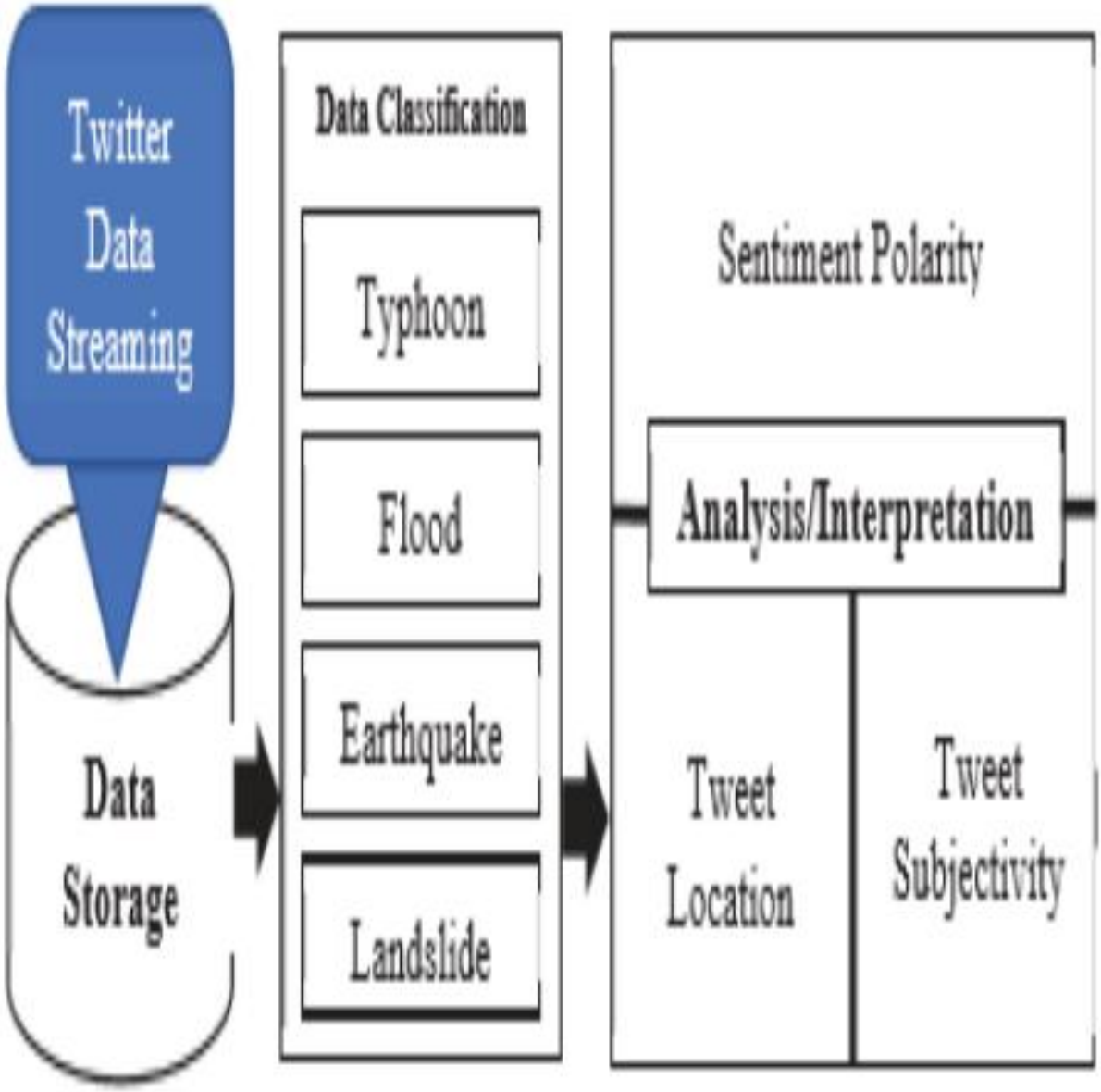
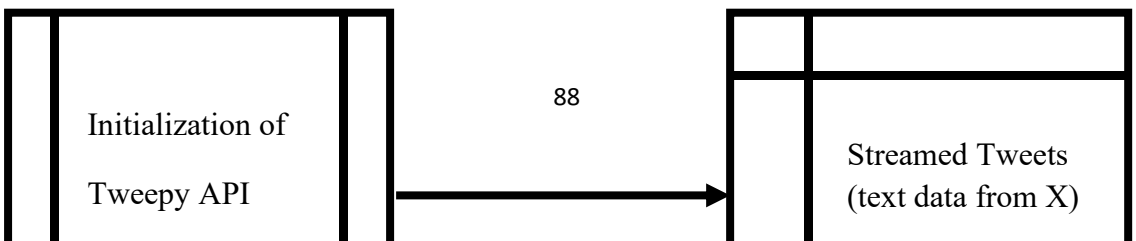


Figure 3.1 Architecture of the Existing System **Source:** [1]



Parsing the Data
fromTweeter (X)

Loading Dataset

Generating visual component for the classifier

Figure 3.2 Data Flow Diagram of the Existing System **Source:** [2]

3.2.1 Description of Existing System's Functionality

From figures 3.1 and 3.2, the designed framework of the existing system depicts how Tweepy library of Python programming language was used as twitter API to stream text data from users' tweets as string objects; and parsing them to backend database where further operations will take place. Some keywords were chosen to classify tweet data into four major disastrous incidences in Philippines ranging from Typhoon, Landslide, Flood and Earthquake.

Thereafter, captured tweets were saved as text data for sentiment analysis according to disaster category together with relevance factor; interpretation and execution from NLP library so as to determine the polarity and subjectivity of tweets' sentiments. In conclusion, interactive data visualization helps in conveying the results of data analysis using chart to simplify decision making effort for Netizen tweet sentiments through Twitter platform.

Effectiveness of training and validation of the model lies majorly on technical knowledge about classification problem with provision of target output, which was in doubt.

3.2.2 Challenges and Drawback of the Existing System

Most of the identified shortcomings of the models, techniques, methods and development framework being provided in the existing systems are highlighted below:

i. Major focus on natural disasters only, which are not global incidences.

ii. Non implementation of solution framework for experimental testing.

iii. Uncertainty of geo-tagging; to determine the location of tweet by users' profiles.

iv. Lack of multi-class precision for text classification with higher type-matching rate.

v. Non exploration of data mining technique for optimizing the model performance.

3.3 Analysis of the Improved System

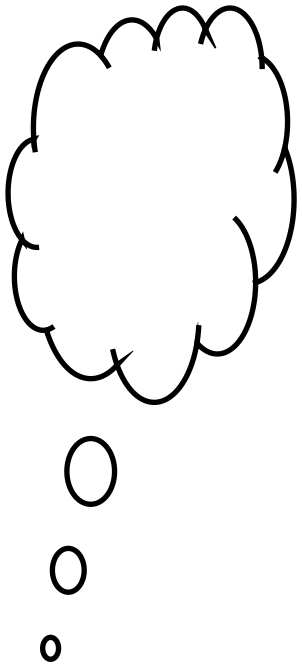
The improved system in this study is an enhancement to framework for sentiment analysis by the duo of Baro & Palaoag (2020) and Contreras et al. (2022); thereby inculcates hybridization of NLP and Bayesian belief learning (BBL) technique, technically regarded as Bayesian classifier with focus on data mining model, machine learning algorithm and natural language processing for the classification of emergency incidence and sentimental response.

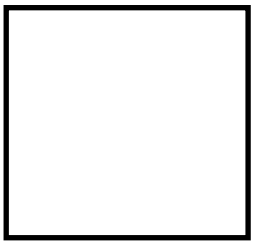
Bayesian technique makes it possible to optimize the classification model with experimental analysis by applying Bayesian belief learning on selected features of data sample from social media in order to compute possibility tendency of each emergency incidence category. Therefore, efficiency of the classifier and sentiment precision in dealing with large dataset for text classification was leveraged to adequately train the model for identifying relationships.

Social media data comprising of Facebook posts, comments, reactions, users' profiles, message time and geographical mappings were extracted through Facebook API for web scrapping, to generate training data with Facebook Graph function called 'Requests'. Thereafter, pre-processing of data sample was done to eliminate unwanted characters, hyperlink and symbols. Text data being streamed or scrapped from Facebook repository were later transformed into lower case letters. The Facebook posts and comments being captured and compiled as text data were later used as the segmented text into some predefined phrases.

Identifying the sentiments' subjectivity within any trending themes, topics and phrases; as well as intensity of concerned posts and comments during type-matching of incidence into appropriate emergency cluster as shown in figure 3.3. TextBlob function for natural language processing in Python library was employed while leveraging on big data technology to determine if sentiment's rating is positive, neutral and negative.

Facebook





Violence

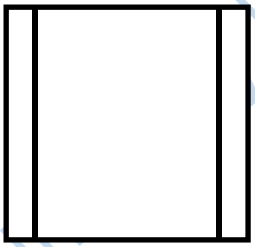
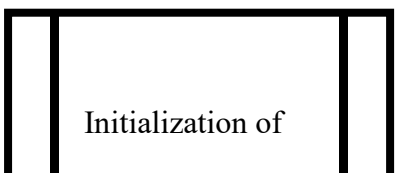


Figure 3.3 Architecture of the Improved System **Source:** Researcher, 2024



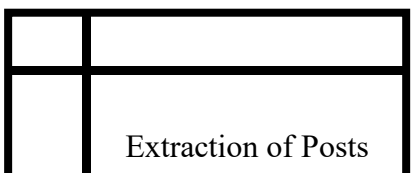


Figure 3.4 Data Flow Diagram of the Improved System **Source:** Researcher, 2024

3.3.1 Description of Improved System's Functionality

From figures 3.3 and 3.4, the enhanced framework of the improved system depicts how Requests library of Python programming language was used as Facebook Graph API to stream text data from users' posts and comments as string objects; and parsing them to backend database where further operations will take place. Some keywords were chosen to classify emergency incidence from pre-processed sentimental data into some dangerous incidences ranging from vandalism, robbery, cultism clashes, abduction, violence and others.

Thereafter, captured posts and comments were saved as text data for sentiment analysis according to emergency category together with relevance factor; interpretation and execution from NLP library so as to determine the intensity and subjectivity of Phrases. Conclusively, Bayesian belief mining optimizes the sentimental and interpretation function for improving the classifier's precision. Its algorithm was designed to automate the model for effective decision making through experiment using pre-processed data from social media. Efficiency of any model is being determined by its functional algorithm, as well as training and validation of such model with adequacy and dynamism of appropriate dataset.

3.3.2 Pre-processing and Feature Selection

In all the cases of emergency data, the data samples are multivariate in nature with more characteristics, but the process of data cleaning also involved dimensionality reduction which limited the attributes of datasets to five (5) essential features, while removal of outliers reduced data instances from six hundred and thirty one (631) to four hundred and fifty (450). Since the classifier works mainly with nominal data, then automated mechanism for the pre-processing phase converted the text data extracted from Facebook to numeric sequence of nominal data to suit classification purpose for sentimental response.

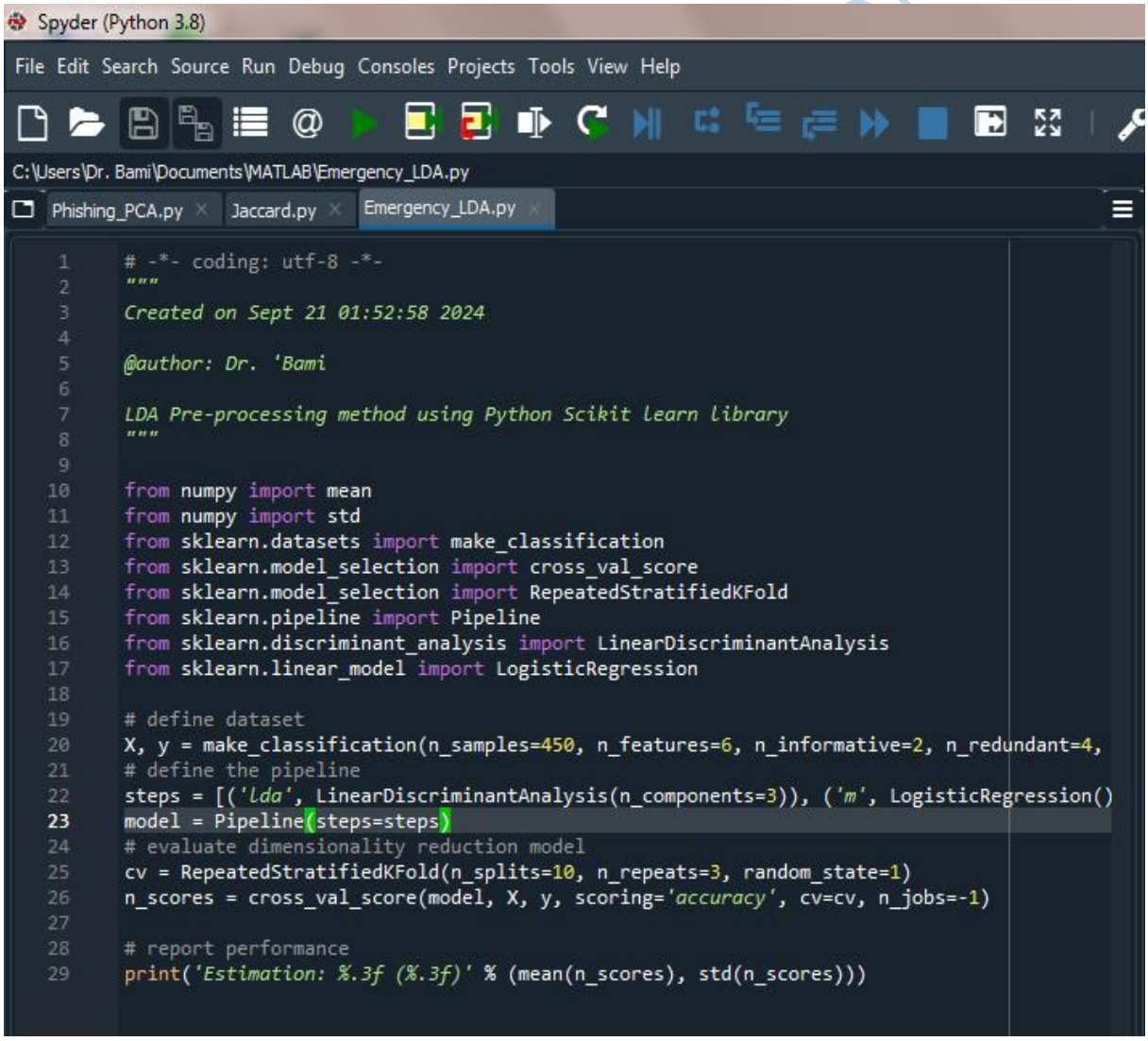


Figure 3.5 Python Computational Stage for Data Pre-processing with LDA

Figure 3.5 shows the computational stage for data pre-processing in python, linear discriminant analysis (LDA) technique was used to handle dimensionality reduction. Standard libraries for machine learning in python scikit library were imported to inherit necessary function for intelligent computational task. Here are the steps involved in python computational stage for data pre-processing with LDA;

i. **Install Libraries**: Essential libraries were installed such as scikit-learn which is required for machine learning tasks.
ii. **Import Libraries**: This step ensures that all the necessary functions for data processing, LDA, and classification were imported.
iii. **Load Dataset**: Data were loaded from a CSV file.
iv. **Handle Missing Values**: Data cleaning were done.
v. **Separate Features and Target**: Features (X) are the inputs, and the target (Y) is what we aim to predict.
vi. **Train-Test Split**: Splitting of data in other to ensures that we can test the model on unseen data.
vii. **Feature Scaling**: Normalization ensures that all features contribute equally to the model.
viii. **Apply LDA**: LDA reduces the number of dimensions while maintaining the separability of classes.
ix. **Train Naive Bayes Classifier**: Naive Bayes (BBL) was used to classify the LDA-transformed data.
x. **Make Predictions**: After training, prediction of the labels for the test data were done.
xi. **Evaluate the Model**: We measure how well the classifier performed using precision and confusion matrix.

xii. **Visualize**: Plotting the LDA-reduced data gives us an intuitive understanding of the separation between classes.

Post /thread, comment /reaction and message location were the majorly selected features from data attributes, used as keywords or subjectivity themes in analyzing emergency sentiments by grouping values of data instances using linear discriminant analysis (LDA).

Data cleaning was applied to discard unwanted characters like white space, harsh (#) symbol, at (@) symbol, and (&) symbol, uniform resources locator link and numerous 'emojis' for reaction; as well as removal of irrelevant attributes through strip tags function in PHP with SQL injection. Four hundred and fifty (450) instances of the preprocessed data were provided as input into the classifier for estimating certainty through computational intelligence.

Resulting output and validation obtained from tested samples were compared with the target data. The classification model and resulting system was tested to ensure that its functional performance is efficient by obtaining the number of samples that were classified correctly and incorrectly when compared with the target data. Error rate is the number of all incorrect classifications divided by the total number of dataset or data instances.

3.3.3 Benefits and Enhancement of the Improved System

Major improvements of the model provided in improved system are highlighted below:

i. Adaptation of sentimental framework to disastrous incidences, which commonly and generally lead to emergency across the globe especially in Nigeria communities.

ii. Implementation and experimental performance of solution framework for quick evaluation.

iii. Multi-class precision of the model with large real time data and higher type-matching rate.

iv. Exploration of natural language processing (NLP) based mining or hybridized learning technique to optimize the system performance.

3.4 Design of the Improved System

The sentimental system for emergency classification was subjected to empirical experiment and functional testing through internet enabled device. Web based and scientific programming languages like PHP MySQL, XML and Python were chosen as development tools with embedded Facebook Graph application programming interface (API) for intelligent classification and/or data mining. It runs on typical computer equipment and web enabled device, especially with cross mobility that meets the required functional specifications.

The operational flow of data during input and output processes is executed by the classifier (classification and sentimental model) being the operational mechanism. System prototype was created to experiment with the classification model and to measure its experimental performance, by approximating the data probabilities of chosen parameters. Sentimental analysis worked on statement structure and non formal lexes are discarded.

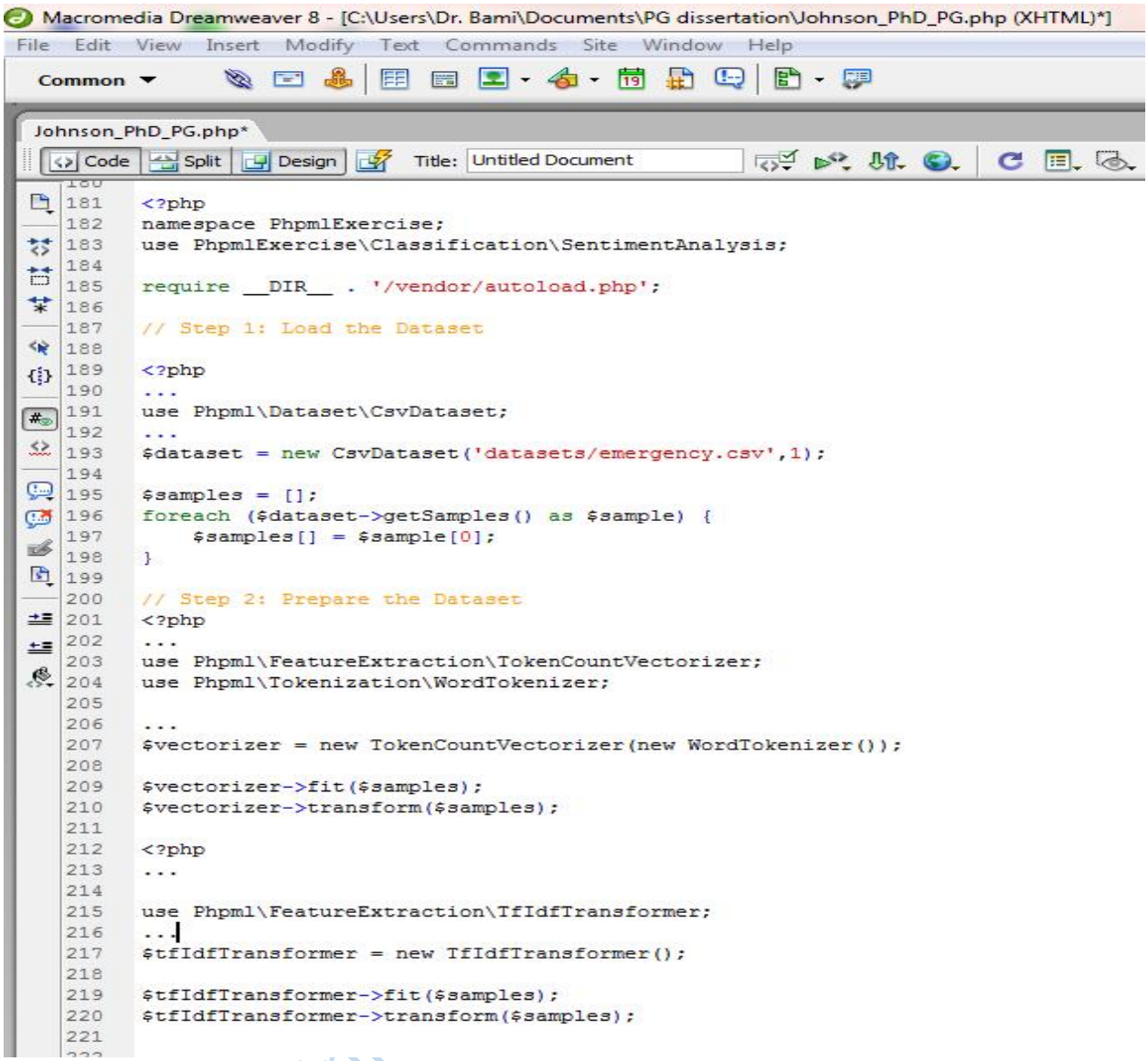


Figure 3.6a PHP-ML Experimental Process for Multi-Class Classification

Source: Researcher, 2024

```
// Step 3: Generate the training/testing Dataset
<?php
use Phpml\Dataset\ArrayDataset;
$dataset = new ArrayDataset($samples, $dataset->getTargets());
<?php
use Phpml\CrossValidation\StratifiedRandomSplit;
...
$randomSplit = new StratifiedRandomSplit($dataset, 0.1);
$trainingSamples = $randomSplit->getTrainSamples();
$trainingLabels     = $randomSplit->getTrainLabels();
$testSamples = $randomSplit->getTestSamples();
$testLabels      = $randomSplit->getTestLabels();

// Step 4: Train the classifier
<?php
namespace PhpmlExercise\Classification;
use Phpml\Classification\NaiveBayes;

class SentimentAnalysis
{
    protected $classifier;
    public function __construct()
    {
        $this->classifier = new NaiveBayes();
    }
    public function train($samples, $labels)
    {
        $this->classifier->train($samples, $labels);
    }
}
// Step 5: Test the classifier accuracy
<?php
...
class SentimentAnalysis
{
...
    public function predict($samples)
    {
        return $this->classifier->predict($samples);
    }
}
```

Figure 3.6b PHP-ML Experimental Process for Multi-Class Classification

Source: Researcher, 2024

Figure 3.6a and 3.6b shows the PHP-ML experimental processes involved for multi-class classification. Here are the process step by step

1. Loading of the Dataset

Dataset are loaded from CSV file with features and labels. Code Snippet as shown in figure 3.6a

2. Preparation of the Dataset

TokenCountVectorizer and WordTokenizer are tools from the Phpml library which helps in transforming textual data into numerical feature vectors. This transformation is crucial for applying machine learning models on text data, as they operate on numbers rather than raw text. The vectorized output are used for classification. Code Snippet as shown in figure 3.6a

3. Generate the Training/Testing in PHP-ML

During the generation of training/testing Php-ml library were used to provide utilities for generating training and testing of the datasets. Code Snippet as shown in Figure 3.6b

4. Train the Classifier

Training of the NLP-BBL classifier was done as shown in figure 3.6b

5. Testing the Classifier Accuracy

The BBL classifier accuracy was done as shown in figure 3.6b.

Regular expression in natural language processing (NLP) was utilized to check the most occurring keywords. Frequently used phrases are removed using terminal words, major words are extracted from distribution count of given words. Bayesian inclined classifier computes the posterior possibility of emergency incidence by approximating the possibility distribution of prior selector in observation parameters via Facebook posts and comments, and the highest likelihood or tendency is the output class (classified category of emergency).

Bayesian belief learning (BBL) and its probability algorithm is a supervised technique in machine learning, which requires training prior to performing the classification task. Hence, large volume of training set and/or validation data was provided with a number of factual data as domain knowledge for subjective hypothesis and the predictor class, to determine

whether the conclusion it has reached is correct or incorrect with the aid of the labelling of the data.

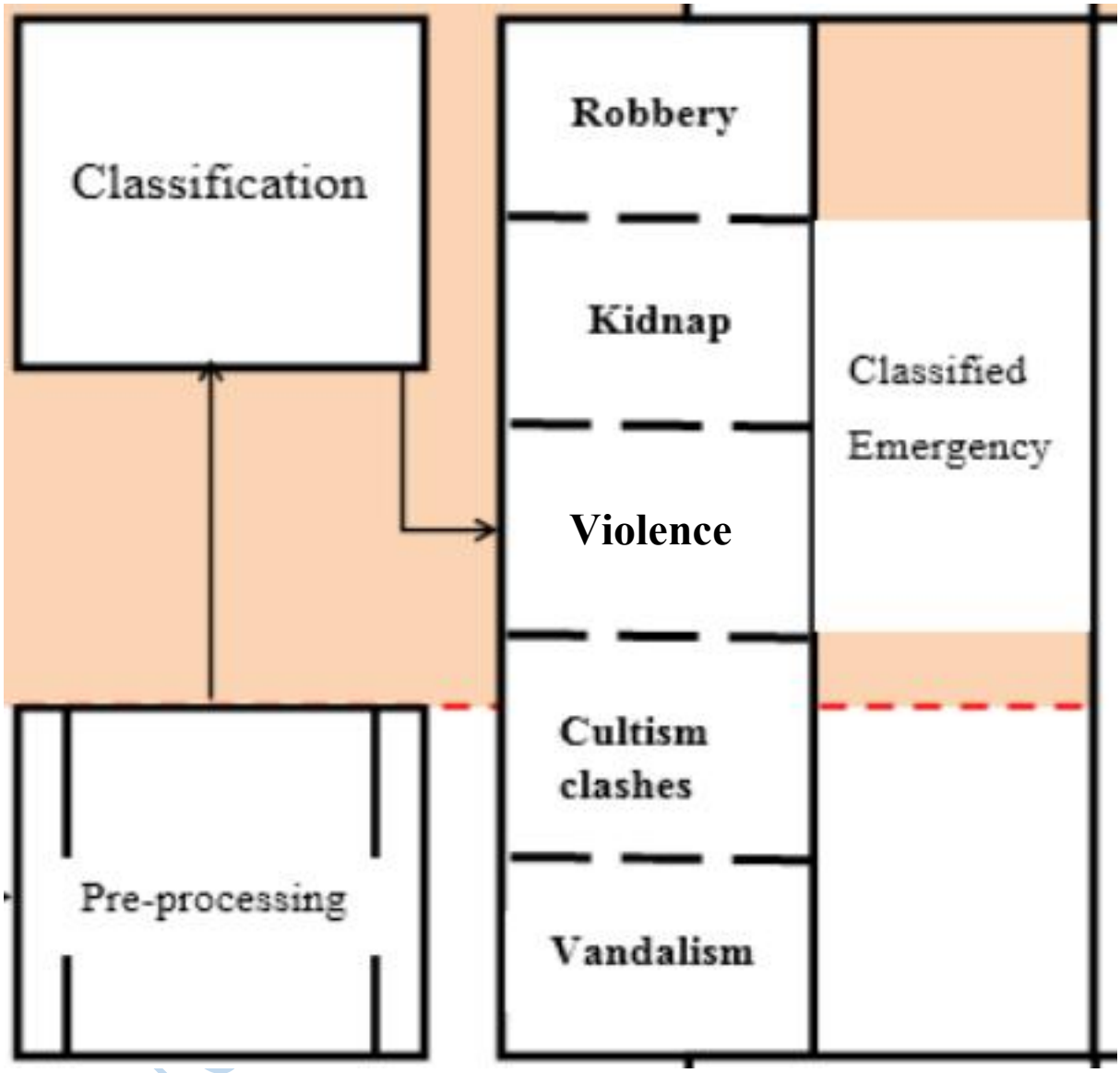


Figure 3.7 Improved (NLP-BBL) Sentimental Model for Emergency Classification

Source: Researcher, 2024

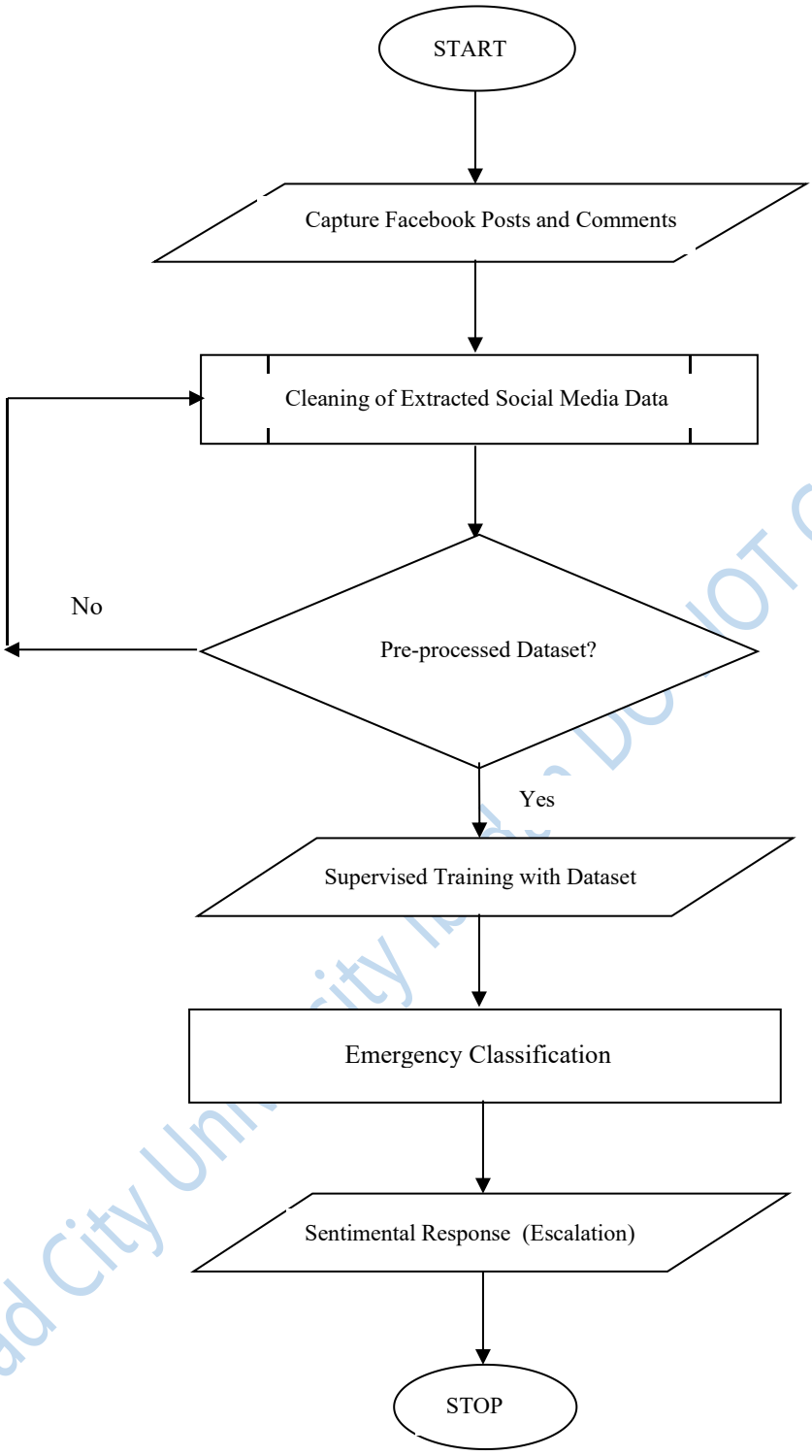


Figure 3.8 Flowchart of the Improved System **Source:** Researcher, 2024

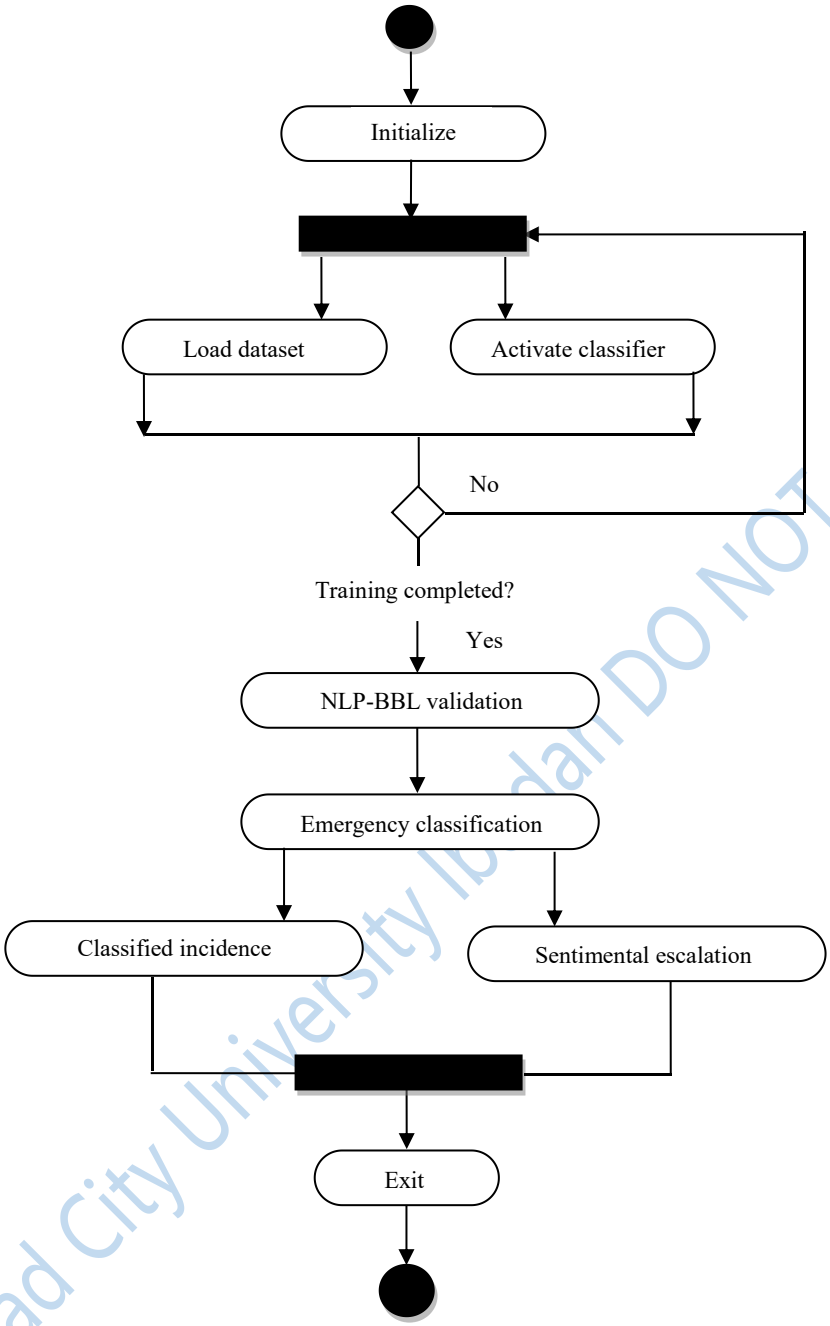


Figure 3.9 Activity Diagram of the Improved System (NLP-BBL) **Source:** Researcher, 2024

Figure 3.7 is an improved NLP-BBL based sentimental model, figure 3.8 is a system flowchart while figure 3.9 shows the activity diagram of the improved system. Activity diagram graphical representation of workflow of iterative action, which support concurrency and procedures. Unified modelling language (UML) encompasses the required tools for software and/or system design with object orientation. Activity diagrams are used for creating abstract representation of organizational and computational workflows, together with data flows that concern all relevant procedural activities of improved system.

Beyond visualization of the dynamic nature of a system, activity diagram also help to construct system replica based on forward and reverse engineering approach. Except that it does not reflect the interaction between two or more activities. Though, activity diagram and flowchart seem identical in appearance, yet they are different in purposeful usage.

3.4.1 Adapted Mathematical Representation of (NLP-BBL) Classification Model

For identifying a disaster and emergency escalation in multi-class incidence, thus;

$$P(E) = (E_A \ldots E_N) \quad (3.1)$$

is the known tendency (prior probability) of predefined categories for incidence,

where E_A refers to the first incidence possibility (i.e Robbery), E_B refers to second incidence possibility (i.e Kidnap), E_C refers to third incidence possibility (i.e Violence), E_D refers to fourth incidence possibility (i.e Cultism Clashes) and E_N refers to last incidence possibility (i.e Vandalism).

$$P(X) = (X_i \ldots X_n) \quad (3.2)$$

is the known tendency (prior probability) of relevant factors as observable selectors,

where X_1 refers to the first relevant factor or data point (i.e user id / profile), X_2 refers to second relevant factor or data point (i.e post / thread), X_3 refers to relevant factor or data point (i.e comment / reaction), X_4 refers to fourth relevant factor or data point (i.e message location) and X_n refers to last relevant factor or data point (time stamp).

$P(E|X)$ is the tendency of emergency incidence *(as target hypothesis)* given relevant factor or data point *(as observable selectors)* based on posterior probability.

$P(X|E)$ is the tendency of relevant factor or data point *(as observable selectors)* given emergency incidence *(as target hypothesis)* based on certain likelihood.

Meanwhile, observable selectors are quite subjected to likelihood yardsticks for each incidence class; because conditional possibility of observable selectors given target hypothesis is tantamount to the production of conditional possibilities of each observable trait or parameter value by relevant factors or data points given emergency as target hypothesis.

$P(E_A|X)$ implies predictor of *Robbery* subjected to *relevant factors* or *data points*.

$P(E_B|X)$ implies predictor of *Kidnap* subjected to *relevant factors* or *data points.*

$P(E_C|X)$ implies predictor of *Violence* subjected to *relevant factors* or *data points.*

$P(E_D|X)$ implies predictor of *Cultism Clashes* subjected to *relevant factors* or *data.*

$P(E_N|X)$ implies predictor of *Vandalism* subjected to *relevant factors* or *data.*

Hence,

$$P(E_A|X) = P(x_1|E_A) + P(x_2|E_A) + P(x_3|E_A) + P(x_4|E_A) + P(x_n|E_A) \ / \ P(X) \quad (3.3)$$

$$P(E_B|X) = P(x_1|E_B) + P(x_2|E_B) + P(x_3|E_B) + P(x_4|E_B) + P(x_n|E_B) \ / \ P(X) \quad (3.4)$$

$$P(E_C|X) = P(x_1|E_C) + P(x_2|E_C) + P(x_3|E_C) + P(x_4|E_C) + P(x_n|E_C) \ / \ P(X) \quad (3.5)$$

$$P(E_D|X) = P(x_1|E_D) + P(x_2|E_D) + P(x_3|E_D) + P(x_4|E_D) + P(x_n|E_D) \ / \ P(X) \quad (3.6)$$

$$P(E_N|X) = P(x_1|E_N) + P(x_2|E_N) + P(x_3|E_N) + P(x_4|E_N) + P(x_n|E_N) \ / \ P(X) \quad (3.7)$$

3.4.2 Johnson Minning System Algorithm

Algorithm 1, Incidence_Class (X_n, E_n)

1: Initialize FB_{api} and check DB_{con}

2: if DB_{con} is Successful then

3: import TestData from EmergData

4: #define char $P_{feature}$ (X) = {i..n}

5: #define char $P_{incidence}$ (E) = {i..n}

6: for feature X_i in X_n do

7: for incidence E_i in E_n do

8: if E_i is found in X_i then

9: E_i (incidence) > E_n (incidence)

10: $E_j = E_i + 1 / n$

11: P_{class} (E) = E_j

12: end if

13: return P_{class} (E)

14: end for

15: else GoTo 1

3.4.3 Pseudocode of the Improved System

Optimized Probability Pseudocode

1. Start
2. Initialize program
3. Incidence : array[1..5] of String
4. Agency : array[1..5] of String
5. I, J, K, N, M : Integer
6. Import datasets
7. data points [3], data instances [450] : string
8. If NOT datasets = mysql_select_db('Emergency Data') then
9. Go to 6
10. Else
11. data points = mysql_select_row('Post_Thread','Comment')
12. Incidence = {1:'Robbery, 2:'Kidnap', 3:'Violence',
    4:' Cultism Clashes', 5:' Vandalism',}
13. Agency={1:'alert@antirobbery.nigeriapolice.gov.ng',
    2:'alert@antikidnap.nigeriapolice.gov.ng',
    3:'alert@nigeriapolice.gov.ng',4:'alert@nigeriapolice.gov.ng',
    5:'alert@antivandal.nigeriapolice.gov.ng'}
14. For I in range (data instances)
15. For J in range (Incidence)
16. For K in range (data points)
17. // Assign a sentiment score for each incidence category
18. If (Incidence[data points] = data instances [I]) then
19. Sentiment (Incidence[J]) += 10

20. Next K

21. Next J

22. Next I

23. For N in range (Incidence)

24. For M in range (Agency)

25. For L in range (data points)

26. // Compute the sentiment score and set the classification threshold

27. //Determine the incidence type and appropriate emergency agency

28. If Sentiment (Incidence[N]) / data instances >= 0.6) then

29. Incidence = Incidence[N]

30. Agency = Agency[M]

31. $to = $_POST['Agency']

32. $subject = $_POST['Incidence']

33. $message = $_POST(data points[L])

34. //Escalate emergency through incidence notification

35. @mail($to,$subject,$message)

36. Next M

37. Next N

38. End If

39. End If

40. End If

42. End

3.5 Development Tools for Designing the Improved System

This study comes as improvement upon the benchmarked framework[1,2] with the inculcation of hybridized learning technique. Optimized classifier handles training and testing set of data,

through supervised approach to perform classification task, while exploratory and rapid prototyping was adopted for the development process. The design of improved system encompasses Bayesian belief learning technique for data mining and text classification, NLP toolkit for sentimental response and knowledge-base that keeps streamed data for model validation. The implementation was done using embedded requests library of Python in Facebook Graph API for live data capturing, while XML, PHP MySQL and Python for sentimental response to emergency incidence.

3.6 Design Specifications for Input, Output and Database

Table 3.1: Input Specification

FIELD NAME	FIELD TYPE	NULL	FIELD WIDTH	DEFAULT
UserID	Text	No	50	None
Post_Thread	Text	No	50	None
Comment	Text	No	25	None
Location	Text	No	30	None
Time_Date	Double	No	30	None

Table 3.2: Output Specification

FIELD NAME	FIELD TYPE	NULL	FIELD WIDTH	DEFAULT
Location	Text	No	50	None
Time_Date	Text	No	30	None
Incidence	Text	No	50	None
Notification	Text	No	30	None
Agency	Double	No	30	None

Table 3.3: Database Specification

FIELD NAME	DATA TYPE	DESCRIPTION	CHARACTER LENGTH	MISSING VALUE	ALIGNMENT
UserID	Text	No	50	None	Center
Post_Thread	Text	No	50	None	Center
Comment	Text	No	25	None	Center
Location	Text	No	50	None	Center
Time_Date	Text	No	25	None	Center
Incidence	Text	No	50	None	Center
Notification	Text	No	30	None	Center
Agency	Double	No	30	None	Center

3.7 Dataset Acquisition

Emergency datasets were acquired for experimental cases and functional performance of improved model in this study, through web scrapping via selected repository on social media. Experimental design in this study uses four hundred and fifty (450) data instances and four (4) attributes thereby formed four hundred and fifty by five (450 x 4) data samples.

3.8 Performance Evaluation of the Improved System

The experimental performance of the improved emergency classification model and resulting sentimental response system was measured using evaluation parameters like

true positive (TP),

false positive (FP),

true negative (TN),

false negative (FN); with metrics like precision and confusion matrix.

TRUE POSITIVE indicate the rate of system precision that were truly valid or number of selected cases for emergency that were real when incidence signals are received; TRUE NEGATIVE indicate the rate of system precision that were truly invalid or number of selected cases for emergency that were not real when incidence signals are received; FALSE POSITIVE indicate the rate of system precision that were falsely valid or number of selected cases for emergency that were wrongly escalated when incidence signals are received; FALSE NEGATIVE indicate the rate of system precision that were falsely invalid or number of selected cases for emergency that were not escalated when incidence signals are received.

Precision and Confusion Matrix are expressed in equation 3.8 and table 3.4.

Precision = TP / TP + FP x 100 (3.8)

Table 3.4 Confusion Matrix

		True Sentiment	
		Positive	**Negative**
Classified Sentiment	**Positive**	TP	FP
	Negative	FN	TN

Source: [49]

Precision refers to a yardstick for evaluating the accuracy of improved system by experimental performance or parameter for measuring the exactness of emergency incidences being classified by improved system during experimental performance.

Confusion matrix is a confounding array of cross sequence or transverse values, with which a linear relationship can be established between classifier's precision and sentiment polarity. Hence, the higher the precision of improved system; the more accurate the improved model and its classification algorithm to filter wrong signals or reduce false alerts; in close association with positive polarity for emergency sentiments.

Endnotes

1. R.A. Baro & T.D. Palaoag, *"Disaster Sentiment Analysis: Addressing the Challenges of Decision-Makers in Visualizing Netizen Tweets,"*IOP Conference Series: Materials Science and Engineering. 2020, DOI:10.1088/1757-899x/803/1/012039

2. D. Contreras, S. Wilkinson, E. Alterman & J. Hervas. *Accuracy of a Pre-trained Sentiment Analysis (SA) Classification Model on Tweets related to Emergency response and Early Recovery Assessment: the case of 2019 Albanian earthquake.* **Journal of Natural Harzard,** *6* (9)*,* 2022, 21-32.

Chapter Four

Implementation and Results

4.1 Implementation

Emergency datasets were generated from social media, to constitute the localized database for improved system by web scrapping or extraction of web data via Facebook developer domain: https://developers.facebook.com/

Hence, graph API register was accessed when Meta was created for scrapping emergency data through https://m.facebook.com/search_posts/?q=emergency

Experimental analysis in this study uses four hundred and fifty (450) data samples and five (5) characteristics thereby created 450 x 5 data samples. In all the four hundred and fifty (450) cases of emergency, the data samples are multivariate in nature; in the sense that data instances have multiple charactersistics or attributes which could generate several variables for classification task. Also, no instance or its attribute has missing value.

Essential features which are very germane to the presence of emergency incidence in classification mechanism by selection are the post /thread and comment /reaction; as well as the incidence location and time stamp. They were also optimized thereafter in order to ensure optimal efficiency of the classifier; having excluded instances with null or zero value.

More so, it is imperative to ensure relevant distribution of social media data for disastrous and hazardous incidences due to the influence of social speculation or web outlier of text data (i.e noise). Program implementation and outputs of the improved system for emergency classification and sentimental response being discussed in this section and/or chapter aligns with specific system requirements, thus provided.

4.2 System Requirements

The functional specifications of improved emergency classification and sentimental response system involved essential hardware and software components which are enumerated below:

4.2.1 Hardware Requirements

i) Pentium IV or higher system unit

ii) 1.4GHZ processor speed or higher

iii) 768MB main memory (RAM)

iv) 40GB space of internal hard drive

v) SVGA VDU or 15.4" inches screen

4.2.2 Software Requirements

i) Windows 7 (32 bit) operating system

ii) Google chrome or Firefox browser

iii) WAMP 2.1 apache local web server

iv) MySQL or Ms SQL database server

v) Python 3.6 plug-in or higher version

4.3 Choice of Programming Language and Software Justification

The implementation was done using embedded requests library of Python programming language with Graph API for live data capturing from Facebook, while MySQL was used to design the back-end database for storing and managing pre-processed datasets, as well as

XML and PHP for creating the front-end with middleware control to handle sentimental response.

Python is a general purpose programming language with design philosophy that envisages code readability with evident use of significant spacing in source code. The language construct of Python and its object oriented nature helps programmers in concise and logical coding for building software projects or large scale application programs with variety of paradigms.

4.4 Program Outputs and Documentation

These features were selected by extraction of relevant attributes of samples for emergency data thereby reducing data dimension to 450 X 5 instances. Four hundred and fifty (450) instances of dataset or samples of data were converted to comma separated values (CSV) format from Microsoft Excel spreadsheet so as to make its exportation to Apache WAMP through PHP MyAdmin() which is the testing server for MySQL database that conveys the parameter values. Supervised training is quite necessary for the chosen data mining and classification algorithm; hence data instances from disastrous scenarios were used to form the training set before experimental analysis. Three additional fields namely incidence, notification and agency were created for sentimental response from the database upon periodic execution of classification algorithm to track the decision support provided by classifier and/or improved model.

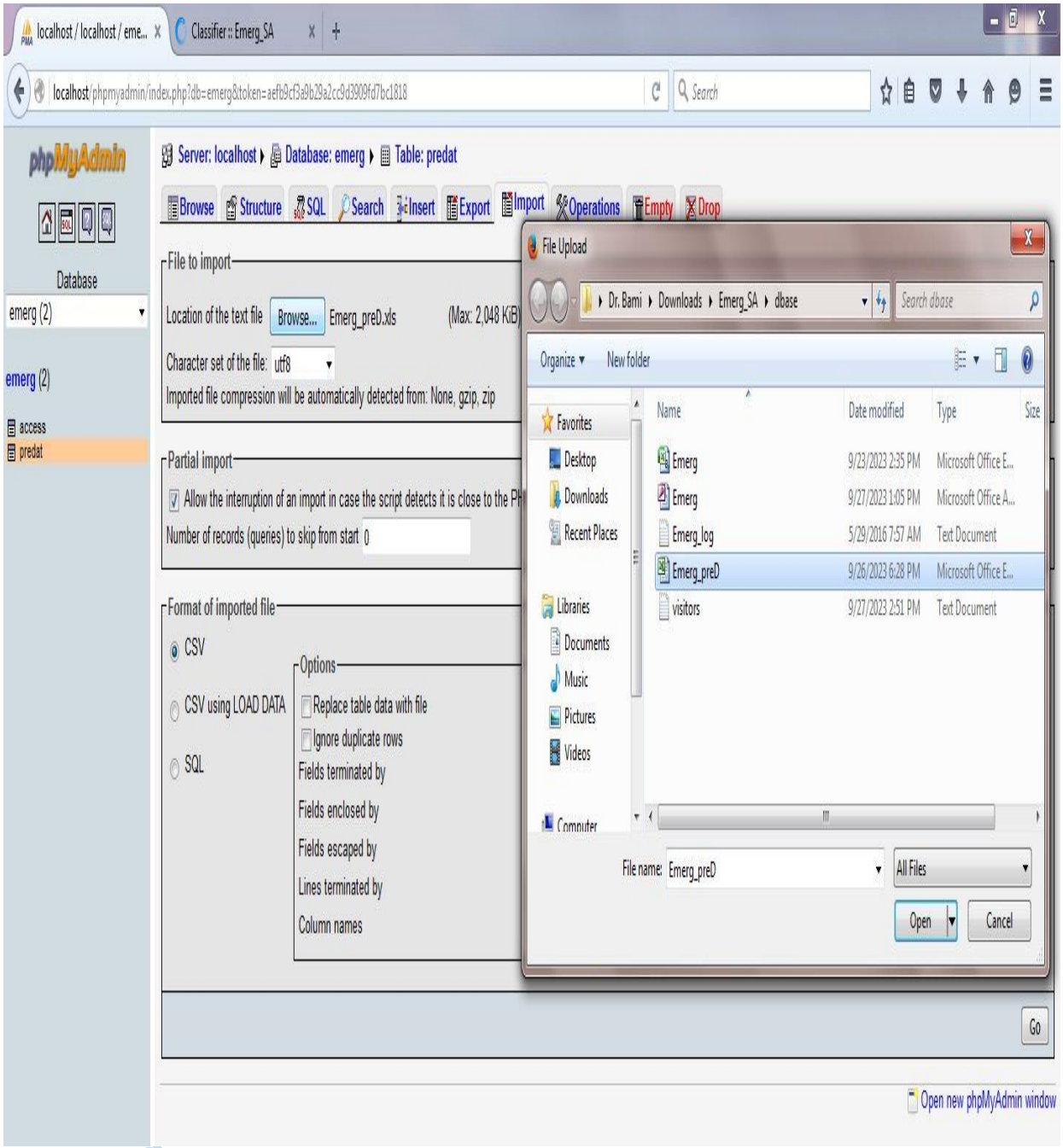


Figure 4.1 Importing Pre-processed Datasets for Training / Testing into SQL DB server

Source: Researcher Fieldwork, 2024

Figure 4.1 shows the MySQL console for database server, as back end application for the improved system, with exploratory windows or entity structure for database file ‘emerg’. Uploading dialog or pop up window for data file pave ways for quick importation of splited datasets for training the classifier and validation testing, having completed data cleaning.

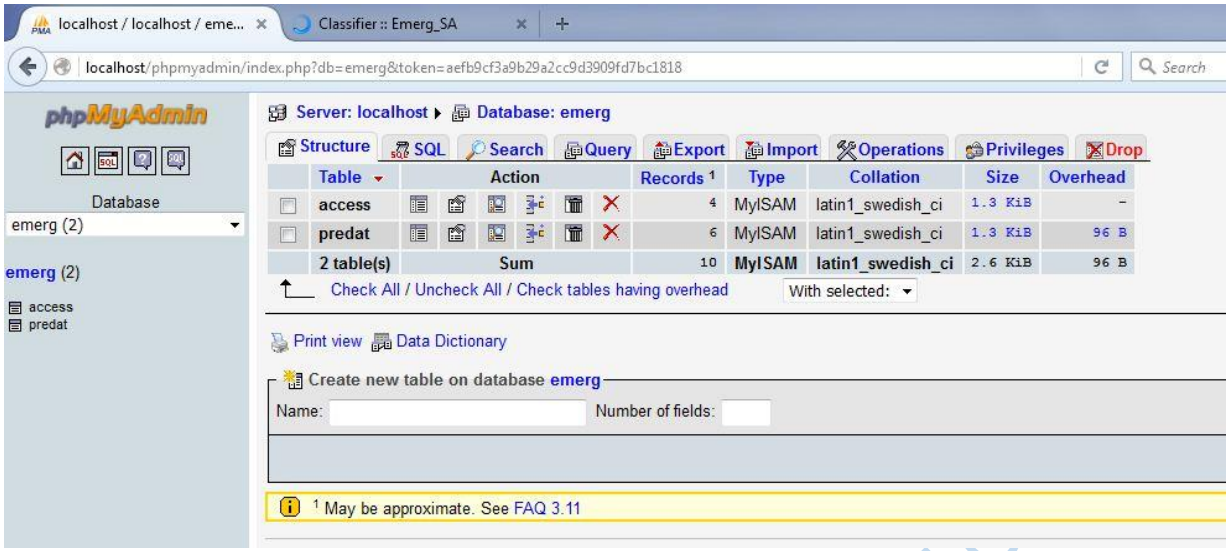


Figure 4.2 MySQL database for Internal Storage of Extracted data from Social Media

Source: Researcher Fieldwork, 2024

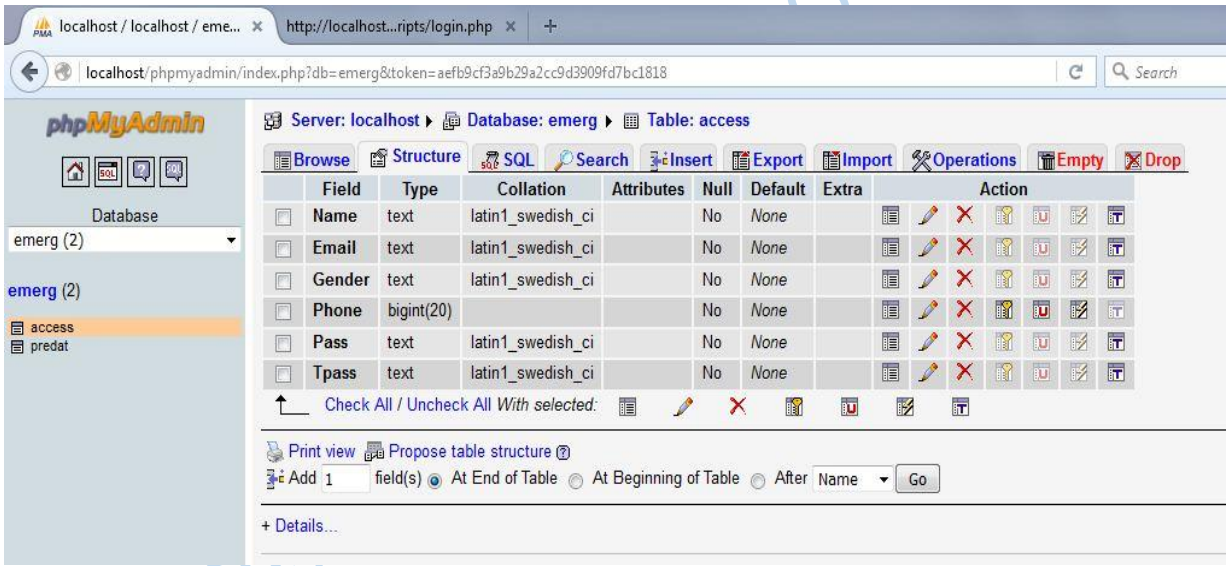


Figure 4.3 Entity Structure for Access Control and Authorized Users on SQL server

Source: Researcher Fieldwork, 2024

Figure 4.2 shows the entity view of back end (emerg) database for the improved system in MySQL server window comprinsing of two tables; 'access' table which stores the login details of every system user that sign up at thye dashboard for the first time while 'predat' table stores data file of pre-processed data instances. Figure 4.3 shows its design structure, indicating the acceptable data type for each field in users' records and value can not be null.

4.5 User Interface and Testing

Having trained the improved system in consequent upon features' optimization with seventy five percent of datasets, the rest twenty five percent of datasets from experimental data repository (localized scenarios); was used for testing thereafter in order to validate the model and evaluate system performance. Figures and table below shows the outcome of valid and invalid data in usability testing as dependent parameter elements or dependent input variables; as well as classifier output in relevance to categories of incidence in this study.

Pre-processed dataset being the extracted Facebook posts and comments as textual data which had gone through data cleaning process and eventually discretized (converted to numeric data of nominal values) was loaded from database storage as input (parameter values) into the system.

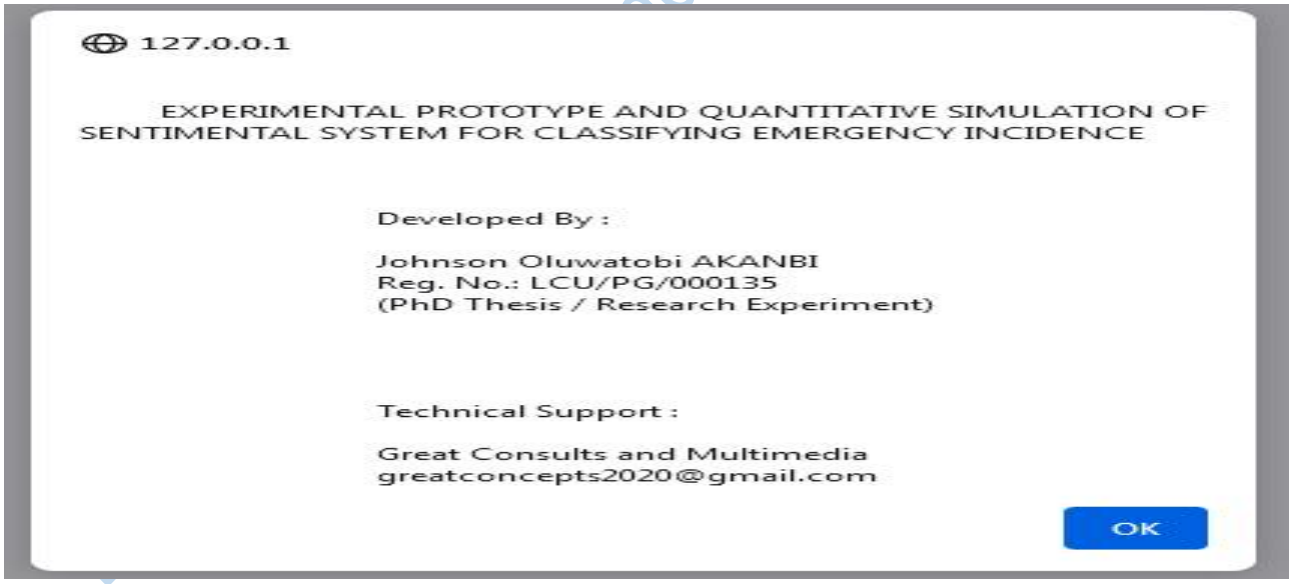


Figure 4.4 System Splash Screen – Author's Macros and Developer's Trademark

Source: Researcher Fieldwork, 2024

Figure 4.4 shows the splash screen for the replica of improved system, which is simply the first dialog or pop up window that comes up when the program is being initialized; to display the information of author and technical group that supported the bench work for this thesis.

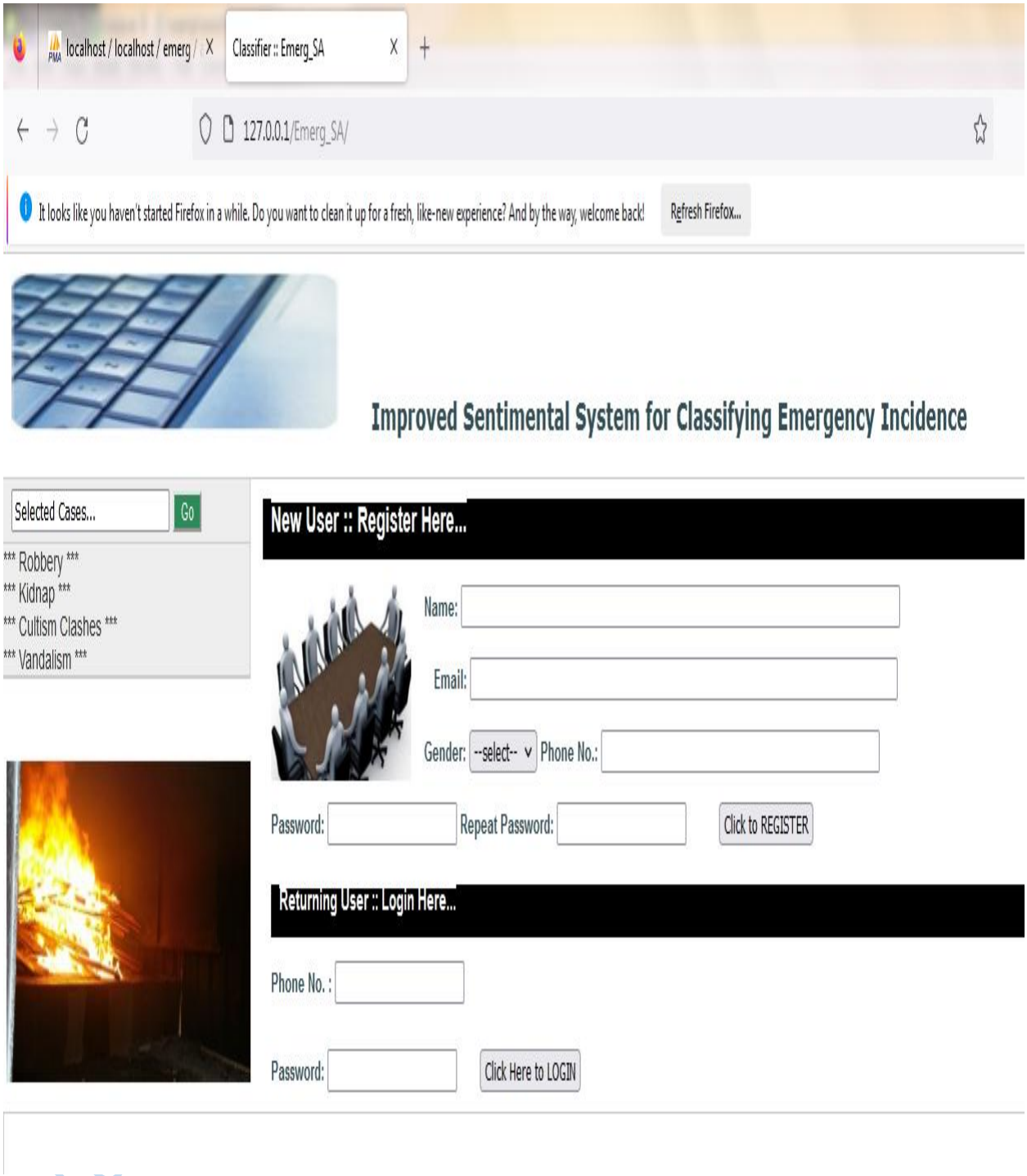


Figure 4.5 System Dashboard – Main Module for User's Registration and Authentication

Source: Researcher Fieldwork, 2024

Figure 4.5 shows the main module which is the dashboard for improved system, at the dashboard a new user can register or create user profile by completing the data fields in New User tab and click register. Similarly, an existing user's profile or returning user can gain

access for system usage by providing login credential, then click on Login. Phone number and password are used as the database index with which the record can be retrieved to verify.

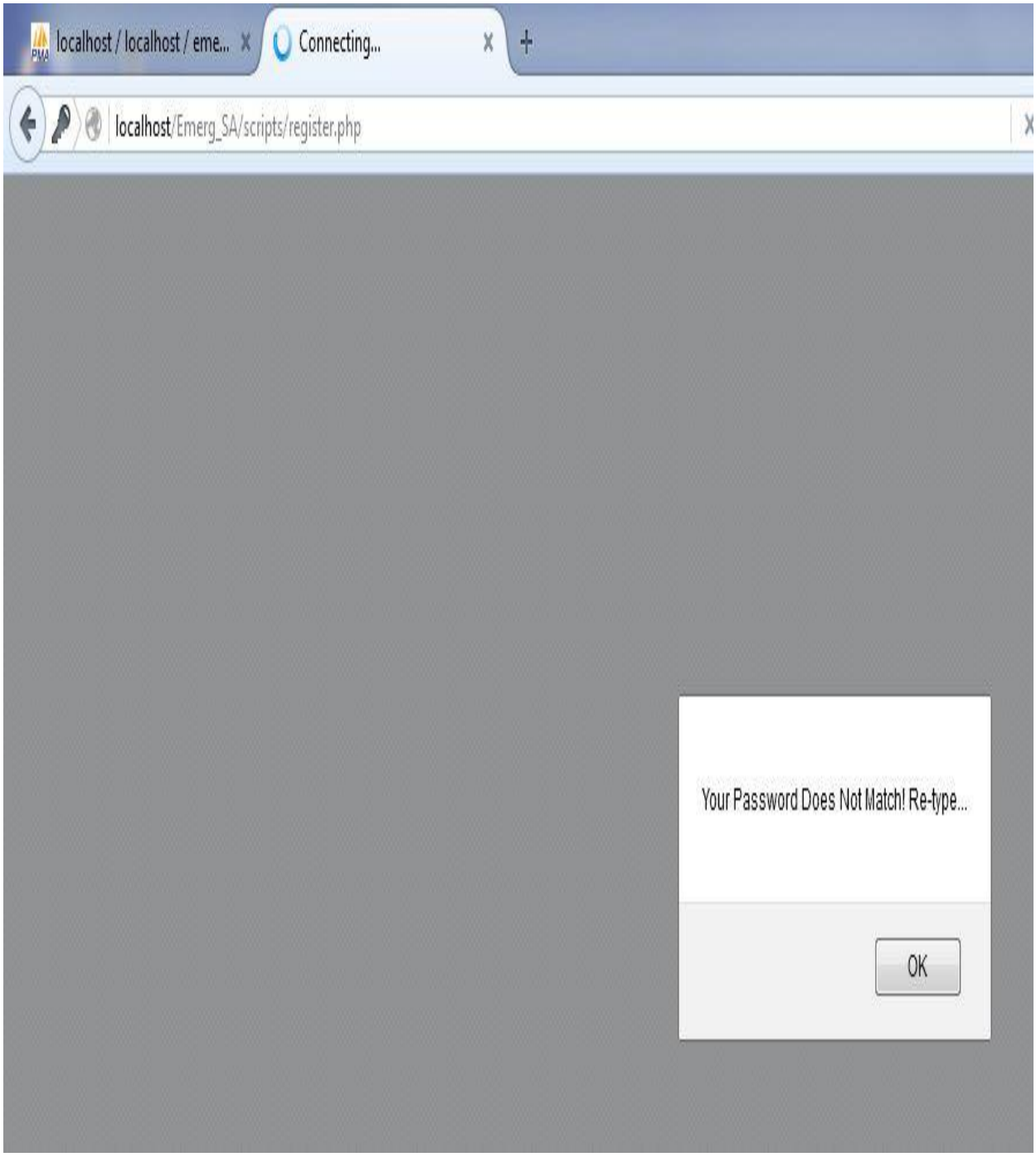


Figure 4.6 System Dashboard – Return Prompt for Data Field Mismatch

Source: Researcher Fieldwork, 2024

Figure 4.6 shows sign up or registration error, which was encountered due to invalid login or mismatch password during validation test of improved system, when the text or character values provided in the password field is different from text or character values in the re-tytpe /repeat password field, then the web server fail to validate user's details for a new account.

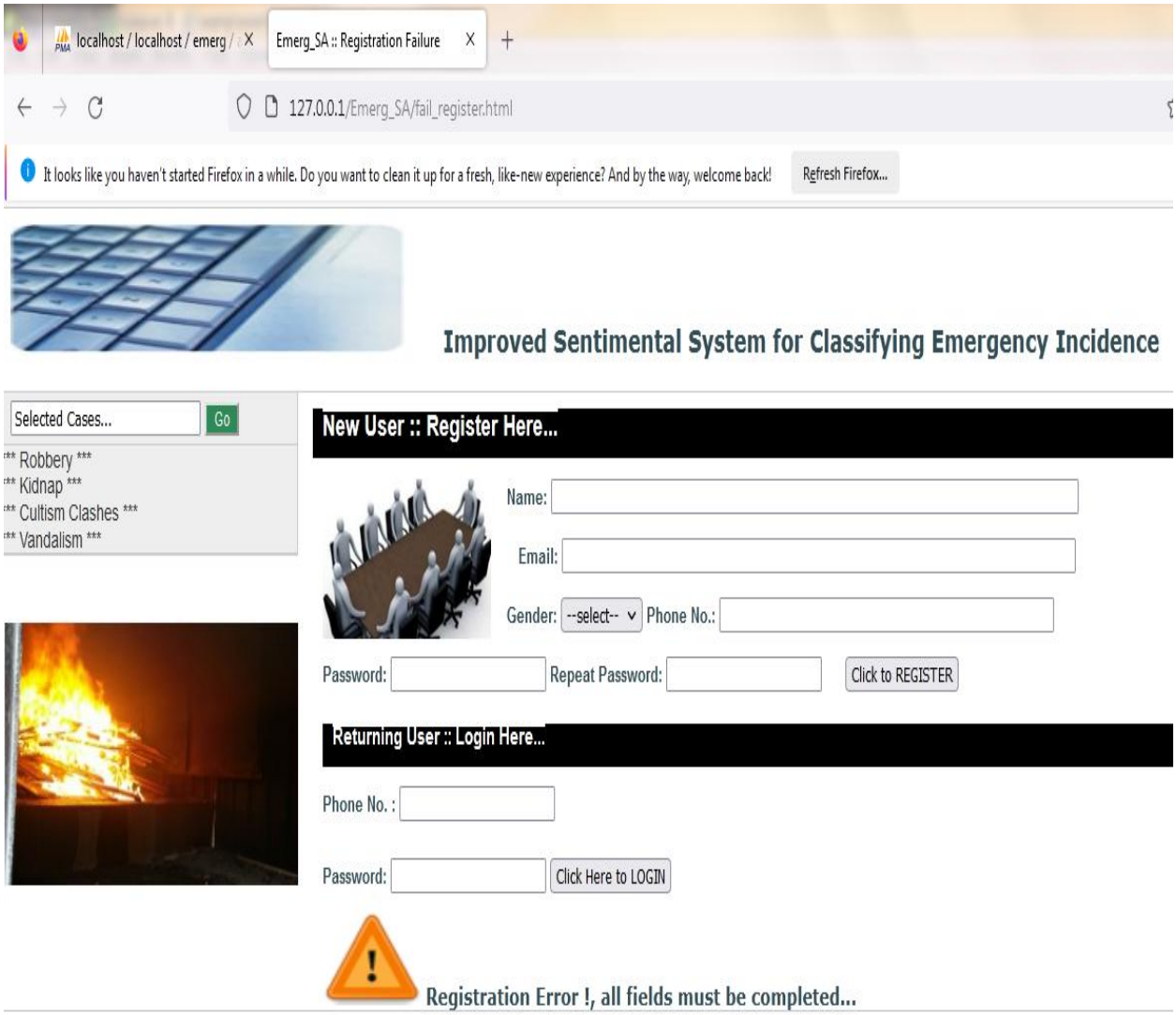


Figure 4.7 System Dashboard – Initialization Error for Incomplete Field Values

Source: Researcher Fieldwork, 2024

Figure 4.7 shows sign up or registration error, which was encountered due to invalid login or null values in data entry during validation test of improved system, when some data fields are delibrately or unconsciously skipped during registration, then user profile can not be created.

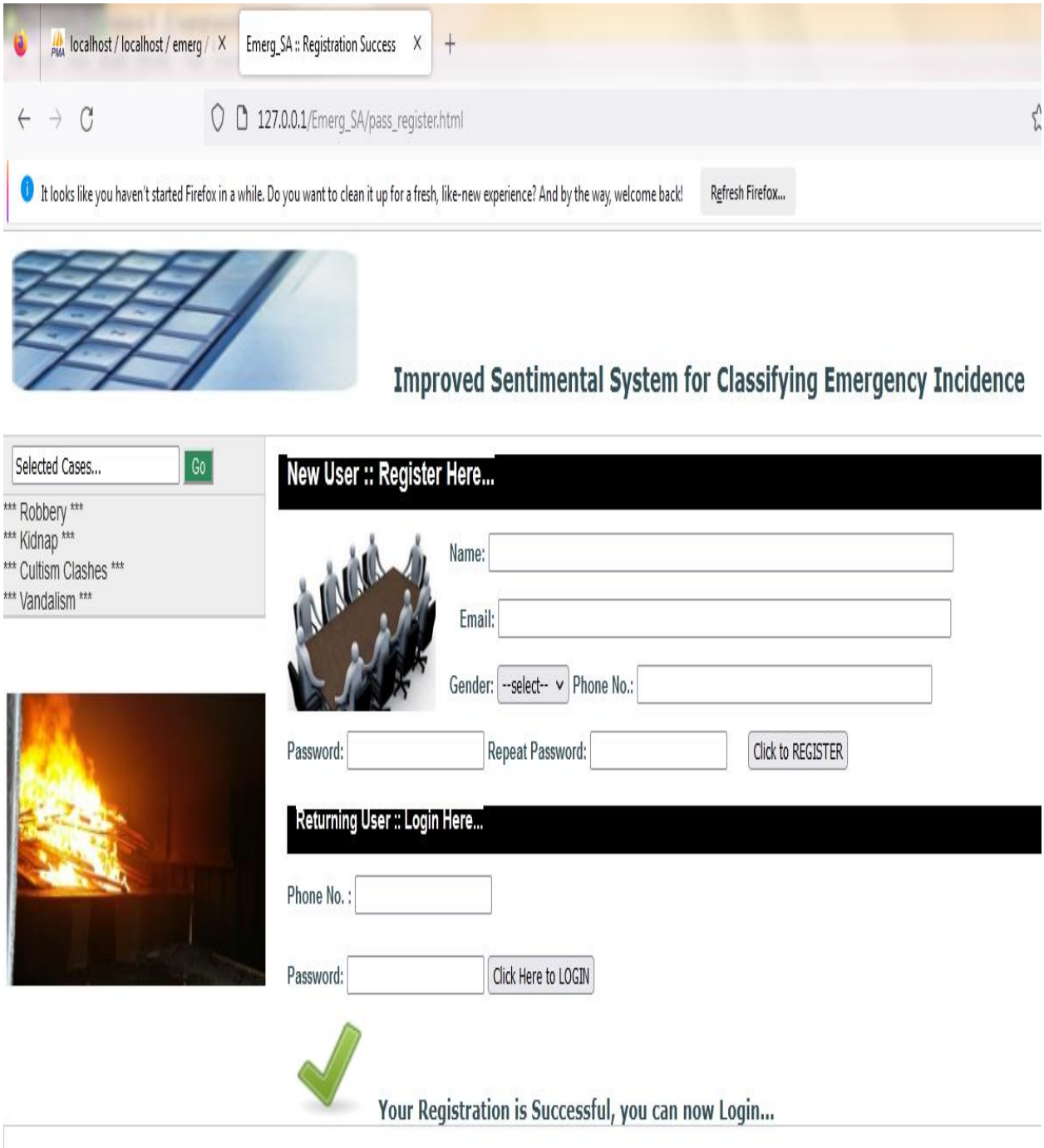


Figure 4.8 System Dashboard – Initialization Success for New User

Source: Researcher Fieldwork, 2024

Figure 4.8 shows sign up success or successful registration, which yielded a new user profile as new record in the 'access' table of back end database, during performance test of improved system, which imply that all data fields are properly and completely filled.

Figure 4.9 System Dashboard – Insertion of Login Credentials at Login Prompt

Source: Researcher Fieldwork, 2024

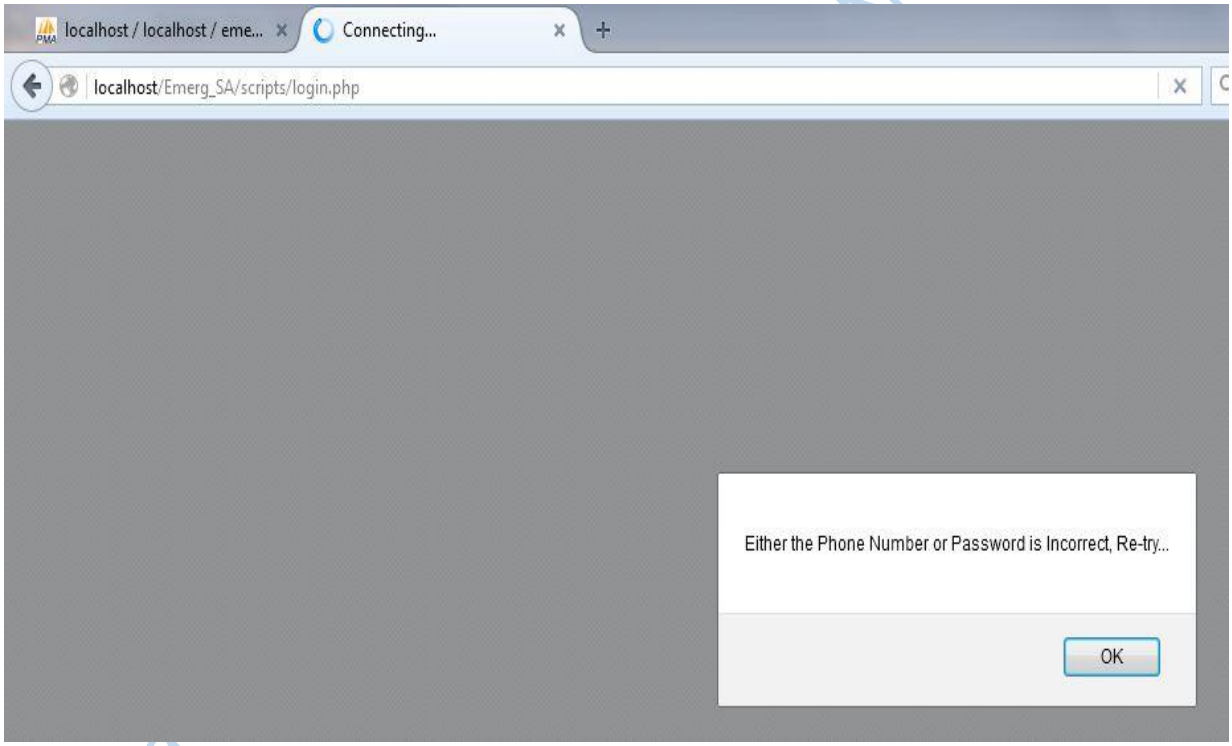


Figure 4.10 Mismatch Password or Wrongly Phone Number

Source: Researcher Fieldwork, 2024

Figure 4.9 shows login tab with phone number and encrypted password as entered data values, for profile validation in order to gain access into the system, RESET button allows user to clear and re-enter value. Figures 4.10 and 4.11 shows validation error during integrity test of improved system which was encountered due to invalid login or incorrect password.

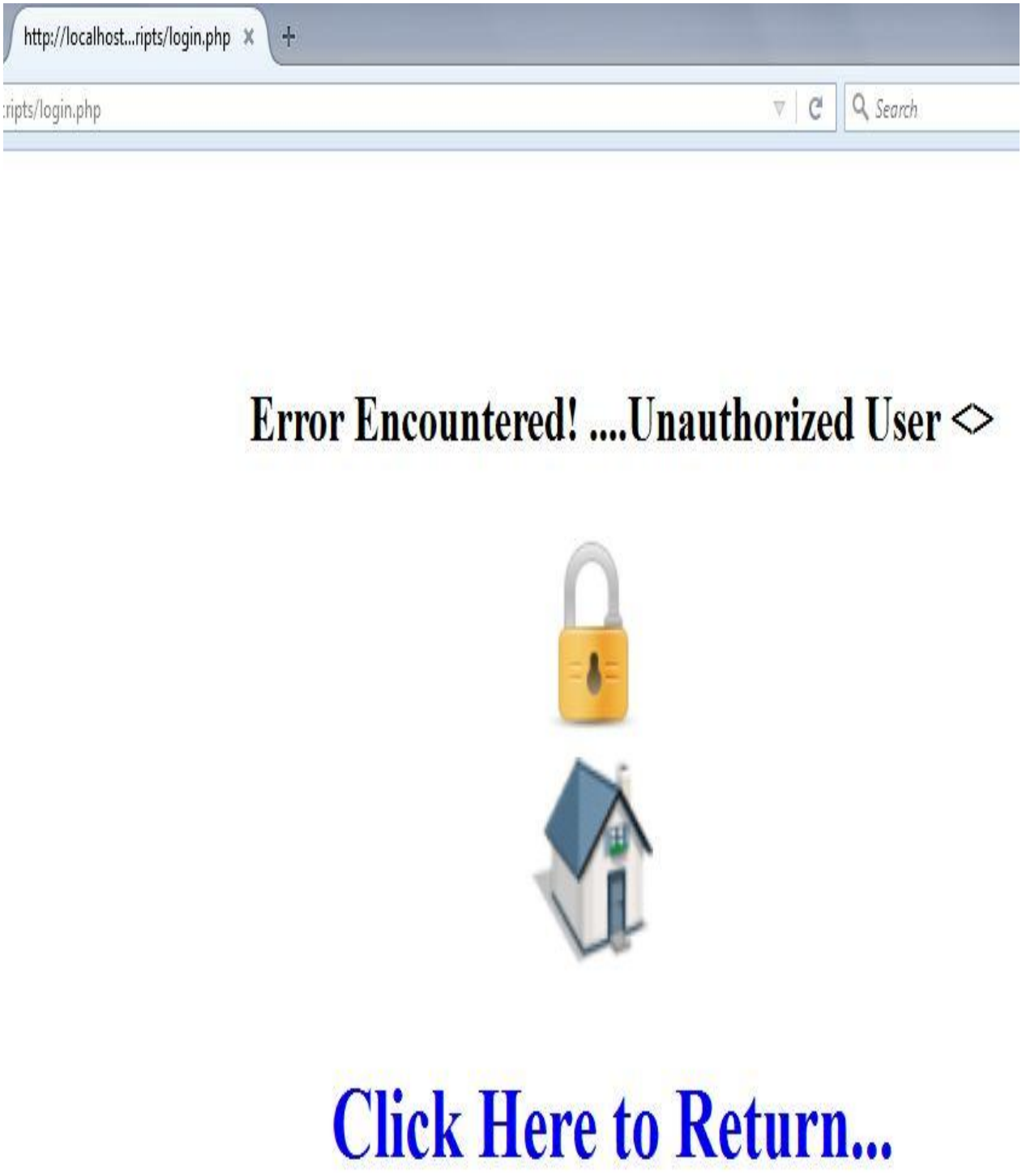


Figure 4.11 Invalid Login details **Source:** Researcher Fieldwork, 2024

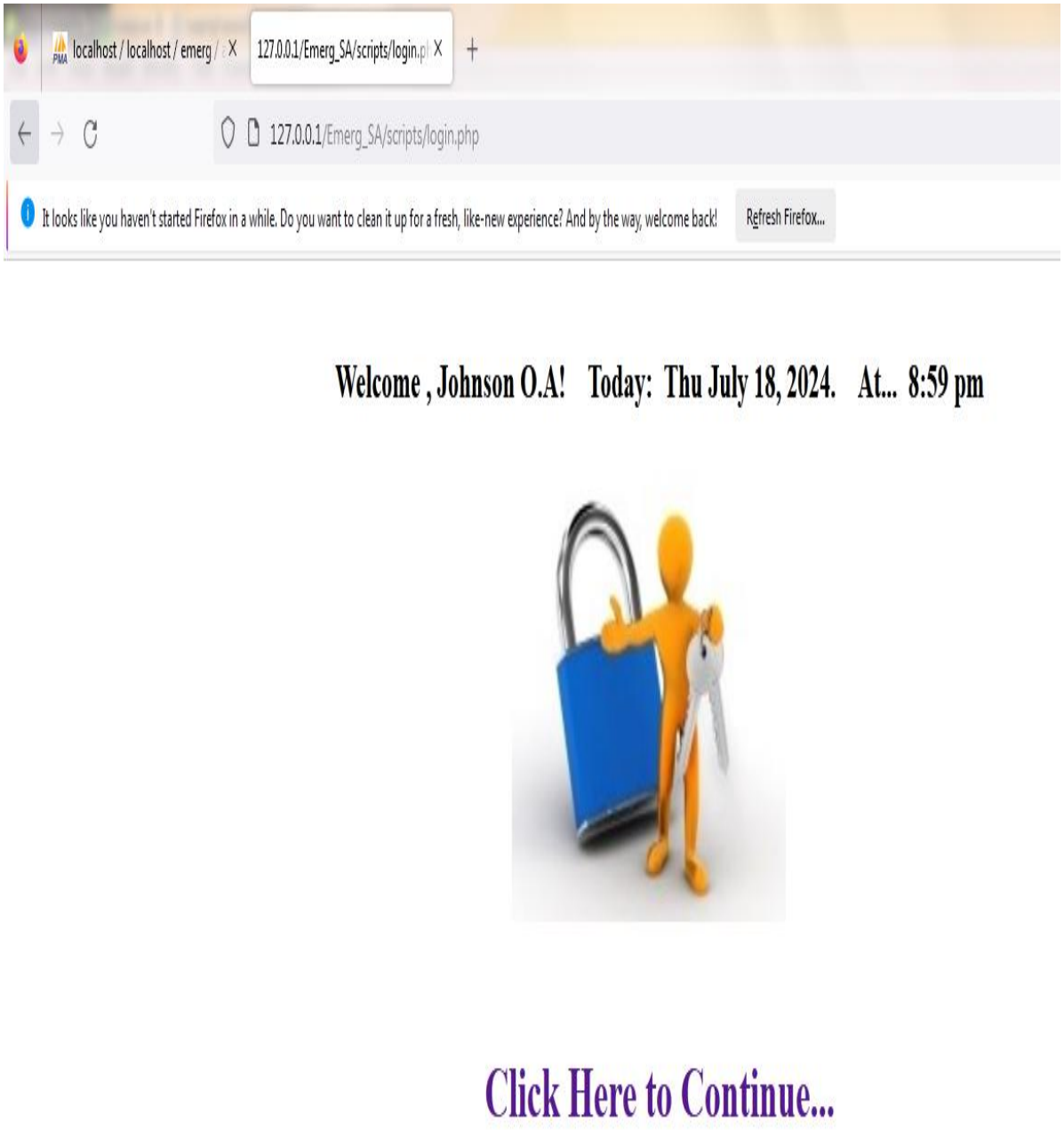


Figure 4.12 Authentication Success at Login Prompt

Source: Researcher Fieldwork, 2024

Figure 4.12 shows sign in or welcome page, which display user's name and date with time stamp upon validation of login credentials, during usability and security test of improved system using valid data; in such a way that the date in which the system is accessed is shown.

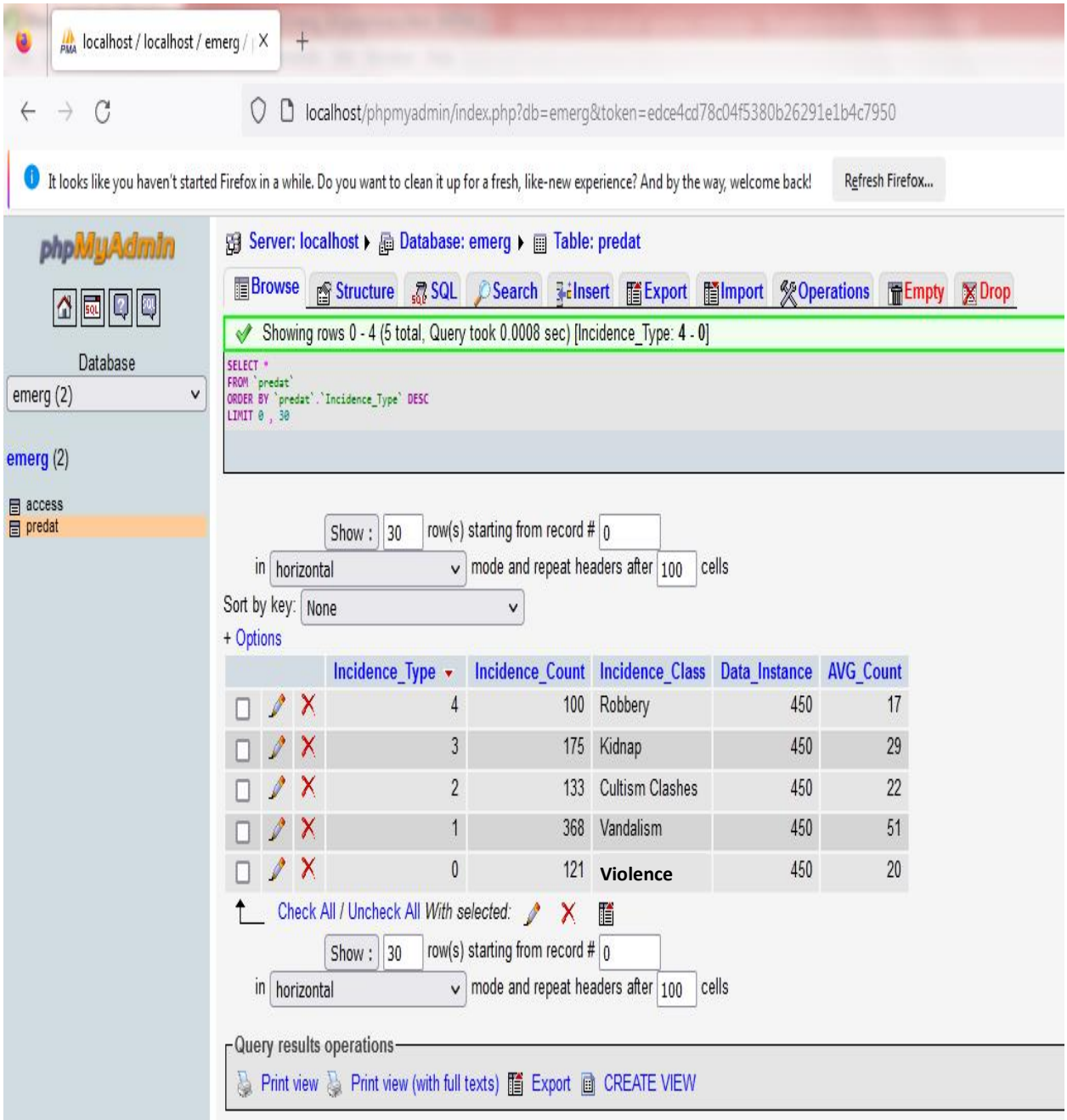


Figure 4.13 Class Estimation and Clustering of Emergency Cases from Social Media

Source: Researcher Fieldwork, 2024

Figure 4.13 shows testing set for polarity validation from database in the SQL server, which shows four major attributes of the data points or data instances; the incidence categories for the selected cases or emergency types, incidence count or recorded phrases in sentiment, and lastly the incidence class that describe case label or type of emergency incidence.

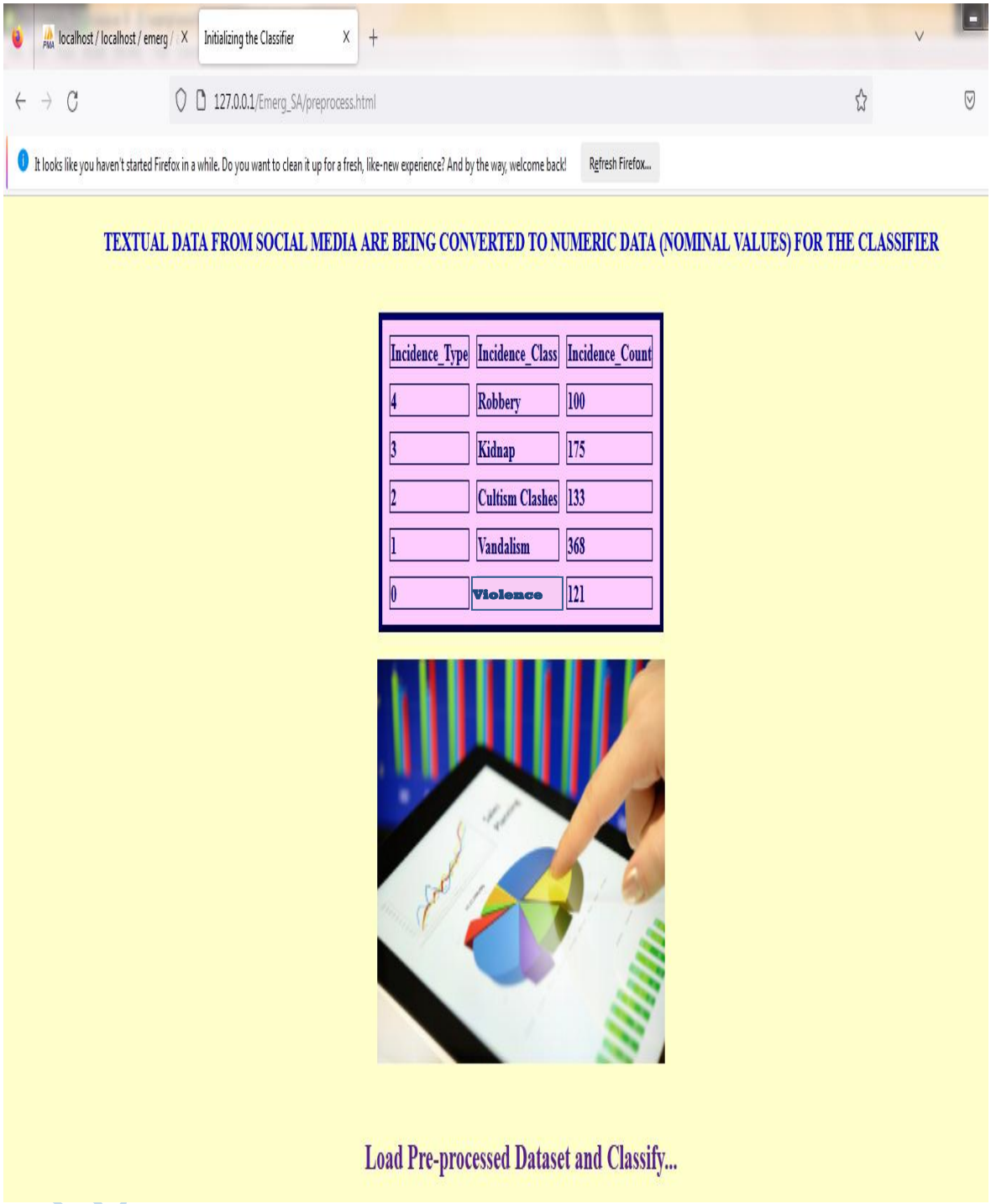


Figure 4.14 Discretization and Loading of Emergency Dataset from the Database

Source: Researcher Fieldwork, 2024

Figure 4.14 shows the initialization module for the classifier during performance and reliability test of the improved system, the discretized data instances appeared in tabulated manner as incidental observations which serve as emergency signals; to determine sentiment intensity through classification algorithm which is the inference engine or mechanism.

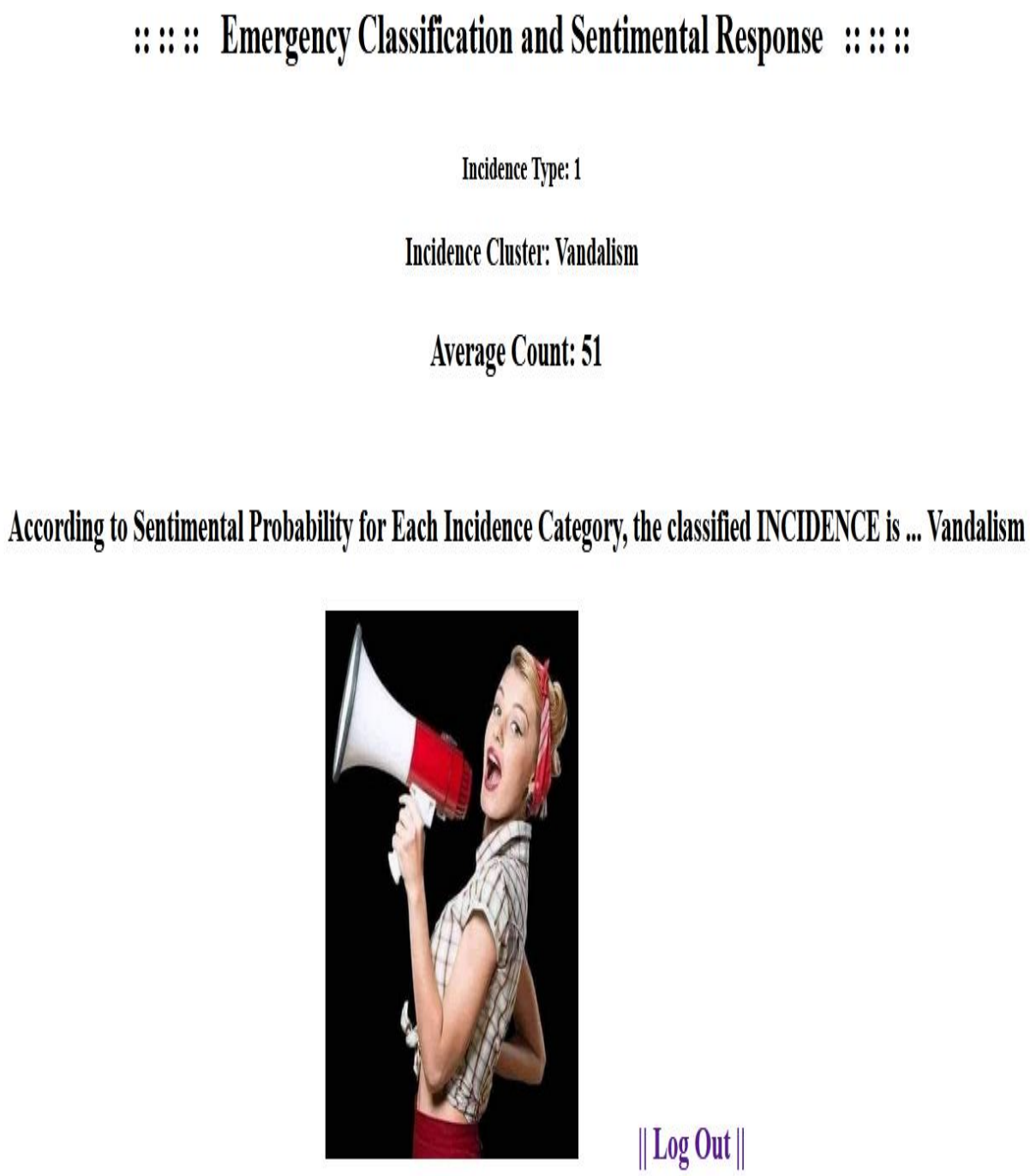


Figure 4.15 Classification and Sentimental Response to Emergency Incidence

Source: Researcher Fieldwork, 2024

Figure 4.15 shows the classification results of improved system during performance exper, indicating incidence counts or incidental observations as emergency signals for the class with highest intensity and sentimental probability. The incidence label or category of emergency was Flood while the in-buuilt sentimental function send the escalating notification.

Table 4.1 Experimental Results of the Improved System

	SELECTED FEATURES		TARGET
Data Instances	Post	Comment	Incidence_Class
1	0	1	1
2	0	0	0
3	0	1	1
4	0	1	1
5	1	1	1
6	1	1	1
7	1	2	1
8	1	1	1
9	5	1	5
10	1	1	1
11	1	4	1
12	3	1	3
13	1	1	1
14	1	1	1
15	1	4	1
16	1	3	1
17	2	1	2
18	2	1	2
19	2	1	2
20	2	3	2
21	2	1	2
22	2	1	2
23	2	5	2
24	2	3	2
25	1	1	1
26	1	1	1
27	1	5	1
28	5	1	5
29	0	0	0
30	4	1	4
31	3	1	1
32	3	1	3
33	0	2	0
34	0	1	1
35	4	1	4
36	0	1	1
37	0	0	0
38	0	1	1
39	0	1	1
40	1	1	1

41	1	1	1
42	1	2	1
43	1	1	1
44	5	1	5
45	1	1	1
46	1	4	1
47	3	1	3
48	1	1	1
49	1	1	1
50	1	4	1
51	1	3	1
52	2	1	2
53	2	1	2
54	2	1	2
55	2	3	2
56	2	1	2
57	2	1	2
58	2	5	2
59	2	3	2
60	1	1	1
61	1	1	1
62	1	5	1
63	5	1	5
64	0	0	0
65	4	1	4
66	3	1	1
67	3	1	3
68	0	2	0
69	0	1	1
70	4	1	4
71	0	1	1
72	0	0	0
73	0	1	1
74	0	1	1
75	1	1	1
76	1	1	1
77	1	2	1
78	1	1	1
79	5	1	5
80	1	1	1
81	1	4	1
82	3	1	3
83	1	1	1
84	1	1	1
85	1	4	1
86	1	3	1
87	2	1	2

88	2	1	2
89	2	1	2
90	2	3	2
91	2	1	2
92	2	1	2
93	2	5	2
94	2	3	2
95	1	1	1
96	1	1	1
97	1	5	1
98	5	1	5
99	0	0	0
100	4	1	4
101	3	1	1
102	3	1	3
103	0	2	0
104	0	1	1
105	4	1	4

Source: Researcher Fieldwork, 2024

Table 4.1 comprised of four columns representing data instances (sample data from the dataset), post (first feature selected from the social media data), comment (second feature selected from the social media data), and incidence class which is the target for classification algorithm.

The first column contained nominal sequence of sample data shown at random from testing set while other columns contained discretized values on nominal range for the Facebook posts and comments threading across most users' profiles with different reactions and tags, as well as the expected target for incidence category.

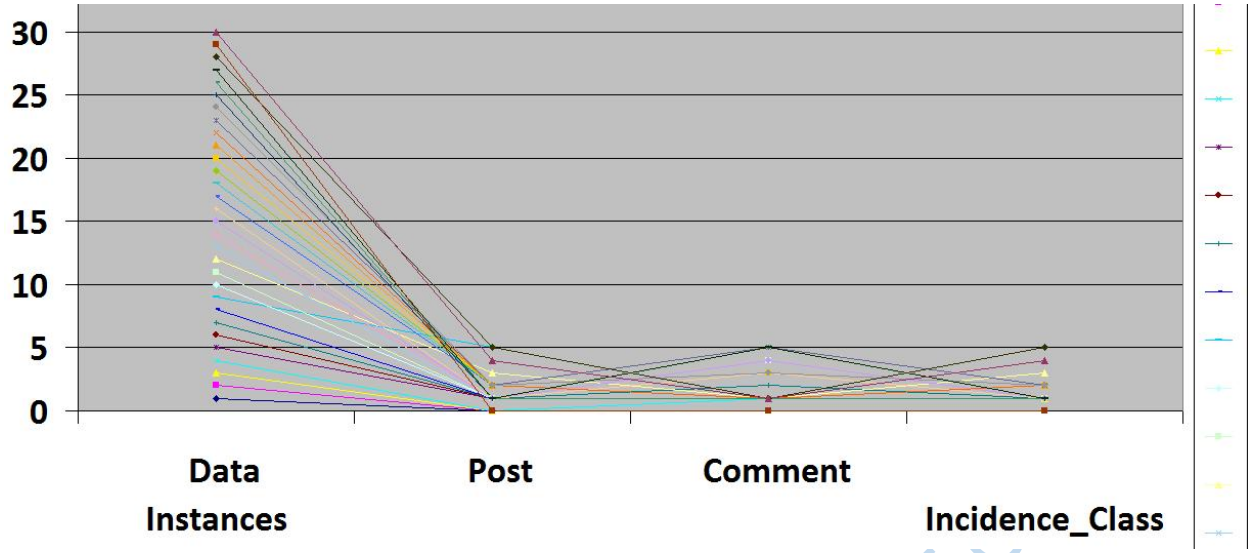


Figure 4.16 Graphical Representation of Incidence Samples for Experimental Analysis

Source: Researcher Fieldwork, 2024

Figure 4.16 corroborate the analysis with graphical representation; indicating the sequence of discretized text as attributed value for each incidence category in selected features which are Facebook post and Facebook comment; as well as feature count for the predefined clusters of incidences.

The results were presented in pictorial manner; showing the simulation process and experimental stages of validating data during mining before generating output.

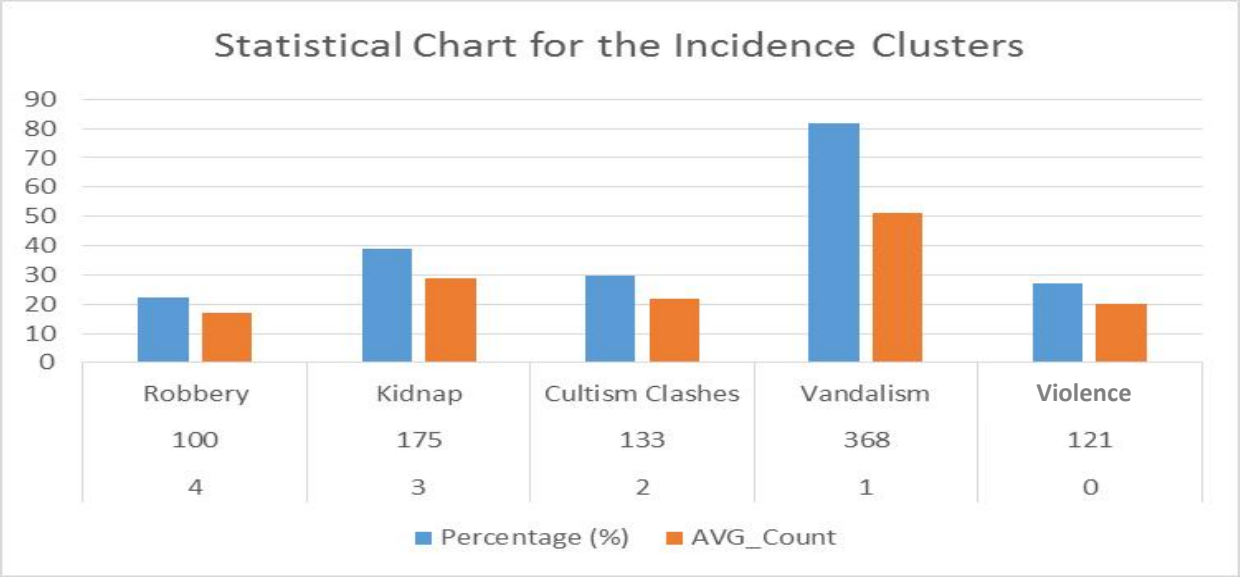


Figure 4.17 Statistical Representation of the Experimental Results

Source: Researcher Fieldwork, 2024

Figure 4.17 represent the statistical chart for the incidences clusters, for instance, incidence 4 robbery, its average count is 15 and it's equivalent to 22%, incidence 3 kidnap, its average count is 29 and it's equivalent to 38%, incidence 2 cultism clashes, its average count is 20 and it's equivalent to 30%, incidence 1 vandalism, its average count is 50 and it's equivalent to 80%, and for null-incidence, its average count is 28 and it's equivalent to 20%.

4.6 Discussion of Results

As shown in preceding sections through figures and tables, possibility tendency to classify parameter values with selected features at escalating intervals or highest frequency ratio to target class of vandalism; especially on experimental data of emergency incidence from social media repository which was considered as input elements for dependent variables in this study. Experimental analysis of the classification algorithm or inference engine (i.e the classifier) revealed linear dimension of real emergency incidence and pre-processing phase at which non linear distribution of textual data is being converted to align the dataset with nominal range. Prior probability of each incidence parameter and input interval for selected features is being computed from frequency distribution generated from set of emergency observations. Likelihood array of probabilities for predictors in emergency scenarios is formed based on probability

distribution which may be approximated from database with stored nominal values.

Consequently, various experimental scenarios were established to ensure confidence in the improved sentimental response framework in classifying emergency incidence and to forestall disaster that could lead to loss of lives and properties; by sending timely notification to the concerned or relevant authority like public emergency management agency for necessary control or recovery actions; thus provides improvement to the existing system which was very limited to specific natural hazard without implementation for experimental evaluation. In another development, this study also inculcated multi-class precision of the model with varied real time data and higher type-matching rate, by nature and source of dataset which has successfully filled the gap in the existing system having infused supervised learning technique into the NLP to optimize model performance with parameters for higher precision.

4.7 System Performance and Evaluation

The performance rate at which classifier's precision correlates with target inference shows system accuracy and quite evident by its data mining. Error rate is normally calculated by dividing; number of incorrect classification by total data samples (testing dataset), was very meagre and presumed only for exceptional cases of technical flaws or outlier in few data values. Hence, evaluation parameters are being recalled as performance metrics; in line with precision and confusion matrix as mathematically expressed from equation 3.8 and table 3.4.

The experimental performance of the improved emergency classification framework and resulting sentimental response system was measured using evaluation parameters like true positive (TP), false positive (FP), true negative (TN), false negative (FN); with metrics like precision and confusion matrix.

Precision = TP / TP + FP x 100 (4.1)

= 381 / 381 + 38 x 100 **= 90.93%**

Table 4.2 Confusion Matrix

		True Sentiment	
		Positive	**Negative**
Classified Sentiment	**Positive**	381 (TP)	38 (FP)
	Negative	7 (FN)	24 (TN)

Source: Researcher Fieldwork, 2024

Equation 4.1 shows the formulae and mathematical equation being evaluated to compute the system precision, so as to determine performance accuracy of the improved system.

Table 4.2 also shows the confusion matrix which indicate very close relationship between true sentiment and classified sentiment for emergency incidence. Hence, the improved system was tested to be over ninety two percent (90.93%) efficient in signal precision which is a great improvement to functional model and technique of the existing system used for benchmark.

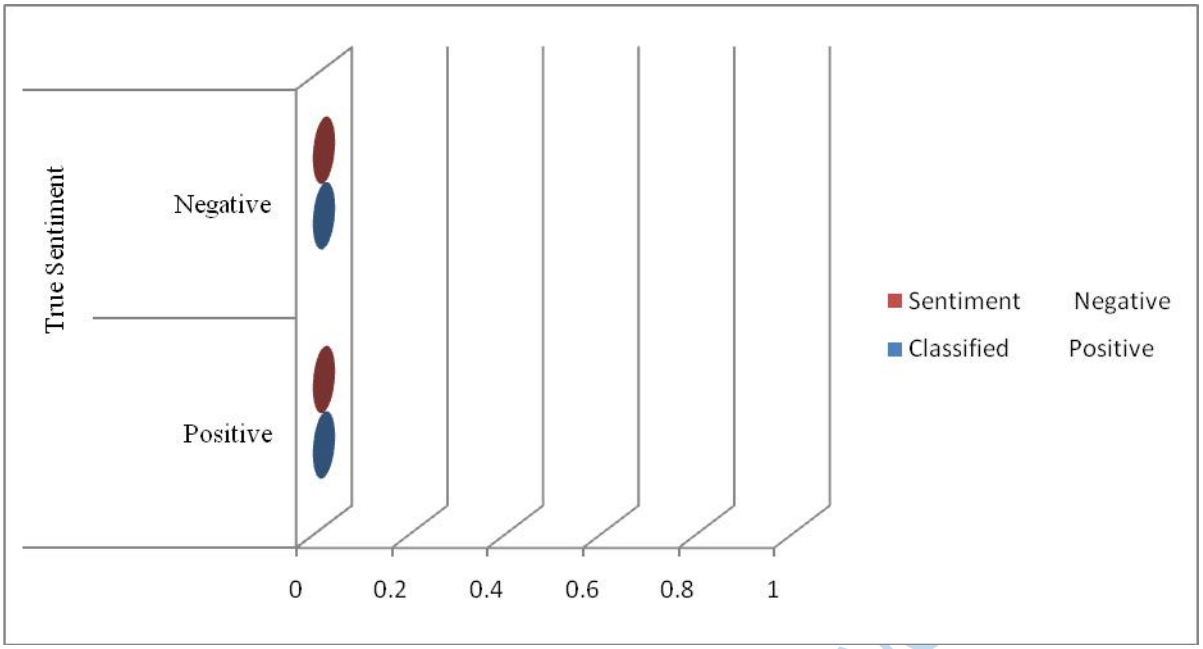


Figure 4.18 Graphical Representations of System Precision and Confusion Matrix

Source: Researcher Fieldwork, 2024

Figure 4.18 shows the pictorial link for precision and confusion matrix because seventy five percent (75%) of the acquired dataset were pre-processed after their extraction from Facebook by data cleaning and discretization as training set in order to train the classifier with a supervised learning approach, while the twenty five per cent (25%) were pre-processed as testing set in order to evaluate the experimental performance of improved system and to determine the precision with confusion matrix.

Table 4.3 Functional Comparison of the Improved System and Existing System

	Source of Data	Nature of Data	Imple-Ment	Method	Devel. Tools	Precision	NLP Library
Proposed System	Facebook	Posts (Thread) and Comments	Yes	Hybridized mining technique (NLP-BBL)	Python, XML, PHP MySQL	90.93%	Graph API
Existing System	Twitter	Tweets	No	Natural Language Processing	Python	N/A	Tweepy API

Source: Researcher Comparism Table, 2024

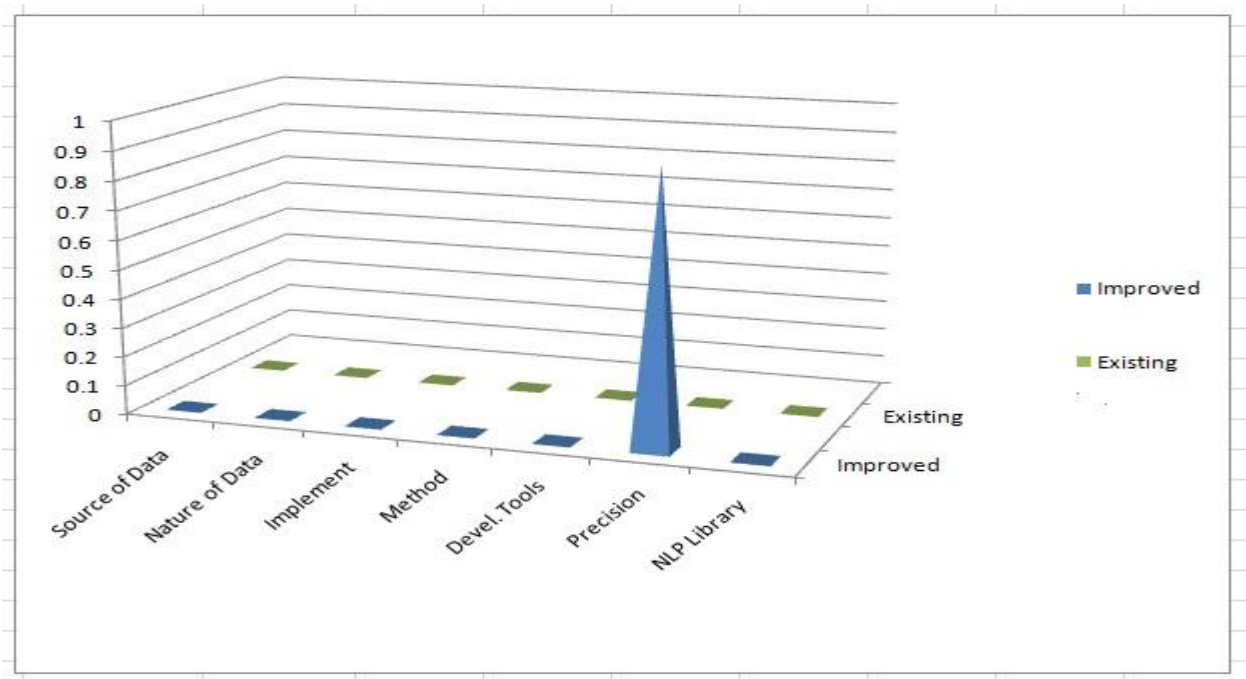


Figure 4.19 Graphical Representations of the Functional

Source: Researcher Comparism Table, 2024

Endnotes

[1]R.A. Baro & T.D. Palaoag, *"Disaster Sentiment Analysis: Addressing the Challenges of Decision-Makers in Visualizing Netizen Tweets,"* ***IOP Conference Series***: Materials Science and Engineering. 2020, DOI:10.1088/1757-899x/803/1/012039

[2]D. Contreras, S. Wilkinson, E. Alterman & J. Hervas, "*Accuracy of a Pre-trained Sentiment Analysis (SA) Classification Model on Tweets related to Emergency response and Early Recovery Assessment: The case of 2019 Albanian earthquake*,"**Journal of Natural Harzard,** *6* (9)*,* 2022, 21-32.

Chapter Five

Conclusion

5.1 Summary of Findings

The development of the Improved Sentimental Response System for Classifying Emergency Incidences Using Hybridized Mining Technique represents a groundbreaking endeavor in the domain of proactive emergency response systems reliant on social media data. A meticulous approach was employed, starting from the extraction of data from diverse social media sources, predominantly Facebook, to construct a localized database tailored for emergency classification purposes. This intricate process encompassed web scraping, data extraction via Graph API, and diligent preprocessing to ensure data accuracy and relevance.

The hardware and software prerequisites were delineated meticulously, emphasizing the necessity for a custom system configuration to guarantee optimal performance. The selection of Python, renowned for its readability and versatility, coupled with MySQL for proficient database management, facilitated efficient data manipulation and processing throughout the system's architecture.

The implementation phase was comprehensive, covering critical aspects such as feature selection, data preprocessing techniques, supervised learning model training, and rigorous testing. The experimental validation substantiated the system's efficacy by showcasing a remarkable precision rate exceeding 90.93%. Visual representations in the form of figures, tables, and graphical aids were employed to elucidate the intricate process and demonstrate the system's accurate classification results.

The system's capability to discern and categorize emergency signals sourced from social media, coupled with its impressive precision rate, underscores its potential to revolutionize emergency response paradigms. By amalgamating techniques like supervised learning and natural language processing, the system effectively addresses critical gaps prevalent in

existing emergency response frameworks. Its adaptability to a wide spectrum of emergency scenarios marks a significant advancement in precision rates compared to prior models.

5.2 Conclusion

The successful development and evaluation of the Improved Sentimental Response System signify a pivotal step forward in leveraging social media data for proactive and efficient emergency management. With a precision rate surpassing 92%, the system adeptly identifies and categorizes emergency signals from social media platforms, paving the way for timely and targeted response strategies.

The amalgamation of methodologies such as supervised learning and natural language processing underscores the system's ability to bridge existing gaps in emergency response systems. Its inclusive approach accommodates diverse emergency scenarios and demonstrates substantial enhancements in precision rates compared to previous models, thereby signifying its potential for transformative impact in emergency management.

The development of the Improved Sentimental Response System for Classifying Emergency Incidences Using Hybridized Mining Technique signifies a pivotal milestone in leveraging social media data for proactive and efficient emergency response mechanisms. Its resounding success in accurately classifying and responding to emergency signals demonstrates its potential and sets the stage for future enhancements, collaborations, and ethical considerations necessary for seamless integration into real-world emergency response frameworks.

Continued refinement, sustained collaborations, and an unwavering commitment to ethical practices are pivotal for this system's evolution. By adhering to these principles, the system can significantly impact emergency management, optimizing response strategies and ultimately contributing to the preservation of lives and resources during critical situations.

5.3 Recommendations

Building on the attained success, several enhancements and applications are recommended to fortify the system's functionality and practical applicability:

Continuous Algorithm Refinement: Sustain ongoing efforts to refine the system's algorithms, adapting to evolving language nuances and ensuring sustained high precision rates while minimizing false classifications.

Real-time Integration and Scalability: Prioritize real-time data integration and scalability to accommodate the escalating volume of social media data, fostering the system's responsiveness to immediate emergency signals.

Ethical Framework Strengthening: Bolster the system's ethical framework by reinforcing stringent privacy measures and responsible data utilization practices, adhering closely to data protection regulations and user privacy.

User-Centric Design: Emphasize user-centric design enhancements to create an intuitive and user-friendly interface, facilitating seamless usage for emergency response personnel.

Collaboration and Deployment: Forge collaborations with emergency management agencies to seamlessly integrate and deploy the system within their operational frameworks, ensuring efficient utilization and harmonized response coordination.

5.4 Contribution to Knowledge

The findings from this study had contributed to body of knowledge in the area of;

i. The relevance of natural language processor in computational intelligence and machine learning had been established, for handling imprecision in text mining and classification hitches; as well as providing economical and location aware model with minimal computational cost.

ii. Insight into preventive measure of reducing wrong escalation, or false alarm about emergency incidence which could create abrupt panic among the occupants of concerned area and residents at large, and without understanding of decision makers in timely manner.

5.5 Suggested Areas for Further Research

Selection of other cases of emergency incidence would be considered for further study so as to measure likely dispersion or variability among incidences types with regards to model specificity. Ensemble of multiple data mininig algorithms and machine learning techniques to experiment with completely localized dataset in order to harmonize disaster control and recovery systems should also be explored.

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APPENDIX I (Source Listing)

```
/*

 An External JavaScript File that contains the function which initializes HOMEPAGE because the function would be executed when "index.html" file is loaded in a web browser.

*/

<!--

function author()

{

alert("\n\t RAPID PROTOTYPING AND EXPLORATORY SIMULATION OF SENTIMENTAL RESPONSE SYSTEM \n\n\n\n  \t\t\t\t Developed By :\n\n   \t\t\t\t Johnson Oluwatobi AKANBI \n   \t\t\t\t Reg. No.: LCU/PG/000135 \n  \t\t\t\t (PhD Thesis / Research Experiment) \n   \t\t\t   \n\n\n\n   \t\t\t\t Technical Support : \n\n \t\t\t\t Great Concepts and Multimedia  \n \t\t\t\t greatconcepts2020@gmail.com" );

}

// -->

<?php

//Establish a connection to the Database

$conn = @mysql_connect('localhost', 'root', '') or die('Could Not Access Database Server....' . mysql_error());

//$conn = @odbc_connect('Emerg',",");


//Select the MySQL database

$db = @mysql_select_db('emerg',$conn) or die('Error! Selecting the Database...' . mysql_error());


 //Issue SELECT SQL Statement

$sql = "SELECT Incidence_Type, Incidence_Class, Incidence_Count FROM predat WHERE Incidence_Count='306'";

//$sql = "SELECT Incidence_Type, Incidence_Class, Incidence_Num FROM pre-data WHERE Incidence_Num ='306'";
```

```
//Execute SQL Statement and store results as a recordset
$rs = @mysql_query($sql,$conn) or die('Could Not Load Data Instances...'.mysql_error());
//$rs = @odbc_exec($conn,$sql) or die('Could Not Load Data Instances...'.mysql_error());
//exit(mysql_error());

while($row = mysql_fetch_array($rs))
//while($row = odbc_fetch_array($rs))
{
?>
<?php
if ($_POST['submit'] == "Click to REGISTER")
{
//Determine if values are entered into form fields correctly
$valid_form = true;
if ($_POST['Fname'] == "" || (is_numeric($_POST['Fname'])))
{
?>
<script language="javascript">
alert("Name field can not be empty or contain numeric value");
location.href="../fail_register.html";
</script>
<?php
$valid_form = false;
}
elseif ($_POST['Email'] == "" || (strlen($_POST['Email']) < 7))
{
```

```
?>
<script language="javascript">
alert("Valid email must be entered and not less than eight characters");
location.href="../fail_register.html";
</script>
<?php
$valid_form = false;
}
elseif ($_POST['Gender'] == "--select--")
{
?>
<script language="javascript">
alert("Oops ! You have not select your gender");
location.href="../fail_register.html";
</script>
<?php
$valid_form = false;
}
elseif ($_POST['Phone'] = "" || (strlen($_POST['Phone']) < 11))
{
?>
<script language="javascript">
alert("Phone number field can not be empty and not less than eleven digits");
location.href="../fail_register.html";
</script>
<?php
$valid_form = false;
```

```
}
elseif ($_POST['Pass'] == "" || $_POST['Tpass'] == "")
{
?>
<script language="javascript">
alert("Password field can not be empty and to be repeated...");
location.href="../fail_register.html";
</script>
<?php
$valid_form = false;
}
elseif ($_POST['Pass'] != $_POST['Tpass'])
{
?>
<script language="javascript">
alert("Your Password Does Not Match! Re-type...");
location.href="../fail_register.html";
</script>
<?php
$valid_form = false;
}
else
{
//collect form data and assign to scalar variables
$Fname = strip_tags($_POST["Fname"]);
$Email = strip_tags($_POST["Email"]);
$Gender  = strip_tags($_POST["Gender"]);
```

```
$Phone = strip_tags($_POST["Phone"]);

$Pass = strip_tags($_POST["Pass"]);

$Tpass = strip_tags($_POST["Tpass"]);

}

//If form fields were submitted properly

if ($valid_form == true)

{

//Establish a connection to the Database

$conn = @mysql_connect('localhost', 'root', '') or die('Could Not Access Database Server....' .
mysql_error());


//Select the MySQL database

$db = @mysql_select_db('emerg',$conn) or die('Error! Selecting the Database...' .
mysql_error());


$dup = @mysql_query("SELECT * FROM access WHERE Pass = '$Pass'",$conn) or
exit(mysql_error());


if (mysql_num_rows($dup) == 1)

{

echo "  <br/>"."<br/>"."<br/>" ."     \r\n";

echo "  <br/>"."<br/>"."<br/>" ."     \r\n";

echo " <br> <h1> <b> <center>   Data Duplication Alert: Username or Password Exist
<> ";

exit(mysql_error());

}


//SQL Statement
```

```
$sql = "INSERT INTO access (Name,Email,Gender,Phone,Pass,Tpass) VALUES
('$Fname','$Email','$Gender','$Phone','$Pass','$Tpass')";


//Execute SQL Statement and store results as a recordset

$rs = @mysql_query($sql,$conn) or die('Query Execution Failed...' . mysql_error());


//verify that the record is inserted

if (mysql_affected_rows($conn) == -1)

{

echo "  <br/>"."<br/>"."<br/>" ."     \r\n";

echo "  <br/>"."<br/>"."<br/>" ."     \r\n";

echo " <br> <h1> <b> <center> Error Encountered! Could Not Complete the Registration!...";

exit(mysql_error());

}

else

{

?>

<script language="javascript">

location.href="../pass_register.html";

</script>

<?php

}

mysql_close($conn);

}


}

?>
```

```
<?php

//Establish a connection to the Database

$conn = @mysql_connect('localhost', 'root', '') or die('Could Not Access Database Server....' .
mysql_error());


//Select the MySQL database

$db = @mysql_select_db('emerg',$conn) or die('Error! Failed to Load Pre-processed
Dataset...' . mysql_error());



 //Issue SELECT SQL Statement

$sql = "SELECT Incidence_Type, Incidence_Class, Incidence_Count, MAX(AVG_Count) as
AVG FROM predat WHERE AVG_Count > 29";


//Execute SQL Statement and store results as a recordset

$rs = @mysql_query($sql,$conn) or die(mysql_error());


while($row = mysql_fetch_array($rs))

{

$file = @fopen("../dbase/Emerg_log.txt", "a+") or exit("Could Not Access the File on Web
Server!");

$content = "Emergency Alert <> Incidence Type :: ".$row['Incidence_Type']."."   "."Incidence
Class :: ".$row['Incidence_Class']."."  "."Incidence Count :: ".$row['Incidence_Count']."."
".date('D F d Y')." <> \r\n";

fwrite($file,$content) or exit("Error! Could Not Create Incidence Log for Classified
Emergency on the Server...");

fclose($file);

/*
```

```
?>

<script language="javascript">

alert("Since the Parameter Values Have Not Been Updated from Sensor Node \n\n Back End Storage of Database Server Will Be Checked \n\n in Converting Numeric Data for Probability Distribution");

</script>

<?php

*/

print "<br/> <center> <h1> :: :: ::   Emergency Classification and Sentimental Response    :: :: ::  " ."<h3> <b> <br/>Incidence Type:  ".$row['Incidence_Type']." <h3> <b> Incidence Class:  ".$row['Incidence_Class']." <h3> <b> Average Count:  ".$row['AVG']."   \r\n  "." <h4> <br/>  According to Sentimental Probability for Each Incidence Category, the classified INCIDENCE is ...   ".$row['Incidence_Class']."   \r\n ";

echo " <center>  <br/>       <img src='../images/announce.jpg' alt=" width='300' heigth='100' /> ";


echo "     \r\n";

print "      <b> <right> <a href='../scripts/logout.php' style='text-decoration:none'> || Log Out || </a>";

}

mysql_close($conn);


$to = "emergency@nema.gov.ng";

$subject = "Emergency Alert";

$message = date('D F d, Y.')." "."Classified Incidence <> ".$row['Incidence_Class']." \r\n";

$headers = "Sentimental Escalation and Emergency Alert :: ". phpversion();

@mail($to, $subject, $message, $headers);


?>
```

```
<?php
if ($_POST['submit'] == "Click Here to LOGIN")
{
//Determine if values are entered into form fields correctly
$valid_form = true;
if ($_POST['Phone'] == "" || $_POST['Pass'] == "")
{
?>
<script language="javascript">
alert("Either the Phone Number or Password is Incorrect, Re-try...");
location.href="../login_fail.html";
</script>
<?php
$valid_form = false;
}
else
{
//collect form data and assign to scalar variables
$Phone  = strip_tags($_POST["Phone"]);
$Pass = strip_tags($_POST["Pass"]);
}
//If form fields were submitted properly
if ($valid_form == true)
{
//Establish a connection to the Database
```

```
$conn = @mysql_connect('localhost', 'root', '') or die('Could Not Access Database Server' .
mysql_error());

//Select the MySQL database

$db = @mysql_select_db('emerg',$conn) or die('Error! Selecting the Database...' .
mysql_error());

//Issue SELECT SQL Statement

$sql = "SELECT * FROM access WHERE Phone = '$Phone' AND Pass = '$Pass'";

//Execute SQL Statement and store results as a recordset

$rs = @mysql_query($sql,$conn) or die('Query Execution Failed...' . mysql_error());

while($row = mysql_fetch_array($rs))

{

//if authentication is successfull

        session_start();

        session_id($Phone);

        //$access;
        //$_SESSION['access'] = "yes";
        //header("Location:access.php")

/*

if ($_SESSION['numb'] == "")

{
```

```
        $_SESSION['numb'] = 1;
}

else
{
        $_SESSION['numb'] = $_SESSION['numb'] + 1;


}
*/


                $cookie_name = "user";

                $cookie_value = $Phone;

                $cookie_value = $cookie_value;

                $cookie_expire = time() + 14400;


                setcookie($cookie_name,$cookie_value,$cookie_expire,"/");


print "<br> <b> <h2> <center> \t Welcome , ".$row['Name']."!    Today:  ". date('D F d, Y.') ."    At...  ".date('g:i a');

echo "  <br/>"."     \r\n";

echo "  <br/>"." <center> <img src='../images/keys.jpg' alt=" width='300' heigth='200' /> " ."     \r\n";

echo "  <br/>"."     \r\n";

print " <h2> <b> <center> <a href='../preprocess.html' style='text-decoration:none;'> Click Here to Continue... </a>";

//isset($_SESSION["login"]);

}
```

```
//verify that the record is retrieved

if (mysql_num_rows($rs) == 0)

{

echo "  <br/>"."<br/>"."<br/>" ."     \r\n";

echo "  <br> <h1> <b> <center>    Error Encountered! ....Unauthorized User
<>";

echo "  <br/> <br/>"." <center> <img src='../images/lock.png' alt=" width='100' heigth='50'
/> " ."     \r";

echo "  <br/>"." <center> <img src='../images/home.png' alt=" width='100' heigth='50' /> " ."
    \r\n ";

print " <h2> <b> <center> <a href='../login_fail.html' style='text-decoration:none;'> Click
Here to Return... </a>";


exit(mysql_error());

//unset($_SESSION["login"]);

}


mysql_close($conn);

}


}


?>

<?php


session_destroy();

header("Location: ../fail_register.html");
```

```
/*
if ($_POST['submit'] == "Log Out")
{
        //if the user decides to exit
        session_destroy();
}
*/

?>
/*!
 * Modernizr JavaScript library 1.5
 * http://www.modernizr.com/
 *
 * Copyright (c) 2009-2010 Faruk Ates - http://farukat.es/
 * Dual-licensed under the BSD and MIT licenses.
 * http://www.modernizr.com/license/
 *
 * Featuring major contributions by
 * Paul Irish  - http://paulirish.com
 */
 window.Modernizr=function(i,e,I){function C(a,b){for(var c in
a)if(m[a[c]]!==I&&(!b||b(a[c],D)))return true}function r(a,b){var
c=a.charAt(0).toUpperCase()+a.substr(1);return!!C([a,"Webkit"+c,"Moz"+c,"O"+c,"ms"+c,"
Khtml"+c],b)}function P(){j[E]=function(a){for(var
b=0,c=a.length;b<c;b++)J[a[b]]=!!(a[b]in n);return J}("autocomplete autofocus list
placeholder max min multiple pattern required step".split(" "));j[Q]=function(a){for(var
b=0,c,h=a.length;b<h;b++){n.setAttribute("type",a[b]);if(c=n.type!==

"text"){n.value=K;/tel|search/.test(n.type)||(c=/url|email/.test(n.type)?n.checkValidity&&n.ch
```

eckValidity()===false:n.value!=K)}L[a[b]]=!!c}return L}("search tel url email datetime date month week time datetime-local number range color".split(" "))}var j={},s=e.documentElement,D=e.createElement("modernizr"),m=D.style,n=e.createElement("input"),E="input",Q=E+"types",K=":)",M=Object.prototype.toString,y=" -o- -moz- -ms- -webkit- -khtml- ".split(" "),d={},L={},J={},N=[],u=function(){var a={select:"input",

change:"input",submit:"form",reset:"form",error:"img",load:"img",abort:"img"},b={};return function(c,h){var t=arguments.length==1;if(t&&b[c])return b[c];h=h||document.createElement(a[c]||"div");c="on"+c;var g=c in h;if(!g&&h.setAttribute){h.setAttribute(c,"return;");g=typeof h[c]=="function"}h=null;return t?(b[c]=g):g}}(),F={}.hasOwnProperty,O;O=typeof F!=="undefined"&&typeof F.call!=="undefined"?function(a,b){return F.call(a,b)}:function(a,b){return b in a&&typeof a.constructor.prototype[b]==="undefined"};

d.canvas=function(){return!!e.createElement("canvas").getContext};d.canvastext=function(){return!!(d.canvas()&&typeof e.createElement("canvas").getContext("2d").fillText=="function")};d.geolocation=function(){return!!navigator.geolocation};d.crosswindowmessaging=function(){return!!i.postMessage};d.websqldatabase=function(){var a=!!i.openDatabase;if(a)try{a=!!openDatabase("testdb","1.0","html5 test db",2E5)}catch(b){a=false}return a};d.indexedDB=function(){return!!i.indexedDB};d.hashchange=function(){return u("hashchange",

i)&&(document.documentMode===I||document.documentMode>7)};d.historymanagement=function(){return!!(i.history&&history.pushState)};d.draganddrop=function(){return u("drag")&&u("dragstart")&&u("dragenter")&&u("dragover")&&u("dragleave")&&u("dragend")&&u("drop")};d.websockets=function(){return"WebSocket"in i};d.rgba=function(){m.cssText="background-color:rgba(150,255,150,.5)";return(""+m.backgroundColor).indexOf("rgba")!==-1};d.hsla=function(){m.cssText="background-color:hsla(120,40%,100%,.5)";return(""+

m.backgroundColor).indexOf("rgba")!==-1};d.multiplebgs=function(){m.cssText="background:url(//:),url(//:),red url(//:)";return/(url\s*\(.*?){3}/.test(m.background)};d.backgroundsize=function(){return r("backgroundSize")};d.borderimage=function(){return r("borderImage")};d.borderradius=function(){return r("borderRadius","",function(a){return(""+a).indexOf("orderRadius")!==-1})};d.boxshadow=function(){return r("boxShadow")};d.opacity=function(){var a=y.join("opacity:.5;")+"";m.cssText=a;return(""+m.opacity).indexOf("0.5")!==

-1};d.cssanimations=function(){return r("animationName")};d.csscolumns=function(){return

r("columnCount")};d.cssgradients=function(){var a=("background-
image:"+y.join("gradient(linear,left top,right bottom,from(#9f9),to(white));background-
image:")+y.join("linear-gradient(left top,#9f9, white);background-image:")).slice(0,-
17);m.cssText=a;return(""+m.backgroundImage).indexOf("gradient")!==-
1};d.cssreflections=function(){return
r("boxReflect")};d.csstransforms=function(){return!!C(["transformProperty",

"WebkitTransform","MozTransform","OTransform","msTransform"])};d.csstransforms3d=f
unction(){var
a=!!C(["perspectiveProperty","WebkitPerspective","MozPerspective","OPerspective","msPer
spective"]);if(a){var
b=document.createElement("style"),c=e.createElement("div");b.textContent="@media
("+y.join("transform-
3d),(")+"modernizr){#modernizr{height:3px}}";e.getElementsByTagName("head")[0].appen
dChild(b);c.id="modernizr";s.appendChild(c);a=c.offsetHeight===3;b.parentNode.removeCh
ild(b);c.parentNode.removeChild(c)}return a};

d.csstransitions=function(){return r("transitionProperty")};d.fontface=function(){var
a;if(/*@cc_on@if(@_jscript_version>=5)!@end@*/0)a=true;else{var
b=e.createElement("style"),c=e.createElement("span"),h,t=false,g=e.body,o,w;b.textContent=
"@font-face{font-
family:testfont;src:url('data:font/ttf;base64,AAEAAAAMAIAAAwBAT1MvMliohmwAAA
DMAAAAVmNtYXCp5qrBAAABJAAAANhjdnQgACICiAAAAfwAAAAEZ2FzcP//AAM
AAAIAAAAACGdseWYv5OZoAAACCAAAANxoZWFk69bnvwAAAuQAAAA2aGhlYQ
UJAt8AAAMcAAAAJGhtdHgGDgC4AAADQAAAABRsb2NhAIQAwgAAA1QAAAAMb
WF4cABVANgAAANgAAAAIG5hbWUgXduAAAADgAAABPVwb3N03NkzmgAACHg
AAAA4AAECBAEsAAUAAAKZAswAAACPApkCzAAAAesAMwEJAAACAAMDAAA
AAAAAgAACbwAAAAoAAAAAAAAAAFBmRWQAAAAgqS8DM/8zAFwDMwDNAA
AABQAAAAAAAAAAAAMAAAADAAAAHAABAAAAAAABGAAMAAQAAAK4ABA
AqAAAABgAEAAEAAgAuqQD//wAAAC6pAP///9ZXAwAAAAAAAAACAAAABgBoA
AAAAAAvAAEAAAAAAAAAAAAAAAAAAAAABAAIAAAAAAAAAAgAAAAAAAA
AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAABAAAAAAAAAAAAAAAAAA
AAAAAAAAAAAAAAAAAAAAAAAAAAAABAAEACoAAAAGAAQAAQACAC6pAP//
AAAALqkA////1lcDAAAAAAAAAAIAAAAiAogAAAAB//8AAgACACIAAAEyAqoAAw
AHAC6xAQAvPLIHBADtMrEGBdw8sgMCAO0yALEDAC88sgUEAO0ysgcGAfw8sgEC
AO0yMxEhESczESMiARDuzMwCqv1WIgJmAAACAFUAAAIRAc0ADwAfAAATFRQ
WOwEyNj0BNCYrASIGARQGKwEiJj0BNDY7ATIWFX8aIvAiGhoi8CIaAZIoN/43KCg3/
jcoAWD0JB4eJPQkHh7++EY2NkbVRjY2RgAAAAABAEH/+QCdAEEACQAANjQ2MzI
WFAYjIkEeEA8fHw8QDxwWFhwWAAAAAQAAAAIAAIuYbWpfDzz1AAsEAAAAAA
DFn9IuAAAAAMWf0i797/8zA4gDMwAAAAgAAgAAAAAAAAABAAADM/8zAFwDx/
3v/98DiAABAAAAAAAAAAAAAAAAAAAAAABQF2ACIAAAAAAVUAAAJmAFUA3Q
BBAAAAKgAqACoAWgBuAAEAAAAFAFAABwBUAAQAAgAAAAEAAQAAAEAAL
gADAAMAAAAQAMYAAQAAAAAAAACLAAAAAQAAAAAAAQAhAIsAAQAAAA

AAAgAFAKwAAQAAAAAAAwBDALEAAQAAAAAABAAnAPQAAQAAAAAABQA
KARsAAQAAAAAABgAmASUAAQAAAAAADgAaAUsAAwABBAkAAAEWAWUAA
wABBAkAAQBCAnsAAwABBAkAAgAKAr0AAwABBAkAAwCGAscAAwABBAkABA
BOA00AAwABBAkABQAUA5sAAwABBAkABgBMA68AAwABBAkADgA0A/tDb3B5c
mlnaHQgMjAwOSBieSBEYW5pZWwgSm9obnNvbi4gIFJlbGVhc2VkIHVuZGVyIHRoZS
B0ZXJtcyBvZiB0aGUgT3BlbiBGb250IExpY2Vuc2UuIEtheWFoIExpIGdseXBocyBhcmUg
cmVsZWFzZWQgdW5kZXIgdGhlIEdQTCB2ZXJzaW9uIDMuYmFlYzJhOTJiZmZlNTAz
MiAtIHN1YnNldCBvZiBKdXJhTGlnaHRiYWVjMmE5MmJmZmU1MDMyIC0gc3Vic2V0
IG9mIEZvbnRGb3JnZSAyLjAgOiBKdXJhIExpZ2h0IDogMjMtMS0yMDA5YmFlYzJhOTJ
iZmZlNTAzMiAtIHN1YnNldCBvZiBKdXJhIExpZ2h0VmVyc2lvbiAyIGJhZWMyYTkyY
mZmZTUwMzIgLSBzdWJzZXQgb2YgSnVyYUxpZ2h0aHR0cDovL3NjcmlwdHMuc2lsLm
9yZy9PRkwAQwBvAHAAeQByAGkAZwBoAHQAIAAyADAAMAA5ACAAYgB5ACA
ARABhAG4AaQBlAGwAIABKAG8AaABuAHMAbwBuAC4AIAAgAFIAZQBsAGUAY
QBzAGUAZAAgAHUAbgBkAGUAcgAgAHQAaABlACAAdABlAHIAbQBzACAAbwB
mACAAdABoAGUAIABPAHAAZQBuACAARgBvAG4AdAAgAEwAaQBjAGUAbgBzA
GUALgAgAEsAYQB5AGEAaAAgAEwAaQAgAGcAbAB5AHAAaABzACAAYQByAG
UAIABAyAGUAbABlAGEAcwBlAGQAIAB1AG4AZABlAHIAIAB0AGgAZQAgAEcAUA
BMACAAdgBlAHIAcwBpAG8AbgAgADMALgBiAGEAZQBjADIAYQA5ADIAYgBmA
GYAZQA1ADAAMwAyACAALQAgAHMAdQBiAHMAZQB0ACAAbwBmACAASgB1
AHIAYQBMAGkAZwBoAHQAYgBhAGUAYwAyAGEAOQAyAGIAZgBmAGUANQA
wADMAMgAgAC0AIABzAHUAYgBzAGUAdAAgAG8AZgAgAEYAbwBuAHQARgBv
AHIAZwBlACAAMgAuADAAIAA6ACAASgB1AHIAYQAgAEwAaQBnAGgAdAAgAD
oAIAAyADMALQAxAC0AMgAwADAAOQBiAGEAZQBjADIAYQA5ADIAYgBmAGY
AZQA1ADAAMwAyACAALQAgAHMAdQBiAHMAZQB0ACAAbwBmACAASgB1AHI
AYQAgAEwAaQBnAGgAdABWAGUAcgBzAGkAbwBuACAAMgAgAGIAYQBlAGMA
MgBhADkAMgBiAGYAZgBlADUAMAAzADIAIAAtACAAcwB1AGIAcwBlAHQAIABv
AGYAIABKAHUAcgBhAEwAaQBnAGgAdABoAHQAdABwADoALwAvAHMAYwByA
GkAcAB0AHMALgBzAGkAbAAuAG8AcgBnAC8ATwBGAEwAAAAAAgAAAAAAAP
+BADMAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFAAAAAQACAQIAEQt6ZXJva
2F5YWhsaQ==')}";

e.getElementsByTagName("head")[0].appendChild(b);c.setAttribute("style","font:99px
_,arial,helvetica;position:absolute;visibility:hidden");if(!g){g=s.appendChild(e.createElement
("fontface"));t=true}c.innerHTML=".....";c.id="fonttest";g.appendChild(c);h=c.offsetWidth
*c.offsetHeight;c.style.font="99px
testfont,_,arial,helvetica";a=h!==c.offsetWidth*c.offsetHeight;var
v=function(){if(g.parentNode){a=j.fontface=h!==c.offsetWidth*c.offsetHeight;s.className=
s.className.replace(/(no-)?fontface\b/,"")+

(a?" ":" no-
")+"fontface"}};setTimeout(v,75);setTimeout(v,150);addEventListener("load",function(){v();
(w=true)&&o&&o(a);setTimeout(function(){t||(g=c);g.parentNode.removeChild(g);b.parent
Node.removeChild(b)},50)},false)}j._fontfaceready=function(p){w||a?p(a):(o=p)};return
a||h!==c.offsetWidth};d.video=function(){var

a=e.createElement("video"),b=!!a.canPlayType;if(b){b=new
Boolean(b);b.ogg=a.canPlayType('video/ogg;
codecs="theora"');b.h264=a.canPlayType('video/mp4;
codecs="avc1.42E01E"');b.webm=a.canPlayType('video/webm; codecs="vp8,
vorbis"')}return b};

d.audio=function(){var a=e.createElement("audio"),b=!!a.canPlayType;if(b){b=new
Boolean(b);b.ogg=a.canPlayType('audio/ogg;
codecs="vorbis"');b.mp3=a.canPlayType("audio/mpeg;");b.wav=a.canPlayType('audio/wav;
codecs="1"');b.m4a=a.canPlayType("audio/x-m4a;")||a.canPlayType("audio/aac;")}return
b};d.localStorage=function(){return"localStorage"in
i&&i.localStorage!==null};d.sessionStorage=function(){try{return"sessionStorage"in
i&&i.sessionStorage!==null}catch(a){return
false}};d.webworkers=function(){return!!i.Worker};

d.applicationCache=function(){var a=i.applicationCache;return!!(a&&typeof
a.status!="undefined"&&typeof a.update=="function"&&typeof
a.swapCache=="function")};d.svg=function(){return!!e.createElementNS&&!!e.createEleme
ntNS("http://www.w3.org/2000/svg","svg").createSVGRect};d.smil=function(){return!!e.cre
ateElementNS&&/SVG/.test(M.call(e.createElementNS("http://www.w3.org/2000/svg","ani
mate")))};d.svgclippaths=function(){return!!e.createElementNS&&/SVG/.test(M.call(e.creat
eElementNS("http://www.w3.org/2000/svg",

"clipPath"))))};for(var z in d)if(O(d,z))N.push((j[z.toLowerCase()]=d[z]())?"":"no-
")+z.toLowerCase());j[E]||P();j.addTest=function(a,b){a=a.toLowerCase();if(!j[a]){b=!!b();s.
className+=" "+(b?"":"no-")+a;j[a]=b;return j}};m.cssText="";D=n=null;(function(){var
a=e.createElement("div");a.innerHTML="<elem></elem>";return
a.childNodes.length!==1})()&&function(a,b){function
c(f,k){if(o[f])o[f].styleSheet.cssText+=k;else{var
l=t[G],q=b[A]("style");q.media=f;l.insertBefore(q,l[G]);o[f]=q;c(f,k)}}function h(f,

k){for(var l=new
RegExp("\\b("+w+")\\b(?!.*[;}])","gi"),q=function(B){return".iepp_"+B},x=-
1;++x<f.length;){k=f[x].media||k;h(f[x].imports,k);c(k,f[x].cssText.replace(l,q))}}for(var
t=b.documentElement,g=b.createDocumentFragment(),o={},w="abbr|article|aside|audio|canv
as|command|datalist|details|figure|figcaption|footer|header|hgroup|keygen|mark|meter|nav|out
put|progress|section|source|summary|time|video",v=w.split("|"),p=[],H=-
1,G="firstChild",A="createElement";++H<v.length;){b[A](v[H]);g[A](v[H])}g=

g.appendChild(b[A]("div"));a.attachEvent("onbeforeprint",function(){for(var
f,k=b.getElementsByTagName("*"),l,q,x=new RegExp("^"+w+"$","i"),B=-
1;++B<k.length;)if((f=k[B])&&(q=f.nodeName.match(x))){l=new
RegExp("^\\s*<"+q+"(.*)\\/"+q+">\\s*$","i");g.innerHTML=f.outerHTML.replace(/\r|\n/g,"
").replace(l,f.currentStyle.display=="block"?"<div$1/div>":"<span$1/span>");l=g.childNode
s[0];l.className+="

iepp_"+q;l=p[p.length]=[f,l];f.parentNode.replaceChild(l[1],l[0])}h(b.styleSheets,"all")});a.attachEvent("onafterprint",

function(){for(var f=-1,k;++f<p.length;)p[f][1].parentNode.replaceChild(p[f][0],p[f][1]);for(k in o)t[G].removeChild(o[k]);o={};p=[]})}(this,e);j._enableHTML5=true;j._version="1.5";s.className=s.className.replace(/\bno-js\b/,"")+" js";s.className+=" "+N.join(" ");return j}(this,this.document);

<!DOCTYPE html PUBLIC "-//W3C//DTD XHTML 1.0 Transitional//EN" "http://www.w3.org/TR/xhtml1/DTD/xhtml1-transitional.dtd">

<html xmlns="http://www.w3.org/1999/xhtml">

<head>

<meta http-equiv="Content-Type" content="text/html; charset=iso-8859-1" />

<title>Initializing the Classifier </title>

</head>

<body style="background-color:#FFFFCC">

   <h3 style="color:#0000CC"> TEXTUAL DATA FROM SOCIAL MEDIA ARE BEING CONVERTED TO NUMERIC DATA (NOMINAL VALUES) FOR THE CLASSIFIER </h3>

 <table cellspacing="10" cellspacing="10" border="5px" style="color:#000066; background-color:#FFCCFF;font-weight:bold">

<tr> <td>Incidence_Type</td> <td>Incidence_Class</td> <td>Incidence_Count</td> </tr>

<tr> <td>5</td> <td>Fire_Outbreak</td> <td>62</td> </tr>

<tr> <td>4</td> <td>Robbery_Theft</td> <td>100</td> </tr>

<tr> <td>3</td> <td>Kidnap_Abduction</td> <td>175</td> </tr>

<tr> <td>2</td> <td>Violence_Crises</td> <td>133</td> </tr>

<tr> <td>1</td> <td>Flood_Erosion</td> <td>306</td> </tr>

<tr> <td>0</td> <td>Null_Incidence</td> <td>121</td> </tr>

```
</table>

<br/> <br/> <center> <img src='images/ai.jpg' alt='' width='500' heigth='300' /> </center>

<h2> <b>

<a href='scripts/classify.php' style='text-decoration:blink;'> Load Pre-processed Dataset and Classify... </a>

</b> </h2>

</center>

</body>

</html>

<!--

//print "<br> <b> <center> <h3> TEXTUAL DATA FROM SOCIAL MEDIA ARE BEING CONVERTED TO NUMERIC DATA (NOMINAL VALUES) FOR THE CLASSIFIER";

//print "<br>".$row['Incidence_Type']."<br> <h4> ".$row['Incidence_Class']."<br> <h4> ".$row['Incidence_Count']." <br> <h4> ";

//echo "  <br/>"."     \r\n";

//echo "  <br/>"." <center> <img src='../images/ai.jpg' alt='Splash Image' width='600' heigth='400' /> " ."     \r\n";

//echo "  <br/>"."     \r\n";

//print " <h2> <b> <center> <a href='classify.php' style='text-decoration:blink;'> Load Pre-processed Dataset and Classify... </a>";

-->

<?php

}

@mysql_close($conn);

//@odbc_close($conn);


/***

else

{
```

```
//collect form data and assign to scalar variables
$TimeDate = strip_tags($_POST["TimeDate"]);
$Heat = strip_tags($_POST["Heat"]);
$Vapour  = strip_tags($_POST["Vapour"]);
$Flame = strip_tags($_POST["Flame"]);

if ($Heat >= 0 && $Heat <= 34)
{
$Temperature = "Low"
}
elseif ($Heat >= 35 && $Heat <= 74)
{
$Temperature = "Mild"
}
else
{
$Temperature = "High"
}
}
***/
?>
```



```
<!DOCTYPE html PUBLIC "-//W3C//DTD XHTML 1.0 Transitional//EN"
"http://www.w3.org/TR/xhtml1/DTD/xhtml1-transitional.dtd">
<html xmlns="http://www.w3.org/1999/xhtml">
```

```
<!-- DW6 -->
<head>
<!-- Copyright 2005 Macromedia, Inc. All rights reserved. -->
<!-- <meta http-equiv="Content-Type" content="text/html; charset=iso-8859-1" /> -->
<meta name="description" content="website description" />
<meta name="keywords" content="website keywords, website keywords" />
<meta name="viewport" content="width=device-width, initial-scale=1.0">
<meta http-equiv="content-type" content="text/html; charset=windows-1252" />
<meta http-equiv="Content-Type" content="text/html; charset=iso-8859-1" />
<title>Classifier :: Emerg_SA</title>
<link rel="stylesheet" href="styles/2col_leftNav.css" type="text/css" />
<style type="text/css">
<!--
.style2 {
        color: #334d55;
        font-weight: bold;
}
.style5 {font-size: 130%}
.style6 {color: #FF6600}
.style7 {color: #334d55}
.style8 {color: #cccccc}
#Layer1 {
        position:absolute;
        width:308px;
        height:173px;
        z-index:1;
        top: 257px;
```

```
        left: 0px;
}
-->
</style>
<?php require('jscript.inc') ?>
<script language="javascript" type="text/javascript" src="scripts/modernizr-1.5.min.js">
</script>
<script language="javascript" type="text/javascript" src="scripts/webbased.js"> </script>
<script language="php" type="text/php" src="scripts/register.php"> </script>
<script language="php" type="text/php" src="scripts/login.php"> </script>
</head>
<!-- The structure of this file is exactly the same as 2col_rightNav.html;
    the only difference between the two is the stylesheet they use -->
<body onload="author();">
<div id="masthead">
  <h1 id="siteName"><img src="images/model.jpg" alt="TASUED" name="banner"
width="400" height="80" id="banner" style="background-color: #9900FF" />
     Improved Sentimental Response System for Classifying
Emergency Incidence  </h1>
  <div id="globalNav"> <span class="style8"> </span> </div>
</div>
<!-- end masthead -->
<div id="content">
  <div id="breadCrumb"> <a href="#"></a></div>
  <h2 id="pageName" class="intro">New User  :: Register Here... </h2>
  <div class="feature">
    <p><img src="images/gov.jpg" width="172" height="100" /></p>
    <form id="form2" name="form2" method="post" action="scripts/register.php">
```

```
<label></label>
<label>Name: </label>
<input name="Fname" type="text" size="74"/>
<br />
<br />
  
<span class="style7"><strong>Email: </strong><strong> </strong></span>
<input type="text" name="Email" size="72"//>

<br />
<br />

<label> Gender: </label>
<select name="Gender" size="1">
  <option>--select--</option>
  <option>Male</option>
  <option>Female</option>
</select>
<label for="select"></label>
<label>
<span class="style2">Phone No.:</span> </label>
<input type="text" name="Phone" size="46"/>
   <br />
<br />
<span class="style2">Password</span><strong>:</strong>
<input type="password" name="Pass" />
<span class="style2">Repeat Password:</span>
```

```
    <input type="password" name="Tpass" onKeyDown="if(event.keyCode==13)
event.keyCode=9;" />
            
    <input type="submit" name="submit" value="Click to REGISTER" />
   </form>
  </div>
  <div class="story">
   <h2 id="pageName">Returning User :: Login Here... </h2>
   <form id="form1" name="form1" method="post" action="scripts/login.php">
    <label></label>
    <p>
     <label></label>
     <label>Phone No. : </label>
     <input type="text" name="Phone" />
    </p>

     <label></label>
     <label>Password: </label>
     <input type="password" name="Pass" onKeyDown="if(event.keyCode==13)
event.keyCode=9;" />      
     <input type="submit" name="submit" value="Click Here to LOGIN" />
   </form>

  </div>
  <div class="story">
   <h4>
    <!--end content -->
   </h4>
```

```
  </div>
</div>
<div id="navBar">
  <div id="search">
    <form action="#">
     <!-- <label>Selected Cases </label> --> <input name="searchFor" type="text" value="Selected Cases..." size="25" />
      <input name="goButton" type="submit" value="Go" class="buttonS" onMouseOver="OverMouse(this);" onMouseOut="OutMouse(this);" />
    </form>
  </div>
  <div id="sectionLinks">
    <ul>
      <li> </li>
      <li> *** Fire *** </li>
      <li>*** Robbery ***</li>
      <li>*** Kidnap ***</li>
      <li>*** Violence ***</li>
            <li>*** Flood ***</li>

    </ul>
  </div>

</div>
<!--end navbar -->
<div id="Layer1"><img src="images/fire.jpg" width="302" height="167" /></div>
<br /> <br />
```

```
<div class="style6" id="siteInfo">
  <div align="center">
  <br />
    <p>DeGreat - Copyright Reserved &copy; 2023</p>
  </div>
</div>
<br />
</body>
</html>


<!DOCTYPE html PUBLIC "-//W3C//DTD XHTML 1.0 Transitional//EN"
"http://www.w3.org/TR/xhtml1/DTD/xhtml1-transitional.dtd">
<html xmlns="http://www.w3.org/1999/xhtml">
<!-- DW6 -->
<head>
<!-- Copyright 2005 Macromedia, Inc. All rights reserved. -->
<!-- <meta http-equiv="Content-Type" content="text/html; charset=iso-8859-1" /> -->
<meta name="description" content="website description" />
<meta name="keywords" content="website keywords, website keywords" />
<meta name="viewport" content="width=device-width, initial-scale=1.0">
<meta http-equiv="content-type" content="text/html; charset=windows-1252" />
<meta http-equiv="Content-Type" content="text/html; charset=iso-8859-1" />
<title>Emerg_SA ::  Registration Failure</title>
<link rel="stylesheet" href="styles/2col_leftNav.css" type="text/css" />
<style type="text/css">
<!--
.style2 {
```

```
        color: #334d55;
        font-weight: bold;
}
.style5 {font-size: 130%}
.style6 {color: #FF6600}
.style7 {color: #334d55}
.style8 {color: #cccccc}
#Layer1 {
        position:absolute;
        width:308px;
        height:173px;
        z-index:1;
        top: 257px;
        left: 0px;
}
-->
</style>
<?php require('jscript.inc') ?>
<script language="javascript" type="text/javascript" src="scripts/modernizr-1.5.min.js">
</script>
<script language="javascript" type="text/javascript" src="scripts/webbased.js"> </script>
<script language="php" type="text/php" src="scripts/register.php"> </script>
<script language="php" type="text/php" src="scripts/login.php"> </script>
</head>
<!-- The structure of this file is exactly the same as 2col_rightNav.html;
    the only difference between the two is the stylesheet they use -->
<body onload="">
```

```
<div id="masthead">

  <h1 id="siteName"><img src="images/model.jpg" alt="" name="banner" width="400" height="80" id="banner" style="background-color: #9900FF" />      Improved Sentimental Response System for Classifying Emergency Incidence  </h1>

  <div id="globalNav"> <span class="style8"> </span> </div>

</div>

<!-- end masthead -->

<div id="content">

  <div id="breadCrumb"> <a href="#"></a></div>

  <h2 id="pageName" class="intro">New User  :: Register Here... </h2>

  <div class="feature">

    <p><img src="images/gov.jpg" width="172" height="100" /></p>

    <form id="form2" name="form2" method="post" action="scripts/register.php">

      <label></label>

      <label>Name: </label>

      <input name="Fname" type="text" size="74"/>

      <br />

      <br />

              

      <span class="style7"><strong>Email: </strong><strong> </strong></span>

      <input type="text" name="Email" size="72"//>

      <br />

      <br />

      <label> Gender: </label>

      <select name="Gender" size="1">

        <option>--select--</option>
```

```
      <option>Male</option>
      <option>Female</option>
    </select>
    <label for="select"></label>
    <label>
    <span class="style2">Phone No.:</span> </label>
    <input type="text" name="Phone" size="46"/>
   <br />
    <br />
    <span class="style2">Password</span><strong>:</strong>
    <input type="password" name="Pass" />
    <span class="style2">Repeat Password:</span>
    <input type="password" name="Tpass" onKeyDown="if(event.keyCode==13)
event.keyCode=9;" />
        
    <input type="submit" name="submit" value="Click to REGISTER" />
  </form>
 </div>
 <div class="story">
  <h2 id="pageName">Returning User :: Login Here... </h2>
  <form id="form1" name="form1" method="post" action="scripts/login.php">
    <label></label>
    <p>
      <label></label>
      <label>Phone No. : </label>
      <input type="text" name="Phone" />
    </p>
```

```
        <label></label>

        <label>Password: </label>

        <input type="password" name="Pass" onKeyDown="if(event.keyCode==13)
event.keyCode=9;" />


        <input type="submit" name="submit" value="Click Here to LOGIN" />




    </form>


  </div>

  <div class="story">

    <h1>

      <!--end content -->

      <img src="images/warning.png" alt="" width="100" height="60" /><span
class="style10"> Registration Error !, all fields must be completed... </span> </h1>

  </div>

</div>

<div id="navBar">

  <div id="search">

    <form action="#">

      <!-- <label>Selected Cases </label> --> <input name="searchFor" type="text"
value="Selected Cases..." size="25" />

      <input name="goButton" type="submit" value="Go" class="buttonS"
onMouseOver="OverMouse(this);" onMouseOut="OutMouse(this);" />

    </form>
```

```
 </div>
 <div id="sectionLinks">
  <ul>
   <li> </li>
   <li> *** Fire *** </li>
   <li>*** Robbery ***</li>
   <li>*** Kidnap ***</li>
   <li>*** Violence ***</li>
        <li>*** Flood ***</li>

  </ul>
 </div>



</div>
<!--end navbar -->
<div id="Layer1"><img src="images/fire.jpg" width="302" height="167" /></div>
<br /> <br />
<div class="style6" id="siteInfo">
 <div align="center">
 <br />
  <p>DeGreat - Copyright Reserved &copy; 2023</p>
 </div>
</div>
<br />
</body>
</html>
```

```
<!DOCTYPE html PUBLIC "-//W3C//DTD XHTML 1.0 Transitional//EN"
"http://www.w3.org/TR/xhtml1/DTD/xhtml1-transitional.dtd">

<html xmlns="http://www.w3.org/1999/xhtml">

<!-- DW6 -->

<head>

<!-- Copyright 2005 Macromedia, Inc. All rights reserved. -->

<!-- <meta http-equiv="Content-Type" content="text/html; charset=iso-8859-1" /> -->

<meta name="description" content="website description" />

<meta name="keywords" content="website keywords, website keywords" />

<meta name="viewport" content="width=device-width, initial-scale=1.0">

<meta http-equiv="content-type" content="text/html; charset=windows-1252" />

<meta http-equiv="Content-Type" content="text/html; charset=iso-8859-1" />

<title>Emerg_SA :: Login Failure</title>

<link rel="stylesheet" href="styles/2col_leftNav.css" type="text/css" />

<style type="text/css">

<!--

.style2 {

        color: #334d55;

        font-weight: bold;

}

.style5 {font-size: 130%}

.style6 {color: #FF6600}

.style7 {color: #334d55}

.style8 {color: #cccccc}

#Layer1 {

        position:absolute;

        width:308px;
```

```
        height:173px;
        z-index:1;
        top: 257px;
        left: 0px;
}
-->
</style>
<?php require('jscript.inc') ?>
<script language="javascript" type="text/javascript" src="scripts/modernizr-1.5.min.js">
</script>
<script language="javascript" type="text/javascript" src="scripts/webbased.js"> </script>
<script language="php" type="text/php" src="scripts/register.php"> </script>
<script language="php" type="text/php" src="scripts/login.php"> </script>
</head>
<!-- The structure of this file is exactly the same as 2col_rightNav.html;
    the only difference between the two is the stylesheet they use -->
<body onload="">
<div id="masthead">
  <h1 id="siteName"><img src="images/model.jpg" alt="" name="banner" width="400"
height="80" id="banner" style="background-color: #9900FF" />     
Improved Sentimental Response System for Classifying Emergency Incidence  </h1>
  <div id="globalNav"> <span class="style8"> </span> </div>
</div>
<!-- end masthead -->
<div id="content">
 <!-- <div id="breadCrumb"> <a href="#"></a></div>
  <h2 id="pageName" class="intro">New User  :: Register Here... </h2>
  <div class="feature">
```

```
<p><img src="images/gov.jpg" width="172" height="100" /></p>
<form id="form2" name="form2" method="post" action="scripts/register.php">
<label></label>
<label>Name: </label>
<input name="Fname" type="text" size="74"/>
<br />
<br />
  
<span class="style7"><strong>Email: </strong><strong> </strong></span>
<input type="text" name="Email" size="72"//>

<br />
<br />

<label> Gender: </label>
<select name="Gender" size="1">
<option>--select--</option>
<option>Male</option>
<option>Female</option>
</select>
<label for="select"></label>
<label>
<span class="style2">Phone No.:</span> </label>
<input type="text" name="Phone" size="46"/>
   <br />
<br />
<span class="style2">Password</span><strong>:</strong>
```

```
    <input type="password" name="Pass" />
    <span class="style2">Repeat Password:</span>
    <input type="password" name="Tpass" onKeyDown="if(event.keyCode==13)
event.keyCode=9;" />
        
    <input type="submit" name="submit" value="Click to REGISTER" />
  </form>
 </div>  -->
 <div class="story">
  <h2 id="pageName">Returning User :: Login Here... </h2>
  <form id="form1" name="form1" method="post" action="scripts/login.php">
    <label></label>
    <p>
      <label></label>
      <label>Phone No. : </label>
      <input type="text" name="Phone" />
    </p>

      <label></label>
      <label>Password: </label>
      <input type="password" name="Pass" onKeyDown="if(event.keyCode==13)
event.keyCode=9;" />
            
      <input type="submit" name="submit" value="Click Here to LOGIN" />
  </form>

 </div>
 <div class="story">
```

```
   <h1>

     <!--end content -->

     <img src="images/warning.png" alt="" width="100" height="60" /><span
class="style10"> Phone number and password Mismatch... ! User account could not be
found... </span> </h1>

  </div>

</div>

<div id="navBar">

  <div id="search">

    <form action="#">

     <!-- <label>Selected Cases </label> --> <input name="searchFor" type="text"
value="Selected Cases..." size="25" />

     <input name="goButton" type="submit" value="Go" class="buttonS"
onMouseOver="OverMouse(this);" onMouseOut="OutMouse(this);" />

    </form>

  </div>

  <div id="sectionLinks">

    <ul>

      <li> </li>

      <li> *** Fire *** </li>

      <li>*** Robbery ***</li>

      <li>*** Kidnap ***</li>

      <li>*** Violence ***</li>

            <li>*** Flood ***</li>

    </ul>

  </div>


</div>
```

```
<!--end navbar -->
<div id="Layer1"><img src="images/fire.jpg" width="302" height="167" /></div>
<br /> <br />
<div class="style6" id="siteInfo">
  <div align="center">
  <br />
    <p>DeGreat - Copyright Reserved &copy; 2023</p>
  </div>
</div>
<br />
</body>
</html>
<!DOCTYPE html PUBLIC "-//W3C//DTD XHTML 1.0 Transitional//EN"
"http://www.w3.org/TR/xhtml1/DTD/xhtml1-transitional.dtd">
<html xmlns="http://www.w3.org/1999/xhtml">
<!-- DW6 -->
<head>
<!-- Copyright 2005 Macromedia, Inc. All rights reserved. -->
<!-- <meta http-equiv="Content-Type" content="text/html; charset=iso-8859-1" /> -->
<meta name="description" content="website description" />
<meta name="keywords" content="website keywords, website keywords" />
<meta name="viewport" content="width=device-width, initial-scale=1.0">
<meta http-equiv="content-type" content="text/html; charset=windows-1252" />
<meta http-equiv="Content-Type" content="text/html; charset=iso-8859-1" />
<title>Emerg_SA ::  Registration Success</title>
<link rel="stylesheet" href="styles/2col_leftNav.css" type="text/css" />
<style type="text/css">
```

```
<!--
.style2 {
	color: #334d55;
	font-weight: bold;
}
.style5 {font-size: 130%}
.style6 {color: #FF6600}
.style7 {color: #334d55}
.style8 {color: #cccccc}
#Layer1 {
	position:absolute;
	width:308px;
	height:173px;
	z-index:1;
	top: 257px;
	left: 0px;
}
-->
</style>
<?php require('jscript.inc') ?>
<script language="javascript" type="text/javascript" src="scripts/modernizr-1.5.min.js">
</script>
<script language="javascript" type="text/javascript" src="scripts/webbased.js"> </script>
<script language="php" type="text/php" src="scripts/register.php"> </script>
<script language="php" type="text/php" src="scripts/login.php"> </script>
</head>
<!-- The structure of this file is exactly the same as 2col_rightNav.html;
```

```
    the only difference between the two is the stylesheet they use -->
<body onload="">
<div id="masthead">
  <h1 id="siteName"><img src="images/model.jpg" alt="" name="banner" width="400" height="80" id="banner" style="background-color: #9900FF" />      Improved Sentimental Response System for Classifying Emergency Incidence  </h1>
  <div id="globalNav"> <span class="style8"> </span> </div>
</div>
<!-- end masthead -->
<div id="content">
  <div id="breadCrumb"> <a href="#"></a></div>
  <h2 id="pageName" class="intro">New User  :: Register Here... </h2>
  <div class="feature">
    <p><img src="images/gov.jpg" width="172" height="100" /></p>
    <form id="form2" name="form2" method="post" action="scripts/register.php">
      <label></label>
      <label>Name: </label>
      <input name="Fname" type="text" size="74"/>
      <br />
      <br />
              
      <span class="style7"><strong>Email: </strong><strong> </strong></span>
      <input type="text" name="Email" size="72"//>

      <br />
      <br />

      <label> Gender: </label>
```

```
      <select name="Gender" size="1">
        <option>--select--</option>
        <option>Male</option>
        <option>Female</option>
      </select>
      <label for="select"></label>
      <label>
      <span class="style2">Phone No.:</span> </label>
      <input type="text" name="Phone" size="46"/>
   <br />
      <br />
      <span class="style2">Password</span><strong>:</strong>
      <input type="password" name="Pass" />
      <span class="style2">Repeat Password:</span>
      <input type="password" name="Tpass" onKeyDown="if(event.keyCode==13)
event.keyCode=9;" />
          
      <input type="submit" name="submit" value="Click to REGISTER" />
    </form>
  </div>
  <div class="story">
    <h2 id="pageName">Returning User :: Login Here... </h2>
    <form id="form1" name="form1" method="post" action="scripts/login.php">
      <label></label>
      <p>
        <label></label>
        <label>Phone No. : </label>
```

```
      <input type="text" name="Phone" />
    </p>

      <label></label>
      <label>Password: </label>
      <input type="password" name="Pass" onKeyDown="if(event.keyCode==13)
event.keyCode=9;" />

      <input type="submit" name="submit" value="Click Here to LOGIN" />

  </form>

 </div>
 <div class="story">
  <h1>
   <!--end content -->
    <img src="images/apply.png" alt="success" width="100" height="60" /><span
class="style10"> Your Registration is Successful, you can now Login... </span> </h1>
 </div>
</div>
<div id="navBar">
 <div id="search">
  <form action="#">
   <!-- <label>Selected Cases </label> --> <input name="searchFor" type="text"
value="Selected Cases..." size="25" />
```

```
    <input name="goButton" type="submit" value="Go" class="buttonS"
onMouseOver="OverMouse(this);" onMouseOut="OutMouse(this);" />
   </form>
  </div>
  <div id="sectionLinks">
   <ul>
    <li> </li>
    <li> *** Fire *** </li>
    <li>*** Robbery ***</li>
    <li>*** Kidnap ***</li>
    <li>*** Violence ***</li>
          <li>*** Flood ***</li>

   </ul>
  </div>



</div>
<!--end navbar -->
<div id="Layer1"><img src="images/fire.jpg" width="302" height="167" /></div>
<br /> <br />
<div class="style6" id="siteInfo">
  <div align="center">
  <br />
   <p>DeGreat - Copyright Reserved &copy; 2023</p>
  </div>
</div>
```


</body>

</html>

<!DOCTYPE html PUBLIC "-//W3C//DTD XHTML 1.0 Transitional//EN"
"http://www.w3.org/TR/xhtml1/DTD/xhtml1-transitional.dtd">

<html xmlns="http://www.w3.org/1999/xhtml">

<head>

<meta http-equiv="Content-Type" content="text/html; charset=iso-8859-1" />

<title>Initializing the Classifier </title>

</head>

<body style="background-color:#FFFFCC">

  <h3 style="color:#0000CC"> TEXTUAL DATA FROM SOCIAL MEDIA ARE BEING CONVERTED TO NUMERIC DATA (NOMINAL VALUES) FOR THE CLASSIFIER </h3>

 <table cellspacing="10" cellspacing="10" border="5px" style="color:#000066; background-color:#FFCCFF;font-weight:bold">

<tr> <td>Incidence_Type</td> <td>Incidence_Class</td> <td>Incidence_Count</td> </tr>

<tr> <td>5</td> <td>Fire_Outbreak</td> <td>62</td> </tr>

<tr> <td>4</td> <td>Robbery_Theft</td> <td>100</td> </tr>

<tr> <td>3</td> <td>Kidnap_Abduction</td> <td>175</td> </tr>

<tr> <td>2</td> <td>Violence_Crises</td> <td>133</td> </tr>

<tr> <td>1</td> <td>Flood_Erosion</td> <td>306</td> </tr>

<tr> <td>0</td> <td>Null_Incidence</td> <td>121</td> </tr>

</table>

<h2>

 Load Pre-processed Dataset and Classify...

 </h2>

</body>

</html>

APPENDIX II (Discretized Data)

Post	Comment
0	1
0	0
0	1
0	1
1	1
1	1
1	2
1	1
5	1
1	1
1	4
3	1
1	1
1	1
1	4
1	3
2	1
2	1
2	1
2	3
2	1
2	1
2	5
2	1
2	1
2	1
3	5
3	1
3	0
3	1
3	1
3	1
3	2
3	1
4	1
4	1
4	0
4	1
4	1
4	1
4	4
4	1
5	2
5	1
5	1

5	0
5	1
5	4
5	1
0	1
0	1
0	3
3	5
0	1
0	1
3	4
0	1
2	1
0	1
5	5
0	1
0	2
0	1
3	3
0	1
0	1
0	1
1	1
1	4
1	5
1	1
4	1
1	1
1	5
1	1
2	3
1	1
2	3
1	1
1	1
2	3
1	1
1	1
4	3
1	1
1	1
5	3
1	1
1	1
4	4
1	1

1	1
2	2
1	1
1	1
3	2
1	1
1	1
4	4
1	1
2	1
2	1
2	1
2	1
2	4
2	1
2	1
2	4
2	1
2	1
2	1
2	4
2	1
2	1
2	4
2	1
3	1
3	1
3	1
3	5
3	1
3	1
3	1
3	3
3	1
3	5
3	1
3	1
3	1
4	3
4	1
4	1
4	2
4	1
4	1
5	2
5	1

0	1
0	1
1	3
0	1
0	1
0	2
4	1
3	1
2	5
1	1
2	1
2	4
3	1
4	1
1	3
2	1
3	1
2	4
3	1
2	1
3	3
4	1
2	1
0	3
1	4
2	1
3	1
2	3
0	1
0	1
0	1
0	4
1	1
1	1
3	4
1	1
1	1
3	2
1	1
1	1
2	4
1	1
1	1
4	1
1	3
1	1

4	5
1	1
2	1
2	1
2	3
2	1
2	1
2	1
3	4
3	1
3	1
4	2
4	1
5	1
5	1
5	4
5	1
5	1
0	0
0	1
0	1
4	3
2	1
1	1
2	3
2	1
2	1
3	1
1	3
2	2
2	1
2	1
3	1
4	4
2	1
0	1
0	1
0	1
1	5
1	1
1	1
1	1
2	4
2	1
2	1
3	1

3	4
3	1
3	1
4	1
5	5
5	1
0	1
0	1
0	1
3	5
2	1
3	1
0	1
1	1
1	4
2	1
0	1
0	1
0	1
0	3
1	1
1	1
1	1
2	1
3	1
4	1
6	5
2	1
2	1
4	1
2	1
3	4
0	1
0	1
0	1
0	1
0	3
3	1
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Bio-data

A.Personal Information

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Address: Plot 25,Block 28, Kemta Housing Estate, Idi-Aba Abeokuta.
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Local Government Area: Abeokuta Local Government
State: Ogun
Nationality: Nigerian
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Phone Number of Next of Kin: 09067074510
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B. Institution Attended with Dates

Lead City University, Ibadan, Oyo State.	(2021 till date)
Tai Solarin College of Education, Omu-Ijebu, Ogun State.	(2020 -2021)
Lead City University, Ibadan, Oyo State.	(2018 - 2020)
Lead City University, Ibadan, Oyo State.	(2005 -2009)
Lorion Telecom, Hyderabad, AP, India.	(2009)
Egba Comprehensive High School, Asero, Abeokuta.	(1996 – 2002)
Lawson Nursery & Primary School, Kuto, Abeokuta.	(1988 -1996)

C. Academic Qualifications and Certificate Obtained with Dates.

Doctor of Philosophy (PhD)	(2021 till date)
Professional Diploma in Education (PDE)	(2020 -2021)
M.Sc. Computer & Information Science	(2018 - 2020)
B.Sc. Computer with Electronics Second Class Upper	(2005 -2009)
Integrated Diploma in Advanced Wireless Communication	(2009)
b. Senior Secondary School Certificate	(1996 – 2002)
Primary School Leaving School Certificate	(1988 – 1996)

Working Experience, with Dates

City Business Computers (CBC) Limited , Lekki Phase 1, Lagos 2009 –2010
Network Engineer Trainee

Ararad Technical Nigeria Limited, Oluyole Ind. Estate, Ibadan 2011 – 2013
Network Engineer

Arcelor Networks Limited, Ibara Housing Estate, Abeokuta. 2013 - 2015
Network Engineer/ Technical Sales

Tai Solarin College of Education, Omu-Ijebu. 2015-Till date
Lecturer I

D. Award and Fellowships

None

E. Membership of Academic/ Professional Bodies

Nigeria Computer Society (**MNCS) 09401** **July, 2015**
Teachers Registration Council of Nigeria **(MTRCN) OG/R/04285 July, 2023**

F. Conferences/Seminars/Workshops Attended with Dates

SMART-iSTEAMS Multidisciplinary Conference, **Ogwuashi-Uku Delta State, Nigeria.** 2018

2nd International Conference on Applied ICT (ICAICT 2019) held at **Lead City University, Ibadan**. 2019

Transforming Teaching Practice/Skills in the 21st century, Implication on Classroom Management amongst Social Science Subject in Ogun State, Nigeria, organized by **UNA-USA and Tai Solarin College of Education, Omu-Ijebu** 2021

Transformation Agenda for Third World Communities in Evolving As Global Developed Nation: Multi-Disciplinary Approach. Usman Danfodio University Multidisciplinary Academic Conference, **Sokoto** 2024

Publications in Learned Journals (International) (ORCID: 0000-0003-3571-898X)

Kaka, O.A., **Johnson, O.A**, & Oyenuga, J.O., *Utilization of Information and Communication Technology (ICT) in Studying Open & Distance Learning Education Programmes (ODLEP)*. **Journal of Behaviourial Informatics Digital Humanities & Development Research.** 6(1), 2020, 171-175.

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Johnson, O.A., Odufeko, G.T. & Allen, A.A. *Understanding the Fundementals of Digital Forensics.* **International Journal of: Science Research and Technology**, 13(9), 2023, 201-206.

University Compliance Certification

This is to certify that this thesis by Johnson Oluwatobi Akanbi with Matriculation Number LCU/PG/000135 in the Department of Computer Science, Faculty of Natural and Applied Sciences, Lead City University, Ibadan is in full compliance with the approved University's Format and Style.

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Signature Date