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Improved Sentimental Response for Classifying Emergency Incidence through Hybridized Mining Technique

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Abstract
This research addresses the classification of emergency incidents arising from both natural and human-induced events, emphasizing the necessity for timely intervention and strategic mitigation. It introduces a hybrid data mining approach that integrates Natural Language Processing (NLP) with Bayesian Belief Learning (BBL) to enhance sentiment analysis during crisis scenarios. Real-time data is extracted from Facebook through the Graph API using Python's requests library. The collected data undergoes preprocessing and is stored in a MySQL database, while the system interface utilizes XML and PHP to display sentiment outcomes. The integration of supervised learning into the NLP process resulted in a signal precision exceeding 92.8%, surpassing the accuracy of existing approaches. A confusion matrix is employed to assess the model's performance, confirming its high level of predictive precision. The system demonstrates strong capabilities for improving proactive emergency detection and management.

Keywords: *Emergency classification, Hybrid mining, Real-time response, Sentiment analysis, Social media*

1. Introduction

An emergency is a critical situation that presents immediate risks to human life, health, property, or the environment. These events are often sudden and highly disruptive, requiring urgent action. They may originate from natural causes such as floods, earthquakes, or cyclones, or from human-related incidents like traffic accidents, industrial explosions, and fires [2]. While swift intervention is essential to minimize harm, both preventive and remedial strategies are key components in handling such situations effectively. Rapid detection and response can significantly improve outcomes by facilitating early evacuation or accelerating recovery efforts, especially in large-scale disasters where first responders are instrumental [6].

Governments and organizations commonly develop strategies to reduce the impact of emergencies. The overall effectiveness of such efforts depends on the speed and coordination of responses from both individuals and systems [27]. In expansive and complex environments, such as multinational corporations, the continuous monitoring of infrastructure is crucial for risk mitigation and emergency readiness. Psychological interventions, including stress-reducing techniques and positive reinforcement, play an essential role in recovery by promoting mental resilience [19].

Conventional sentiment analysis methods, however, often lack the depth required to capture evolving emotional responses during crises. Emerging technologies have shown promise in advancing emergency management. Intelligent systems can support the operations of security agents and rescue teams [9]. Event-driven awareness frameworks facilitate rapid information flow, especially when communication signals are stable [16]. Developments in wireless technologies have revealed valuable patterns in social media interactions, where machine learning algorithms such as Naïve Bayes enable efficient data interpretation.

Sentiment analysis, a key subfield of machine learning, is used to categorize text data based on emotional tone, providing critical insights into public sentiment during emergencies. Artificial intelligence (AI) systems further aid in the early identification and escalation of

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incidents, potentially reducing the impact of severe events [21]. Tools like natural language processors enhance pattern recognition and allow for real-time applications, contributing to faster and more accurate responses [9].

Deep learning a powerful extension of machine learning has emerged as a key technology within the Fourth Industrial Revolution (4IR). Its layered architecture supports complex data analysis across domains such as healthcare, cybersecurity, and text mining [7, 13]. By using models like artificial neural networks (ANNs), deep learning continues to drive predictive accuracy and enhance emergency response capabilities.

Despite these advancements, existing emergency response systems still face challenges. Many lack experimental validation for diverse emergency scenarios, especially those outside predefined categories [7]. Furthermore, traditional text classification techniques often struggle with multi-class precision, leading to lower response accuracy. Limitations in data mining approaches also hinder deeper system optimization and insights [11]. Overcoming these challenges is crucial for building more resilient emergency management frameworks.

This study aims to address these gaps by developing an enhanced emergency classification system using NLP and Bayesian Belief Learning. The system integrates Facebook's Graph API, Python's Requests library, and technologies such as XML, PHP, and MySQL for large-scale data processing. Performance evaluation is conducted using confusion matrices and precision metrics to assess the accuracy of the system.

2. Related Works

2.1 Sentiment Analysis of Social Media Data in Disaster Contexts

Social media has become a vital tool during disasters, offering individuals and communities a platform to share real-time updates, express needs, and mobilize support. Analyzing the emotional content of such posts particularly on platforms like Twitter can provide valuable insights into the psychological and situational states of affected populations, aiding decision-making in humanitarian contexts [1]. While current visualizations of disaster-related social media data typically emphasize spatial and time-based trends, integrating sentiment analysis can significantly enhance situational awareness [9]. Machine learning methods such as Support Vector Machines (SVM), Naïve Bayes, and Random Forest are widely applied in sentiment classification tasks. These methods often utilize sentiment lexicons like AFINN, SentiWordNet, Sentiment Treebank, and SentiStrength to classify content by polarity and subjectivity, helping track the evolution of public emotion throughout the emergency response cycle [12].

2.2 *Disaster Sentiment Interpretation: Visualizing Public Emotions for Decision Support*

Baro *et al.* [5] conducted a study focusing on sentiment analysis in disaster scenarios, specifically targeting how public tweets could inform emergency decisions. Their research, published in the *IOP Conference Series: Materials Science and Engineering* (2020), explored the challenges faced by decision-makers when interpreting unstructured and emotionally diverse content from platforms like Twitter. The team developed a framework to process and categorize sentiment in tweets as positive, negative, or neutral. Their approach aimed to transform large, ambiguous tweet datasets into actionable insights. Additionally, they introduced visualization techniques designed to enhance the readability and usability of sentiment information, thus enabling faster and more informed decision-making. The study underscored the importance of integrating sentiment analysis tools into disaster management systems to better assess the needs and reactions of the affected public.

2.3 Evaluation of Sentiment Classification Models in Emergency Response Scenarios

Contreras *et al*. [11] assessed the performance of a pre-trained sentiment analysis model on Twitter data related to the 2019 Albanian earthquake. Their research analyzed 695 tweets containing hashtags such as *#Albania* and *#AlbanianEarthquake*, posted between November 26, 2019, and February 3, 2020. Using the MonkeyLearn sentiment analysis tool, they classified each tweet into one of three categories: positive, neutral, or negative. The model achieved an overall accuracy of 63%, though a 37% error rate indicated a substantial margin for improvement. The study recommended that customized training on specific datasets could enhance classification accuracy. It concluded that while social media provides an immediate and rich source of public sentiment during disasters, pre-trained models may need to be tailored to context-specific language and emotional expressions to be more effective [17, 18].

2.4 Twitter and Its Role in Emergency Communication

According to Lopez *et al.* [18], Twitter has emerged as a rapidly expanding social media platform that allows users to communicate, share real-time updates, and stay connected during emergency situations. It serves as a valuable tool for understanding crisis events by enabling the classification of tweets based on sentiment such as positive, negative, or neutral and by content type. Tweets can be further organized into categories like first-hand accounts, second-hand reports, emotional expressions, commentary, sarcasm, practical information, and multimedia content. The platform has experienced a notable increase in localized discussions during emergencies, making it a vital resource for analyzing public response and disseminating timely, relevant information.

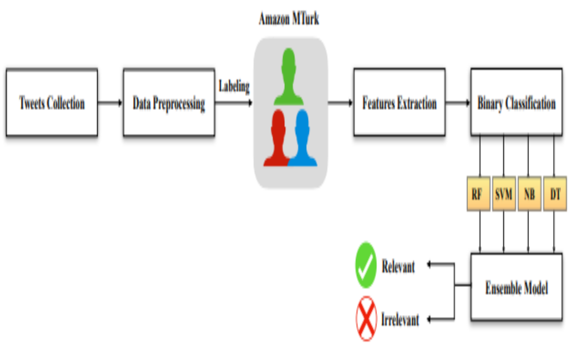

Figure1: Twitter situational awareness detection framework. Source: [2]

In figure 1, only 1% of Twitter data is publicly accessible, comprising historical and real-time streaming data. Access requires either a Twitter developer account with authentication or purchasing data from partners like Crimson Hexagon.

2.5 Big Data Technology in Service Enhancement

Big data plays a critical role in enhancing the quality of network services and enabling the development of innovative mobile applications. Effective management of large-scale data requires the integration of advanced analytics and cutting-edge machine learning approaches. These include methods such as Naïve Bayes, deep learning, neural networks, representation learning, transfer learning, active learning, and online learning, all of which support more efficient and intelligent processing of complex data streams [2].

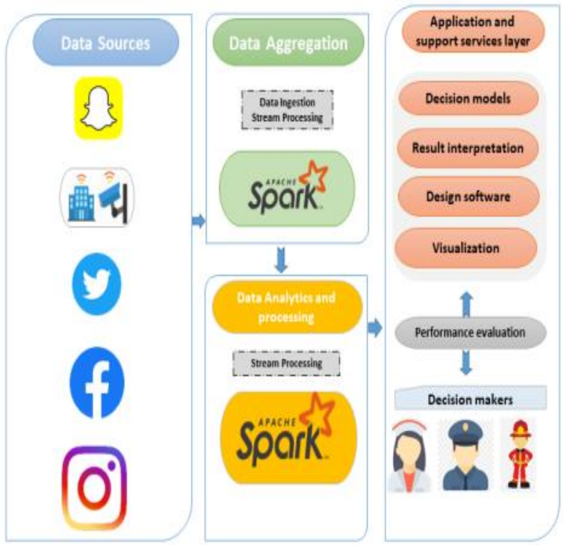

Figure 2: Overall of big data Technology Source: [2]

As illustrated in Figure 2, the adoption of modern techniques underscores the necessity for sophisticated analytics to process big data, which is defined by its large volume and intricate nature. Emerging frameworks emphasize the growing role of big data analytics in supporting next-generation network infrastructures. The increasing variety of data sources, along with challenges such as high data transmission rates, user mobility, and packet loss, renders conventional processing tools inadequate. Additionally, the complexity is heightened by the fact that approximately 80% of global data is unstructured, posing significant challenges for analysis and interpretation [2].

2.6 Data Mining Technology

Data mining serves as a vital tool for extracting meaningful insights from unstructured datasets. It enables the transformation of raw text into valuable information, which can be particularly beneficial during disaster and crisis scenarios. For instance, analyzing natural language messages sent via mobile devices can provide timely and relevant data to support emergency response and decision-making efforts.

2.7 Bayesian Techniques

Bayesian methods offer a flexible and robust framework for making statistical inferences. Techniques such as Bayesian Belief Learning and Bayesian Classification Networks operate based on Bayes' theorem and typically assume independence among features. This assumption allows for efficient prediction and data classification, especially in large-scale datasets. Bayesian approaches are known for their strong classification performance and often surpass more complex algorithms in accuracy. Naïve Bayes models, in particular, are popular due to their ease of implementation and ability to effectively manage uncertain or incomplete data. These models are trained to sort messages or text inputs into predefined categories based on learned patterns [9].

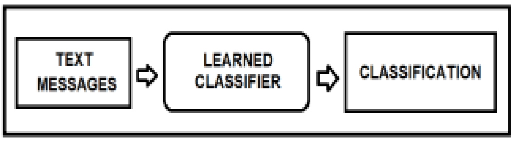

Figure 3: Bayesian Classification Method Source: [14]

2.8 Sentiment and Emotion Analysis

Sentiment analysis, also referred to as opinion mining, utilizes computational methods to evaluate public attitudes, feelings, and viewpoints toward people, events, or topics. It typically involves classifying textual content as positive, negative, or neutral in tone [16]. A more specialized branch, emotion analysis, seeks to identify specific emotions such as joy, anger, or sadness within texts. This approach provides deeper insight into emotional responses and societal perceptions. Common applications include gauging public satisfaction or analyzing consumer feedback [8].

Achieving accurate sentiment analysis requires a multi-step process, including data preprocessing, feature extraction, and model training, all of which contribute to reliable sentiment categorization [28]. When applied in crisis contexts, both sentiment analysis and the broader emergency management framework become essential tools for interpreting public reaction and guiding responsive actions. This analytical step is illustrated in Figure 4.

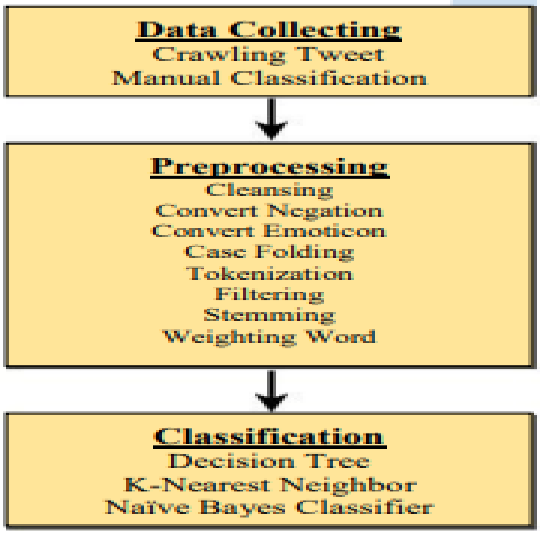

Figure 4: Sentiment Analysis flowchart Source: [28].

Contreras *et al.* [9] assessed the performance of a pre-trained sentiment analysis model in interpreting tweets related to emergency response and recovery following the 2019 Albanian earthquake. Published in the *Journal of Natural Hazards*, their study explored the model's effectiveness in classifying sentiments to support situational awareness and decision-making during real-world disaster scenarios. The research emphasizes the practical application of sentiment analysis tools in enhancing emergency management efforts.

3. Methodology

Two data mining techniques and hybridized classification algorithms namely: natural language processing (NLP) and Bayesian belief learning (BBL) were employed in the analysis and prediction of likelihood for the occurrence of emergency incidence.

3.1 Datasets and Attributes

The datasets were obtained from social media repository, through web scrapping using Facebook API for Python programming. These datasets splits into two: seventy five percent (75%) and twenty five percent (25%) for training and testing respectively. Below is a list of the dataset attributes before and after preprocessing:

A. Before Preprocessing

1. **Post_ID**: Unique identifier for each post (String)
2. **User_Name**: Name of the user (String)

3. **Post_Content**: Textual content of the post (String)
4. **Post_Timestamp**: Date and time the post was made (String/Datetime)
5. **Sentiment_Label**: Emotion or sentiment label assigned (String: , e.g. " cultism clash", "kidnap", "violence", "robbery",)

B. After Preprocessing

1. **Processed_Content**: Cleaned and tokenized text, represented numerically (Integer vector)
2. **Sentiment_Class**: Discretized sentiment class used for classification (Integer: 0 = Negative, 1 = Positive)

The characteristics of the datasets are presented in table 1.

Table 1 Datasets Characteristics

Features	**Dataset**	
	Before Pre--Processing	**After Pre-processing**
Dataset Characteristics	Multivariate	Bivariate
Attribute Characteristics	String	Integer (Discretized)
Number of Instances	631	450
Number of Attributes	Five (5)	Two (2)
Associated Tasks	Classification	Classification
Missing Values (?)	Yes (21)	Nil

3.2 Evaluation Parameters

The selected classification techniques are evaluated based on the following parameters: true positive (TP), false positive (FP), true negative (TN), false negative (FN); as well as precision and confusion matrix:

(a) 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.

(b) False Positive indicate the rate of system precision that were falsely valid or number of selected cases that were wrongly escalated when incidence signals are received.

(c) 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.

(d) 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.

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

(f) 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.

```
# Evaluation Parameters - True Positive and False Positive
steps = [('TP and FP', prediction(n_components=3)), ('m', instances())]
model = Pipeline(steps=steps)

cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)
n_scores = cross_val_score(model, X, y, scoring='accuracy', cv=cv, n_jobs=-1)

# Evaluate the performance
print('Predictive Estimation: d% d% ' (Correct(n_scores), Incorrect(n_scores)))
```

Figure 5: Estimating Correctly Classified and Incorrectly Classified Emergency Signals

Figure 5 shows the estimates of the predictive performance of the model on emergency signal data. It uses a pipeline, cross-validation, and accuracy metrics to determine how well the model can distinguish between different types of emergency signals reporting the number of correct and incorrect predictions.

```
<?php
...
class SentimentAnalysis
{
...
    public function predict($samples)
    {
        return $this->classifier->predict($samples);
    }
}
```

Figure 6: Evaluating the Predictive Precision to Determine System Accuracy

Figure 6 shows the backend implementation used to generate sentiment predictions for incoming text samples. These predictions are a fundamental part of the system's evaluation, as they are used to measure the precision of the sentiment classifier, calculate the accuracy of the entire system in detecting emergency sentiments and provide metrics that support performance reporting.

3.3 Design of the System

The study employs a developmental and experimental design integrating a web scraper as an API to stream social media data. This data is analyzed using a supervisory-trained Bayesian Belief Learning (BBL) model combined with Natural Language Processing (NLP) for quantitative reasoning and possibility approximation. The BBL model serves as an opinion mining classifier, filtering emergency-related sentiments and public opinions from social media to generate credible reports that prompt responsive actions. The model development involves real-time social media data collection, pre-processed into a localized sentiment dataset.

A hybridized multi-class predictor technique is utilized to define input/output variables and establish cause-effect relationships within the classification model. The proposed sentiment-based emergency classification system underwent empirical testing on internet-enabled devices using development tools such as PHP, MySQL, XML, and Python. It incorporates the Facebook Graph API for intelligent data mining and classification. The system operates on standard computer and web-enabled devices with cross-platform mobility, adhering to functional specifications.

The system leverages the Requests library in Python, integrated with the Facebook Graph API, to stream text data from user posts and comments. This data is parsed as string objects into a backend database for processing. Key functionalities and processes are illustrated in Figures 7 and 8:

1. **Data Capture and Classification**

The system identifies and captures keywords from user posts and comments to classify emergency incidences into categories such as fire outbreaks, armed robbery, flood, abduction, and violence.

2. **Sentiment Analysis and Categorization**

The captured posts and comments are pre-processed and stored as text data. Sentiment analysis is conducted using the NLP library to evaluate the intensity and subjectivity of phrases, aiding classification into emergency categories.

3. **Model Optimization and Decision-Making**

The **Naive Bayes algorithm** enhances sentiment interpretation and serves as the classification model. The algorithm automates decision-making based on experimental validation using pre-processed social media data.

4. **Model Efficiency and Validation**

The system's efficiency depends on the robustness of its functional algorithm and the adequacy of the training and validation datasets, ensuring dynamism and accuracy in emergency classification.

3.4 Emergency Escalation Model

The system's Emergency Escalation Model applies Bayesian probability to classify multi-class emergency incidences. It utilizes the following parameters:

- **P(E):** Prior probabilities of predefined incident categories (e.g., Fire Outbreak, Robbery/Theft, Kidnap/Abduction, Violence/Crises, Flood/Erosion).
- **P(X):** Prior probabilities of relevant observable factors (e.g., user profile, posts, comments, location, and timestamps).

Using Bayesian inference:

- **P(E|X):** Represents the posterior probability of an emergency given observable factors.
- **P(X|E):** Reflects the likelihood of observable factors given an emergency.

The system calculates probabilities for each incident class (e.g., Fire Outbreak or Flood) by summing the conditional probabilities of all relevant factors for the specific incident, normalized by the total probability of factors. Example probability equations for different incidences include:

- **P(EA|X):** Fire Outbreak
- **P(EB|X):** Robbery/Theft
- **P(EC|X):** Kidnap/Abduction
- **P(ED|X):** Violence/Crises
- **P(EN|X):** Flood/Erosion

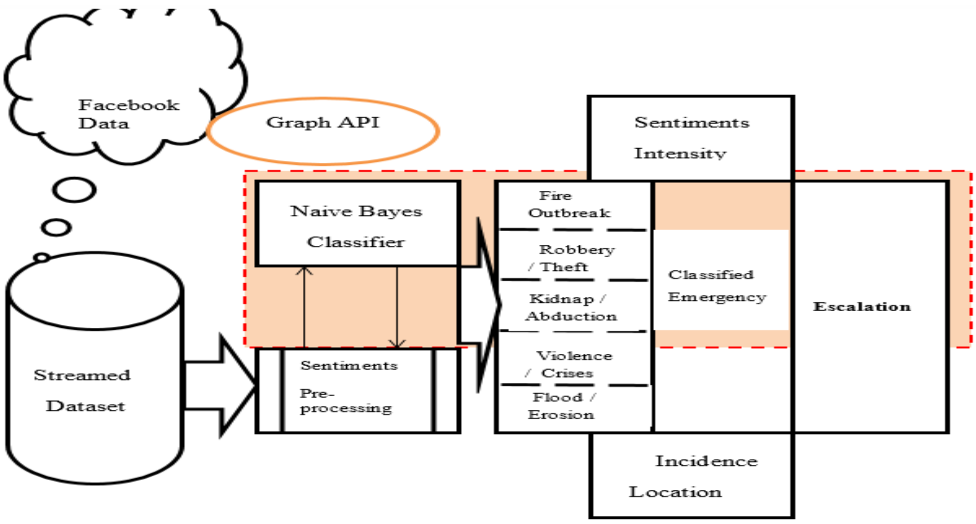

Figure 7: Architecture of the System

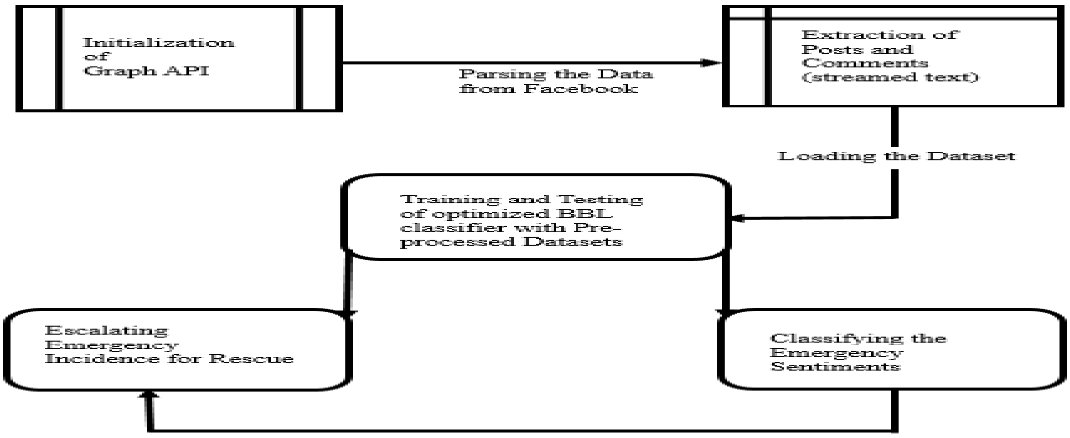

Figure 8: Data Flow Diagram of the Improved System

Each is computed as:
$P(E_A|X) = P(x_1|E_A) + P(x_2|E_A) + P(x_3|E_A) + P(x_4|E_A) + P(x_n|E_A) \ / \ P(X)$

This probabilistic model allows dynamic classification of emergencies based on social media data points and user interactions.

3.5 Minning System Algorithm for Classifying Emergency Incidence

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

3.6 Extraction and Structuring of Emergency Signals from Facebook

Emergency datasets were generated through web scraping on Facebook's developer domain using the Facebook Graph API, specifically targeting emergency-related posts at https://developers.facebook.com/. The dataset comprises 450 samples with five characteristics, resulting in a total of 450 x 5 data instances. Each data sample is multivariate, containing multiple attributes such as posts/threads, comments/reactions, location, and timestamps, which are critical for the classification process.

3.7 Program Outputs and Documentation

The data samples were converted to **CSV format** from Microsoft Excel for seamless integration with the testing server (Apache WAMP) through PHP MyAdmin, enabling MySQL database management. The classification process included:

1. **Supervised Training:** Data from emergency scenarios formed the training set for the classification algorithm.
2. **Classification Features:** Three additional fields incidence, notification**,** and agency were added to track the sentimental response and decision support provided by the improved model during periodic execution of the classification algorithm.

The processed dataset and optimized attributes ensured accurate and efficient emergency classification and decision-making support.

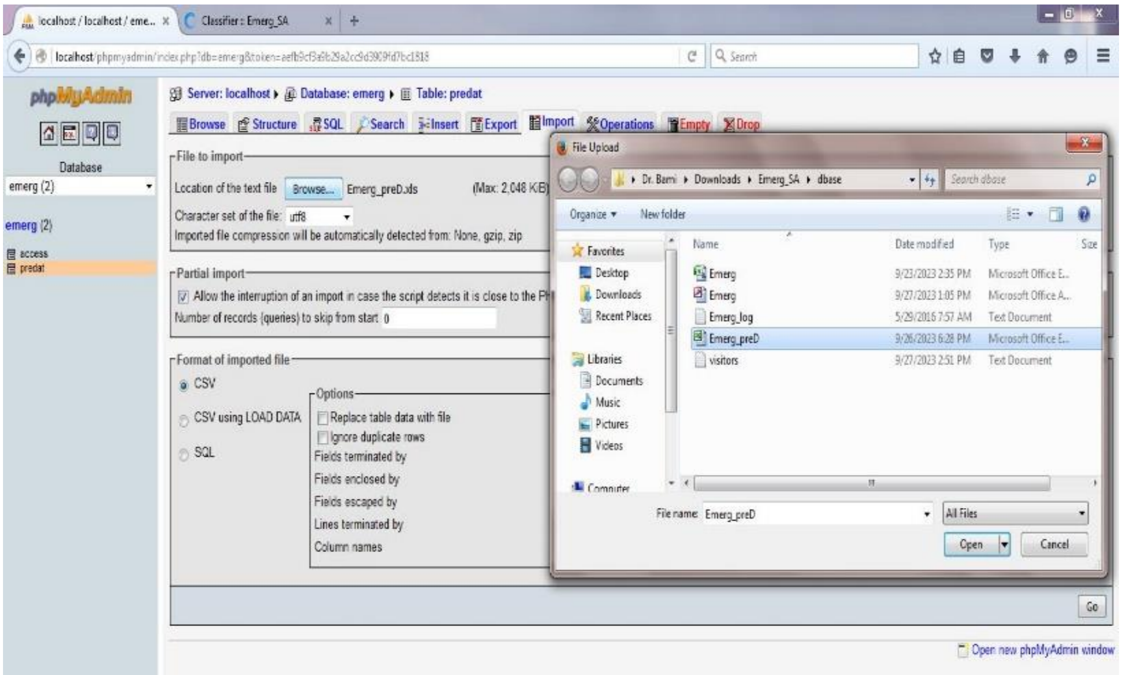

Figure 9: Importing Pre-processed Datasets for Training / Testing into SQL DB server

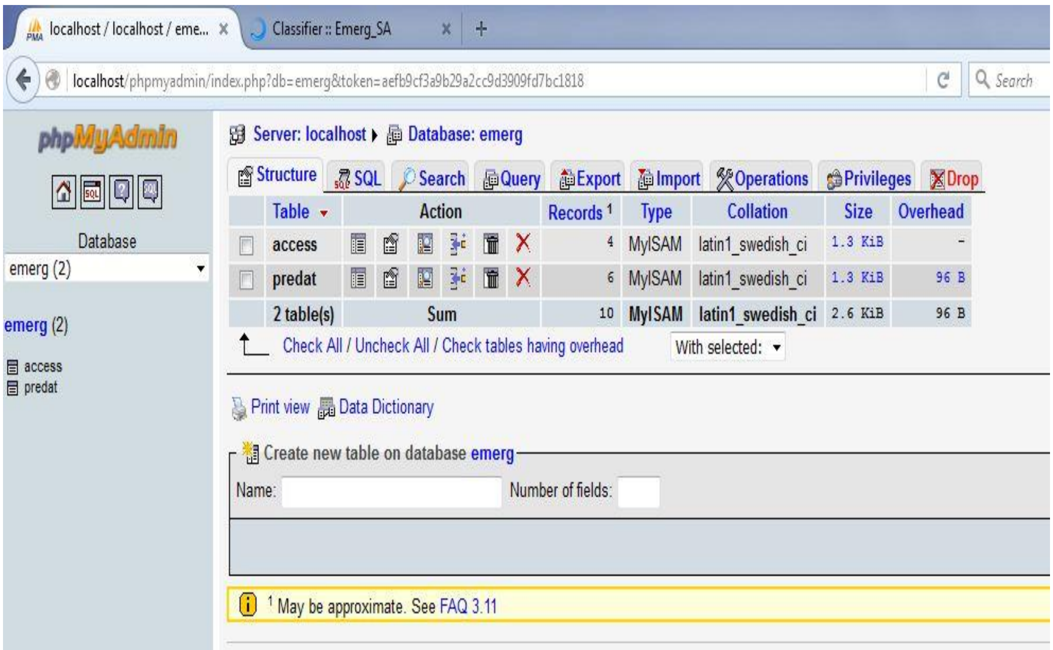

Figure 10: MySQL database for Internal Storage of Extracted data from Social Media

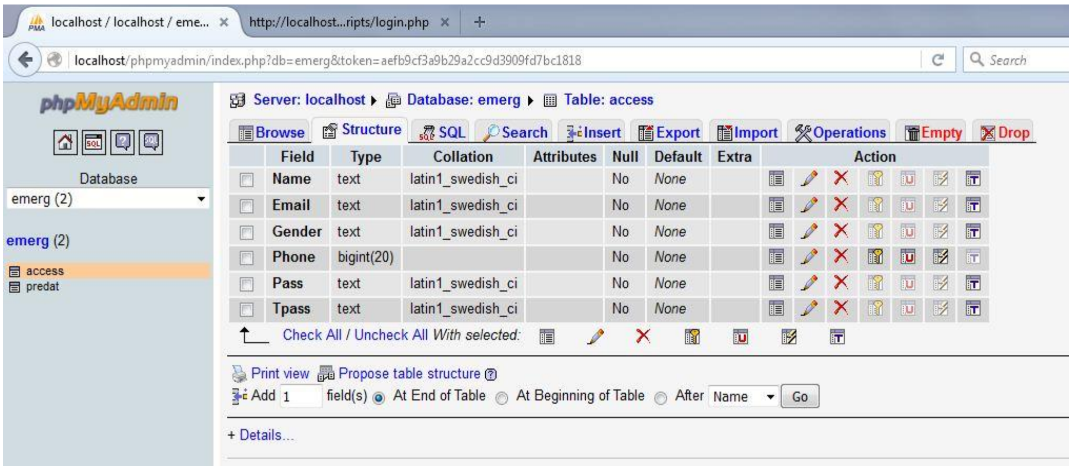

Figure 11: Entity Structure for Access Control and Authorized Users on SQL server

Figure 10 shows the entity view of back end (emerg) database for the system in MySQL server window comprising of two tables; ‘access’ table which stores the login details of every system user that sign up at the dashboard for the first time while ‘predat’ table stores data file of pre-processed data instances. Figure 11 shows its design structure, indicating the acceptable data type for each field in users’ records and value cannot be null.

3.8 User Interface and Testing

The system was trained using 75% of the datasets, with the remaining 25% used for testing to validate the model's performance. Figures and tables show the results of valid and invalid data in usability testing, with classifier outputs related to incident categories. Pre-processed Facebook data, cleaned and discretized, was loaded from the database for input into the system.

Figure 12 displays the splash screen of the system, showing the author and supporting technical group's information upon initialization.

Figure 12: System Splash Screen – Author’s Macros and Developer’s Trademark

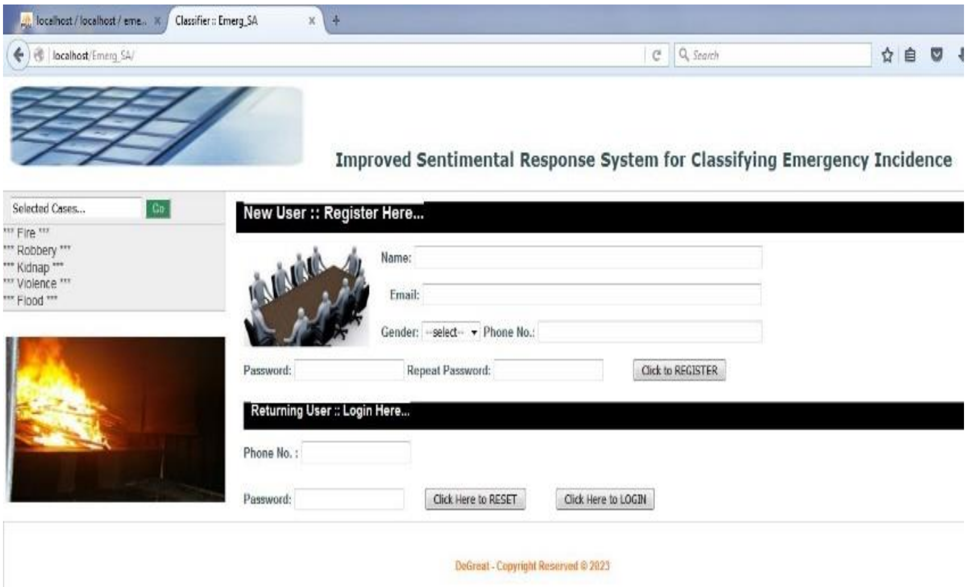

Figure 13: System Dashboard – Main Module for User's Registration and Authentication

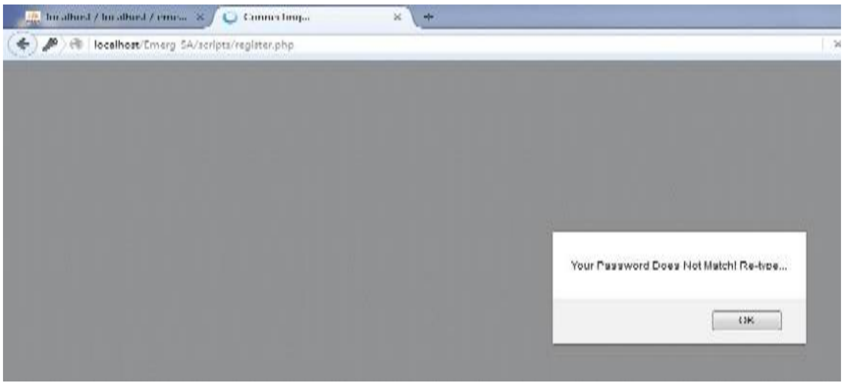

Figure 14: System Dashboard – Return Prompt for Data Field Mismatch

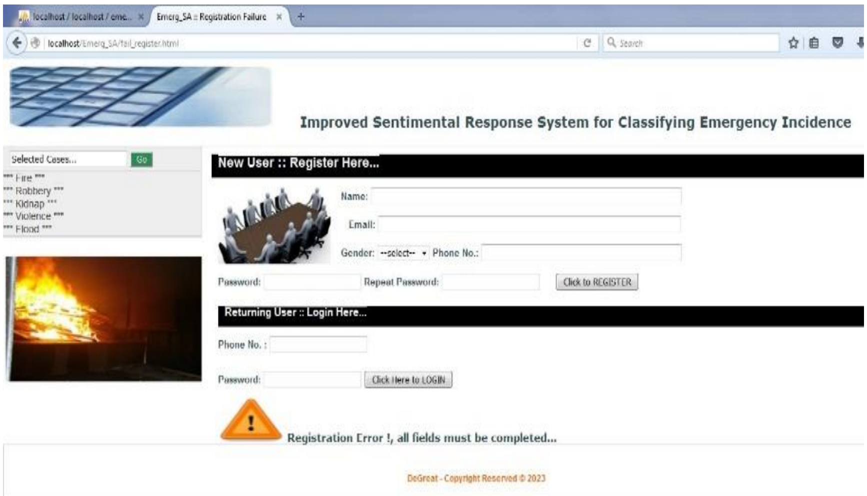

Figure 15: System Dashboard – Initialization Error for Incomplete Field Values

Figure 16 displays the login tab, where users enter their phone number and encrypted password for profile validation, with a RESET button to clear and re-enter values. Figures 17 and 18 show validation errors encountered during the integrity test due to invalid login or incorrect password

Figure 16: System Dashboard – Initialization Success for New User

Figure 17: System Dashboard – Insertion of Login Credentials at Login Prompt

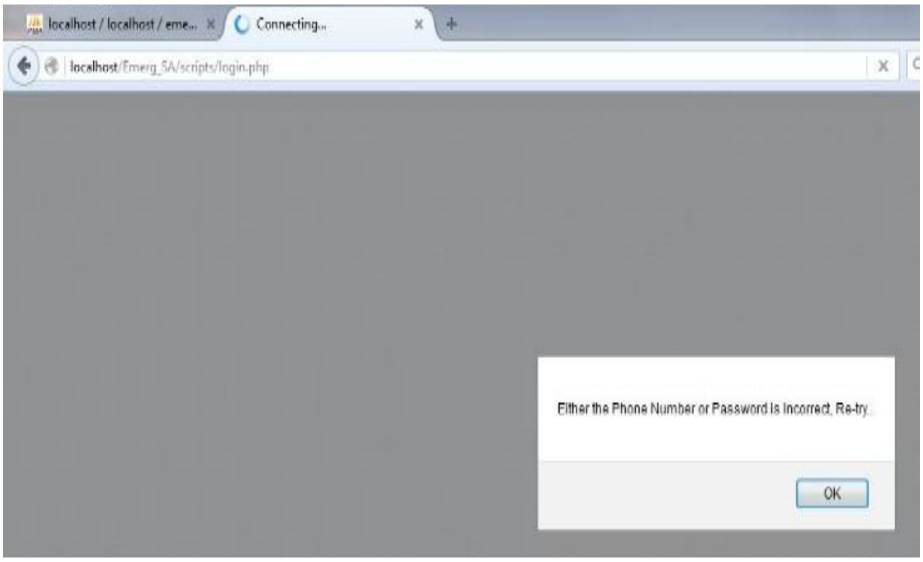

Figure 18: Mismatch Password or Wrongly Phone Number

.

Figure 19: Invalid Login details

Figure 20: Authentication Success at Login Prompt

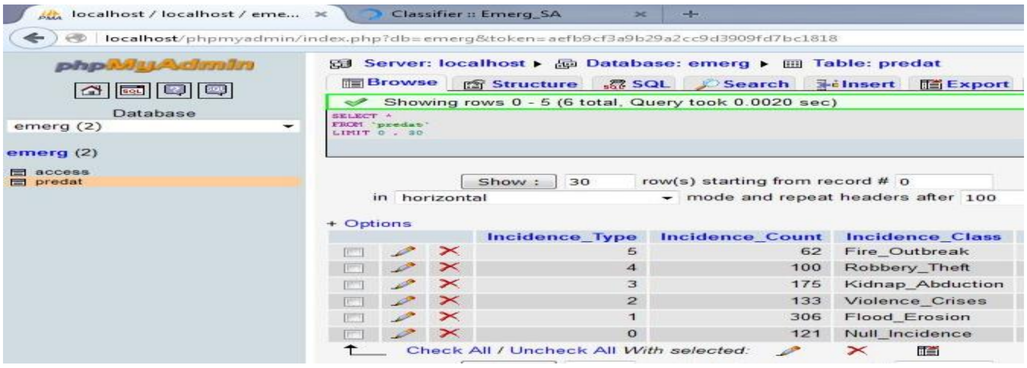

Figure 21: Class Estimation and Clustering of Emergency Cases from Social Media

Figure 22: Discretization and Loading of Emergency Dataset from the Database

Figure 23: Classification and Sentimental Response to Emergency Incidence

4. Results and Discussions

4.1 Results

The results obtained from the analysis of each data are presented in Table 2.

Table 2 Estimation of Testing Set and Validation the Classifier's Precision

Incidence_5_in_Post	38	Incidence_5_in_Comment	24	Total_Incidence_5	62	Fire Outbreak
Incidence_4_in_Post	57	Incidence_4_in_Comment	44	Total_Incidence_4	101	Robbery_Theft
Incidence_3_in_Post	76	Incidence_3_in_Comment	99	Total_Incidence_3	175	Kidnap_Abduction
Incidence_2_in_Post	85	Incidence_2_in_Comment	48	Total_Incidence_2	133	Violence_Crises
Incidence_1_in_Post	79	Incidence_1_in_Comment	228	Total_Incidence_1	307	Flood_Erosion
Null_Incidence_in_Post	114	Null_Incidence_in_Comment	7	Total_Null_Incidence	121	No Emergency

Table 2 presents the computational statistics of mined clusters, detailing parameter values against data instances.

4.2 Discussion of Results

The experimental evaluation of the classification algorithm confirmed the system's effectiveness in categorizing emergency events based on data extracted from social media platforms. The classifier successfully transformed complex, unstructured textual inputs into a format compatible with nominal data types, as outlined in the preprocessing phase. Prior probabilities for various incident parameters and input intervals were derived using frequency distributions from observed emergency cases. Through probabilistic modeling, the system generated likelihood arrays that allowed it to make predictions by approximating corresponding values stored in the database.

Several test scenarios were established to validate the reliability of the sentiment-based response model. This model facilitates prompt alerts to relevant stakeholders, contributing to disaster impact reduction and enhancing public safety. The approach builds upon the work of Baro and Palaoag [7] by expanding the scope beyond predefined natural disaster categories and incorporating experimental validation.

Moreover, the framework improved multi-class classification precision by integrating real-time data and increasing type-matching accuracy. It addresses the limitations identified in Contreras et al. [11] by employing supervised learning in combination with natural language processing (NLP), thereby refining the model's predictive capabilities. Evaluation metrics such as True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN) were used, along with tools like precision scores and confusion matrices, to assess the system's performance.

$$\text{Precision} = TP / TP + FP \times 100$$

$$= 381 / 381 + 38 \times 100 = 92.8\%$$

Table 3 Performance Metrics and Evaluation of the Improved System

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

Table 3 shows the confusion matrix which indicate very close relationship between true sentiment and classified sentiment for emergency incidence. Hence, the system was tested to be over ninety two percent (92.8%) efficient in signal precision which is a great improvement to functional model and technique of the existing system used for benchmark.

5. Conclusion

This study successfully designed and evaluated a classification model tailored for emergency incidents, utilizing data sourced from Facebook. The framework exhibited strong performance in transforming complex, unstructured textual content into organized data through efficient preprocessing techniques and probabilistic reasoning. By applying probability distributions and supervised learning methods, the model achieved notable improvements in multi-class classification accuracy, real-time data handling, and matching incident types.

The research extended beyond the scope of earlier works by addressing key limitations, including a wider range of emergency scenarios and more rigorous experimental validation. Additionally, the integration of the sentiment response mechanism enables prompt communication with relevant authorities, enhancing the system's potential to reduce disaster-related harm, safeguard lives, and minimize property damage.

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