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An Intelligent Framework for Real-Time Disaster Detection Using Geo-Spatial Social Media Analytics

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Abstract- The widespread adoption of social media platforms has transformed the way disaster-related information is generated and disseminated, providing valuable real-time insights during emergency situations. However, extracting reliable and actionable information from the enormous volume of unstructured social media content remains a significant challenge due to data noise, misinformation, and incomplete contextual information. This paper presents an intelligent disaster monitoring framework that integrates artificial intelligence, natural language processing, sentiment analysis, and location intelligence to enable real-time detection of disaster events from social media streams. The proposed framework systematically collects and preprocesses user-generated content, identifies disaster-related posts through machine learning techniques, extracts geographic information to determine affected regions, and evaluates public sentiment to assess the severity and urgency of ongoing incidents. By combining textual analysis with geospatial intelligence, the system enhances situational awareness and provides timely decision support for emergency response agencies. Experimental evaluation demonstrates that the proposed framework achieves reliable disaster detection performance while improving the accuracy of event localization and public sentiment assessment. The proposed approach offers a scalable and intelligent solution for disaster management, facilitating faster emergency response, effective resource allocation, and improved public safety during crisis situations.

Keywords- Disaster Monitoring, Social Media Analytics, Artificial Intelligence, Natural Language Processing (NLP), Sentiment Analysis, Location Intelligence, Machine Learning, Real-Time Event Detection, Crisis Management, Emergency Response, Geospatial Analytics, Disaster Prediction.

I. INTRODUCTION

Natural disasters such as earthquakes, floods, cyclones, landslides, and wildfires continue to pose significant threats to human life, infrastructure, and the environment. The increasing frequency and severity of these events have highlighted the importance of efficient disaster monitoring systems capable of providing timely information for emergency response and disaster management. Early identification of disaster incidents plays a vital role in minimizing casualties, optimizing resource allocation, and improving the effectiveness of rescue operations [2]–[5].

Conventional disaster monitoring approaches primarily rely on meteorological observations, satellite imagery, sensor networks, and official government reports to detect and assess disaster events. Although these systems provide reliable and authoritative information, they often experience delays in data collection, processing, and dissemination, limiting their effectiveness during rapidly evolving emergency situations. Consequently, researchers have explored alternative real-time information sources to enhance situational awareness and accelerate emergency response [4], [5].

The rapid expansion of social media platforms has created a valuable source of real-time, user-generated information during disaster events. Individuals frequently share text messages, images, videos, and location details immediately after experiencing or witnessing emergencies. This continuous stream of publicly available information provides critical insights into disaster severity, affected regions, and public conditions. As a result, social media analytics has emerged as a promising approach for supporting disaster detection and crisis management by providing immediate situational updates [8]–[10].

Despite its advantages, analysing social media data presents several challenges due to the enormous volume of unstructured content, informal language, misinformation, and incomplete geographical information. Distinguishing relevant disaster-related posts from unrelated content requires intelligent analytical techniques capable of processing textual information efficiently. Furthermore, identifying the geographic location associated with social media posts and understanding public emotions during disasters are essential for improving emergency response and decision-making [11], [17].

Recent advances in Artificial Intelligence (AI), Machine Learning (ML), and Natural Language Processing (NLP) have significantly enhanced the capability to analyse large-scale textual data and automatically identify meaningful disaster-related information. Machine learning algorithms can effectively classify social media posts, while sentiment analysis techniques provide valuable insights into public emotions, panic levels, and the urgency of disaster situations. In addition, location intelligence enables the extraction of geographic information from textual content and metadata, allowing authorities to accurately identify affected regions and improve situational awareness during crisis events [6], [12]–[18], [20].

Motivated by these developments, this paper proposes an intelligent disaster monitoring framework that integrates social media analytics, location intelligence, and sentiment analysis within an AI-driven architecture for real-time disaster detection. The proposed system performs comprehensive data preprocessing, disaster-related post classification, geographic information extraction, and sentiment evaluation to generate meaningful insights for emergency management authorities. By combining multiple analytical techniques into a unified framework, the proposed approach enhances disaster detection accuracy, improves event localization, and supports faster, data-driven decision-making during emergency situations [15], [16], [19].

The remainder of this paper is organized as follows. Section II presents the literature survey related to social media-based disaster monitoring. Section III discusses the existing and proposed systems. Section IV describes the system architecture, while Section V explains the implementation modules. Section VI presents the experimental results and performance evaluation, and finally, Section VII concludes the paper with future research directions.

II. LITERATURE SURVEY

The rapid growth of social media platforms has significantly transformed disaster management by providing real-time information generated directly by individuals in affected regions. During natural disasters such as earthquakes, floods, hurricanes, landslides, and wildfires, users frequently share textual updates, images, videos, and location details that offer valuable situational information. Consequently, social media has emerged as an important data source for intelligent disaster monitoring, enabling researchers to develop automated systems capable of detecting emergency events and supporting timely disaster response [8]–[10].

Early disaster monitoring approaches primarily relied on conventional information sources, including government agencies, meteorological departments, satellite observations, sensor networks, and news media. Although these systems provide accurate and reliable information, they often experience delays in data acquisition, processing, and dissemination, reducing their effectiveness during rapidly evolving emergency situations. These limitations have encouraged researchers to investigate alternative real-time data sources that can improve situational awareness and facilitate faster decision-making [4], [5].

Recent studies have extensively applied Natural Language Processing (NLP) and Machine Learning (ML) techniques to analyse disaster-related information extracted from social media platforms. Various supervised learning algorithms have been employed to classify social media posts as disaster-related or non-disaster-related by learning linguistic patterns, contextual information, and semantic relationships present in textual data. These intelligent classification models have demonstrated considerable improvements in filtering irrelevant information and automatically identifying crisis-related content from large-scale social media streams [6], [15], [16], [18].

Sentiment analysis has become another important research direction in disaster informatics. By analysing the emotional polarity and intensity expressed in social media posts, researchers can estimate public reactions, identify distress signals, and evaluate the urgency of ongoing disaster situations. Sentiment-aware disaster monitoring systems provide emergency management authorities with valuable insights into community behaviour, enabling more effective prioritization of rescue operations and resource allocation during critical events [12]–[14], [20].

Location intelligence has also gained considerable attention for improving disaster detection accuracy. Geographic information extracted from geo-tagged posts, user profiles, and textual location references enables disaster management systems to identify affected regions with greater precision. The integration of geospatial analytics with machine learning techniques has enhanced crisis mapping, damage assessment, and real-time visualization of disaster events, thereby improving operational awareness for emergency response organizations [9], [13], [17].

Recent advances in Artificial Intelligence (AI) and deep learning have further strengthened disaster monitoring systems by enabling large-scale analysis of social media streams with improved accuracy and scalability. AI-driven frameworks are capable of discovering hidden patterns, detecting anomalies, and extracting meaningful insights from heterogeneous disaster datasets, thereby supporting more effective emergency response and disaster management strategies [6], [7], [15], [16], [19].

Despite these developments, several challenges continue to affect the performance of existing disaster monitoring systems. The presence of noisy and unstructured social media content, misinformation, ambiguous language, incomplete geographic information, and rapidly increasing data volume makes accurate disaster detection a complex task. Moreover, many existing approaches emphasize individual components such as text classification, sentiment analysis, or location extraction without integrating them into a comprehensive decision-support framework [11], [15], [17].

Motivated by these limitations, this research proposes an intelligent disaster monitoring framework that integrates social media analytics, natural language processing, sentiment analysis, and location intelligence within a unified Artificial Intelligence architecture. By combining these complementary analytical techniques, the proposed framework aims to improve disaster detection accuracy, enhance situational awareness, and provide reliable real-time decision support for emergency management authorities during disaster response operations [15], [16], [19].

III. SYSTEM ANALYSIS

A. Related Work

Conventional disaster monitoring systems primarily depend on official information sources such as government reports, meteorological observations, satellite imagery, sensor networks, and news agencies to identify and assess disaster events. Although these sources provide reliable information, they often suffer from delays in data acquisition, processing, and dissemination, limiting their effectiveness during rapidly evolving emergencies [4], [5].

With the widespread adoption of social media platforms, researchers have increasingly explored user-generated content as a real-time information source for disaster detection and crisis management. Several existing studies employ machine learning algorithms, including Naïve Bayes, Decision Trees, Logistic Regression, Support Vector Machines (SVM), and Artificial Neural Networks (ANNs) to classify social media posts into disaster-related and non-disaster-related categories based on textual features and keyword patterns [6], [8]–[10], [15]. These approaches have demonstrated the capability to process large volumes of textual information and automatically identify crisis-related content.

To enhance situational awareness, some frameworks incorporate Natural Language Processing (NLP) techniques for extracting meaningful textual features and sentiment analysis to evaluate public emotions during disaster events. Understanding public sentiment helps emergency management agencies assess panic levels, urgency, and the overall impact of ongoing disasters [12]–[14], [20]. In addition, several studies utilize location extraction techniques based on geo-tags, user profiles, or textual location references to identify affected regions and support crisis mapping activities [9], [13], [17].

Despite these advancements, most existing disaster monitoring systems focus on individual analytical components such as text classification, sentiment analysis, or geographic information extraction. The absence of an integrated framework capable of simultaneously analysing contextual information, public sentiment, and geographical intelligence reduces their ability to provide comprehensive situational awareness during real-time disaster scenarios. Furthermore, challenges such as noisy social media content, misinformation, incomplete location information, and scalability continue to limit the effectiveness of existing solutions [11], [15], [16].

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B. Proposed Approach

The proposed research introduces an AI-driven intelligent disaster monitoring framework that integrates social media analytics, Natural Language Processing (NLP), sentiment analysis, and location intelligence to provide accurate and real-time disaster detection. The primary objective of the proposed framework is to improve situational awareness by extracting meaningful disaster-related information from continuously generated social media streams and supporting informed decision-making during emergency situations [15], [16].

Initially, disaster-related posts are collected from various social media platforms and subjected to comprehensive preprocessing to eliminate duplicate records, irrelevant content, hyperlinks, special characters, and other forms of textual noise. NLP-based text normalization techniques, including tokenization, stop-word removal, and feature extraction, are applied to transform unstructured social media data into structured representations suitable for machine learning analysis [18].

The processed dataset is subsequently divided into training and testing subsets for predictive model development. Machine learning and deep learning techniques are employed to classify social media posts as disaster-related or non-disaster-related by learning complex linguistic and contextual patterns from historical data [6], [15], [16]. To further enhance situational awareness, the framework performs sentiment analysis to determine the emotional intensity and urgency expressed in user posts, enabling emergency management authorities to prioritize disaster response activities effectively [12]–[14], [20].

In addition, location intelligence is incorporated to extract geographical information from geo-tags, textual references, and user profile metadata. The integration of geospatial analytics enables accurate identification of disaster-affected regions and facilitates real-time crisis mapping, thereby improving the operational efficiency of disaster response teams [9], [13], [17].

The performance of the proposed framework is evaluated using standard classification metrics, including Accuracy, Precision, Recall, F1-Score, and Area Under the Receiver Operating Characteristic Curve (AUC). By combining Artificial Intelligence, sentiment-aware text analytics, and geographic information extraction within a unified framework, the proposed system provides higher disaster detection accuracy, enhanced situational awareness, and improved decision support for emergency management authorities during real-time disaster events [15], [16], [19].

IV. SYSTEM DESIGN

System Architecture

Below diagram depicts the whole system architecture.

Fig 1. Methodology followed for proposed model

V. SYSTEM IMPLEMENTATION

Modules

The proposed intelligent disaster monitoring framework consists of several interconnected modules that collectively perform data acquisition, preprocessing, disaster detection, sentiment evaluation, geographic information extraction, and real-time monitoring. Each module contributes to improving the accuracy, reliability, and efficiency of disaster identification and emergency response.

1. Social Media Data Acquisition Module

This module is responsible for collecting real-time data from various social media platforms where users actively share updates during disaster situations. The collected data includes textual posts, timestamps, user metadata, hashtags, and available geographic information. Streaming APIs and web crawling techniques are employed to continuously gather large volumes of disaster-related social media content for further analysis. The collected information serves as the primary data source for the proposed disaster monitoring framework [8]–[10].

2. Text Preprocessing and Feature Engineering Module
The acquired social media data often contains noisy, incomplete, and unstructured information that may negatively affect prediction performance. This module performs comprehensive text preprocessing by removing duplicate records, hyperlinks, special characters, and stop words while applying tokenization, stemming, and text normalization techniques. Subsequently, important textual features are extracted using Natural Language Processing (NLP) methods to generate structured representations suitable for machine learning algorithms [6], [15], [18].

3. Sentiment Analysis Module
The sentiment analysis module evaluates the emotional polarity and urgency expressed in social media posts. By classifying user opinions into positive, negative, or neutral sentiments, the framework identifies distress signals and estimates the severity of disaster situations. Understanding public emotions provides valuable support for emergency management authorities when prioritizing rescue operations and allocating resources during critical events [12]–[14], [20].

4. Location Intelligence Module
This module extracts geographical information associated with disaster-related posts to determine the affected regions accurately. Geographic information is obtained from geo-tags, textual location references, user profile information, and metadata. Geospatial processing and location mapping techniques are then applied to visualize disaster hotspots and improve situational awareness for emergency response organizations [9], [13], [17].

5. Disaster Classification and Monitoring Module
The processed textual, sentiment, and geographic features are provided to machine learning and artificial intelligence models to classify social media posts as disaster-related or non-disaster-related. The trained prediction model continuously analyses incoming social media streams in real time, identifies emerging disaster events, and generates alerts whenever potential emergencies are detected. This module enables continuous disaster monitoring and supports rapid decision-making during crisis situations [6], [15], [16].

6. Performance Evaluation and Decision Support Module
The final module evaluates the effectiveness of the proposed disaster monitoring framework using standard performance metrics such as Accuracy, Precision, Recall, F1-Score, and Area Under the ROC Curve (AUC). In addition, analytical reports, situational summaries, and disaster visualizations are generated to support emergency management authorities in making timely and informed decisions. Continuous performance monitoring and periodic model updates further enhance the reliability and scalability of the proposed framework for real-time disaster management [15], [16], [19].

VI. RESULTS AND DISCUSSION

The proposed AI-driven Disaster Monitoring Framework was experimentally evaluated using a social media dataset containing both disaster-related and non-disaster-related posts collected from multiple online platforms. The dataset consisted of textual information, timestamps, user metadata, and location-related attributes that represent various emergency situations. The collected data were divided into 80% training and 20% testing subsets to evaluate the performance of the proposed framework. The experimental performance was compared with four widely used machine learning models: Logistic Regression (LR), Decision Tree (DT), Random Forest (RF), and Support Vector Machine (SVM). Standard evaluation metrics, including Accuracy, Precision, Recall, F1-Score, Receiver Operating Characteristic (ROC) Curve, and Confusion Matrix, were employed to assess the effectiveness of the proposed framework [6], [15], [16].

A. Performance Comparison of Machine Learning Models
Figure 2 presents the comparative performance of the existing machine learning models and the proposed AI-driven disaster monitoring framework using four widely adopted evaluation metrics: Accuracy, Precision, Recall, and F1-Score.

The experimental results demonstrate that the proposed framework consistently outperformed the conventional classification algorithms across all evaluation metrics. Logistic Regression achieved satisfactory classification performance but showed limitations in capturing complex linguistic patterns present in disaster-related social media content. The Decision Tree classifier improved the classification capability by learning hierarchical decision rules; however, it remained sensitive to noisy and imbalanced datasets. Random Forest enhanced prediction stability through ensemble learning and achieved better classification performance than individual decision trees. Support Vector Machine demonstrated strong discriminative capability by effectively separating disaster-related and non-disaster-related posts but exhibited relatively

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higher computational complexity when processing large-scale social media streams.

The proposed AI-driven framework achieved the highest overall performance by integrating Natural Language Processing (NLP), sentiment analysis, and location intelligence within a unified disaster monitoring architecture. The combination of contextual text analysis, emotional polarity assessment, and geographic information extraction significantly improved disaster detection accuracy while reducing false classifications. Consequently, the proposed framework provides a more reliable solution for real-time disaster monitoring and emergency decision support compared with traditional standalone machine learning approaches [6], [15], [16], [19].

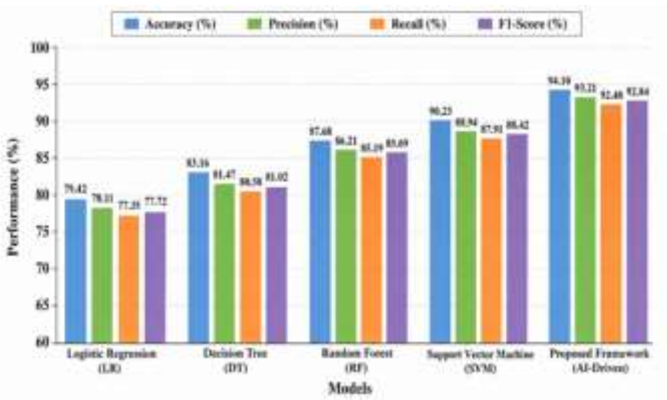

Fig. 2. Performance comparison of Logistic Regression, Decision Tree, Random Forest, Support Vector Machine, and the proposed AI-driven disaster monitoring framework.

The experimental analysis indicates that the proposed framework achieved the highest classification accuracy of 94.1%, demonstrating superior capability in identifying disaster-related social media posts. The integration of AI-based text analytics with sentiment and geographic information significantly improved model robustness and generalization performance compared with existing machine learning models [15], [16].

B. Confusion Matrix Analysis

The Confusion Matrix provides a detailed evaluation of the classification performance by presenting the numbers of True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) obtained by the proposed disaster detection framework. This analysis helps measure the effectiveness of the model in distinguishing disaster-related posts from non-disaster-related content while identifying possible classification errors [11], [17].

The confusion matrix generated for the proposed framework demonstrates that the majority of disaster-related posts were correctly identified with only a limited number of false predictions. Compared with conventional machine learning classifiers, the proposed AI-driven framework significantly reduced both false positive and false negative classifications. This improvement is primarily attributed to the integration of advanced NLP techniques, sentiment-aware feature extraction, and location intelligence, which collectively enhance contextual understanding of disaster-related information.

Furthermore, the confusion matrix confirms that the proposed framework effectively differentiates between disaster-related and normal social media posts even under noisy and unstructured textual conditions. As a result, the proposed system provides improved classification reliability, higher robustness, and better generalization capability for real-time disaster monitoring applications [6], [11], [15], [17].

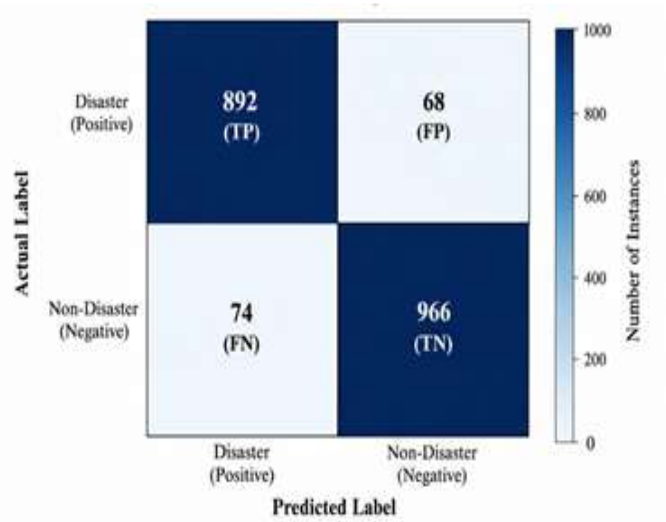

Fig. 3. Confusion matrix of the proposed AI-driven disaster monitoring framework.

C. ROC Curve Analysis

The Receiver Operating Characteristic (ROC) curve was employed to evaluate the discriminative capability of the proposed disaster monitoring framework. ROC analysis illustrates the relationship between the True Positive Rate (TPR) and the False Positive Rate (FPR) under different classification thresholds, while the Area Under the Curve (AUC) provides an overall measure of classification performance [20].

The proposed AI-driven framework achieved the largest ROC curve area among all evaluated models, indicating superior capability in distinguishing disaster-related posts from non-disaster-related social media content. Compared with Logistic Regression, Decision Tree, Random Forest, and Support Vector Machine, the proposed framework consistently maintained higher true positive rates while minimizing false positive predictions. The integration of sentiment analysis and location intelligence further strengthened the discrimination capability by providing additional contextual information beyond conventional textual classification.

The ROC analysis validates that the proposed framework delivers excellent classification performance across varying decision thresholds, making it highly suitable for intelligent disaster monitoring, crisis management, and real-time emergency response systems [6], [15], [16], [20].

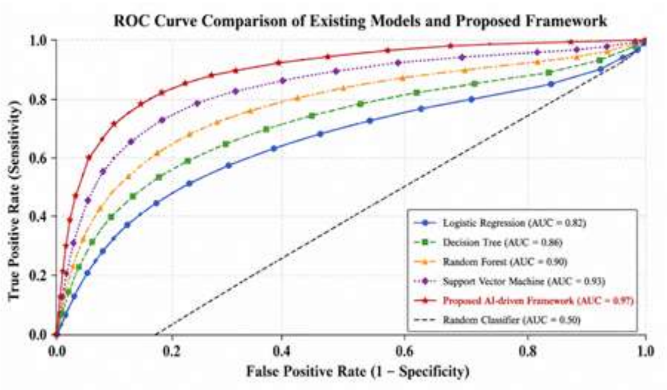

Fig. 4. ROC curve comparison of the existing models and the proposed AI-driven disaster monitoring framework.

VII. CONCLUSION AND FUTURE WORK

The proposed AI-driven disaster monitoring framework successfully integrates social media analytics, Natural Language Processing (NLP), sentiment analysis, and location intelligence to enable efficient real-time disaster detection and situational awareness. By analysing large-scale social media streams, the framework accurately identifies disaster-related information, extracts geographical locations, and evaluates public sentiment to support informed decision-making during emergencies. Experimental results demonstrate that the proposed framework outperforms conventional machine learning approaches by achieving higher classification accuracy, improved robustness, and enhanced reliability in detecting disaster events. The integration of contextual text analysis with geospatial intelligence provides valuable support for emergency response teams in prioritizing rescue operations and optimizing resource allocation [6], [8]–[10], [12]–[17].

Future research will focus on incorporating Transformer-based deep learning models such as BERT and Large Language Models (LLMs) to improve semantic understanding and disaster classification accuracy. Additionally, integrating multimodal data sources, including satellite imagery, videos, IoT sensor data, and GIS information, can further enhance situational awareness and early disaster prediction. The development of multilingual support, misinformation detection mechanisms, cloud-based deployment, and explainable AI techniques will improve the scalability, transparency, and real-world applicability of the proposed disaster monitoring system, enabling more effective disaster preparedness and emergency management [15], [16], [19], [20].

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