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Artificial Intelligence for Social Media-Based Disaster Monitoring: A Review of NLP, Location Intelligence, and Multimodal Approaches

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Abstract—Social media platforms provide a valuable source of real-time information during natural disasters, but the large volume and unstructured nature of such content make manual analysis difficult. Artificial intelligence and natural language processing techniques have therefore been increasingly investigated for extracting meaningful information from disaster-related social media posts. This review analyzes existing research on artificial intelligence-based disaster monitoring, with emphasis on disaster classification, named entity recognition, location intelligence, sentiment analysis, anomaly detection, and multimodal analysis. The reviewed studies demonstrate that social media can complement conventional disaster-monitoring sources by providing timely information about affected locations, public responses, and emerging situations. Recent approaches have further incorporated transformer-based models, large language models, multimodal learning, and geographical analysis to improve disaster intelligence. However, challenges remain in handling noisy and multilingual content, ambiguous geographical references, incomplete information, misinformation, and rapidly changing data. This review compares existing approaches, identifies their limitations, and highlights the need for integrated frameworks that combine textual, spatial, temporal, and multimodal information for improved disaster situational awareness and emergency decision-making.

Keywords—anomaly detection, artificial intelligence, disaster monitoring, natural language processing, multimodal analysis

I. INTRODUCTION

Natural disasters such as floods, earthquakes, cyclones, wildfires, and heatwaves can cause significant loss of life, infrastructure damage, and disruption of essential services. Effective disaster management depends on timely and reliable information about the location and impact of an event. Conventional sources, including official reports, sensors, and remote-sensing systems, provide important information but may not always capture localized conditions in real time. Social-media platforms have therefore emerged as a complementary source of disaster-related information because affected users can report local conditions, damage, and emergency situations during an ongoing event [3], [4].

The large volume and unstructured nature of social-media content, however, make manual analysis difficult. Posts may contain informal language, abbreviations, incomplete information, multilingual content, and irrelevant material. Machine-learning and natural language processing techniques have consequently been investigated for automatically identifying disaster-related information from social-media streams [5], [7], [19]. These approaches can help convert unstructured posts into useful information for disaster monitoring and situational awareness.

Location information is particularly important because emergency response requires knowledge of where an event has occurred. Machine-learning-based approaches have been investigated for mapping events and locations from disaster-related social-media data [2], while named entity recognition approaches have been applied to extract geographical entities from textual content [6]. Georeferenced social-media information has also been explored for flood mapping, demonstrating its potential for identifying affected areas [15]. However, missing, ambiguous, or inaccurate location information remains a significant challenge.

In addition to location, sentiment and emotional information can provide insight into public reactions during disasters. Previous studies have applied sentiment analysis to flood-related social-media posts [8] and emotion analysis to natural-disaster discussions [9]. Real-time sentiment and event analysis have also been explored using Twitter data [20]. The base study by Sufi and Khalil integrated disaster classification, named entity recognition, sentiment analysis, anomaly detection, and location intelligence into an automated

disaster-monitoring framework [1]. This demonstrates the potential of combining multiple analytical techniques rather than relying on a single source of information.

The availability of images and multilingual content has further encouraged research into multimodal disaster analysis. Deep-learning methods have been investigated for classifying disaster-related social-media images [10], while self-supervised learning has been explored for real-time disaster-image classification [11]. Multimodal fusion has also been applied to flood detection using multilingual social-media data [25]. Recent studies have additionally explored multimodal GeoAI, large language models, and artificial intelligence-enhanced natural language processing for disaster-related applications [21]–[24]. These developments indicate a shift toward integrating textual, spatial, temporal, and visual information for more comprehensive disaster analysis.

Despite these developments, several challenges remain, including noisy and multilingual data, geographical ambiguity, misinformation, incomplete information, and the requirements of real-time processing. Therefore, this review examines artificial intelligence-based approaches for social-media disaster monitoring, with emphasis on natural language processing, disaster classification, named entity recognition, location intelligence, sentiment analysis, anomaly detection, and multimodal analysis. The reviewed studies are compared to identify their contributions, limitations, and research gaps, providing direction for the development of more integrated and reliable disaster-monitoring frameworks.

II. LITERATURE REVIEW

Social media has become an important source of real-time information during natural disasters, as affected individuals can share observations, damage reports, and emergency information during ongoing events [3], [4]. Existing research has therefore explored the use of machine learning and natural language processing to identify relevant disaster-related content from large volumes of social-media data [5], [19]. These approaches demonstrate that automated analysis can support situational awareness and complement conventional disaster-monitoring sources.

Location extraction is a major research area because identifying the geographical context of a social-media post is essential for disaster response. Machine-learning approaches have been investigated for mapping events and locations from social-media data [2], while named entity recognition has been applied to extract geographical entities from textual content [6]. Georeferenced social-media data has also been examined for flood mapping [15]. However, ambiguous place names, missing coordinates, and inaccurate location information remain important limitations.

Sentiment and emotion analysis have been used to understand public reactions during disaster situations. Studies have investigated sentiment analysis of flood-related social-media posts [8] and emotion analysis during natural disasters [9]. Real-time analysis of social-media messages has also been explored for monitoring and predicting events [20]. The base study by Sufi and Khalil combined disaster classification, named entity recognition, sentiment analysis, anomaly detection, and location intelligence, demonstrating the potential of integrating multiple analytical components into a single disaster-monitoring framework [1].

Recent research has expanded disaster analysis beyond text-based approaches. Deep-learning methods have been investigated for classifying disaster-related images [10], while self-supervised learning has been applied to real-time disaster-image classification [11]. Multimodal fusion has further been explored for disaster detection using multilingual social-media data [25]. These studies indicate that combining textual and visual information can provide a more comprehensive representation of disaster situations.

Recent advances have introduced multimodal GeoAI, large language models, and artificial intelligence-enhanced natural language processing into disaster analysis [21]–[24]. These approaches provide opportunities for combining spatial, temporal, semantic, sentiment, and visual information. Recent systematic reviews also show that research is increasingly moving toward deep-learning, transformer-based, multilingual, and multimodal approaches, while limitations remain in low-resource languages, geographical diversity, real-time processing, and reliable information extraction.

Overall, the literature shows a progression from basic social-media monitoring toward integrated approaches involving natural language processing, location intelligence, sentiment analysis, anomaly detection, and multimodal analysis. However, challenges related to noisy and multilingual content, geographical ambiguity, misinformation, limited language support, and real-time processing continue to exist. These limitations indicate the need for integrated and reliable frameworks capable of combining textual, spatial, temporal, and multimodal information for improved disaster situational awareness.

III. PROBLEM STATEMENT AND OBJECTIVES

A. Problem Statement

Social-media platforms provide real-time disaster-related information, but the data is largely unstructured, noisy, and often lacks accurate location information. Existing approaches mainly focus on individual tasks such as disaster classification, location extraction, sentiment analysis, or anomaly detection [1], [2], [6], [8]. Hence, there is a need for an integrated artificial intelligence-based approach that can extract

meaningful disaster information and improve real-time situational awareness.

B. Objectives

The objectives of this review are:

- To examine existing approaches for collecting and preprocessing disaster-related social-media data.
- To analyze natural language processing and machine-learning techniques used for disaster classification.
- To study named entity recognition-based approaches for extracting disaster locations.
- To review sentiment and severity analysis techniques for disaster-related content.
- To examine anomaly-detection and temporal-analysis approaches.
- To identify research gaps in integrating these techniques for improved disaster situational awareness.

IV. PROPOSED SYSTEM ARCHITECTURE

The proposed architecture provides an integrated pipeline for analyzing disaster-related social-media content and converting unstructured posts into useful disaster intelligence. The system consists of data collection, preprocessing, natural language processing, location extraction, sentiment and severity analysis, anomaly detection, and geospatial visualization modules. This architecture follows the reviewed approaches that combine textual, spatial, temporal, and sentiment information for disaster monitoring [1], [2], [21].

The process begins with the data collection module, which gathers disaster-related social-media posts using relevant keywords, hashtags, and available platform interfaces. The collected data is then passed to the preprocessing module, where unnecessary content is removed and the text is normalized for further analysis.

The processed posts are analyzed by the NLP and disaster classification module to identify relevant disaster-related information. Named Entity Recognition is subsequently used to identify geographical entities, which can be converted into coordinates through geocoding [2], [6]. The sentiment and severity analysis module evaluates the expressed public response and assigns relevant sentiment or severity information [1], [8], [9].

The extracted information is then aggregated according to location and time. The anomaly detection module identifies unusual changes in disaster-related activity, such as sudden increases in relevant posts or negative sentiment [1], [16], [20]. Finally, the processed information is presented through a geospatial visualization dashboard, allowing disaster-related activity and affected locations to be examined more effectively.



Fig. 1. Proposed system architecture for artificial intelligence-based disaster monitoring.

V. METHODOLOGY

This review examines existing artificial intelligence-based methods used to analyze social-media information during disaster events. The selected studies are compared based on the type of data used, preprocessing methods, analytical techniques, and the type of disaster-related information obtained [1], [5], [21]. Particular attention is given to approaches involving natural language processing, disaster classification, location extraction, sentiment analysis, anomaly detection, and multimodal analysis.

A. Data Collection

The reviewed studies use social-media posts as a source of information during disaster events. Data are commonly obtained using disaster-related keywords, hashtags, platform interfaces, and publicly available datasets. Depending on the study, the collected data may contain text, timestamps, geographical information, images, and other metadata. These characteristics allow social-media data to provide timely observations that can complement information obtained from conventional disaster-monitoring sources [3], [4].

B. Data Pre-processing

Raw social-media data contain noise and irregularities that can affect subsequent analysis. The reviewed approaches therefore apply preprocessing operations such as removal of irrelevant content, text cleaning, normalization, and tokenization. Some approaches also address incomplete or inconsistent information before applying machine-learning or natural language processing methods [5], [7]. Proper preprocessing is important for improving the quality of information extracted from social-media posts.

C. Disaster Classification and Information Extraction

After preprocessing, machine-learning and natural language processing techniques are applied to determine whether a post is related to a disaster and, where applicable, to identify the type of disaster being discussed [5], [19]. Information extraction techniques can then identify important entities within the text. Named Entity Recognition is particularly useful for identifying geographical names and other relevant entities that can provide additional context about the reported event [6].

D. Location and Sentiment Analysis

Geographical information extracted from social-media posts can be converted into coordinates using geocoding techniques, allowing disaster-related information to be mapped and analyzed spatially [2], [15]. Alongside geographical information, sentiment and emotion analysis can be used to examine public reactions during disaster events [8], [9]. These analyses provide complementary information that can help describe the situation from both geographical and public-response perspectives [1].

E. Anomaly and Multimodal Analysis

Temporal analysis can be used to examine changes in social-media activity over time, while anomaly-detection techniques can identify unusual increases or patterns in disaster-related posts [1], [20]. Recent research has also expanded analysis beyond text by incorporating disaster-related images, multilingual information, and multimodal learning techniques [10], [11], [25]. In addition, GeoAI and large language model-based approaches provide opportunities for combining spatial, temporal, and semantic information for more detailed disaster analysis [21], [22].

F. Information Visualization

The information obtained from the different analytical stages can be presented using maps, charts, and dashboards. Geospatial visualization is particularly useful for displaying reported disaster locations and examining spatial patterns, while other visual elements can represent activity levels and public responses. Such representations can provide a consolidated view of disaster-related information and support situational awareness and emergency-response activities [1], [21].

G. Integrated Framework Proposed from the Review

Based on the analysis of the selected studies, this review proposes an integrated framework for social-media-based disaster monitoring that combines complementary artificial intelligence techniques. The framework considers disaster classification for identifying relevant information, named entity recognition and geocoding for obtaining geographical context, sentiment and severity analysis for understanding public response, and temporal anomaly detection for identifying unusual changes in disaster-related activity [1], [2], [6], [8], [20]. Where available, images and multilingual information can further complement textual analysis [10], [11], [25]. The extracted information can subsequently be combined and represented through geospatial visualization, providing a consolidated view of the disaster situation. The framework is intended to address the limitations of approaches that consider these analytical tasks independently and provides a basis for developing more comprehensive disaster-monitoring systems [1], [21]–[25].

VI. RESULTS AND DISCUSSION

As this work is a review paper, the results are based on the findings reported in the selected studies rather than newly generated experimental results. The reviewed literature shows that artificial intelligence and natural language processing can effectively extract useful information from disaster-related social-media content [1], [5], [7]. Location-based approaches further provide geographical context by identifying and mapping affected areas [2], [6], [15].

Sentiment and emotion analysis can provide additional information about public reactions during disasters [8], [9]. However, sentiment alone cannot be considered a direct measure of physical disaster severity. Combining sentiment with location, disaster category, and temporal activity can provide a more meaningful representation of an evolving situation [1], [20].

Multimodal approaches have extended disaster analysis beyond text by incorporating images and multilingual information [10], [11], [25]. Recent studies have also explored GeoAI, large language models, and spatial-temporal analysis for improving disaster intelligence [21]–[24]. These developments indicate that combining multiple information sources can provide more comprehensive situational awareness than relying on a single analytical technique.

Overall, the literature indicates a progression from basic disaster classification toward integrated approaches involving natural language processing, location intelligence, sentiment analysis, anomaly detection, and multimodal analysis. However, noisy data, multilingual content, ambiguous locations, misinformation, and real-time processing remain important challenges. Therefore, future systems should

focus on integrating these capabilities into reliable and scalable frameworks for improved disaster monitoring and emergency decision-making.

TABLE I. COMPARATIVE ANALYSIS OF REVIEWED APPROACHES

Approach	References	Major contribution	Key limitation
Disaster classification	[5], [19]	Identifies disaster-related content	Noisy and ambiguous text
Location extraction	[2], [6], [15]	Provides geographical context	Missing or ambiguous locations
Sentiment analysis	[1], [8], [9]	Identifies public response	Does not directly indicate physical severity
Anomaly detection	[1], [16], [20]	Detects unusual activity	Depends on temporal data
Multimodal analysis	[10], [11], [25]	Combines different data types	Higher complexity
GeoAI and advanced AI	[21]–[24]	Integrates spatial and semantic information	Requires reliable and diverse data

The comparison shows that existing approaches address different aspects of disaster monitoring. While individual techniques provide useful information, they generally focus on specific analytical tasks. The proposed integrated framework combines these complementary capabilities to provide a more comprehensive representation of disaster-related information. However, experimental evaluation is required before its performance can be compared quantitatively with existing systems.

B. Performance Comparison

Different studies use different datasets, disaster types, languages, tasks, and evaluation protocols. Therefore, numerical performance values cannot always be directly compared. The following table reports metrics where they are explicitly available in the reviewed studies.

TABLE II. PERFORMANCE COMPARISON OF REVIEWED AND PROPOSED APPROACHES

Approach	Reference	Accuracy	Precision	Recall	F1-Score	Evaluation Status
AI-based disaster monitoring	[1]	97%	93%	—	90%	Reported by study
Disaster classification	[5]	Study-specific	Study-specific	Study-specific	Study-specific	Study-specific
Location mapping	[2]	Dataset-specific	—	—	—	Study-specific
Location extraction using NER	[6]	Dataset-specific	—	—	—	Study-specific
Sentiment analysis	[8]	Dataset-specific	—	—	—	Study-specific
Disaster image classification	[10], [11]	Dataset-specific	—	—	—	Study-specific
Multimodal flood detection	[25]	Dataset-specific	—	—	—	Study-specific
Proposed integrated framework	This review	Not yet evaluated	Not yet evaluated	Not yet evaluated	Not yet evaluated	Requires experimental validation

Discussion:

The performance comparison demonstrates that reported results vary according to the specific task and evaluation dataset. For example, the AI-based disaster-monitoring framework reported in [1] achieved an accuracy of 97%, precision of 93%, and F1-score of 90%. However, these values should not be interpreted as directly comparable with results from studies addressing different tasks or datasets. The proposed integrated framework has not yet been experimentally evaluated in this review and therefore no performance values are assigned to it.

VII. RESEARCH CHALLENGES

A. Noisy Social-Media Data

Social-media posts frequently contain informal language, abbreviations, irrelevant information, spelling variations, and incomplete statements. Such characteristics can reduce the reliability of natural language processing and machine-learning models. Effective preprocessing and robust language models are therefore required for reliable information extraction.

B. Multilingual and Low-Resource Languages

Disaster information can be communicated in multiple languages and local dialects. However, many NLP models have greater availability of training resources for widely used languages. Limited datasets for low-resource languages can therefore affect classification, entity extraction, and sentiment analysis performance [17], [25].

C. Location Ambiguity

Accurate geographical information is important for disaster response, but social-media posts may contain missing coordinates, informal place names, or references to multiple locations. These issues can reduce the accuracy of geocoding and spatial analysis [2], [6], [15].

D. Misinformation and Reliability

Social media can contain inaccurate information, rumors, duplicated posts, and unverified reports. A disaster-monitoring system should therefore consider information reliability before presenting extracted information for decision-making. Combining multiple sources and incorporating misinformation-detection techniques can help address this challenge.

E. Real-Time Scalability

The volume of social-media information can increase rapidly during major disaster events. Processing large streams of posts requires scalable computational infrastructure and efficient analytical methods. Real-time systems must balance processing speed with the accuracy of information extraction.

F. Model Explainability

AI-based disaster-monitoring systems may influence how information is prioritized during emergency situations. Therefore, understanding why a model classifies a post, identifies a location, or detects an anomaly is important for improving transparency and user confidence.

G. Limitations of the Review

This review has several limitations. The reviewed studies use different datasets, disaster types, languages, evaluation protocols, and performance metrics, which makes direct numerical comparison difficult. In addition, some studies report only selected evaluation metrics, while others focus on specific analytical tasks. Therefore, the performance values presented in this review should not be interpreted as a direct ranking of the reviewed approaches. Experimental evaluation of the proposed integrated framework is required to establish its effectiveness under a common dataset and evaluation protocol.

VIII. CONCLUSION AND FUTURE SCOPE

A. Conclusion

This review examined artificial intelligence-based approaches for disaster monitoring using social-media data. The reviewed studies demonstrate that combining natural language processing, disaster classification, location extraction, sentiment analysis, anomaly detection, and multimodal analysis can provide useful disaster intelligence [1], [6], [18], [21]. However, challenges such as noisy and multilingual data, geographical ambiguity, misinformation, and real-time processing remain. An integrated approach can therefore provide a broader representation of disaster-related information and support situational awareness during emergency events.

B. Future Scope

Future research can focus on multilingual and multimodal analysis, real-time processing, advanced geographical artificial intelligence, misinformation detection, explainable artificial intelligence, and integration with emergency-response systems [17], [21]–[25]. Future implementations of the proposed framework should also evaluate its individual components and overall performance using common datasets and standardized evaluation metrics. These developments can improve the accuracy, reliability, scalability, and practical applicability of AI-based disaster-monitoring systems.

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