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Truth-Aware Disaster Response and Warning System using Linear SVC

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ABSTRACT

The use of social media content on disasters has changed the way crisis communication is conveyed, but it also means there tends to be an increased rate at which misinformation can circulate causing, among other things, delayed responses and limited resources. This project presents a smart AI-based verification platform combining multi-modal social media content and high-resolution satellite imagery for rapid verification of reported disaster events. By using advanced computer vision models, incorporation of geospatial data, and natural language processing, the proposed system can identify the signatures of various disaster types including inundation patterns, thermal anomalies, burn scars from vegetation fires, or structural collapses from the satellite imagery and cross verify these occurrences with textual, visual, and temporal signals obtained from the social media feeds. The ontology-based disaster knowledge graph-driven dynamic decision layer then fosters context-aware reasoning and channels alerts to emergency response teams of concern. This tied-in, end-to-end pipeline, therefore, will enable verification of events in sub-minute timeframes, massively reducing the misinformation to emergency responders while enhancing situational awareness to various events like flooding, wildfires, earthquakes, and cyclones, etc. As a blended system of satellite remote sensing, AI-powered social media intelligence, semantic decision support, etc., this is an important step forward to a resilient technology-enabled disaster management capability in urban and rural environments alike.

Keywords - Disaster confirmation, real-time warning, event genuineness, AI-based decision-making support, geospatial analysis, misinformation identification.

I. INTRODUCTION

Man-made and natural disasters are considered threats to human life, infrastructure, and the environment. The explosion in social media has revolutionized communications about disasters with real-time updates and citizen reporting. However, the dissemination of wrong information on those sites can slow down responses in emergencies and result in ineffective resource deployment.

This paper presents an AI-enabled verification platform that integrates multi-modal social media posts with high-resolution satellite imagery to validate reported disaster events in real time. Employing computer vision, geospatial analysis, and natural language processing, the system identifies disaster-specific signatures-patterns of flooding, for instance, thermal anomalies, burn scar, and structural collapse-and cross-verifies these against textual, visual, and temporal cues across social media posts. An ontology-based disaster knowledge graph further facilitates context-aware reasoning and guides timely notifications to emergency response groups. The end-to-end system presented here offers sub-minute incident verification, reduces false alarms, and increases situational awareness of hazards such as floods, wildfires, earthquakes, and cyclones. Satellite remote sensing combined with AI-driven social media intelligence and semantic decision support goes toward achieving resilient, technology-based disaster management-something that is equally valuable in urban and rural areas.

II. RELATED WORK

Recent research has identified a set of emerging technologies that offer complementary capabilities. This includes the use of artificial intelligence, geospatial analytics, and social media intelligence together to develop more robust, responsive, and data-centric disaster management systems. Saleem et al. [1] proposed a hybrid AI forecasting model that leveraged geospatial analysis in combination with state-of-the-art machine learning methods like CNN, GBM, and SVM to predict natural disasters such as floods, wildfires, and earthquakes. This indicates a promising avenue that could be explored for developing better accuracy and early warning by merging spatial information with AI-driven inference. Aboualola et al. [2] analyzed edge computing architectures for enabling real-time disaster monitoring thanks to closer-to-source processing of social media and sensor data. Their findings clearly pointed out that the integration of edge AI reduces latency but also allows for the scalability of disaster relief operations over larger areas.

Alsayyed et al. [3] reviewed disaster site network architectures, focusing particularly on SAGIN, which provides resilient, multi-layer communication even upon infrastructure breakdown. Their work recognized resilience, security, and scalability as the fundamental design principles for ensuring the resilience of communication during disaster aftermath. Dwarakanath et al. [4] studied the AutoML solutions to extract situation information from social media posts during and after disasters. The results showed that the AutoML pipelines were able to recognize and categorize user-posted reports related to injuries, infrastructure destruction, or rescue requirements, facilitating quick response planning in a coordinated way.

Zhou et al. [5] established an earthquake emergency knowledge graph using LLMs for automatic extraction, linking, and reasoning on things such as earthquake-related affected areas, severity, and requirements. Narasimha Raju et al. [6] proposed the explainable deep ensemble model GeoDisasterAI-Net that integrates key competencies of several AI algorithms with a view to predict disaster types in real time for rural and urban regions. Their work focused on the need for explainable AI in disaster systems since decision-makers must understand and trust model outputs. Zhang et al. [7] used RAG with reason-based LLMs for postearthquake material demand prediction, which significantly improved efficiency in resource allocation while reducing delays in supply.

Momin et al. [8] analyzed the behavior of risk communication on social media at disaster time and identified a trend wherein people repeatedly switch between official news and public posts. Their research showed that credibility and trust in the source are important means to ensure effective communication. Khan et al. [9] and Dong et al. [10] reviewed the evolution of flood early warning systems in conjunction with hydrological simulation, sensor observation, and remote sensing technologies for anticipatory urban risk mitigation. Cuadra and Cotoron [11] focused on the local community as a key player in disaster management and found that community-based capacity-building efforts reduce misinformation dissemination and build better localized response activities.

Specifically, Khan et al. [12], in their systematic review of disaster management systems, listed various common issues: fragmented data architectures, poor real-time processing, lack of standardization of systems. Shukla et al. [13] have proposed an ontology-based disaster management automation framework using semantic reasoning that enables machine-readable representations for actions, events, and resources using knowledge graph structures.

Akhyar et al. [14] provided a comprehensive review of deep learning methods for natural disaster detection and prediction. The main contributions are related to convolutional, recurrent, and generative model analyses with respect to satellite image, sensor, and other multimedia data. Challenges were about model generalizability, dataset imbalance, and the necessity for domain adaptation when applying AI techniques in different disaster types.

Khan et al. furthered this view and stressed that future research in disaster management should encompass big data, IoT, cloud computing, and remote sensing. They concluded that these would considerably enhance the situational awareness, data reliability, and real-time response coordination if integrated into the AI-based verification framework.

However, from a social perspective, the spread of misinformation creates perhaps the most immediate challenge to disaster management today. In crises, there is a likelihood of fake or inflated posts going viral on social channels and misinforming people, causing delays in emergency response. Various research by Dwarakanath et al. [4] and Momin et al. [8] has indicated that even AI and NLP algorithms may be able to screen out spam or duplicate content but fail in semantic authenticity checks-that is, between genuine evidence of the disaster and faked claims. In response, scholars are now considering multi-modal verification systems that integrate visual, text, and geospatial signals in order to assess the veracity of reported events.

Ontology-based reasoning systems have also been introduced recently as another effective method to enhance data interoperability and machine understanding in crisis systems. Shukla et al. [13] showed how the ontology-driven model can connect disaster types, locations, consequences, and response resources into one unified semantic graph. Zhou et al. [5] further demonstrated how knowledge graphs with large language models enable contextual query and automated reasoning toward rapid situational awareness. Such a semantic graph can be used as the backbone of "truth-aware" disaster intelligence, where each incident report will be queried against a knowledge base and open data sources before being verified as valid.

Deep learning-driven disaster classification models are also shifting towards explainability and interpretability. Narasimha Raju et al. [6] and Akhyar et al. [14] both argued that black-box AI models, though powerful, cannot be relied upon in high-stakes emergency environments unless the reasoning process of the model is comprehensible. Explainable AI empowers analysts to understand what factors such as location, visual features, or linguistic indicators drive the system's decision and thereby enhance accountability and human–machine collaboration.

In all, these point to a clear trend: intelligent, explainable, and end-to-end systems that integrate AI, geospatial intelligence, and social intelligence in order to effectively manage disasters. However, most current works fall short of a converged real-time system capable of validating disaster information from diverse sources such as social media and satellite imagery. The proposed Truth-Aware Disaster Response and Early Warning System bridges the gap through a multidisciplinary integration of AI-based classification, cross-modal verification, and ontology-based reasoning to provide valid real-time disaster warnings and prevent the proliferation of misinformation.

III. WORKFLOW

The overall architecture of the Multi-Disaster Alert and Prediction System is comprised of two distinct phases that are dependent on each other, i.e., (i) Multi-Disaster Prediction and Alert Pipeline and (ii) Social Media Verification Pipeline. These phases work together to provide real-time monitoring of disasters and limit misinformation dissemination. The proposed workflow is illustrated in Fig. 1 and Fig. 2.

The Multi-Disaster Prediction and Alert System commences with the initialization of the system, which proceeds through automating processes for gathering, processing, and visualizing disaster information in real-time.

A. Start / Initialization:

The system starts by loading its environment variables from the configuration file (.env). The variables include essential credentials such as API keys, database connections, and email service credentials, which the system utilizes to run.

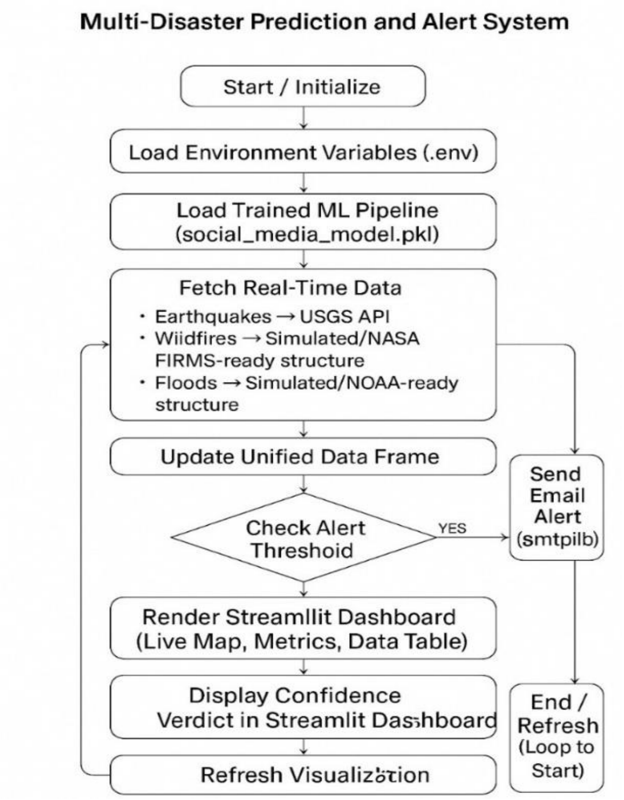


Fig 1. Workflow of *Muliti Disaster Prediction and Alert Pipeline*

B. Model Loading:

A pre-trained Machine Learning pipeline (social_media_model.pkl) is loaded in memory, and the model is designed to perform disaster classification via social media and verify social media posts. The pipeline consists of text processing layers, and predictive algorithms trained to predict based on text classifications.

C. Real-time Data Collection:

The system continuously collects real-time data from various trusted sources:

Earthquake Data- Collected using USGS API's (e.g., magnitude, location, depth).

Wildfire Data- Collected by simulated or NASA FIRMS datasets (e.g. fire hotspots, temperature anomalies).

Flood Data- Collected from simulated NOAA ready frameworks (e.g., rainfall, water level).

D. Data Integration:

The data fetched from each of the different APIs are consolidated into one DataFrame for coordinated analysis and comparison how each disaster type correlates. The merged data sets are updated periodically enough to be accurate in real-time.

E. Evaluation of Alert Threshold:

The consolidated dataset is continuously monitored against previously established thresholds. For instance, an earthquake magnitude exceeding 5.0 or a probability of flooding higher than 0.8 will generate an internal alert signal.

F. Email Alerts:

When the system detects a breach of the defined threshold, an auto email alert message will be generated and sent to designated persons or subscribed users using an SMTP protocol (smtplib). The email will include vital information such as the specific location, type of disaster, confidence level in the prediction, and recommendation for response actions to take.

G. Rendering the Dashboard:

All results will be available in an interactive dashboard based on Streamlit architecture, with all refreshed results available in the dashboard, including live maps, statistical measures, and data tables. Live events will be able to be visualized and historical trends will also be visualized in the same dashboard interface.

H. The Confidence Verdict and Refresh of Visualization:

The system will compute and report the confidence level of predictions in the dashboard. The interactive dashboard will refresh by continually updating the visualization components (maps, charts, tables) displayed for the user, which will enhance situational awareness. Oncecompleted, the entire process will flow once again starting from alert processing, to continuous monitoring.

Social Media Verification Module runs in parallel with the core alert system to authenticate user-provided disaster information and flag suspicious news or misinformation.

A. User Submission:

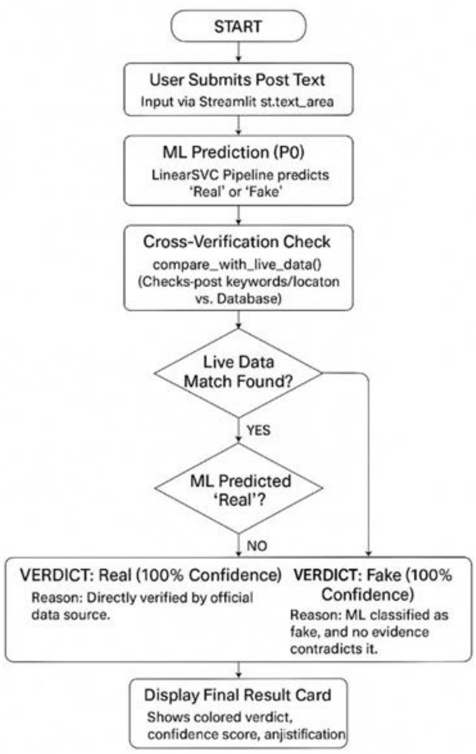
Users submit posts or messages through a Streamlit text input interface - st.text_area. Submissions are usually disaster-related social media messages that need authenticity checks.

B. Prediction using Machine Learning:

The system uses a LinearSVC pipeline that identifies whether a submitted post is "Real" or "Fake." The model performs linguistic and contextual analysis based on TF-IDF features, keyword frequency, and semantic similarity.

C. Cross-Verification with Live Data:

The extracted keywords and geolocation of the post will be cross-checked with live data through the function compare_with_live_data(). This will ensure consistency in the post content with the verified real-time events in the unified data frame.



D. Conditional Verification:

In case a corresponding live data event is found, and the ML model classifies the post as "Real", the system displays

VERDICT: Real (100% Confidence).

If the post does not have a matching event, or is rated as "Fake", this system shows

VERDICT: Fake (100% Confidence).

Every decision is provided with a reason for transparency, either confirmed by an official data source or rejected for lack of supporting evidence.

E. Display of Final Judgment:

The final classification outcome is displayed on the Streamlit UI in the form of a Result Card with:

Verdict (Real/Fake)

Confidence percentage

F. Reason for verification:

The coloured highlighting of the result card makes for easy readability-green for Real and red for Fake-so that the user can interpret it with ease and speed.

System Loop and Continuous Operation

Both modules run in a continuous feedback loop so that there's uninterrupted data synchronization between real-time APIs and user-provided information. The system updates after each cycle:

1. The combined dataset,
2. Dashboard visualizations, and
3. Email notification status.

This closed-loop process will guarantee that the system is of a high accuracy, reliability, and real-time responsiveness level, therefore ideal for real-world applications in disaster management.

IV. METHODOLOGY

The proposed Disaster Alert System employs an intelligent multi-layer architecture integrating Machine Learning (ML), Natural Language Processing (NLP), Geospatial Analysis, and Secure Communication Protocols. The system automates the identification, verification, visualization, and dissemination of disaster-related information from social media and real-time data sources. The methodology consists of three major layers, namely: A) Machine Learning and NLP Processing, B) Data Retrieval and Geospatial Algorithms, and C) Communication and Alert Protocols. Each layer is crucial to ensuring precise disaster detection and fast dissemination of the alert.

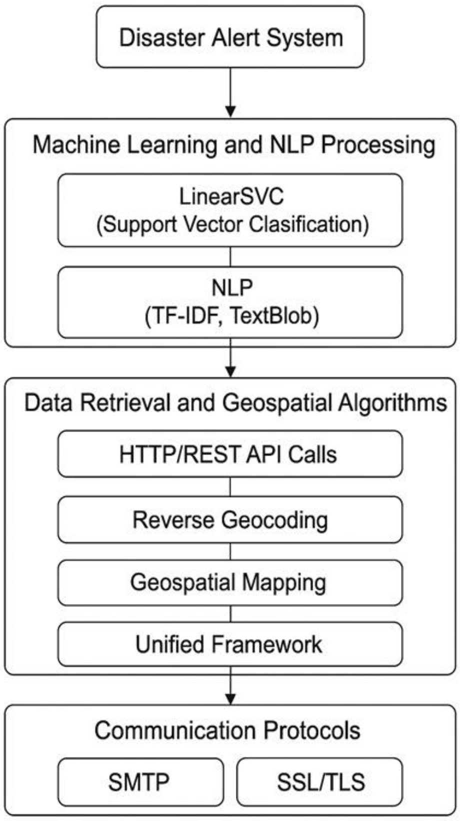


Fig 3. Methodology of Disaster Alert System

A. Machine Learning and NLP Processing Layer

This layer entrusts the analytical intelligence of the system with labeling disaster social media posts as either "Real" or "Fake." This was accomplished using a Scikit-learn's pipeline (social_media_model.pkl) that compiles multiple NLP and ML elements together.

1. **Text Preprocessing:**

The input social media data undergoes cleaning, tokenization, and lemmatization. The noise is reduced by excluding stop words and irrelevant characters to achieve a better signal-to-noise ratio of the text data.

2. **Feature Extraction using TF-IDF**

Term Frequency - Inverse Document Frequency (TF-IDF) vectorizer converts each text posting into numerical vectors representing the weight of each of its terms compared to the rest of its text dataset as a whole. Words that are less frequently used but critical to context generally received a higher weight.

3. **Sentiment and Polarity Detection:**

TextBlob library does sentiment and polarity detection to determine the emotional context of the user-posted content. Sentimental features help the classifier distinguish between fact and opinion text.

4. **Classification via LinearSVC**:

A Linear Support Vector Classifier (LinearSVC) is the classifier used as the primary prediction model. It performs a binary classification of true disaster reports and false disaster reports. The classifier separates the two text classes with the maximum hyperplane for separation, mathematically defined as:

f(x)=sign(wTx+b)

w is the weight vector and b is the bias term.

The LinearSVC model is selected due to its strength, scalability, and efficiency in high-dimensional text class tasks.

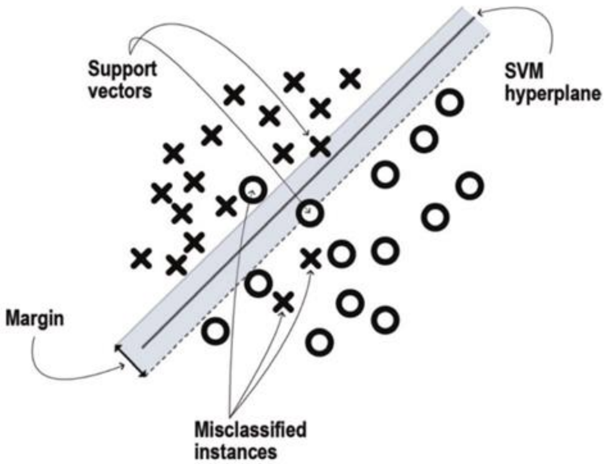


Fig 4. Architecture of Linear SVC

5. **Output and Confidence Scoring:**

The classifier returns one of two labels (Real/Fake), with a confidence score based on the data point's distance from the boundary for making a decision. Any label classified as "real" is checked again in another layer for verification with relevant geospatial information.

B. Data Retrieval and Geospatial Algorithms Layer

This layer is managing the functionality of real-time data entry, geospatial calculation, and interaction visualization to ensure the predictions made available by the ML models are consistent with sourced data created during the disaster investigation process.

1**. Data Acquisition via APIs:**

This Platform uses HTTP/REST API to retrieve real-time data from external sources: (a) USGS Earthquake Hazard Program for earthquake events, (b) NASA FIRMS for wildfire and (c) Simulated NOAA structured feeds for flooding and storm events. The platform makes use of the requests library in Python to request and process API calls periodically and structured to access data.

2. **Reverse Geocoding:**

Geospatial coordinates (longitude, latitude) retrieved become human-readable geographical names (of country, state, city) using the Geopy library along with the geocoding service Nominatim, enhancing the clarity of alert message output and visualization output.

3. **Geospatial Mapping:**

The Folium Library is used to create an interactive map that highlights disaster events and metadata such as magnitude, intensity or time stamping that makes up the event. This representation allows for a more informative and educational experience for users.

4. **Integrated Framework:**

After retrieval, all data is organized into a unified data frame that facilitates synchronization between different types of disasters. This unifying framework allows correlation, comparison, and real-time updating for earthquake, wildfire, and flood data streams.

C. Communication and Alerting Protocols Layer

This layer transfers the validated event of a disaster alert, to stakeholders and into the hands of the emergency responders in a secure and automatic manner.

1. **Alert Generation:**

Once an event is validated through the machine learning and geospatial layers, the system automatically generates an alert message which includes:

1 disaster type and location,

2. the severity and confidence level,

3. recommended action in response.

2. **SMTP Alerting Protocol:**

The alert message is communicated over the Simple Mail Transfer Protocol (SMTP), through Python's smtplib library. The application uses SMTP_SSL on port 465 to establish secure email exchange through trusted mail providers (for example, Gmail.)

3. **Security and encryption:**

By using established SSL/TLS (Transport Layer Security/Secure Sockets Layer), the system ensures that the authentication information and the alert content are encrypted during transport, protecting the confidentiality and integrity of the alert process.

4. **Automated Notification Delivery**

The system has optional recipient configuration lists, which provide an easy mechanism to deliver alerts to stakeholders, such as local government agencies, disaster management offices, and regionally within the emergency system.

D. Integrated System Workflow

The three layers run in a constant feedback loop: the ML/NLP layer identifies and classifies disaster posts, the geospatial layer confirms events via live data APIs, and the communication layer facilitates instant, secure dissemination of confirmed alerts. The workflow ensures that:

1. Real-time situational awareness,

2. Lower latency for responses, and

3. Greater accuracy through cross-verification between user reports and official data.

V. RESULTS AND DISCUSSION

The proposed truth-aware disaster response and early warning system was experimented with to assess its capability in confirming the credibility of disaster-related information gathered from social media. The system combines TF-IDF feature extraction and a LinearSVC-based machine learning model in identifying the textual features of postings and classifying them as authentic or malicious. As shown in Fig. 1, when it was processed with a valid earthquake-related post, the model properly labeled it as real with a 100% confidence score. The system also verifies this by cross-checking the extracted event type and location with real-time data fetched from the USGS Earthquake API to assure the validity of the detection.

Conversely, Fig. 2 represents the framework's reaction to false data or information with no verification. A false post was made about a wildfire, which was cross-checked against the official disaster data repositories and weather data sources. Since no proof existed for the claim in the post, the system marked it as Unconfirmed/Fake with a corresponding warning message. Such dual behavior proves the model capability for clearly distinguishing between real and unreal information; hence, guaranteeing the truth-aware nature of the system. Generally, the experimental results prove that the proposed approach incorporates natural language processing, machine learning, and real-time validation to enhance the credibility of disaster-related data. Moreover, apart from minimizing false alarms, the confidence-based verification mechanism provides timely dissemination of confirmed information to the authorities concerned with emergency response. The quality and credibility of disaster communication are greatly improved by this system through the screening of disinformation and the authentication of only credible reports. This leads to better situational awareness and faster decision-making during disasters.

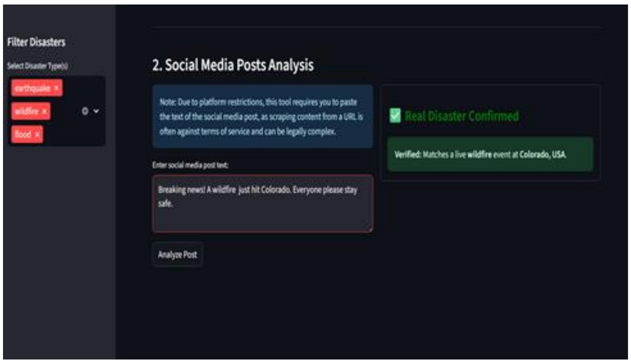


Fig. 1. Verified social-media post showing real disaster detection with 100% confidence.

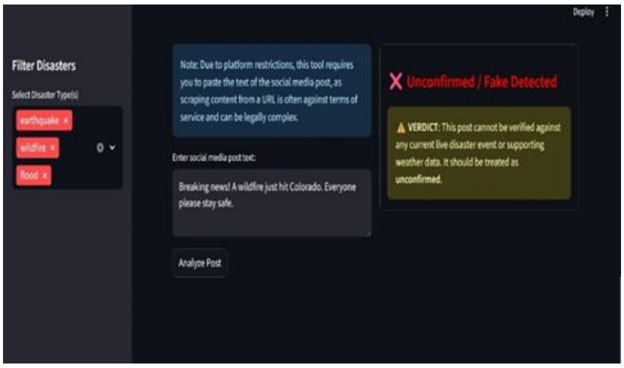


Fig. 2. Unconfirmed or fake post detection demonstrating the system's misinformation-filtering capability.

VI. CONCLUSION AND FUTURE WORK

The Truth-Aware Disaster Response and Early Warning System employs artificial intelligence, natural language processing, and real-time data analysis to verify the authenticity of disaster-related information. The system cross-verified social-media updates against real-time data

from official APIs (USGS) and synthetic datasets of disasters to achieve accurate detection while reducing the spread of misinformation. The ability to distinguish true from false disaster information was enhanced through the use of the LinearSVC classifier with TF-IDF feature extraction and then applied to derive verified information output with high confidence levels.

The main application of the system is to generate real-time verified notifications and visual outputs of reported disasters to assist the decision-making process of authorities to make more timely and informed decisions during a disaster. Future work to develop the system involves including satellite imagery (NASA FIRMS, NOAA) for verification of events, NLP transformer models (BERT, RoBERTa) for improved context of text comprehension, moving the system to cloud environments (AWS, Azure) for surveillance observation on a continuous basis, and scaling. Furthermore, IoT-based environmental sensors and a mobile interface can broaden the responsiveness and accessibility of the system, further improving the reliability of global disaster response infrastructure.

REFERENCES

[1] Saleem, M. A., Benjapolakul, W., Srisiri, W., Chaitusaney, S., and Kaewplung, P., (2025). .*A Hybrid Prediction Model Integrating Artificial Intelligence and Geospatial Analysis for Disaster Management.*

[2] Aboualola, M., Abualsaud, K., Khattab, T., Zorba, N., and Hassanein, H. S., (2023). *Edge Technologies for Disaster Management: A Survey of Social Media and Artificial Intelligence Integration.*

[3] Alsayyed, M. M., Manickam, S., Wulandari, E. R. N., Widia, I. D. M., and Karuppayah, S., (2025). *A Review of Applicable Technologies, Routing Protocols, Requirements, and Architecture for Disaster Area Networks.*

[4] Dwarakanath, L., Kamsin, A., Rasheed, R. A., Anandhan, A., and Shuib, L., (2021). *Automated Machine Learning Approaches for Emergency Response and Coordination via Social Media in the Aftermath of a Disaster: A Review.*

[5] Zhou, W., Huang, M., Liu, S., You, Q., and Meng, F., (2025*). Research on the Construction and Application of Earthquake Emergency Information Knowledge Graph Based on Large Language Models*.

[6] Narasimha Raju, A. S., et al. (2025). *GeoDisasterAlNet: An Explainable Deep Ensemble Framework for Real-Time Urban and Rural Disaster Classification and Resilience.*

[7] Zhang, S., Huang, M., Liu, S., Meng, F., Xie, Y., Ren, X., Zhang, Y., and Shao, W., (2025). *Al-Driven Post-Earthquake Emergency Material Demand Prediction: Integrating RAG With Reasoning Large Language Model.*

[8] Momin, K. A., Sadri, A. M., Olofsson, K., Muraleetharan, K.K., and Gladwin, H., (2025). *Information Switching Patterns of Risk Communication in Social Media During Disasters.*

[9] Khan, T. A., Alam, M. M., Shahid, Z., and Mazliham, M. S., (2020) . *Investigation of Flash Floods on Early Basis: A Factual Comprehensive Review*.

[10] Dong, W., Huang, H., Zhong, M., Wang, H., and Hua, F.,(2024). *Monitoring and early warning mechanism of flood invasion into subway tunnels based on the experimental study of flooding patterns*.

[11] Cuadra, J. M., and Cotoron, V. N., (2025) *Addressing false information through local capacity building in community-based disaster risk management*.

[12] Khan, S. M., Shafi, I., Butt, W. H., Diez, I. d. l. T., Flores, M. A. L., Galán, J. C., and Ashraf, I., (2023).*A Systematic Review of Disaster Management Systems: Approaches, Challenges, and Future Directions.*

[13] Shukla, D., Azad, H. K., Abhishek, K., and .Shitharth, S.,(2023)..*Disaster management ontology- an ontological approach to disaster management automation.*

[14] Akhyar, A., Zulkifley, M. A., Lee, J., Song, T., Han, J., Cho, C., Hyun, S., Son, Y., and Hong, B.-W., (2024).*Deep artificial intelligence applications for natural disaster management systems: A methodological review.*

[15] Khan, S. M., Shafi, I., Butt, W. H., Diez, I. d. l. T., Flores, M. A. L., Galán, J. C., and Ashraf, I., (2023).*A Systematic Review of Disaster Management Systems: Approaches, Challenges, and Future Directions.*