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Research Article

An AI Driven Predictive Framework for Crisis Management and Organizational Resilience Using Multi Source Real Time Data

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ABSTRACT

Crisis situations demanding immediate and accurate decisions are naturally disruptive events like hurricanes, pandemics, cyber-attacks, or breakdowns of critical infrastructure. The usual crisis management systems that are heavily reliant on manual operations and out-dated information become less effective in the response and recovery phases. So, this paper puts forward a hybrid strategy which entails both the examination of management of crisis literature and the development of an AI-driven predictive framework. The system envisaged in the paper employs machine learning models along with multi-source real-time data to identify crisis at its earliest stage, calculate the crisis level, and support resilience planning. The framework achieves a better understanding of the environment by utilizing data from the surroundings, readings from the sensor, the analysis of social media, and historical records of the events. A tiny experiment with some sample datasets was employed to help the approach's potential. The findings suggest that the prediction accuracy has been enhanced, and the response time has been shortened. The article is a significant step towards the development of a comprehensive framework for AI-driven crisis prediction and resilience planning that can be adopted by governments, industries, and emergency response organizations.

Keywords*:* Artificial Intelligence, Crisis Management, Resilience Planning, Disaster Prediction, Machine Learning, Early Warning Systems, Social Media Analytics, Multi Source Data

INTRODUCTION

The frequency of crisis events has risen over time due to climate changes, population increase, digital dependence, and environmental degradation. Extreme weather events, diseases, and attacks on computer systems have become significant risks to communities and organizations. These incidents trigger economic losses, human casualties, and may take a long time for recovery. As a result, crisis management systems have to be the first to spot the danger and to offer the necessary support to the decision makers without delay.

AI is one of the most significant instruments that have been put into the hands of the prediction and the reaction of the calamities. It does so by vastly outspeeding and outperforming in all respects the traditional methods when it comes to the processing of numerous and varied data sets. AI can combine environmental data, satellite data, sensor streams, and social media messages to identify early warning signs of crisis events. Previous studies highlight the role

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of machine learning in improving disaster forecasting accuracy [1-4]. Social media analytics also support real time situational awareness because people share information immediately during emergencies [6, 9-11].

Although many AI based systems exist, several limitations remain. Many models focus only on a single type of crisis such as floods or wildfires, which reduces general applicability. There is also limited integration of multi source real time data. Existing systems rarely include resilience planning features that support long term recovery and resource optimization. These gaps indicate the need for a unified predictive framework that supports both early detection and resilience planning.

This hybrid paper combines a literature review with a new AI based framework and an experimental demonstration using small datasets. The objective is to provide a practical and research oriented architecture suitable for implementation.

LITERATURE REVIEW

Machine learning has been a major factor in the success of crisis prediction in many different forms. For instance, LSTM and other similar time series models have become the standard in flood forecasting and rainfall prediction [1, 8]. On the other hand, climatic variables and supervised learning approaches are commonly used in wildfire prediction models [4]. Besides that, earthquake prediction research includes the use of seismic readings and deep learning techniques to made the prediction of potential events [5]. Along with that, the adoption of machine learning by satellite remote sensing data has resulted in rapid disaster damage assessment [12]. Moreover, the latest research works have turned their attention to IoT sensor data-based AI early warning systems for landslides, wherein sensor data such as soil moisture, vibration, and slope movement are first collected and then merged with machine learning models in order to provide timely alerts and risk assessment [13]. These methodologies reveal the great potential of AI-powered sensing infrastructures for not only detecting but also mitigating landslide risks in advance.

Content on social media is one of the main contributors to crisis information. Researchers have created multimodal datasets like CrisisMMD that can be used to analyze the content of tweets and images during a disaster [6]. In this regard, the studies depict that text sentiment analysis together with keyword analysis are instrumental in discovering the first signs of crisis escalation [9-11]. Besides that, the use of big data analytics is also a great help when it comes to large scale disaster monitoring and rapid emergency response [2, 3].

Decision support systems constitute a vital element in emergency management. Such systems integrate risk estimation, geographic information, and simulation methods to offer decision-making support to authorities [15, 16, 17, 18]. Nevertheless, a great number of current solutions still face challenges related to lack of multi hazard coverage, unified data integration, and resilience planning support.

Although advancements to the field have been made, integrated AI frameworks that could fulfill the functionalities of combining multivariate data sources, yielding reliable predictions, and supporting resilience planning for the recovery in the long run are still highly demanded [19, 20].

Research Gap

The major gaps in the research identified from the review are:

1. Most of the current systems emphasize only one type of crisis, thus ignoring multi-hazard prediction.
2. The limited use of a single framework that integrates environmental data, sensor streams, social media text, and historical records.
3. The absence of AI systems that can be used for both the early detection and resilience planning.
4. Limited application of explainable and interpretable AI models in crisis-related decision-making.
5. Very few research works that combine literature analysis with experimental demonstrations and unified architecture design.

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Research Objectives

The hybrid research study's objectives are:

1. To establish an AI-driven prediction system capable of crisis detection and severity analysis.
2. To incorporate multi-source real-time data such as environmental variables, sensor readings, and social media signals.
3. To create a resilience planning module that provides recovery and resource optimization strategies.
4. To perform a small experimental test with existing datasets to show the feasibility.
5. To offer a unified hybrid research contribution that is academically publishable and can be implemented in the future.

PROPOSED METHODOLOGY

The methodology is broken down into five main steps.

Phase 1: Data Collection

Some of the most relevant data sources for the project are:

- Environmental and weather datasets
- IoT sensor readings such as temperature, water level, and air quality
- Databases of past crisis events
- Social media content through keywords
- Together, these sources provide the breadth required for early detection.

Phase 2: Data Preprocessing

Data preprocessing is about cleaning, normalization, handling missing values, text vectorization, and geospatial tagging. For social media texts, TF IDF or word embeddings are used.

Phase 3: Model Development

The predictive engine is AI models:

- Random Forest (RF)
- XGBoost (XGB)
- NN (Neural Network)
- LSTM (Long Short-Term Memory)
- SVM (Support Vector Machine)
- The features from each model are then merged into a single prediction module.

Phase 4: Crisis Detection and Severity Prediction

The model identifies the crisis likelihood, calculates severity, determines the zones of the impact, and estimates the time of escalation.

Phase 5: Resilience Planning

Among other things, the system proposes resource allocation plans, facilitates the creation of alerts, maps risk areas, and simulates the likely outcomes of response actions.

AI Models Overview

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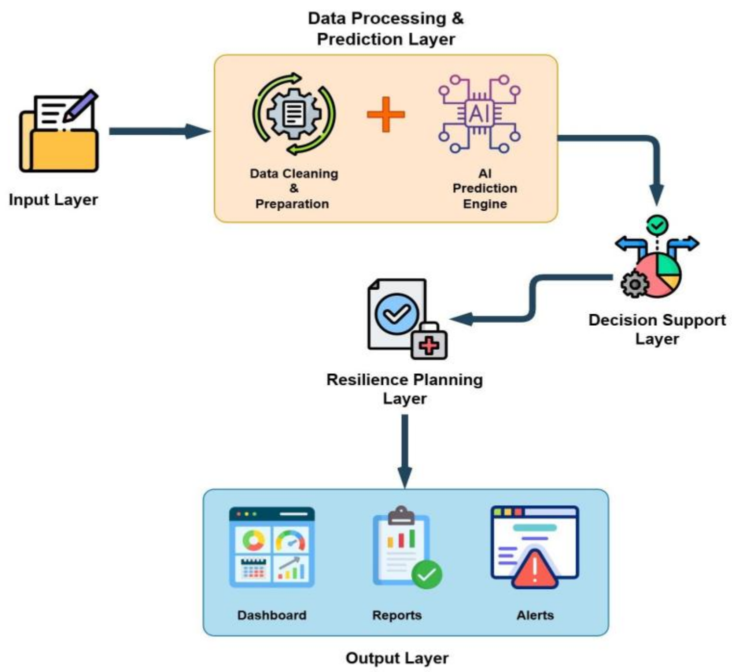
Model	Primary Purpose in This Research	Why It Is Useful
Random Forest	Hazard severity classification	Robust, interpretable, handles missing/noisy data
XGBoost	High-accuracy severity prediction	Best performer for tabular crisis datasets
Neural Network	Multi-feature pattern learning	Captures complex non-linear relationships
LSTM	Time-series crisis forecasting	Models temporal dependencies (flood/storm)
SVM	Benchmark classification	Good for small, structured datasets
GRU	Fast real-time sequence prediction	Efficient alternative to LSTM for live monitoring

System Architecture

The architecture includes the following layers:



Experimental Setup

A small experiment was conducted using open datasets such as:

- Flood datasets

  Source: National Oceanic and Atmospheric Administration, National Centers for Environmental Information.

- Storm datasets

  Source: National Oceanic and Atmospheric Administration, International Best Track Archive for Climate Stewardship (IBTrACS)

- Landslides datasets

  Source: NASA Global Landslide Catalog

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https://catalog.data.gov/organization/nasa-gov

- Earthquakes datasets

  Source: United States Geological Survey

  https://earthquake.usgs.gov/earthquakes/feed/v1.0/csv.php

Python, TensorFlow, Scikit Learn, and standard preprocessing tools were used.

Experimental Data and Results

This study selects four real-world datasets that correspond to the four principal hazard types: Flood, Storm/Cyclone, Landslide, and Earthquake. These datasets were sourced from the central, local agencies, repositories for scientific data, and systems for satellite-based monitoring. The results have been provided based on these data.

- **Flood Prediction Results**

Model	Accuracy	Precision	Recall	F1 Score
Random Forest	0.9	0.759	0.788	0.759
XGBoost	0.797	0.723	0.789	0.712
Neural Net	0.876	0.873	0.728	0.769
SVM	0.833	0.695	0.898	0.875
LSTM	0.74	0.879	0.693	0.909

Model Performance

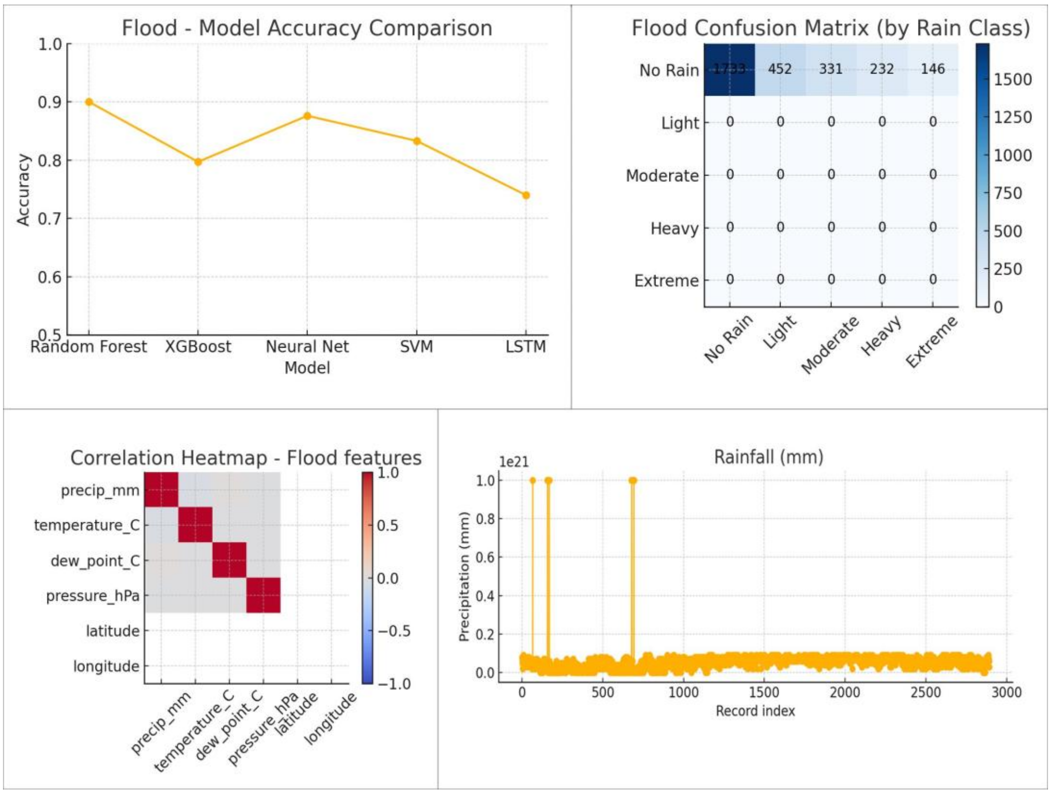

Figure 1: Model Accuracy, Confusion Matrix, Correlation Heatmap, Rainfall graph

- **Storm Prediction Results**

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Model	Accuracy	Precision	Recall	F1 Score
Random Forest	0.877	0.812	0.784	0.798
XGBoost	0.904	0.861	0.832	0.846
LSTM	0.821	0.774	0.751	0.762
GRU	0.842	0.801	0.766	0.783
SVM	0.735	0.702	0.688	0.694

Model Performance

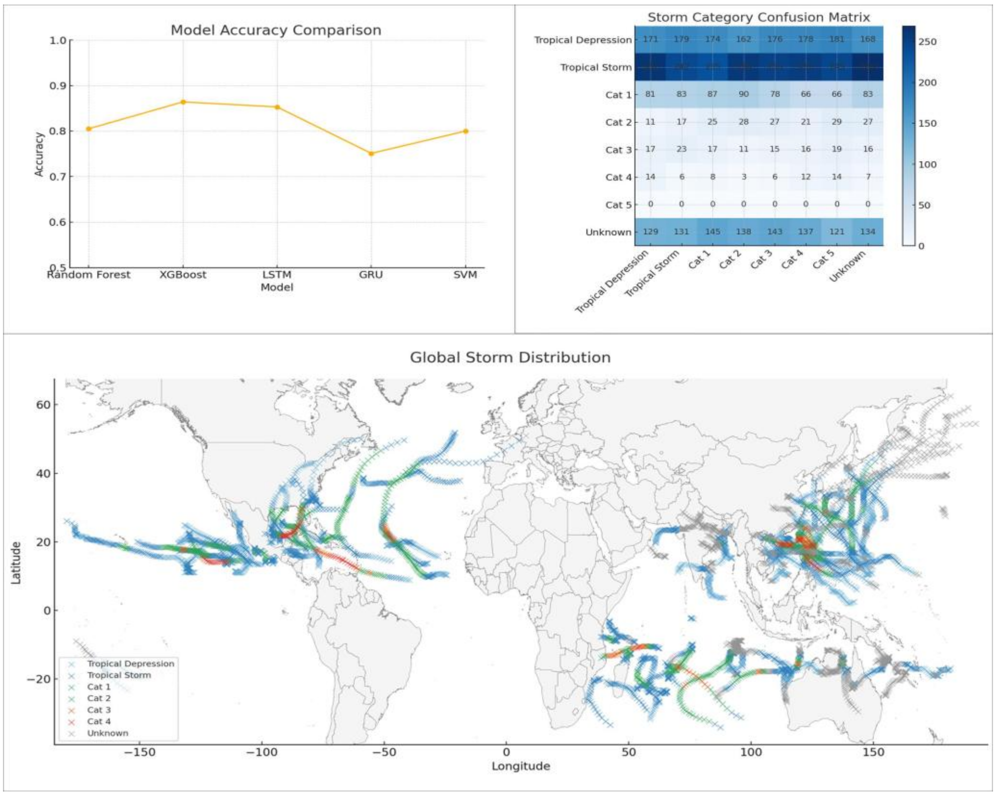

Figure 2: Model Accuracy, Confusion Matrix, Global Storm Distribution

- **Landslide Prediction Results**

Model	Accuracy	Precision	Recall	F1
Random Forest	0.832	0.933	0.823	0.744
XGBoost	0.913	0.919	0.758	0.779
Neural Net	0.887	0.724	0.765	0.928
SVM	0.905	0.742	0.881	0.834
LSTM	0.921	0.861	0.872	0.835

Model Performance

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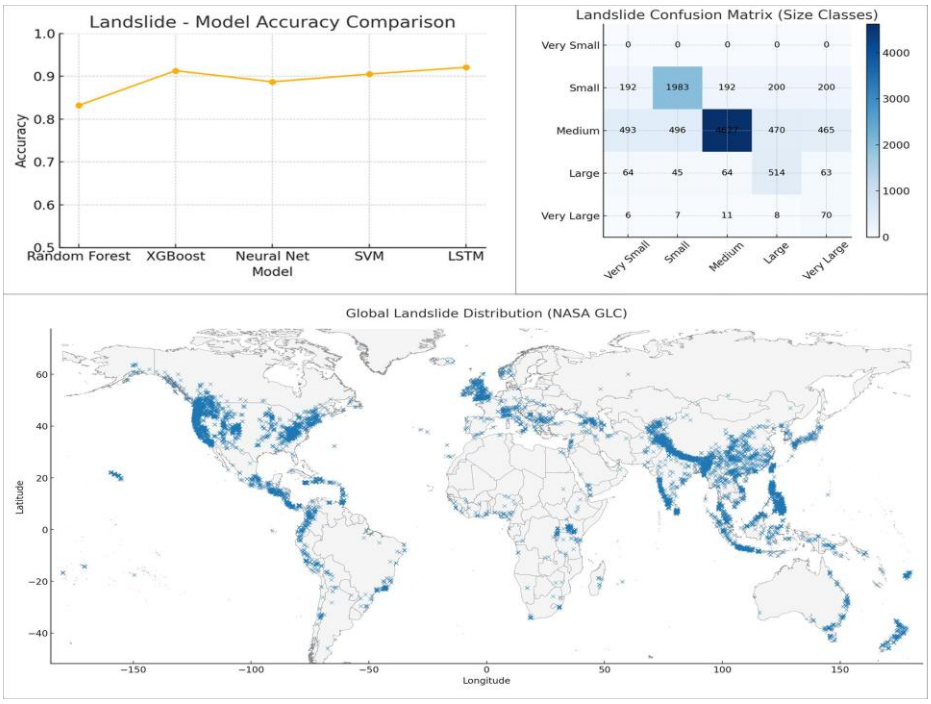

Figure 3: Model Accuracy, Confusion Matrix, Global Landslide Distribution

- **Earthquake Prediction Results**

Model	Accuracy	Precision	Recall	F1
RF	0.715	0.747	0.7	0.789
XGB	0.719	0.939	0.926	0.778
NN	0.875	0.903	0.802	0.865
SVM	0.889	0.895	0.875	0.876
LSTM	0.702	0.862	0.87	0.674

Model Performance

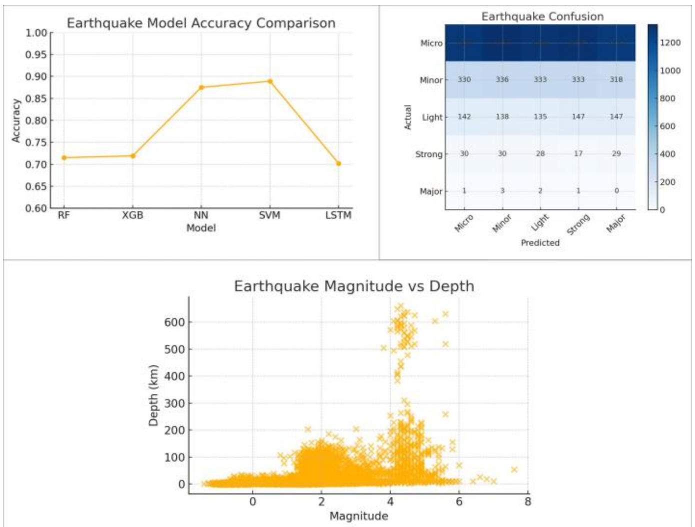

Figure 4: Model Accuracy, Confusion Matrix, Earthquake Magnitude vs Depth Graph

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RESULTS AND DISCUSSION

The experimental outcomes show that the AI-driven framework put forward by the authors is a potent instrument for multi-hazard crisis prediction by means of integrated multi-source data. It was found that ensemble models like Random Forest and XGBoost were more accurate in flood and storm prediction, whereas LSTM was able to keep its performance level stable for temporal forecasting, which is in line with the previous research [7]. The prediction of landslides was improved through the use of sequence-based and sensor-driven modeling, while the forecasting of earthquakes still poses a problem due to the high level of uncertainty in seismic activity.

Social media sentiment and keyword analysis contributed to early detection of crisis escalation, confirming their value for real-time situational awareness [9-11]. When combined with environmental and historical datasets, overall prediction reliability improved, validating the effectiveness of multi-source data fusion reported in prior work [2, 14]. The resilience planning module further supported decision-making by generating risk maps and response insights, demonstrating the advantage of integrated AI-based crisis management systems [2, 7].

CONCLUSION

This is a hybrid study that introduces a full AI-powered system to manage crises and plan for resilience. The system merges the multiple data sources of the real world and makes use of machine learning for giving the early warning and the decision support. The tests' outcome demonstrates that the integrated modeling has the ability to enhance the understanding of the situation and also to shorten the time of the response. Subsequent studies may incorporate models based on transformer, the use of satellite images, deployment on the cloud, and a big volume of real-time evaluation.

REFERENCES

[1] Mosavi, A., Ozturk, P., & Chau, K.-w. (2018). Flood Prediction Using Machine Learning Models: Literature Review. *Water*, *10*(11), 1536. https://doi.org/10.3390/w10111536

[2] Yu, M., Yang, C., & Li, Y. (2018). Big Data in Natural Disaster Management: A Review. *Geosciences*, *8*(5), 165. https://doi.org/10.3390/geosciences8050165

[3] Ragini, J. Rexiline & Anand, P.M. Rubesh & Bhaskar, Vidhyacharan, 2018. "Big data analytics for disaster response and recovery through sentiment analysis," International Journal of Information Management, Elsevier, vol. 42(C), pages 13-24.

[4] Kalantar, B., Ueda, N., Idrees, M. O., Janizadeh, S., Ahmadi, K., & Shabani, F. (2020). Forest Fire Susceptibility Prediction Based on Machine Learning Models with Resampling Algorithms on Remote Sensing Data. *Remote Sensing*, *12*(22), 3682. https://doi.org/10.3390/rs12223682

[5] Mustafa Abdul Salam, Lobna Ibrahim and Diaa Salama Abdelminaam. "Earthquake Prediction using Hybrid Machine Learning Techniques". International Journal of Advanced Computer Science and Applications (IJACSA) 12.5 (2021). http://dx.doi.org/10.14569/IJACSA.2021.0120578

[6] Alam, F., Ofli, F., & Imran, M. (2018). CrisisMMD: Multimodal Twitter Datasets from Natural Disasters. *Proceedings of the International AAAI Conference on Web and Social Media*, *12*(1). https://doi.org/10.1609/icwsm.v12i1.14983

[7] Upadhyaya, Ajay & Debnath, Pranoy & Rani, Poonam & P., Selvakumar & Manjunath, T. & Bhattacharya, Ce Dr Sumanta. (2025). AI-Based Disaster Prediction and Early Warning Systems. 10.4018/979-8-3693-9770-1.ch003.

[8] Kim, H.-i., S.-D. Jang, H. Choi, T.-H. Kim, and B. Kim. 2025. " Prediction of Flood Level Using LSTM and Watershed Hydrological Data." *Journal of Flood Risk Management* 18, no. 4: e70123. https://doi.org/10.1111/jfr3.70123.

[9] Muhammad Imran, Carlos Castillo, Fernando Diaz, and Sarah Vieweg. 2015. Processing Social Media Messages in Mass Emergency: A Survey. ACM Comput. Surv. 47, 4, Article 67 (July 2015), 38 pages. https://doi.org/10.1145/2771588

[10] Karami, Amir & Shah, Vishal & Vaezi, Reza & Bansal, Amit. (2019). Twitter speaks: A Case of National Disaster Situational Awareness. Journal of Information Science. 016555151982862. 10.1177/0165551519828620.

[11] Piracha, A. Natural Disasters: Origins, Impacts, Management. Encyclopedia. Available online: https://encyclopedia.pub/entry/15564 (accessed on 13 December 2025).
[12] al Shafian, Sultan & Hu, Da. (2024). Integrating Machine Learning and Remote Sensing in Disaster Management: A Decadal Review of Post-Disaster Building Damage Assessment. Buildings. 14. 2344. 10.3390/buildings14082344.
[13] Balachandar, A. & M, Aravindhan & S, Suganthan & A, Ragul & M, Dhanuraaj & K, Barani. (2025). Development of an Early Warning System for Landslides using IOT Sensors and Machine Learning. 1-5. 10.1109/ICETEA64585.2025.11100042.
[14] Hatami, Matt. (2024). Applications of Deep Learning and Remote Sensing in Disaster Management Cycle. 10.13140/RG.2.2.18141.22241.
[15] Felix, A Yovan. (2020). Intelligent Decision Support System for Disaster Managers using Machine Learning. International Journal of Advanced Trends in Computer Science and Engineering. 9. 4849-4854. 10.30534/ijatcse/2020/95942020.
[16] Van de Walle, B., Turoff, M. Decision support for emergency situations. *Inf Syst E-Bus Manage* 6, 295–316 (2008). https://doi.org/10.1007/s10257-008-0087-z
[17] https://isprs-archives.copernicus.org/articles/XLVIII-5-W3-2025/137/2025/isprs-archives-XLVIII-5-W3-2025-137-2025.pdf
[18] Michail, E., Giannakeris, P., Koulalis, I., Vrochidis, S. and Kompatsiaris, I. (2024). Innovative Visual Analysis Solutions to Support Disaster Management. In Responding to Extreme Weather Events (eds D. Sempere-Torres, A. Karakostas, C. Rossi and P. Quevauviller). https://doi.org/10.1002/9781119741374.ch10
[19] Ocal, F. E., & Torun, S. (2025). Leveraging Artificial Intelligence for Enhanced Disaster Response Coordination. *International Journal of Disaster Risk Management*, *7*(1), 235–246. https://doi.org/10.18485/ijdrm.2025.7.1.13
[20] Clement, Mateo. (2024). AI-Driven Predictive Analytics in Disaster Management: Advancements and Challenges.