



AI-Driven Multi-Source Disaster Response System Using Machine Learning

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Abstract. Natural disasters such as floods, earthquakes, and landslides have become a global concern due to their destructive effects on the environment. These events have become more frequent due to massive climate change, which demands the need for an automated system that can analyze these effects and manage them efficiently. This study presents a system designed for disaster response that will analyze disaster management approaches and integrate information from diverse data streams, such as aerial imagery, historical disaster images, and social media disaster tweets. The system combines different machine learning (ML) models, such as supervised learning (SVM, LR, Naïve Bayes, and LSTM), to process data streams for identifying natural hazards. This utilises advanced technologies such as Machine Learning (ML), Artificial Intelligence (AI), and Deep Learning (DL) to identify the disaster events, classify them, and filter out misleading information. Used Natural Language Processing (NLP) to analyze textual data from online platforms and Computer Vision (CV) to examine visual evidence from images. The evaluation gives the idea that the proposed dashboard-based multi-source approach gives better results than traditional single-source systems in detecting accuracy and optimization. The system also used Flask-API as a database to store the outputs. Also, the system provides an interactive dashboard to deliver clear insights about the data accuracy. These tools will help emergency authorities and rescue teams to track ongoing incidents and evaluate risk zones. In the long run, this system will help in early rescue operations, reduce damage and save more lives.

Keywords: disaster management, early detection, machine learning, natural disasters, disaster response, deep learning.

1 Introduction

Disasters are among the most destructive and unpredictable phenomena affecting life on Earth. Over the last few decades, due to massive climate change, events such as earthquakes, floods, fires, and landslides have become more frequent and severe [5]. Disasters like floods, earthquakes, and landslides have created pressure on emergency responders, government agencies, and communities due to their extensive capacity to damage infrastructure and threaten human lives [10],[11],[16]. The main cause of this problem is the lack of awareness and poor access to modern technologies, which warn citizens about the potential disasters in their area [3]. There were many disasters that occurred in which resources were not available, and this led to tragic outcomes [1]. Earthquakes pose a significant threat to human life, stability, and infrastructure, and making proper predictions is required to handle all these situations [18]. As the effects of climate change and environmental instability continue to accelerate, developing an intelligent and efficient disaster management system and utilizing the resources properly and on time are most important during these times. Traditional management systems primarily depend on manual and slow processes and limited data sources. As a result, they struggle to handle the complex data needed for early alerts and quick action. All disasters are indirectly linked to human responses. The success or failure depends on the planning, preparedness, and implementation of effective mitigation and response strategies. One hazard often triggers another; for instance, an undersea earthquake can generate a tsunami, which can cause extensive coastal flooding. Artificial Intelligence (AI) acts as a revolutionary and essential element in shaping the future. It acts as a powerful enabler in disaster management by strengthening the ability to safeguard lives and property during an emergency. Through the processing and interpretation of extensive real-time data, AI improves the accuracy of predictions, facilitates early warning systems, and enhances the efficiency of disaster response [4].

Recent advancements in ML and DL have significantly improved the detection and prediction of natural disasters by processing aerial, social media, and historical data. The combination of these techniques facilitates in-depth analysis of disaster patterns and progression across different regions, informing more accurate and informed disaster management decisions. ML approaches commonly used in the domain include logistic regression (LR); DL methods employ advanced neural network architectures such as convolutional neural networks (CNNs), and ResNet architectures are employed for image-based disaster detection and classification tasks. These models enable automated feature extraction and high-accuracy predictions using large-scale, multimodal data [2]. The project is developed to create an intelligent framework for detecting and maintaining natural disasters using multiple data sources. The proposed system integrates AI, ML, NLP, and DL technologies to collect, analyze, and visualize information from various sources. By integrating these models, the system enhances its ability to detect early signs of natural disasters and improve overall situational awareness. The integrated system will allow the system to make early decisions to prevent more losses. Fig. 1 shows the workflow of the system, which has good accuracy and reliability.

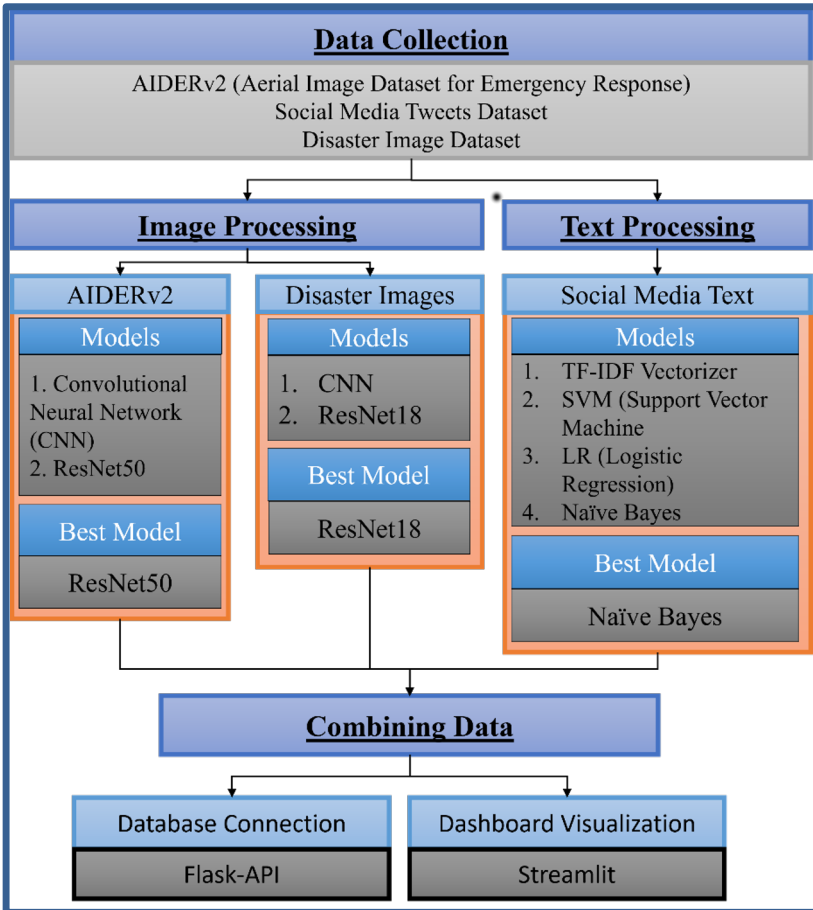


Fig. 1. Data Workflow Diagram of Disaster Management System

The following sections are organized in a way to provide a clear understanding of the system. The literature review gives an overview of the existing research and technologies that are somehow related to disaster detection and management. The methodology section provides the details of the data sources, steps taken to process the data, and integration of the model to analyze the text and visual data. The result section presents the performance of the system. The conclusion part gives the overview of the whole project, and finally, the future scope presents the possible improvements that can be done to make it more compatible for future terms.

2. Literature Review

Over the past few years, the frequency and intensity of natural disasters have increased, putting the lives of many humans in danger and also having a significant role in the destruction of infrastructure and global economies. The huge damage potential of the

China floods in 1931 and the Mexico City earthquake in 1985 had a negative effect on human settlements [7]. According to recent research, the new technologies, such as AI and remote sensing, have extensively modified strategies and preparedness for disasters. The new data-driven approaches play a vital role in reducing damage and loss of lives [2]. Recent disaster management systems integrate multiple fields, such as computer science, social governance, and geospatial science, to predict different types of disasters [15]. For crisis communication, AI-based models such as ML, DL, and Reinforcement Learning are used in damage prediction, resource optimization, and social media real-time monitoring for different types of disaster communication [12], [16].

2.1 CNN-Based Early Fire Detection System

Fire disaster is a major global concern for threatening human lives and economic losses. Fire detection technologies previously suffered from various disadvantages, such as delayed response times and high dependency on heat sources, but the new technology introduced new fire detection techniques that have wider coverage. Innovation is CNN-based early fire detection. This used some pre-trained networks to detect stages under different environmental conditions. This approach enhanced real-time detection accuracy [15].

2.2 CNN-Based Early Fire Detection System

Communication is a crucial part of disaster management, as it informs about the zones and locations of disaster occurrence. The Social-Mediated Crisis Communication (SMCC) model provides information regarding the communication of influencers and organizations in social media platforms [13].

2.3 CNN-Based Early Fire Detection System

Indonesia is one of the most disaster-prone countries. Due to its climatic conditions, it frequently faces earthquakes, landslides, and floods. Due to limited funding, fewer technical experts, and weak long-term planning, they are facing many challenges in the rescue [17]. Decision-making during these times is commonly hindered by time pressure and incomplete information. Emergency Decision-Making (EDM) provides stages of disaster management, including pre-planning, prevention, and recovery after the disaster [14]. Satellite imagery gives a high-resolution visualization, which allows authorities to monitor changes and take recovery actions early [3]. The innovations such as smartphones and social media play a crucial role in spreading public awareness during emergencies and also help in working on disaster management systems by highlighting automation and understanding large amounts of data. Platforms like Twitter will help in the rapid spread of real-time information about the disaster, affected areas, and relief agencies [6]. The advancement in the application of AI and ML makes it easier to detect and reduce disaster risk, as it has the capability of processing large amounts of data. Many techniques have been applied, such as retrieving the information, searching for humans going through danger and rescuing them, and saving the data after a disaster

for future purposes [5]. For a proper visualization and detection of image-based disasters, technologies such as DL and CNNs have been used [6]. All the models reduce the time to identify the areas and work on the rescue operations effectively.

Social media such as Twitter plays a vital role in sharing the information early, also generating a large amount of data, some of which is not true and has to be ignored, and some of which is very important, including text messages and images, which will help in early response [8]. AI and ML techniques have some benefits as they are used to filter noise, removing irrelevant data and using the relevant data only for the predictions, but they also have some risks, such as algorithmic bias, lack of transparency, and resource allocation and response strategies [9]. Making AI-driven disaster management, ensuring its transparency, and reducing risk are essential for the decision-making process.

3. Methodology

The system concentrates on AI-driven multi-source disaster management, using multiple datasets such as social media tweets, aerial images, and disaster images. Working of the system consists of preprocessing multiple datasets individually for better results, then combining them, and creating a dashboard with good accuracy and results.

3.1 Datasets: The system is utilizing three datasets.

Dataset [19] contains the aerial images of disasters taken from satellites and drones, including earthquakes, floods, fires, and normal views. This will help to train the system so that it can visualize the image and tell about the disaster occurring. While preprocessing the data, some sample images were printed and given in Fig. 2.

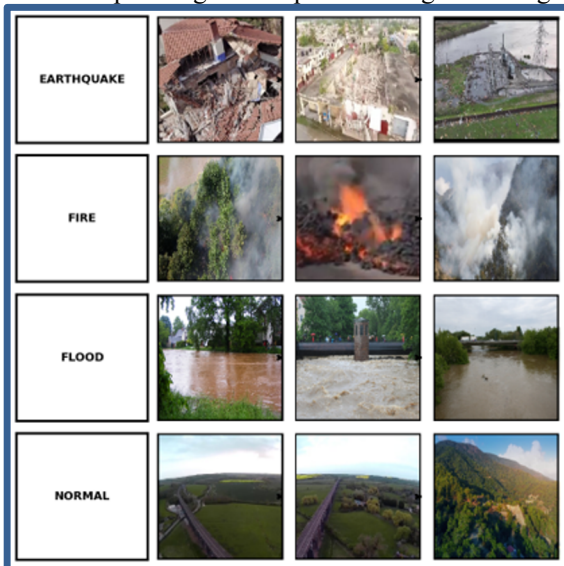


Fig. 2. Disaster aerial images taken from the dataset

In [20] the textual data helps the model to analyze the texts and give accurate results. If some data or text is given to the model, it will tell whether it is spam or real. Table 1 shows the data after filtering out, before, and after cleaning the dataset. The dataset contains a total of 10,876 rows and 13 classes.

Table 1. Social Media Tweets Dataset used for Text Classification

Text	Choose one.	Clean_text
0 Just happened a terrible car crash.	1.0	A terrible car crash happened.
1 Our deeds are the reason for earthquake M...	1.0	Deeds' reason for the earthquake. May Allah forgive us.
⋮	⋮	⋮
⋮	⋮	⋮
⋮	⋮	⋮
10874 Meg issues a hazardous weather outlook.	1.0	Meg issues a hazardous weather outlook.
10875 City of Calgary has activated its municipal emergency...	1.0	The City of Calgary activated its municipal emergency plan...

The dataset [20] contains the images of disasters taken on the ground, such as individual damage, utility damage, and rescue operations (Fig. 3). This will help in finding the areas where damage occurs and rescue operations are started and where teams have not arrived. This dataset contains 13,796 images, including 9991 train images and 3805 test images with an image size of 244*244.

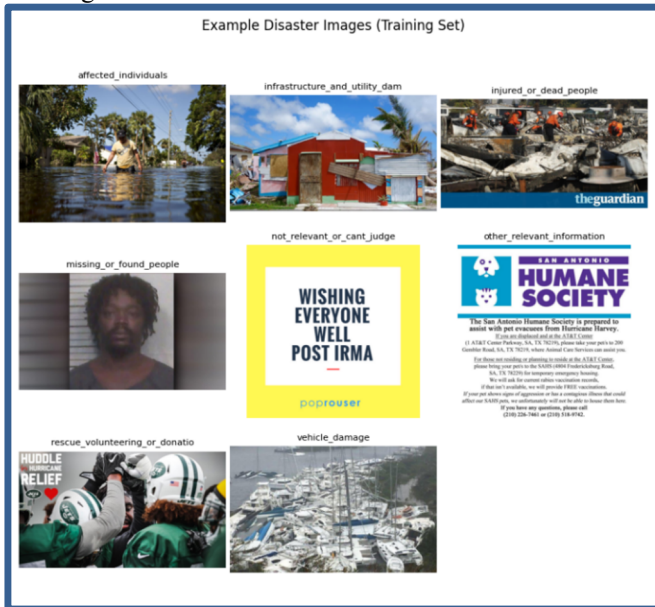


Fig. 3. Disaster images for different views

All the datasets are taken from some online source and are useful for the model. Pre-processing and training steps are taken in each model to make it more accurate.

3.2 Data preprocessing and machine learning models and algorithms used

The steps taken to ensure readiness: all three datasets were preprocessed and trained individually.

Dataset 1: In dataset [19] the aerial image dataset, the comparison of CNN and ResNet50 models has been done to check the accuracy and save the data that are more accurate. This dataset was pretrained with 80% for training, 10% for testing and the remaining 10% for validation data. The dataset contains a total of 16,723 aerial images having an image size of 244*244, which are further divided into 4 classes (Table 2).

Table 2. Aerial image dataset classification [19]

	Train	Validation	Test	Total
Earthquakes	1927	239	229	2405
Floods	4063	505	502	5070
Fire	3509	439	436	4384
Normal	3900	487	477	4864
Total	13399	1670	1654	16723

Convolutional Neural Network (CNN): It is optimized for image classification on a preprocessed dataset. It consists of multiple convolutional and fully connected layers. Using convolutional layers with 32, 64, and 128 filters with a ReLU activation function and batch normalization. To optimize the model, the Adam Optimizer with a learning rate of 1e-4 is used to train the data and save the best-performing model.

ResNet50: This is a deep CNN having 50 layers used to improve training. It is used for image classification as it overcomes the vanishing gradients problem and also gives higher accuracy.

Dataset 2: In [20] The Social Media Tweets dataset contains the textual data of social media disaster tweets. NLP is used to preprocess this data by removing stopwords, irrelevant texts, punctuation, and hashtags and also removing irrelevant columns and only taking relevant columns for the training to reduce the size of the training data and to stay safe from overfitting. Split the training and testing part as 80% and 20%. Applied TF-IDF vectorization, and after that, different Machine Learning (ML) models, such as SVM, LR, and Naïve Bayes, were used to train and compare the accuracies to find the best model for training.

- **TF-IDF (Term Frequency-Inverse Document Frequency):** It is used to convert the unstructured textual data into numerical feature vectors.
- **SVM (Support Vector Machine):** For text classification, LinearSVC is used to best separate classes such as relevant and non-relevant.
- **LR (Logistic Regression):** Used with TF-IDF vectorization to handle large vectors effectively.

- **Naive Bayes:** This algorithm is based on Bayes' Theorem, which assumes the features belong to a particular class or not.

Dataset 3 In [21] this dataset contains different disaster images, which are used to recognise the situations. Split the data as 80% for training and 20% for testing for better performance. Comparing different models, such as CNN and ResNet18, to get better results gets the best model to train. Applied a batch size of 32 with a shuffled training dataset and also used the Adam optimizer with a learning rate of 0.001 for 10 epochs for training.

- **CNN:** It is a deep learning model that mainly does image processing, face recognition, and object detection.
- **ResNet18:** It is the small version of the ResNet family, having 18 layers.

3.3 Combining and integrating all the data

After training the datasets, all the trained data is saved and combined in a file, and the Flask API is used for combining and collecting all the data, creating an integrated dashboard which will help in finding accuracies by using different real-time images and texts.

4. Results

The proposed system presents a Streamlit dashboard for end users to check if the data, either image or text, is a real disaster or not. Multiple datasets are used, such as aerial images, social media tweets, and disaster images, and trained individually using different ML and DL models. The result of the different training processes is combined in the dashboard to give text-based as well as visual analysis of the disaster management.

4.1 Dataset Results

[19] The proposed dataset is used for visualizing aerial disaster images, giving an accuracy of 97.16% (Table 3). It predicts the images such as earthquakes, fire, floods, and normal. Compared CNN and ResNet50 for better results. Using the batch size of 32 and 20 epochs, CNN and ResNet50 gave the best result of model evaluation: Accuracy: 97.16%. Classification Report:

Table 3. Classification Report for Aerial Images

	Precision	Recall	F1-Score	Support
Earthquake	0.97	0.95	0.96	239
Fire	0.99	0.98	0.99	436
Flood	0.96	0.98	0.97	502
Normal	0.96	0.97	0.97	477
Accuracy			0.97	1654
Macro average	0.97	0.97	0.97	1654
Weighted avg.	0.97	0.97	0.97	1654

The final confusion matrix (Fig. 4) for this model shows the overall division of the data through which further processing has been done.

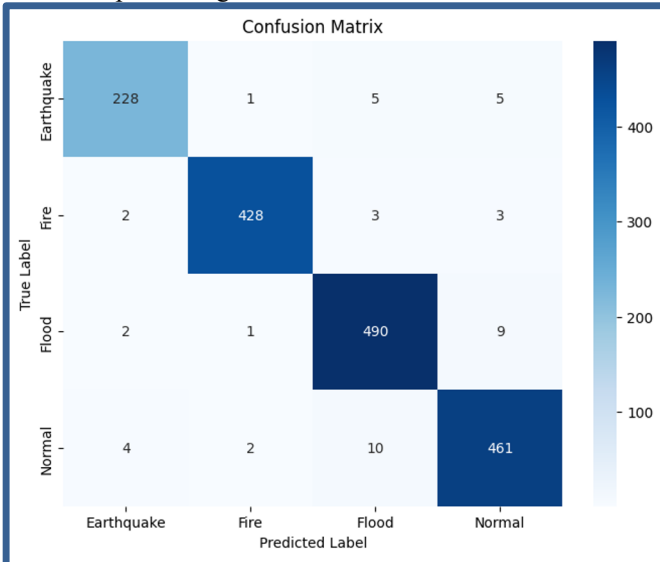


Fig. 4. Confusion Matrix for Aerial Images

Social Media Tweets: Dataset [20] was taken for recognizing and predicting textual data. The classification was performed using different algorithms such as SVM, logistic regression, and Naïve Bayes, in which Naïve Bayes gave the best accuracy of 81.12% (Table 4). This model divides the data into relevant and non-relevant tweets, which helps the model to support disaster detection. Model Evaluation: Accuracy: 81.12%: Classification Report.

	Precision	Recall	F1-Score	Support
0.0	0.78	0.93	0.84	1237
1.0	0.87	0.66	0.75	935
Accuracy			0.81	2172
Macro Average	0.83	0.79	0.80	2172
Weighted Avg	0.82	0.81	0.81	2172

Table 5 shows the classification report for the given dataset, which is very important, as the accuracy matters in every phase of the model building. It also includes a confusion matrix of the best algorithm (Fig. 5).

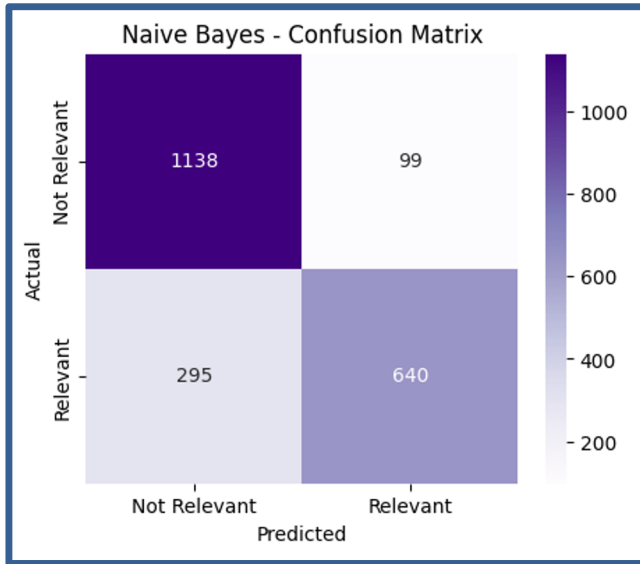


Fig. 5. Confusion Matrix for Disaster Tweet Data

Disaster Image Dataset [21]: We are training this dataset for visualizing the types of disasters that can occur, such as individual or utility damage. Used CNN and ResNet18 for training this dataset, in which, for now, ResNet18 is giving more accuracy than CNN, but accuracy is very low (Table 5). Model Evaluation: Accuracy: 51%, Classification Report:

Table 5. Classification report of disaster image dataset

	Preci- sion	Re- call	F1- score	Sup- port
Affected_individuals	0.15	0.05	0.08	118
Infrastructure_and_utility_damage	0.19	0.13	0.15	397
Injured_or_dead_people	0.19	0.11	0.14	152
Missing_or_found_people	0.00	0.00	0.00	7
Not_relevant_or_cant_judge	0.15	0.17	0.09	272
Other_relevant_information	0.56	0.67	0.61	1809
Rescue_volunteering_or_donation_effort	0.47	0.51	0.49	1030
Vehicle_damage	0.14	0.05	0.07	20
Accuracy			0.48	3805
Macro average	0.23	0.20	0.20	3805
Weighted avg.	0.44	0.48	0.45	3805

The classification report indicates that the accuracy is 48.04%, and the performance of rescue volunteering or donation effort category has the highest representation in the dataset. The limitation of the current approach is that the data is noisy and can be improved in future work after data balancing and using advanced modelling techniques.

The confusion matrix (Fig. 6) shows the result of the disaster image dataset more clearly.

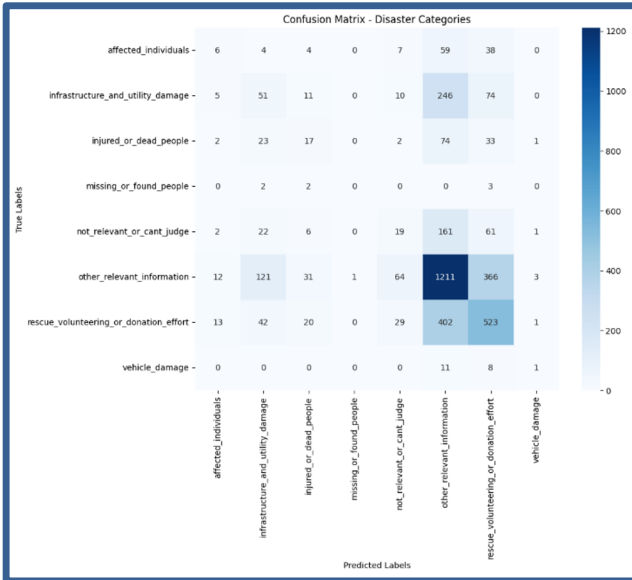


Fig. 6. Confusion Matrix for Disaster Image Dataset

4.2 Dataset Connection and Dashboard Integration

At first, all three models were combined, and Flask-API (Fig. 7) was used to create a database to store the combined results of all models, which was then connected to a Streamlit dashboard, which was designed to automatically classify the disaster-related texts and images we are providing. Flask-API and Streamlit were used as a multimodal approach for these datasets.

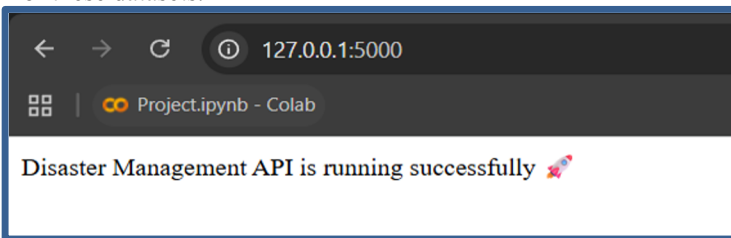


Fig. 7. Flask API running in a browser

Monitoring the results manually became tough and time-consuming, and the system provides real-time analysis, which makes it easier to monitor and store the results. Then the Streamlit dashboard was created with different navigation bars (Fig. 8) for images and textual data, where a user can write their text or upload an image, and it will classify whether it is a disaster or not.



Fig. 8. Sample Dashboard Visualization of Disaster Detection

The results will be stored in the Flask-API, where we can monitor the past results (Fig. 9).

Fig. 9. Flask-API logs

5. Conclusion

This study gives a practical approach towards multi-model AI disaster management. Combining different data, such as social media data, aerial images, and disaster images, makes it more optimized and accurate to verify the disasters occurring all over the

world. Applying different machine learning and deep learning algorithms, such as SVM, LR, and Naïve Bayes for textual datasets, and Models such as CNN, ResNet18, and ResNet50 for image datasets to get effective and accurate results. Among all of them, Naïve Bayes, ResNet18, and ResNet50 gave the best accuracies in their datasets. Comparing all the models and algorithms helps in finding the best-suited algorithm for the dataset we are working on. This work represents the use of deep learning for most of the disaster management process. Flask API is used to combine all the data and make a database, and connect Streamlit to it for prediction, which gives the practicality of the model, which will be used for future innovations. This work also has some limitations, such as the size of the datasets being small, which restricts the model's ability to learn diverse properties. Another limitation is the dataset is noisy, i.e., data contains unnecessary information which can negatively impact model training. Also, diversity is lacking, as it currently does not represent real-time variations, but all the limitations can be improved in the future.

6. Future Scope

The system can be extended using more real-time data, including real-time reports, images, and videos, and integrating a real-time disaster monitoring and early detection system. It can be extended to a multimodal framework where all the datasets are combined and analyzed jointly. Using a multi-model approach and more advanced algorithms and models will give a robust and more accurate version of the model. Deployment of the model on online platforms allows users to use the system for their safety and security.

References

- [1] S. M. Khan, I. Shafi, W. H. Butt, I. D. L. T. Diez, M. A. L. Flores, J. C. Galán, and I. Ashraf, "A systematic review of disaster management systems: approaches, challenges, and future directions," *Land*, vol. 12, no. 8, p. 1514, 2023.
- [2] V. Linardos, M. Drakaki, P. Tzionas, and Y. L. Karnavas, "Machine learning in disaster management: recent developments in methods and applications," *Machine Learning and Knowledge Extraction*, vol. 4, no. 2, 2022.
- [3] P. P. Ray, M. Mukherjee, and L. Shu, "Internet of things for disaster management: State-of-the-art and prospects," *IEEE Access*, vol. 5, pp. 18818–18835, 2017.

- [4] S. K. Abid, N. Sulaiman, S. W. Chan, U. Nazir, M. Abid, H. Han, and A. Vega-Muñoz, "Toward an integrated disaster management approach: how artificial intelligence can boost disaster management," *Sustainability*, vol. 13, no. 22, p. 12560, 2021.
- [5] L. Tan, J. Guo, S. Mohanarajah, and K. Zhou, "Can we detect trends in natural disaster management with artificial intelligence? A review of modelling practices," *Natural Hazards*, vol. 107, no. 3, pp. 2389–2417, 2021.
- [6] H. S. Munawar, F. Ullah, S. Qayyum, S. I. Khan, and M. Mojtahedi, "UAVs in disaster management: Application of integrated aerial imagery and a convolutional neural network for flood detection," *Sustainability*, vol. 13, no. 14, p. 7547, 2021.
- [7] M. Krichen, M. S. Abdalzaher, M. Elwekeil, and M. M. Fouda, "Managing natural disasters: An analysis of technological advancements, opportunities, and challenges," *Internet of Things and Cyber-Physical Systems*, vol. 4, pp. 99–109, 2024.
- [8] M. Imran, C. Castillo, J. Lucas, P. Meier, and S. Vieweg, "AIDR: Artificial intelligence for disaster response," in *Proc. 23rd Int. Conf. World Wide Web*, 2014, pp. 159–162.
- [9] C. M. Gevaert, M. Carman, B. Rosman, Y. Georgiadou, and R. Soden, "Fairness and accountability of AI in disaster risk management: Opportunities and challenges," *Patterns*, vol. 2, no. 11, 2021.
- [10] S. Uckardesler and T. Yomralioglu, "Multi-source geospatial analysis for disaster risk management in smart cities: Integration of GIS & remote sensing," *Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci.*, vol. 48, pp. 137–145, 2025.
- [11] M. Wang, H. Zhu, J. Yao, L. Hu, H. Kang, and A. Qian, "Assessing large-scale flood risks: A multi-source data approach," *Sustainability*, vol. 17, no. 11, p. 5133, 2025.

- [12] S. Abbas, M. A. Talib, Q. Nasir, O. Belal, M. E. Al-Haidary, and I. Ahmed, "A survey of disaster management datasets," *J. Inf. Telecommun.*, pp. 1–23, 2025.
- [13] Y. Jin, B. F. Liu, and L. L. Austin, "Examining the role of social media in effective crisis management: The effects of crisis origin, information form, and source on publics' crisis responses," *Commun. Res.*, vol. 41, no. 1, pp. 74–94, 2014.
- [14] Y. Sawada and Y. Takasaki, "Natural disaster, poverty, and development: An introduction," *World Dev.*, vol. 94, pp. 2–15, 2017.
- [15] K. Muhammad, J. Ahmad, and S. W. Baik, "Early fire detection using convolutional neural networks during surveillance for effective disaster management," *Neurocomputing*, vol. 288, pp. 30–42, 2018.
- [16] W. Sun, P. Bocchini, and B. D. Davison, "Applications of artificial intelligence for disaster management," *Nat. Hazards*, vol. 103, no. 3, pp. 2631–2689, 2020.
- [17] R. I. Hapsari and M. Zenurianto, "View of flood disaster management in Indonesia and the key solutions," *Am. J. Eng. Res.*, vol. 5, no. 3, pp. 140–151, 2016.
- [18] S. Morya, S. Kumari, M. Blossom, A. Sharma, and S. Sharma, "A data-driven approach for earthquake prediction: AI and machine learning," in *Proc. IEEE Int. Conf. Next-Gen Technol. (EarthSense)*, 2025, pp. 1–6.
- [19] D. Shianios and C. Kyrkou, "AIDERv2 (Aerial Image Dataset for Emergency Response Applications)," *Zenodo*, 2024. [Online]. Available: <https://doi.org/10.5281/zenodo.10821561>
- [20] Kaggle, "Social Media Disaster Tweets & CrisisMMD Datasets," *Kaggle Datasets*, 2024. [Online]. Available: <https://www.kaggle.com/datasets>.

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