

A Hybrid Neural Network and Xgboost Framework for Accurate Disaster Prediction and Management

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Abstract- Natural disasters such as floods, wildfires, and earthquakes cause severe damage to human life, infrastructure, and the global economy. As the frequency and intensity of these disasters continue to increase due to climate change and environmental factors, the need for reliable disaster prediction systems has become more critical than ever. Traditional disaster prediction methods often rely on historical patterns and statistical models, which are limited in their ability to handle complex and imbalanced datasets. This study proposes a hybrid machine learning framework that integrates Neural Networks and XGBoost to improve the accuracy and reliability of disaster prediction. In the proposed approach, neural networks are used to automatically extract meaningful and high-level features from disaster datasets, while XGBoost performs the final classification of disaster types. To address the common issue of class imbalance in disaster datasets, the Synthetic Minority Over-sampling Technique (SMOTE) is applied during data preprocessing. The model is evaluated using a real-world disaster dataset containing records of floods, wildfires, and earthquakes. Experimental results demonstrate that the proposed hybrid model significantly outperforms traditional machine learning techniques such as Random Forest, Support Vector Machines, and Logistic Regression. The proposed system achieves high prediction accuracy and improved F1-scores across all disaster categories. Overall, the hybrid Neural-XGBoost framework provides a robust and efficient solution for disaster prediction and management. The system can support disaster management agencies by enabling early warning systems, improving preparedness strategies, and assisting in better resource allocation during emergency situations.

Keywords: Disaster Prediction, Machine Learning, Neural Networks, XGBoost, Hybrid Models, SMOTE, Data Preprocessing, Disaster Management, Artificial Intelligence.

I. INTRODUCTION

Natural disasters such as floods, earthquakes, wildfires, and hurricanes pose significant threats to human life, infrastructure, and environmental sustainability. These catastrophic events often occur unpredictably and can lead to large-scale damage, economic losses, and disruption of critical services. In recent decades, the increasing impact of climate change, rapid urbanization, and environmental degradation has contributed to a rise in both the frequency and intensity of disaster events worldwide. Consequently, developing effective disaster prediction and management systems has become a critical priority for governments, researchers, and international disaster management organizations. Studies conducted by global disaster monitoring institutions have highlighted the

growing occurrence of climate-related disasters and their widespread impact on communities across different regions [3], [4].

Traditionally, disaster prediction and risk assessment have relied on historical data analysis, statistical models, and expert-driven monitoring systems. These conventional approaches provide valuable insights into disaster patterns and environmental risks; however, they often struggle to capture the complex relationships present in large-scale environmental and geospatial datasets. Natural disasters are influenced by multiple dynamic factors, including meteorological conditions, geological activities, environmental variations, and human interventions. Due to the multidimensional nature of these factors, traditional analytical models may not always deliver accurate or timely predictions required for effective disaster preparedness and response planning [5], [10].

Recent advancements in artificial intelligence and data analytics have introduced new opportunities for improving disaster prediction and management systems. Machine learning techniques have demonstrated strong capabilities in processing large volumes of data and identifying hidden patterns that may not be easily recognized using traditional analytical methods. Various machine learning algorithms, including decision trees, support vector machines, and ensemble learning techniques, have been applied to disaster prediction tasks such as flood forecasting, tsunami prediction, and environmental risk assessment [7], [9], [18]. These approaches enable more accurate modelling of disaster-related variables and support data-driven decision-making in disaster management.

Despite their advantages, conventional machine learning models may still face challenges when dealing with highly complex datasets, nonlinear relationships, or severe class imbalance problems that frequently occur in disaster-related datasets. Handling imbalanced data is particularly important because disaster events often represent rare but critical occurrences compared to normal environmental conditions. Several studies have highlighted the importance of advanced sampling techniques and imbalance-aware learning methods to improve predictive performance in such scenarios [11], [12], [17].

In recent years, deep learning methods have gained significant attention due to their ability to automatically learn complex representations from large datasets. Neural networks are capable of extracting meaningful features and modelling nonlinear relationships between different environmental and climatic variables. Deep learning approaches have been successfully applied in disaster-related research areas such as atmospheric river detection, flood forecasting, and environmental monitoring systems [1], [14]. In addition, ensemble learning techniques such as Extreme Gradient Boosting (XGBoost) have demonstrated strong predictive performance in classification and regression tasks due to their efficiency in handling structured datasets and reducing model overfitting [15].

Motivated by these advancements, this research proposes a hybrid disaster prediction framework that integrates neural networks with the XGBoost algorithm to improve disaster forecasting accuracy. In the proposed approach, neural networks are employed to extract meaningful features and complex patterns from disaster-related datasets, while the XGBoost model performs the final classification and prediction of disaster types. Furthermore, the Synthetic Minority Over-sampling Technique (SMOTE) is applied to address the problem of class imbalance commonly found in disaster datasets, thereby improving model learning and prediction reliability [12], [17].

The primary objective of this study is to develop an intelligent prediction model capable of enhancing the accuracy and reliability of disaster forecasting systems. By combining neural networks with the XGBoost algorithm, the proposed framework aims to support disaster management authorities in making faster and more informed decisions. Such intelligent systems can play a vital role in early warning mechanisms, disaster preparedness planning, and efficient allocation of resources during emergency situations.

II. LITERATURE SURVEY

In recent years, disaster prediction and management have become significant research areas due to the increasing frequency and impact of natural disasters such as floods, earthquakes, and wildfires. The growing availability of environmental datasets, geospatial information, and sensor-based monitoring systems has encouraged researchers to apply data-driven techniques for disaster forecasting and risk assessment. Several studies have highlighted the importance of intelligent prediction models in supporting disaster preparedness and emergency response planning [4], [5].

Early research in disaster prediction primarily relied on traditional machine learning algorithms such as Logistic Regression, Support Vector Machines (SVM), Decision Trees, and Random Forest. These algorithms were used to analyse historical disaster

datasets and identify patterns that could help predict potential disaster events. Machine learning models have been applied to various disaster prediction tasks including tsunami forecasting, flood prediction, and environmental risk analysis [7], [9], [18]. Although these methods provided useful insights into disaster patterns, their performance was often limited when dealing with large-scale and complex datasets because they relied heavily on manually engineered features and predefined parameters.

To overcome these limitations, researchers began exploring deep learning techniques capable of automatically extracting meaningful patterns from large datasets. Neural networks, particularly deep learning architectures, have demonstrated strong capabilities in modelling nonlinear relationships and learning complex representations from environmental and climatic data. These models have been successfully applied in several disaster-related applications, including atmospheric event detection and large-scale environmental monitoring systems [1], [14]. Deep learning methods can significantly improve prediction accuracy by learning hierarchical representations of input data. However, such models often require large volumes of training data and substantial computational resources, which can limit their practical deployment in real-time disaster management environments.

More recently, hybrid approaches have been proposed to combine the strengths of both machine learning and deep learning techniques. Hybrid models typically utilize neural networks for feature extraction while employing advanced machine learning algorithms for final classification and prediction tasks. For instance, ensemble-based learning algorithms such as Extreme Gradient Boosting (XGBoost) have gained significant popularity due to their high prediction accuracy, scalability, and ability to efficiently handle structured datasets. XGBoost is widely recognized as a powerful gradient boosting framework capable of capturing complex data relationships while reducing overfitting during model training [15].

In addition to hybrid frameworks, several researchers have explored ensemble learning techniques in disaster prediction systems. Ensemble models combine the predictions of multiple base learners to improve prediction accuracy and model robustness. Such approaches are particularly beneficial in disaster management applications where accurate and timely predictions are essential for early warning systems and effective emergency planning [7], [18].

Another major challenge in disaster-related datasets is class imbalance, where disaster events occur much less frequently compared to normal environmental conditions. Imbalanced datasets can significantly affect the predictive performance of machine learning models. To address this issue, researchers have proposed advanced resampling techniques such as the Synthetic Minority Over-sampling Technique (SMOTE) and related algorithms. These techniques generate synthetic samples for minority classes and improve model performance by balancing the dataset distribution [12], [17]. Additionally, systematic reviews have highlighted the importance of addressing missing data and data imbalance issues to enhance the reliability of disaster prediction models [10], [11].

Despite these advancements, several challenges still remain in the development of efficient disaster prediction systems. These challenges include handling heterogeneous environmental datasets, integrating geospatial and climatic information, managing real-time data streams, and improving prediction reliability in highly uncertain environments. Therefore, there is an increasing need for intelligent hybrid frameworks that combine the feature extraction capabilities of deep learning models with the classification strength of advanced machine learning algorithms.

Motivated by these challenges, the current study proposes a hybrid disaster prediction framework that integrates neural networks for feature extraction with the XGBoost algorithm for disaster classification. By combining deep learning-based representation learning with gradient boosting-based classification, the proposed system aims to

improve prediction accuracy, enhance model robustness, and provide a more reliable decision-support tool for disaster prediction and management.

III.SYSTEM ANALYSIS

A. Existing System

In earlier disaster prediction systems, researchers primarily relied on traditional machine learning models to analyse historical disaster data and identify patterns associated with natural hazards. These approaches typically employ algorithms such as Naïve Bayes, Decision Trees, Random Forest, Logistic Regression, and Support Vector Machines (SVM) to predict disaster events based on environmental, meteorological, and geographical information collected over time. Machine learning techniques have been widely used in disaster-related studies such as flood prediction, tsunami forecasting, and environmental risk assessment due to their ability to analyse large datasets and discover underlying relationships among multiple variables [7], [9], [18].

Many research studies compare the performance of different machine learning models to determine the most effective algorithm for predicting disaster events. In some cases, ensemble learning methods are adopted, where multiple models are combined to improve prediction accuracy and reduce classification errors. Ensemble techniques can enhance model stability and provide more reliable predictions by aggregating the outputs of several learning algorithms. Such methods have shown promising results in disaster prediction tasks and environmental monitoring systems [7], [15].

Despite these advancements, traditional machine learning approaches often encounter limitations when dealing with large and complex disaster-related datasets. Many of these models depend heavily on manually selected features, which may not fully capture the hidden relationships and nonlinear patterns present within environmental data. Disaster prediction involves numerous interconnected variables, including weather conditions, geological factors, hydrological

indicators, and climate patterns. Conventional machine learning algorithms may struggle to effectively represent these complex relationships, leading to reduced predictive performance in real-world scenarios [4], [5].

Another significant challenge in disaster prediction systems is the presence of data imbalance and missing information within environmental datasets. Disaster events are relatively rare compared to normal environmental conditions, which leads to highly imbalanced datasets. If not properly addressed, such imbalance can cause machine learning models to bias predictions toward the majority class, reducing their ability to detect rare but critical disaster events. Several studies have emphasized the importance of addressing class imbalance and missing data issues to improve prediction reliability in disaster research [10], [11], [12], [17].

Furthermore, as the volume of environmental and geospatial data continues to increase, traditional machine learning systems may face challenges related to computational complexity and scalability. Processing large-scale environmental datasets often requires efficient algorithms capable of handling high-dimensional data and complex feature interactions. Without appropriate optimization techniques, conventional models may experience increased training time and reduced prediction efficiency, particularly when applied to large-scale disaster monitoring systems [1], [5].

Disadvantages Of The Existing System

Limited Feature Learning:

Traditional machine learning models rely heavily on manually engineered features, which may fail to capture complex nonlinear relationships present in disaster datasets [9].

Overfitting and Underfitting:

Many conventional models may either overfit the training data or fail to adequately learn important patterns, resulting in reduced prediction accuracy when applied to new data.

High Data Complexity:

Disaster datasets often contain numerous environmental variables such as temperature, rainfall, seismic activity, and atmospheric conditions, making it difficult for simple models to accurately analyse the relationships among these factors [4], [5].

Computational Challenges:

Processing large-scale environmental and geospatial datasets can require significant computational resources, which may limit the efficiency of traditional prediction systems.

Imbalanced Datasets:

Disaster-related datasets typically contain fewer samples representing disaster events compared to normal environmental conditions. This imbalance can significantly affect classification performance and reduce model reliability [12], [17].

Limited Prediction Accuracy:

Traditional models often struggle to capture nonlinear relationships and hidden patterns within complex environmental data, leading to lower predictive performance.

Scalability Issues:

As environmental monitoring systems generate increasingly large datasets, existing prediction models may face difficulties in efficiently processing and analysing large volumes of information.

B. Proposed System

To overcome the limitations of existing disaster prediction approaches, the proposed system introduces a hybrid framework that integrates neural networks with the Extreme Gradient Boosting (XGBoost) algorithm for improved disaster prediction and management. The proposed framework combines the feature extraction capability of deep learning models with the strong classification performance of gradient boosting algorithms to enhance prediction accuracy and system robustness.

In the proposed architecture, disaster-related datasets are first collected from environmental,

meteorological, and geographical data sources. These datasets typically contain multiple variables such as rainfall patterns, temperature variations, atmospheric pressure, seismic indicators, and other environmental factors associated with disaster events. The collected data undergo preprocessing steps to improve data quality and ensure efficient model training. Preprocessing includes handling missing values, removing redundant information, normalizing feature values, and preparing the dataset for machine learning algorithms. Proper data preprocessing is essential in disaster prediction systems because environmental datasets often contain incomplete records and inconsistent measurements [10].

After preprocessing, a neural network model is employed to automatically extract meaningful features from the dataset. Neural networks are capable of learning complex nonlinear relationships among multiple environmental variables, enabling them to capture hidden patterns that may not be detected using traditional feature engineering methods. Deep learning models have demonstrated strong performance in various environmental and disaster-related prediction tasks due to their ability to process high-dimensional datasets and learn hierarchical feature representations [1], [14].

The features extracted by the neural network are then provided to the XGBoost classifier, which performs the final prediction of disaster categories. XGBoost is a widely used gradient boosting algorithm known for its high prediction accuracy, scalability, and efficiency in handling structured datasets. By combining multiple decision trees in a boosting framework, XGBoost reduces prediction errors and improves model generalization. Previous research has shown that XGBoost performs effectively in complex prediction tasks and large-scale data analysis scenarios [15].

To further improve the performance of the prediction model, the Synthetic Minority Over-sampling Technique (SMOTE) is applied to address the issue of class imbalance commonly found in disaster datasets. Since disaster events occur less frequently than normal environmental conditions,

datasets often contain significantly fewer samples representing disaster events. SMOTE generates synthetic samples for minority classes, thereby improving the learning capability of machine learning models and enhancing classification accuracy [12], [17].

The proposed hybrid model is evaluated using several performance metrics, including accuracy, precision, recall, and F1-score, which are commonly used for evaluating classification models in disaster prediction systems. These evaluation metrics provide a comprehensive assessment of the model's ability to correctly identify disaster events while minimizing false predictions.

By combining the feature learning capabilities of neural networks with the powerful classification performance of XGBoost, the proposed system aims to provide a more accurate, scalable, and reliable disaster prediction framework. Such intelligent prediction systems can significantly support disaster management authorities by enabling early warning mechanisms, improving disaster preparedness, and facilitating efficient resource allocation during emergency situations.

IV.SYSTEM DESIGN

System Architecture

Below diagram depicts the whole system architecture.

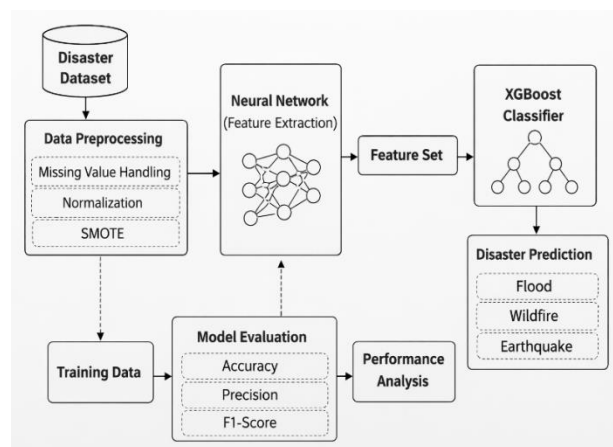


Fig 1. Methodology followed for proposed model

V. SYSTEM IMPLEMENTATION

Modules

Data Collection and Preprocessing

The first stage of the proposed disaster prediction system involves collecting disaster-related datasets from reliable sources such as historical disaster records, environmental monitoring systems, meteorological databases, and publicly available datasets. These datasets typically include information related to earthquakes, floods, storms, and other natural disasters. Reliable disaster databases and monitoring institutions play an important role in providing structured information for disaster research and prediction analysis [3], [4]. After data collection, preprocessing is performed to improve data quality and ensure that the dataset is suitable for machine learning model training. Environmental datasets often contain missing values, noise, and inconsistencies that may negatively affect prediction performance. Therefore, preprocessing techniques are applied to remove missing values, correct inconsistencies, normalize numerical attributes, and transform raw data into a structured format suitable for machine learning analysis. Proper preprocessing significantly improves the reliability and efficiency of predictive models in disaster management systems [10].

Feature Extraction and Selection

Once the dataset has been cleaned and prepared, important features that contribute to disaster prediction are identified. Feature extraction techniques are applied to derive meaningful attributes from the raw environmental data. These features may include environmental indicators, historical disaster patterns, climatic conditions, and geographical parameters that influence the occurrence of disaster events.

Feature selection methods are then used to identify the most relevant attributes that contribute significantly to prediction accuracy. By selecting only the most informative features, the system reduces data dimensionality, improves computational efficiency, and enhances the predictive performance of the model. Effective

feature engineering and selection have been widely recognized as important steps in developing accurate disaster prediction models [9].

Neural Network-Based Pattern Learning

In this module, a neural network model is employed to analyse complex patterns present in the disaster dataset. Neural networks are capable of capturing nonlinear relationships and hidden patterns within large and high-dimensional datasets.

By learning hierarchical representations of environmental data, neural networks can identify complex relationships between different variables that may contribute to potential disaster events.

Deep learning techniques have demonstrated strong capabilities in modelling complex environmental patterns and improving prediction accuracy in disaster-related applications such as atmospheric event detection and environmental monitoring systems [1], [14].

The neural network in the proposed system extracts meaningful features that represent critical conditions associated with disaster occurrences.

Hybrid Prediction Using XGBoost

After the neural network extracts useful features, the processed information is passed to the XGBoost classifier for final prediction. XGBoost is an advanced gradient boosting algorithm that combines multiple decision trees to improve classification accuracy and reduce prediction errors. It is widely recognized for its scalability, efficiency, and ability to handle structured datasets with complex feature interactions.

The integration of neural networks with XGBoost allows the system to benefit from both deep learning-based feature extraction and gradient boosting-based classification. This hybrid approach improves model robustness and enhances prediction accuracy in disaster prediction systems [15].

Disaster Prediction and Alert Generation

Based on the trained hybrid model, the system predicts the likelihood of different types of

disasters. The model analyses environmental conditions and historical patterns to estimate the probability of potential disaster events. When the predicted probability exceeds a predefined threshold, the system generates alerts to notify disaster management authorities.

Such early warning mechanisms can support disaster preparedness strategies and enable authorities to take preventive measures, thereby reducing potential damage and improving emergency response planning. Intelligent disaster prediction systems play a crucial role in supporting effective disaster management and resource allocation during critical situations [5].

Model Evaluation and Monitoring

The final module focuses on evaluating and monitoring the performance of the proposed hybrid prediction model. Several evaluation metrics are used to assess model performance, including accuracy, precision, recall, and F1-score. These metrics provide a comprehensive assessment of the model's ability to correctly identify disaster events while minimizing false predictions.

In addition, continuous monitoring of the model ensures that it maintains consistent performance over time. As new environmental data becomes available, the system can be updated and retrained to adapt to evolving data patterns. Continuous model improvement is essential for maintaining reliable disaster prediction systems in dynamic environmental conditions [7], [18].

VI .RESULTS AND DISCUSSION

To evaluate the performance of the proposed hybrid disaster prediction framework, several machine learning experiments were conducted using disaster-related datasets containing environmental and geographical attributes. The dataset was divided into training and testing sets to ensure reliable model evaluation and to measure the generalization capability of the predictive model. The proposed hybrid model integrates neural network-based feature extraction with the XGBoost classification algorithm, allowing the

system to effectively learn complex patterns and perform accurate disaster classification.

During the experimentation phase, the model was trained using cross-validation techniques to minimize training bias and improve model reliability. Hyperparameters of the XGBoost model, including learning rate, number of estimators, and tree depth, were tuned to obtain optimal prediction performance. Previous studies have demonstrated that gradient boosting algorithms such as XGBoost can significantly improve classification performance in complex prediction tasks due to their ability to capture nonlinear feature interactions and reduce prediction errors [15].The performance of the proposed hybrid model was compared with several traditional machine learning algorithms including Decision Tree, Logistic Regression, and Random Forest. These models were selected because they are widely used in disaster prediction and environmental data analysis [7], [9], [18]. The comparison was conducted using standard performance metrics such as accuracy, precision, recall, and F1-score, which are commonly used to evaluate classification models in disaster prediction systems.

Table 1
Performance Comparison of Disaster Prediction Models

Model	Accuracy (%)	Precision	Recall	F1-Score
Logistic Regression	85.3	0.83	0.82	0.82
Decision Tree	87.1	0.85	0.84	0.84
Random Forest	90.4	0.89	0.88	0.88
Neural Network + XGBoost (Proposed)	94.2	0.93	0.92	0.92

From Table 1, it can be observed that the proposed Neural-XGBoost hybrid model achieved the highest accuracy of 94.2%, outperforming traditional machine learning models. This improvement is mainly due to the ability of neural networks to capture complex relationships among environmental variables, while XGBoost enhances classification performance through its gradient boosting mechanism.

ROC Curve Analysis

The Receiver Operating Characteristic (ROC) curve is used to analyse the classification performance of the proposed model by examining the trade-off between the True Positive Rate (TPR) and False Positive Rate (FPR) across different decision thresholds

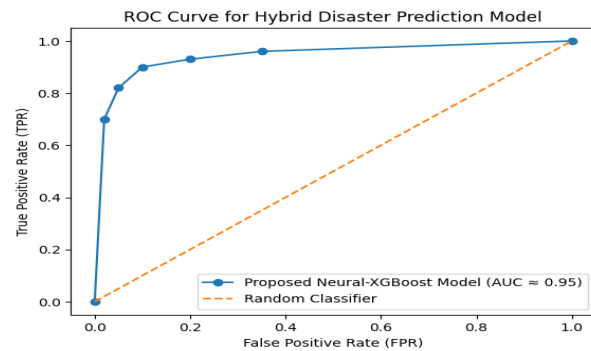


Fig. 2. ROC Curve for Hybrid Disaster Prediction Mode

The ROC analysis shows that the proposed hybrid model achieved an Area Under the Curve (AUC) value of approximately 0.95, indicating strong predictive capability in distinguishing disaster events from normal environmental conditions. A ROC curve closer to the top-left corner of the graph represents a highly effective classification model with a low false positive rate and high detection accuracy.

Overall, the experimental results demonstrate that the proposed Neural Network–XGBoost hybrid framework significantly improves disaster prediction performance compared to traditional machine learning approaches. The integration of deep learning-based feature extraction with gradient boosting classification enables the system

to effectively analyse complex environmental datasets and generate reliable disaster predictions. Such intelligent predictive systems can play an important role in early warning systems, disaster preparedness, and efficient disaster management planning.

VII. CONCLUSION

This study presented a hybrid machine learning framework for disaster prediction and management by integrating neural networks with the Extreme Gradient Boosting (XGBoost) algorithm. The proposed system processes disaster-related datasets, performs data preprocessing and feature extraction using neural networks, and applies the XGBoost classifier for accurate disaster prediction. The hybrid approach leverages the feature learning capability of deep learning models together with the strong classification performance of gradient boosting algorithms to enhance predictive accuracy.

Experimental results demonstrate that the proposed hybrid model achieves improved prediction performance compared to traditional machine learning approaches. By effectively capturing complex nonlinear relationships within environmental and disaster-related datasets, the system provides reliable predictions that can support disaster preparedness and risk mitigation strategies. Machine learning and ensemble-based prediction systems have shown strong potential in disaster forecasting applications such as flood prediction, tsunami detection, and environmental risk analysis [7], [9], [18]. Furthermore, advanced boosting algorithms such as XGBoost have been widely recognized for their ability to handle structured datasets efficiently and improve prediction accuracy in complex classification tasks [15].

The proposed system can assist disaster management authorities by enabling early prediction of potential disaster events and supporting timely decision-making processes. Early warning systems and predictive analytics play a crucial role in improving disaster preparedness,

optimizing resource allocation, and reducing the socioeconomic impact of natural disasters [4], [5]. By identifying potential disaster risks in advance, the proposed framework contributes to strengthening disaster management strategies and improving community resilience.

For future work, the proposed system can be enhanced by integrating real-time environmental monitoring systems, satellite imagery, and Internet of Things (IoT) sensor data to improve prediction accuracy and enable continuous disaster monitoring. The integration of large-scale environmental datasets and geospatial information can further improve the reliability of predictive models in disaster management applications. Additionally, advanced deep learning architectures and ensemble learning techniques can be explored to improve model scalability and predictive performance in large-scale disaster monitoring systems [1], [14]. Addressing challenges such as class imbalance, missing data, and heterogeneous environmental datasets will also be essential for developing more robust and efficient disaster prediction frameworks [10], [11], [17].

Overall, the integration of deep learning and gradient boosting techniques represents a promising approach for developing intelligent disaster prediction systems capable of supporting effective disaster risk management and early warning mechanisms in modern environmental monitoring systems.

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