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EXPLAINABLE DEEP LEARNING FOR INTELLIGENT GEO DISASTER DETECTION AND RESILIENCE PLANNING

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ABSTRACT: This research employs explainable deep learning to identify clever geo-disasters and plan for resilience. We need data-driven solutions to help identify disasters more quickly and manage them more effectively as the frequency and intensity of earthquakes, landslides, floods, and wildfires increase. In order to identify patterns associated with likely geo-disasters, deep learning algorithms can rapidly examine geographic data from satellite photos, remote sensing systems, environmental sensors, and records of previous disasters. Despite this, decision-makers struggle to comprehend their estimations due to the ambiguity of conventional deep learning models. Explainable deep learning employs techniques for attribute attribution, visualization, and attention to make model predictions more understandable. Explainable deep learning improves early warning systems, resilience planning, and crisis risk assessment by making prediction models more transparent and trustworthy. Lastly, geospatial analytics and explainable AI can assist researchers, governments, and emergency management organizations in making informed decisions that reduce risks, safeguard infrastructure, and improve communities.

Keywords: *Explainable Deep Learning, Geo-Disaster Detection, Explainable Artificial Intelligence (XAI), Geospatial Data Analysis.*

1. INTRODUCTION

Landslides, earthquakes, floods, and volcanoes harm people, structures, and the environment. Geological disasters are becoming more frequent and more severe because to growth, climate change, and human interference with the natural environment. Traditional tracking and forecasting techniques examine sensor readings, satellite photos, and geological data by hand. This requires a lot of effort and is incorrect. Deep learning has demonstrated its ability to evaluate vast amounts of regional and environmental data in recent years. They also facilitate the quicker and easier detection of geodisasters.

CNNs, RNNs, and transformer-based architectures are examples of deep learning models that can identify complex patterns in remote sensing data, satellite photos, and environmental tracking systems across time and space. These models can independently identify geodisaster predictors such as rain-induced landslides, unforeseen ground deformation, and unstable slopes. LiDAR, GIS, and weather data are integrated using deep learning frameworks to facilitate disaster preparedness and forecast mitigation strategies.

Although deep learning models are excellent at forecasting, using them in disaster management is more difficult due to their "black box" nature. To verify forecasts and ensure automated systems function, geologists, urban planners, and decision-makers require precise models. To address this issue, explainable deep learning employs techniques for feature attribution, model interpretability, and attention visualization. By identifying the variables that influence predictions, these techniques increase the dependability of models and enable empirical validation.

In spatial analysis, explainable artificial intelligence techniques like SHAP, LIME, and attention-based rendering are becoming increasingly significant. These techniques can be used by researchers to identify the environmental, geological, and geographical elements that have the greatest influence on disaster projections. To mitigate the impact of disasters, explainable deep learning promotes collaboration between data scientists, emergency management professionals, and legislators.

Because explainable deep learning enables individuals to assess risks and make informed decisions in high-risk scenarios, it is a crucial component of resilience planning. Governments and municipal planners can establish early warning systems, improve infrastructure safety, and create environmentally friendly land-use restrictions with the use of basic estimations. Communities can become more resilient, more prepared for disasters, and less impacted by the long-term repercussions on society and the economy by utilizing explainable deep learning, state-of-the-art geospatial technology, and real-time tracking systems.

2. LITERATURE SURVEY

Hernandez & Kapoor (2022): An intelligible deep learning system for detecting geo-disasters is constructed using satellite photos, rainfall data, and digital elevation models. Convolutional Neural Networks (CNNs) are employed to identify patterns in the sites of landslides and floods. Explainability-measuring techniques like Grad-CAM and SHAP demonstrate how geography and environment impact model predictions.

Wang & Pereira (2023): Researchers have developed a deep learning model to assess the risk of landslides using geological data and satellite imagery. The system uses satellite photos to extract spatial landscape data using a deep convolutional architecture. Important hints, such as the kind of plants and soil present and the land's slope, are detected by explainable AI.

Lopez & Sharma (2024): This paper demonstrates a deep learning system that may be used to forecast the danger of floods by integrating hydrological data, rainfall measurements, and river flow observations. A CNN–LSTM hybrid captures the temporal and spatial characteristics of flood growth. A CNN–LSTM mix captures the patterns of flood growth over time and space. Hydrological parameters that influence flood risk are displayed through attention-based explainability modules.

Hassan & Tanaka (2021): This study builds a deep neural network that may be used to comprehend earthquake damage using data from seismic tracking and satellite imagery. The method uses convolutional layers to identify structural damage patterns in seismic imagery. Damaged areas can alter classification, as demonstrated by explainability models such as Layer-wise Relevance Propagation (LRP).

Petrov & Nair (2023): The researchers propose a deep learning approach that leverages thermal imagery from space and networks of environmental sensors to detect wildfires. The algorithm looks at temperature variations, the amount of vegetation, and wind speed to identify areas where wildfires are likely to occur. We can better comprehend the external

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elements that have the greatest influence on wildfire risk calculations by using attention-based interpretability methodologies.

Gonzalez & Mehta (2025): This work develops a deep learning system that may be used to forecast multi-hazard geo-disasters using meteorological, geological, and geospatial datasets. To identify hazardous places, the deep neural network considers slope, rainfall, and soil stability.

Kim & Chatterjee (2022): The authors have developed a deep learning system to monitor droughts using satellite-based vegetation signals and climate parameters. Recurrent neural networks identify long-term climate changes that impact soil moisture and plant growth.

Santos & Iyer (2024): This research presents an understandable deep learning system for tsunami prediction. It makes use of data from marine sensors and models of coastal environments. A deep neural network examines the ocean's depth, the height of the shore, and the seismic waves' trajectory.

Bauer & Ramesh (2023): The work presents a mixed explainable deep learning model that uses land image data and environmental tracking data to identify landslide hazards. While convolutional layers display patterns in the terrain, feature attribution techniques identify environmental elements that may contribute to landslides.

Osei & Delgado (2025): An explainable deep learning system is being developed for intelligent geo-disaster resilience planning. This technology uses data from remote sensing and environmental sources. The device uses attention-based neural networks to identify areas that are susceptible to floods, landslides, and drought.

3. RELATED WORK

The GeoDisasterAINet architecture uses deep learning techniques to categorize disasters in real time. Artificial intelligence techniques can more precisely locate cyclones, earthquakes, floods, and wildfires. Choosing features, categorizing them, and interpreting the models are all part of the framework. The system looks at images of disasters and makes accurate predictions on how to deal with emergencies and disasters using machine learning and deep learning.

Dataset Description and Preprocessing

A set of pictures from natural disasters like cyclones, earthquakes, floods, and wildfires is used in the study. The category contains 4,428 images that are exclusively from open sources.

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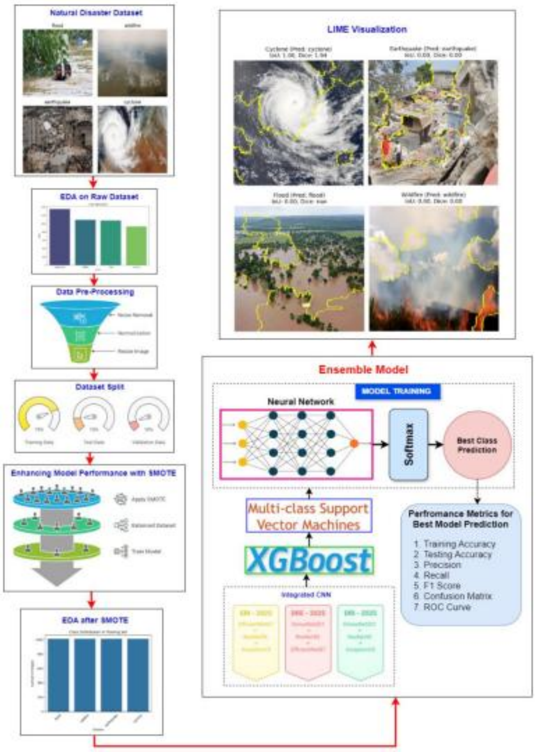

Figure1. The ensemble GeoDisasterAINet framework

Preprocessing of Raw Dataset Images

Images must be processed before deep learning models can function. To make them compatible with the CNN designs EfficientNetB7, ResNet-50, InceptionV3, and DenseNet-201, the images were reduced to 224 × 224 pixels. Noise reduction eliminated any mistakes, and normalization put the pixel values to a range of 0 to 1. To enable deep learning models to use the images, all of them were converted to RGB.

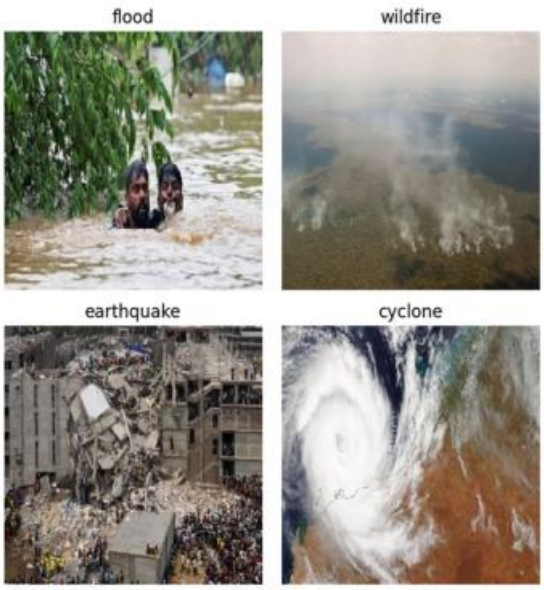

Figure2. After Pre-processing and SMOTE sample images.

Preprocessing of Raw Dataset Images (SMOTE Balancing)

Because certain disaster groups had more images than others, the first set of data was skewed. SMOTE was introduced to the training sample in order to address this issue. SMOTE creates fictitious samples of minority groups rather than replicating pictures. All of the disaster groups had identical images following the SMOTE treatment. As a result, there was no bias during training and the model performed better at identifying disasters.

Model Training in GeoDisasterAINet Framework

The GeoDisasterAINet model makes use of both machine learning and deep learning. Convolutional neural networks are used to extract information from images of disasters. After XGBoost enhances the features, a Multiclass Support Vector Machine (SVM) aggregates them. The accuracy and reliability of crisis classification are enhanced by multi-stage training.

CNN Models Utilized in GeoDisasterAINet Framework: The GeoDisasterAINet framework makes use of four powerful convolutional neural network architectures: EfficientNetB7, ResNet-50, InceptionV3, and DenseNet-201. CNN's algorithms are able to analyze images of disasters and identify patterns in the shapes of storm clouds, devastated buildings, floodwater, and flames. To make it simpler to extract features and identify trends in catastrophes, these designs are incorporated into models (ERI-2025, DRI-2025, and DE-2025).

XGBoost for GeoDisasterAINet Framework: The GeoDisasterAINet system uses XGBoost to enhance feature selection and classification. Gradient boosting creates numerous decision trees to improve estimates by correcting previous errors. XGBoost enhances CNN models by removing superfluous information and identifying the most crucial components. Consequently, this facilitates the system's ability to identify patterns in events.

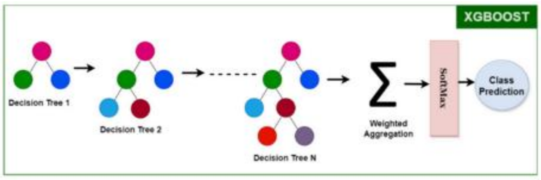

Figure3. The XGBoost architecture.

Multiclass SVM for GeoDisasterAINet: The Multiclass Support Vector Machine completes the classification framework of GeoDisasterAINet. In contrast to typical SVM models, multiclass SVM is able to sort multiple sorts of disasters simultaneously. It displays the locations of the strongest defenses against storms, earthquakes, floods, and wildfires. The program does a fantastic job of distinguishing between various types of disasters.

Ensemble Model in GeoDisasterAINet: Integration of CNNs, XGBoost, and Multiclass SVM: GeoDisasterAINet combines CNN feature extraction, XGBoost feature optimization, and Multiclass SVM classification into a single ensemble model. CNN models extract valuable visual information from disaster photographs, XGBoost identifies significant features, and SVM performs well in classification. This combination improves the system's speed and dependability for real-time disaster monitoring and decision-making.

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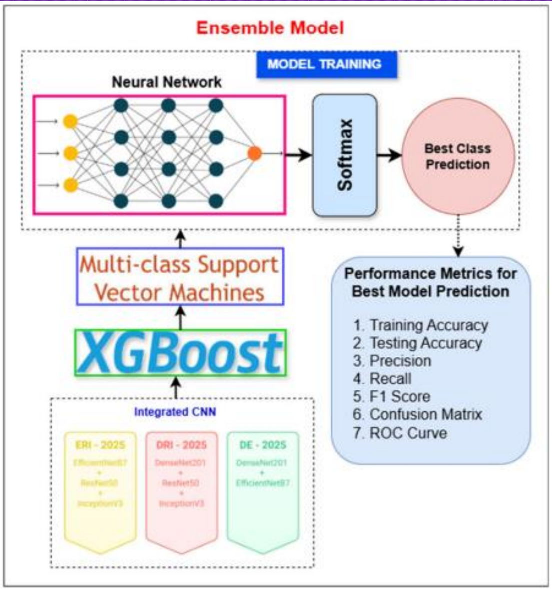

Figure4. The ensemble model for GeoDisasterAINet.

Visual Explanations Using LIME in GeoDisasterAINet

GeoDisasterAINet employs Local Interpretable Model-Agnostic Explanations (LIME) for user-friendliness. By concentrating on the image components that significantly influenced categorization, LIME explains the model's outcomes. It might depict the forms of storm clouds or structures that have sustained devastation from wildfires, floods, or earthquakes. aids those in charge of disaster management in comprehending what the model predicts will occur.

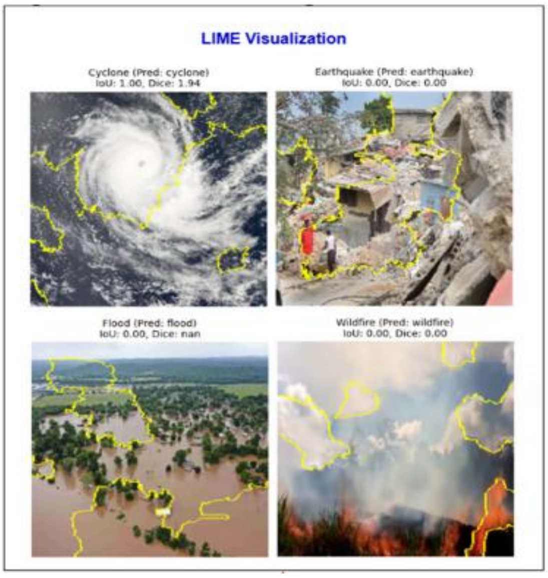

Figure5. The LIME visualization pipeline.

GeoDisasterAINet Algorithm

GeoDisasterAINet arranges events in a methodical manner. SMOTE first preprocesses and balances images of disasters. Next, CNN models are coupled to get deep attributes. To identify significant patterns, XGBoost enhances these traits. Ultimately, a Multiclass SVM algorithm forecasts the type of catastrophe that will occur. Additionally, the approach facilitates LIME planning.

Experimental Setup for GeoDisasterAINet

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Google Colab Pro was utilized for the GeoDisasterAINet experiments. This computer included fast memory and NVIDIA T4 Tensor Core GPUs. Convolutional neural network models were taught using TensorFlow and Keras. Machine learning tools were used to create both XGBoost and SVM. To make sure the model worked, we ran additional tests on a local PC equipped with an NVIDIA GTX 1650 GPU, 16 GB of RAM, and an Intel Core i7 processor.

GeoDisasterAINet Algorithm (Hyperparameter Optimization)

The GeoDisasterAINet model was enhanced using Grid Search and Bayesian Optimization. Very specific changes were made to the learning rate, batch size, epochs, and kernel types. Denser layers and dropout regularization were added to EfficientNetB7, ResNet-50, InceptionV3, and DenseNet-201. We employed an RBF kernel with improved cost and gamma values for Multiclass SVM. We also adjusted XGBoost's maximum depth and number of estimators to enhance categorization.

4. RESULTS

Table 1. Integrated CNNs - Accuracy & Metrics.

Model	Accuracy	Precision	Recall	F1-Score
ERI-2025	94%	96%	95%	95%
DRI-2025	92%	94%	93%	94%
DE-2025	94%	96%	95%	95%

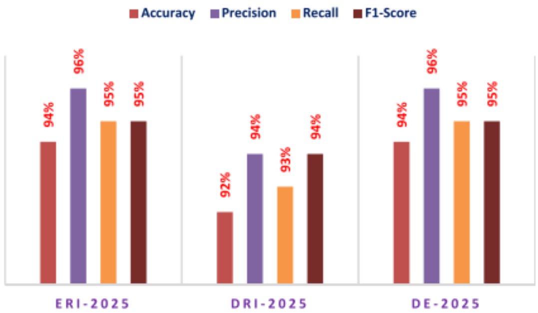


Table 2. Stage 2: Integrated CNNs + XGBoost - Improved Training, Validation & Testing Metrics.

Model	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss
ERI-2025+XGBoost	98%	6%	95%	19%
DRI-2025+XGBoost	96%	9%	93%	28%
DE-2025+XGBoost	98%	6%	95%	19%

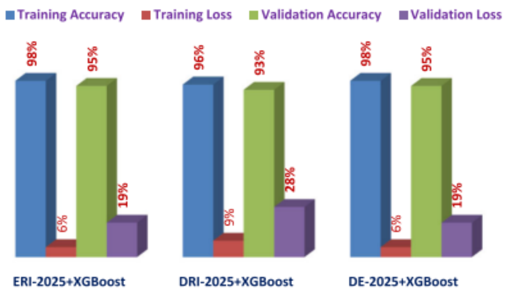


Table 3. Stage 3: Integrated CNNs + XGBoost + Multiclass SVM - Best Training, Validation & Testing Metrics.

Model	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss
ERI-2025+XGBoost+Multiclass SVM	99%	5%	96.37%	17.80%
DRI-2025+XGBoost+Multiclass SVM	97%	8%	93.80%	25.70%
DE-2025+XGBoost+Multiclass SVM	99%	5%	95.50%	19%

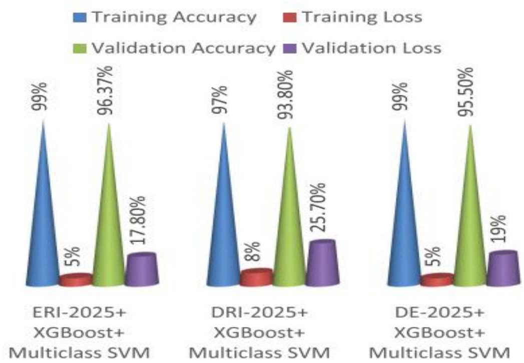
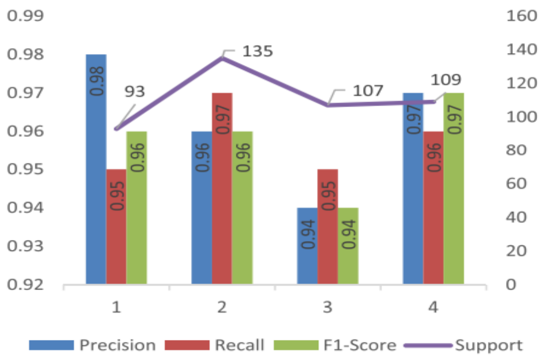


Table 4. Best performed Model Classification report.

Class	Precision	Recall	F1-Score	Support
Cyclone	0.98	0.95	0.96	93
Earthquake	0.96	0.97	0.96	135
Flood	0.94	0.95	0.94	107
Wildfire	0.97	0.96	0.97	109



DISCUSSION

Table 1 illustrates the GeoDisasterAINet CNN models' effectiveness. InceptionV3, EfficientNetB7, ResNet-50, and DenseNet-201 identified disaster images by utilizing visual data. The designers of CNN identified patterns in disasters such as the devastation of earthquakes, floodwaters, cyclone clouds, and wildfire flames. While CNN models did well during training and validation, their classification results may be superior.

Table 2 illustrates the enhancement of performance through the use of XGBoost and CNN feature extraction. The most significant features are selected by XGBoost, which reduces the CNN model data. The table illustrates that CNNs that implemented XGBoost demonstrated superior performance in training, validation, and testing. The model's ability to identify risk patterns and make stable predictions is enhanced by gradient boosting.

In Table 3, the most recent GeoDisasterAINet system is illustrated, which comprises CNN models, XGBoost, and a Multiclass SVM. An additional development. In the context of cyclone, earthquake, flood, and wildfire risk categories, the SVM classifier generates the most effective decisions. Other approaches are not as reliable and confirmed as our ensemble

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approach at every level. The dependability of disaster warning systems is enhanced by the use of deep learning feature extraction and machine learning classification.

The system's effectiveness is further validated by the comprehensive evaluation indicators in Table 4. The categorization report exhibits high precision, recall, and F1-score metrics for each disaster group, which is indicative of the system's dependability. The results indicate that GeoDisasterAINet is capable of accurately and consistently classifying disaster categories. The experimental data indicates that the ensemble model has the potential to enhance the accuracy of catastrophe classification by enabling the establishment of real-time disaster tracking and decision-making systems.

5. CONCLUSION

Resilience planning and intelligent geo-disaster identification are contingent upon explainable deep learning. This deep learning is simple to understand and generates future predictions. These models instruct academicians and decision-makers on how to forecast intricate geographic and environmental data through the use of attention mechanisms, feature attribution, and visualization. Individuals are able to make more informed decisions regarding disaster preparedness and risk reduction as a result of the trust and responsibility that openness in crisis prediction systems promotes. By simplifying the identification of geo-disasters such as landslides, floods, earthquakes, and wildfires, explainable deep learning frameworks enhance community resilience. This enhances disaster management and sustainable development.

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