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**Research Paper**

# GeoDisasterAINet: An Explainable Deep Ensemble Framework for Real-Time Urban and Rural Disaster Classification and Resilience

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***Abstract*— Urban and rural areas are increasingly vulnerable to natural disasters, including floods, cyclones, earthquakes, and wildfires, requiring accurate and timely classification for resilient communities. Traditional disaster detection approaches often rely on manual analysis or single-model predictions, which struggle to generalize across diverse environments and disaster types. Using the Natural Disaster Image Dataset from Kaggle, comprising labeled images of multiple disaster events, GeoDisasterAINet employs a multi-stage ensemble framework. Initial models, ERI-2025, DRI-2025, and DE-2025, are trained without additional preprocessing, while SMOTE and standard scaling are applied to enhanced models, ERI-2025 + XGBoost, DRI-2025 + XGBoost, and DE-2025 + XGBoost, for balanced training. In the final stage, multiclass SVM is combined with XGBoost-enhanced models, with only standard scaling applied, to improve classification accuracy. Convolutional neural networks, Xception, ResNet50, and a Hybrid Ensemble of Xception and ResNet50, further extract deep features. Evaluation using accuracy, precision, recall, and F1-score highlights ResNet50 as the best-performing model with 99.2% test accuracy. Explainable AI techniques, including Grad-CAM and LIME, generate heatmaps and feature importance visualizations to interpret model decisions effectively. A Flask-based interface enables users to upload images and receive real-time predictions with confidence scores. Overall, the framework provides high-accuracy, interpretable, and deployable disaster classification for resilient urban and rural communities.**

***"Keywords— Natural Disaster Classification, Deep Learning, Hybrid Ensemble, Explainable AI, XGBoost, Multiclass Support Vector Machine (SVM)".***

## I. Introduction

Natural disasters continue to pose severe threats to human life, economic stability, and environmental sustainability, with their intensity and frequency increasing due to rapid urbanization, climate variability, and environmental degradation [1]. Events such as floods, cyclones, earthquakes, and wildfires result in substantial casualties, displacement, and infrastructure destruction across both developed and developing regions. Global statistics indicate that disaster-related incidents have affected millions of individuals annually, causing extensive socio-economic losses and long-term environmental consequences [2]. Developing nations experience heightened vulnerability due to limited preparedness infrastructure, population density, and resource constraints. India remains highly exposed to extreme weather events, with floods, cyclones, and heatwaves contributing significantly to mortality and economic disruption [3]. The rising occurrence of these hazards underscores the urgent necessity for advanced technological frameworks that support efficient disaster monitoring and response.

Despite the availability of conventional monitoring techniques, existing disaster management mechanisms often rely on manual inspection, historical analysis, and static observational methods that limit their capability to respond to rapidly evolving disaster scenarios [4]. These approaches frequently struggle to provide accurate and real-time classification across diverse environmental conditions, resulting in delayed emergency responses and inefficient resource allocation. Moreover, existing solutions often lack scalability and adaptability, making them less effective when dealing with heterogeneous disaster types and geographic variations [5]. Data imbalance, limited interpretability, and insufficient integration of multi-source information further restrict the reliability of current predictive systems, thereby highlighting the need for more robust and intelligent disaster classification frameworks [6].

The primary objective of this investigation is to develop an advanced framework capable of accurately classifying multiple natural disasters in both urban and rural environments while supporting real-time decision-making. The framework is designed to enhance disaster identification accuracy, improve system reliability, and provide interpretable outcomes that assist authorities in emergency planning and risk mitigation. It focuses on integrating diverse data sources and creating a unified platform that supports large-scale disaster monitoring and classification. Additionally, the framework aims to provide an accessible interface that allows users to obtain rapid predictions and confidence-based insights, thereby strengthening disaster preparedness strategies and operational coordination [7].

The proposed framework contributes significantly to sustainable development by supporting global initiatives aimed at strengthening resilient communities and disaster-resilient infrastructure [8]. Accurate and timely disaster classification can improve emergency response planning, reduce economic losses, and enhance public safety measures. The integration of intelligent analytical mechanisms enables authorities and policymakers to implement proactive mitigation strategies and optimize resource deployment [9]. Furthermore, the framework promotes transparency and trust in automated decision-making systems by facilitating interpretable results, thereby encouraging the adoption of intelligent disaster management solutions. The overall implementation is expected to strengthen resilience planning and support sustainable urban and rural disaster management practices worldwide [10].

## II. LITERATURE REVIEW

Recent advancements in artificial intelligence have substantially enhanced disaster monitoring and response. Sun et al. [11] provided a comprehensive overview of AI applications in disaster management, highlighting improvements in risk assessment, early warning, and response coordination through predictive analytics and automated monitoring frameworks. However, their study focused on conceptual analysis and lacked practical strategies for multi-disaster classification across heterogeneous environments. Rathod et al. [12] explored convolutional neural networks combined with ensemble learning for automated disaster image classification, achieving improved accuracy and robustness. Despite promising results, challenges remained in handling class imbalance and limited interpretability, restricting real-world deployment.

Geospatial and environmental vulnerability analysis has also leveraged machine learning. Rahman et al. [13] proposed a flood susceptibility mapping framework integrating machine learning with multi-criteria decision analysis, improving spatial prediction accuracy but limited to a single disaster type. Yu et al. [14] developed a multimodal disaster information identification system using social media data, enhancing heterogeneous data extraction but suffering from reliability issues due to noisy content. Similarly, Islam et al. [15] combined natural language processing and CNNs for social media-based disaster detection, achieving better accuracy but facing inconsistencies and reduced real-time operational reliability due to dependency on user-generated content.

Deep learning approaches have been extensively applied for disaster damage assessment. Alisjahbana et al. [16] introduced a deep learning framework for building damage segmentation using satellite imagery, demonstrating high post-disaster accuracy but requiring high-resolution data, limiting real-time deployment. Umeike et al. [17] applied deep learning for rapid tornado damage assessment, reducing manual inspection time and improving response efficiency; however, their approach was restricted to a single disaster type. Jankovic et al. [18] proposed a transformer-based framework supported by UAVs for real-time monitoring, achieving efficient aerial surveillance but facing scalability issues due to specialized hardware requirements.

Interpretability and class imbalance remain key challenges. Bhowmick et al. [19] emphasized threshold-based evaluation metrics to enhance explainable AI (XAI) for disaster response, improving transparency but not optimizing performance across diverse disaster categories. Chawla et al. [20] introduced the Synthetic Minority Over-sampling Technique (SMOTE) to address imbalanced datasets, improving minority class detection, though oversampling may introduce synthetic bias if not carefully integrated with advanced classification frameworks.

Collectively, these studies highlight substantial improvements in disaster detection, prediction, and damage assessment. Nonetheless, gaps persist in achieving unified multi-disaster classification, scalable deployment, balanced training, and interpretable decision support. The present investigation addresses these limitations by introducing a comprehensive framework integrating diverse data sources, balanced training mechanisms, and interpretable prediction strategies, thereby enhancing reliability and real-time applicability across urban and rural environments.

## III. MATERIALS AND METHODS

The proposed GeoDisasterAINet framework is designed to enable accurate classification of natural disasters across urban and rural environments using the Natural Disaster Image Dataset obtained from Kaggle. The system follows a structured processing pipeline involving data ingestion, transformation, and partitioning to support efficient model development [21]. A multi-stage classification strategy is adopted in which baseline models, ERI-2025, DRI-2025, and DE-2025, are initially trained to establish foundational performance. Model robustness and generalization are improved by integrating XGBoost with the baseline models, supported by Synthetic Minority Over-sampling Technique for class balancing and standard scaling for feature normalization. In the final stage, multiclass Support Vector Machine is combined with XGBoost-enhanced models to refine classification accuracy [22]. Deep feature extraction is further strengthened using advanced convolutional neural networks, including Xception, ResNet50, and a hybrid ensemble architecture. Explainable Artificial Intelligence techniques, including LIME and Grad-CAM, provide interpretable decision visualization, while a Flask-based interface enables real-time deployment, ensuring scalable, transparent, and reliable disaster classification.

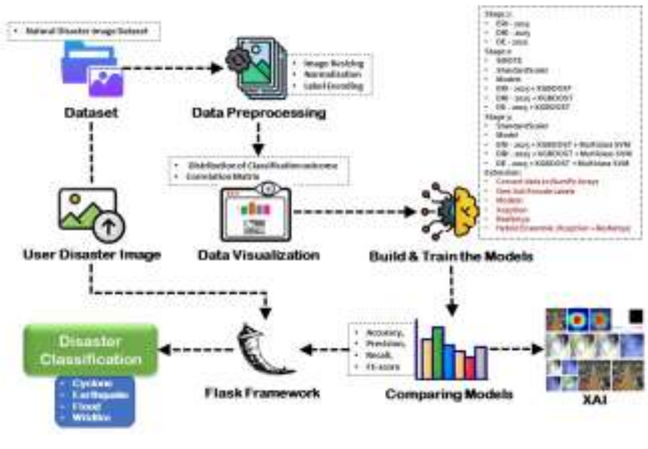


Fig. 1. Proposed Architecture

The system architecture begins with the Natural Disaster Image Dataset, which undergoes preprocessing including image resizing, normalization, and label encoding. Data visualization examines classification distributions and correlations. Multi-stage models—ERI-2025, DRI-2025, DE-2025, XGBoost, and multiclass SVM—are trained and extended with Xception, ResNet50, and hybrid ensembles. Performance metrics including accuracy, precision, recall, and F1-score are analyzed to compare models. Explainable AI techniques generate visual interpretations, while the Flask framework enables users to upload images for real-time disaster classification across cyclones, earthquakes, floods, and wildfires [23].

*A) Dataset Collection*

The Natural Disaster Image Dataset, obtained from a publicly available Kaggle repository, is utilized to support disaster classification tasks. The dataset contains 4,428 labeled images categorized into four disaster classes: cyclone, earthquake, flood, and wildfire. It is divided into training (3,322 samples), validation (444 samples), and testing (662 samples) subsets. The dataset includes diverse environmental scenes and image formats, enabling robust feature representation. Its balanced multi-class structure and real-world variability make it suitable for developing and evaluating reliable disaster classification models.

Fig.2 Natural Disaster Image Dataset

*B) Pre-Processing*

The preprocessing stage prepares disaster image data for effective classification by improving image quality, standardizing input formats, balancing class distributions, and optimizing feature representation, thereby enhancing model stability, learning efficiency, and predictive reliability.

*Normalization:* Image normalization and transformation are performed to standardize pixel intensity distributions and align input data with pretrained model expectations. Normalization scales pixel values to controlled ranges, stabilizing gradient propagation and accelerating convergence during training. Backbone-specific transformations ensure compatibility with pretrained feature extraction networks, preserving learned visual representations. This preprocessing step enhances feature quality, improves model generalization, and ensures efficient utilization of transfer learning capabilities for extracting discriminative and meaningful representations from disaster imagery.

*Feature Extraction:* Deep feature extraction is conducted using multiple pretrained convolutional neural network architectures to capture hierarchical and discriminative visual patterns from disaster images. Features extracted from different networks are combined to create a unified representation that incorporates complementary spatial and contextual information. This fusion enhances feature richness, improves classification reliability, and reduces dependency on individual model biases. The integration of multiple deep feature sources strengthens representation learning and supports robust classification across diverse disaster categories.

*Label Encoding:* Categorical class labels are transformed into numerical representations to facilitate supervised learning and efficient model training. This transformation ensures compatibility between classification outputs and learning algorithms, enabling accurate mapping between features and corresponding disaster categories. Structured feature vector preparation standardizes input data format, ensuring consistent training and evaluation across models. This preprocessing stage is essential for maintaining systematic data organization, improving training efficiency, and enabling seamless integration of machine learning classifiers.

*Synthetic Minority Over-Sampling and Class Balancing:* Class balancing is performed using synthetic sample generation techniques to address dataset imbalance across disaster categories. Minority class samples are artificially expanded to improve representation diversity and reduce classification bias toward majority classes. This step enhances model fairness, improves minority class detection, and stabilizes overall classification performance. Balanced training data contributes to improved generalization capability and ensures that predictive models maintain reliable performance across all disaster classes.

*Feature Selection:* Feature selection is applied to identify the most informative attributes contributing to classification performance while removing redundant or less significant features. This dimensionality reduction improves computational efficiency and reduces model complexity. Standardization is subsequently performed to normalize feature distributions, ensuring consistent scale across selected attributes. These processes enhance classification accuracy, improve model convergence stability, and reduce overfitting risks by focusing learning processes on the most relevant and discriminative feature components.

*C) Algorithms*

*ERI-2025:* ERI-2025 functions as a foundational deep feature extraction and classification model that captures hierarchical spatial characteristics from disaster imagery [24]. It provides stable feature embeddings, enabling consistent visual representation learning and supporting reliable baseline performance for subsequent ensemble and optimization stages.

*DRI-2025:* DRI-2025 enhances disaster recognition by learning deeper semantic representations and structural variations within complex disaster scenes [25]. It improves discrimination between visually similar disaster categories and contributes complementary feature perspectives, strengthening classification consistency and reducing model bias.

*DE-2025:* DE-2025 operates as an ensemble-oriented deep architecture that aggregates multi-level feature representations to improve classification stability. By combining complementary deep features, it enhances robustness against environmental noise and variability while supporting strong generalization across diverse disaster scenarios [26].

*ERI-2025 + XGBoost:* This hybrid configuration combines deep feature learning with gradient-boosted decision optimization to improve classification accuracy [27]. Boosting-based refinement emphasizes informative features, enhances decision boundaries, reduces redundancy, and strengthens predictive stability across multiple disaster categories.

$$\hat{y}_i = \sigma\left(\sum_{k=1}^{K} f_k(x_i)\right), f_k \in F \qquad (1)$$

*DRI-2025 + XGBoost:* This model integrates deep semantic feature extraction with boosting-based optimization to enhance classification reliability [28]. It improves discrimination of complex disaster patterns, strengthens robustness against imbalance, and refines feature importance, resulting in consistent and stable classification performance.

*DE-2025 + XGBoost:* This approach merges ensemble deep feature extraction with gradient boosting to enhance feature discrimination and reduce overfitting. The boosting mechanism iteratively refines feature relevance, improving class separability and providing improved robustness across varied disaster environments.

*ERI-2025 + XGBoost + Multiclass SVM:* This multi-stage hybrid model combines deep representation learning, boosting-based optimization, and margin-based classification [29]. The integration improves decision boundary precision, enhances robustness against noise and overlapping classes, and ensures stable and reliable multi-class disaster classification.

$$minimize\ \frac{1}{2}\,||W||^2 + C\sum_{i=1}^{n}\xi_i \qquad (2)$$

*DRI-2025 + XGBoost + Multiclass SVM:* This three-stage framework integrates deep semantic representation, boosting-based feature refinement, and margin-based classification. The approach strengthens class separation, reduces misclassification in visually similar disasters, and improves overall classification stability and generalization performance.

*DE-2025 + XGBoost + Multiclass SVM:* This advanced hybrid architecture integrates ensemble deep feature diversity, boosting-based feature optimization, and support vector classification. The synergy enhances robustness against class imbalance, improves feature discrimination, and achieves stable, high-accuracy classification across diverse disaster categories [30].

*Xception:* Xception is an end-to-end convolutional architecture utilizing depthwise separable convolutions to efficiently capture spatial and channel-wise visual features. It enhances feature extraction efficiency, supports rapid convergence, and provides strong discriminative capability for accurate disaster classification.

$$O_{i,j,k} = \sum_{m,n} X_{i+m,j+n,c}\, W_{m,n,k} \qquad (3)$$

*ResNet50:* ResNet50 employs residual learning to enable deep network training while maintaining stable gradient propagation. Its skip-connection architecture supports hierarchical feature learning, improves representation of complex disaster patterns, and ensures strong classification accuracy and generalization capability.

*Hybrid Ensemble (Xception + ResNet50):* The hybrid ensemble integrates complementary architectural strengths of depthwise separable and residual learning models. Aggregating predictions reduces individual model bias, enhances robustness, and improves classification consistency, delivering superior discriminative performance across multiple disaster categories.

### *D) Integration of XAI & Flask Framework*

The Integration of XAI & Flask Framework module enables real-time interpretability and deployment of the GeoDisasterAINet disaster classification system. It connects the trained deep learning models with a Flask-based web interface, allowing users to upload images of disaster events and receive immediate predictions with confidence scores. Simultaneously, explainable AI (XAI) techniques such as Grad-CAM, LIME, SHAP, SmoothGrad, Integrated Gradients, and Score-CAM generate visual explanations, highlighting critical regions and features that influenced the model's decision. This ensures transparency and helps users understand the reasoning behind each classification, enhancing trust in automated predictions.

The module seamlessly overlays these explanations on the input images, producing intuitive heatmaps and masks. The Flask interface manages the backend logic, handles image preprocessing, invokes model inference, and renders the XAI visualizations dynamically on the frontend. By combining real-time prediction with interpretability, the system not only supports rapid disaster response but also provides actionable insights for emergency planning, risk assessment, and resilience strategies across urban and rural communities.

## IV. Experimental Results

*Accuracy:* The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

$$Accuracy = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \quad (4)$$

*Precision:* Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

$$Precision = \frac{\text{True Positive}}{\text{True Positive } + \text{False Positive}} \quad (5)$$

*Recall:* Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

$$Recall = \frac{\text{TP}}{\text{TP} + \text{FN}} (6)$$

*F1-Score:* F1 score is a machine learning evaluation metric that measures a model's accuracy. It combines the precision and recall scores of a model. The accuracy metric computes how many times a model made a correct prediction across the entire dataset.

$$F1\ Score = 2 * \frac{Recall \text{ X } Precision}{Recall + Precision} * 100 (7)$$

Table. 1. Performance Evaluation Table

| ML Model | Accuracy | Precision | Recall | F1_score |
|---|---|---|---|---|
| ERI-2025 + XGBoost + SVM | 0.931 | 0.938 | 0.937 | 0.935 |
| DRI-2025 + XGBoost + SVM | 0.931 | 0.936 | 0.936 | 0.934 |
| DE-2025 + XGBoost + SVM | 0.902 | 0.915 | 0.911 | 0.908 |
| Xception | 0.985 | 0.986 | 0.985 | 0.985 |
| ResNet50 | 0.992 | 0.992 | 0.992 | 0.992 |
| Hybrid-Ensemble | 0.991 | 0.991 | 0.991 | 0.991 |

The performance evaluation table compares multiple models, showing that ResNet50 and Hybrid-Ensemble achieve the highest accuracy and balanced precision, recall, and F1-score, outperforming traditional XGBoost-SVM combinations.

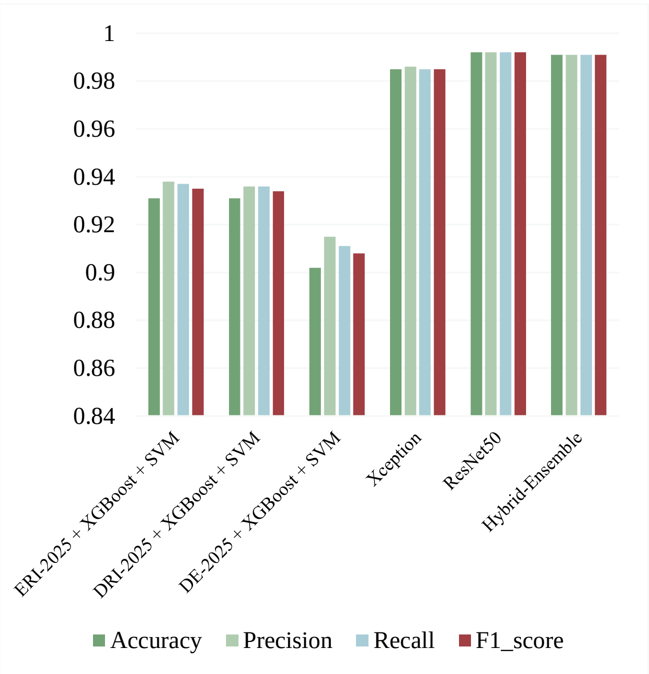


Fig.3. Comparison Graph

The comparison graph illustrates performance metrics across models, highlighting superior accuracy, precision, recall, and F1-score for ResNet50 and Hybrid-Ensemble, while XGBoost–SVM variants demonstrate comparatively lower yet consistent results.

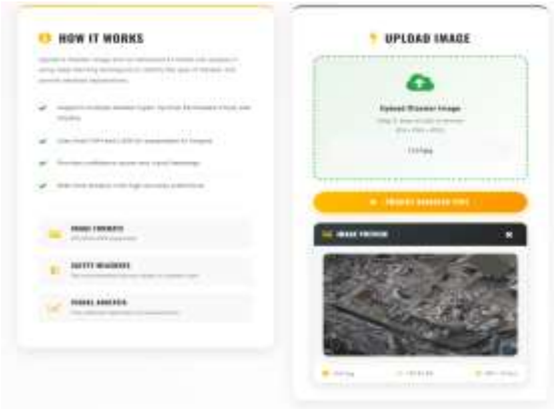


Fig.3 Upload the Image

Fig.2 illustrates the user interface for disaster image input, showing the upload process, image preview, and prediction option used to classify disaster types using the proposed AI-based system.


Fig.4 Predicted Result

Fig.4 presents the prediction result identifying an earthquake with 100.00% confidence, accompanied by safety measures and recommended actions to guide users in taking appropriate precautions during such disaster events.

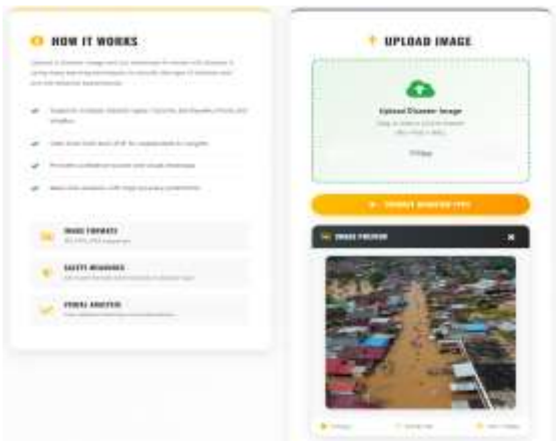

Fig. 5 Upload the Image

Fig. 5 presents an uploaded aerial image depicting severe urban flooding, where muddy water inundates streets and homes, displayed in the disaster prediction interface for preview before disaster type classification.

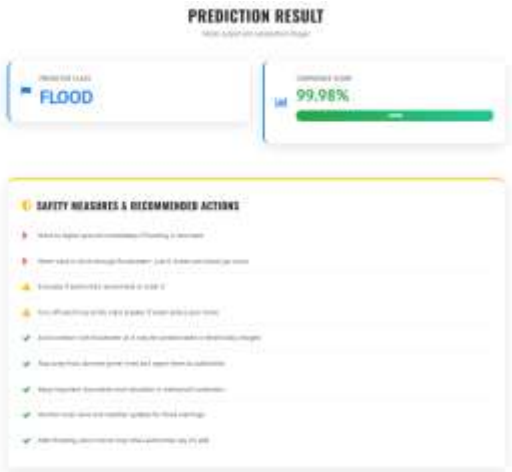


Fig. 6 Predicted Result

Fig. 6 shows the prediction result identifying the disaster as Flood with a 99.98% confidence score, along with recommended safety measures and actions to support effective emergency response and preparedness.

## V. Conclusion

Accurate and timely classification of natural disasters in urban and rural areas is critical for enhancing community resilience and mitigating the impact of floods, cyclones, earthquakes, and wildfires. GeoDisasterAINet addresses this challenge by employing a multi-stage ensemble framework on the Natural Disaster Image Dataset from Kaggle, comprising labeled images of various disaster events. The methodology integrates base models ERI-2025, DRI-2025, and DE-2025, enhanced through XGBoost combined with SMOTE and standard scaling for balanced training. In the final stage, multiclass SVM is applied to the XGBoost-enhanced models with standard scaling, while deep feature extraction is performed using convolutional neural networks Xception, ResNet50, and a Hybrid Ensemble of Xception and ResNet50. Evaluation metrics, including accuracy, precision, recall, and F1-score, demonstrate the effectiveness of the system, with ResNet50 achieving a test accuracy of 99.2%. Enhancements such as Grad-CAM and LIME provide explainable AI visualizations, highlighting key image regions influencing predictions, while a Flask-based interface facilitates real-time deployment and user interaction. Overall, GeoDisasterAINet delivers high-accuracy, interpretable, and scalable disaster classification, supporting reliable decision-making and automated operational support for disaster management in both urban and rural environments.

The system's future scope includes expanding disaster categories like landslides, tsunamis, and droughts, and integrating multimodal data such as satellite imagery, sensors, and real-time weather for improved accuracy. Advanced architectures, including attention-based and transformer models, can enhance feature extraction. Cloud or edge deployment enables large-scale real-time monitoring, while enhanced explainability and interactive dashboards provide intuitive insights, supporting rapid decision-making, resource allocation, and effective disaster management across diverse geographic regions.

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