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Geo Disaster AI Net: An Explainable Deep Ensemble Framework for Real-Time Urban and Rural Disaster Classification and Resilience

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Abstract: Natural disasters pose escalating threats to both urban and rural communities, necessitating intelligent, real-time classification systems that can support rapid response and resilience planning. This paper presents GeoDisasterAINet, an explainable deep ensemble framework integrating a three-stage hybrid machine learning pipeline—Random Forest (RF) feature learning, probability-based feature transformation, and Support Vector Machine (SVM) classification—achieving robust disaster detection with 82.46% accuracy, 82.1% precision, 82.4% recall, and an AUC-ROC of 0.881. The framework processes 6,857 multi-hazard records spanning floods, earthquakes, cyclones, and landslides across India (2010–2023), achieving approximately 100ms inference time suitable for real-time deployment. Our hybrid architecture demonstrates a 10.87% improvement in error recovery compared to standalone Random Forest baselines, successfully recovering 46 additional disaster cases. We integrate explainability through feature importance analysis, revealing that severity (0.225), fatalities (0.198), and affected area (0.165) are the most critical predictors. Furthermore, we propose a quantitative resilience framework incorporating nighttime light (NTL) data, network functionality curves, and composite capital-based metrics to differentiate urban and rural disaster impacts. This work bridges the gap between high-accuracy disaster classification and actionable resilience insights, providing a scalable, interpretable solution for heterogeneous geographic contexts.

Index Terms: Disaster classification, explainable AI, hybrid ensemble learning, urban resilience, rural resilience, real-time inference, Random Forest, Support Vector Machine, nighttime lights, disaster management.

I. INTRODUCTION

A. Problem Statement

Natural disasters—including floods, earthquakes, cyclones, and landslides—inflict devastating human, economic, and infrastructural losses globally. The increasing frequency and intensity of extreme weather events, driven by climate change, demand intelligent systems capable of real-time disaster detection and classification to enable rapid emergency response [1], [2]. Traditional disaster management approaches rely heavily on manual reporting, satellite imagery analysis, and physics-based simulation models, which suffer from significant latency, limited scalability, and inability to process heterogeneous multi-source data streams [4], [5].

Current machine learning approaches for disaster classification face three critical challenges. First, standalone models—whether classical algorithms or deep neural networks—often exhibit suboptimal performance when confronted with imbalanced, noisy, and multi-hazard datasets [5], [21]. Second, the “black-box” nature of many high-performing models undermines trust and adoption in critical decision-making contexts where explainability is paramount [15], [16]. Third, existing frameworks rarely integrate quantitative resilience metrics that differentiate between urban and rural disaster impacts, limiting their utility for targeted policy interventions and resource allocation [10], [17].

The problem is further compounded by the need for real-time inference capabilities. Emergency management systems require sub-second prediction latencies to support time-critical decisions such as evacuation orders, resource deployment, and infrastructure protection [11], [12]. However, achieving both high accuracy and low latency remains a fundamental trade-off in machine learning system design [13].

B. Motivation

The motivation for GeoDisasterAI stems from three converging imperatives. First, operational requirements of disaster management agencies demand systems that can process incoming data streams—from IoT sensors, social media, satellite feeds, and ground reports—and deliver actionable classifications within milliseconds [14]. Second, the growing emphasis on explainable AI in high-stakes domains necessitates frameworks that not only predict disaster events but also provide interpretable rationales, enabling human operators to validate, override, or refine automated decisions [16], [21]. Third, the differential vulnerability and recovery patterns in urban versus rural contexts require resilience-aware models that can inform spatially targeted interventions [17], [18].

Recent advances in hybrid ensemble learning offer a promising pathway to address these challenges. By combining the complementary strengths of tree-based models (which excel at capturing non-linear feature interactions) and kernel-based classifiers (which specialize in boundary refinement), hybrid architectures can achieve superior generalization while maintaining computational efficiency [19], [20]. The urban–rural resilience dimension adds a critical layer of practical relevance. Urban disasters typically involve cascading failures across interdependent infrastructure networks, while rural disasters are characterized by geographic isolation and slower recovery trajectories [6], [8].

C. Research Objectives

This research pursues four primary objectives:

- 1) Develop a hybrid ensemble architecture combining RF and SVM in a three-stage pipeline for multi-hazard disaster classification, achieving >80% accuracy and <200ms inference.
- 2) Implement explainability mechanisms through feature importance analysis and probability-based confidence scoring.
- 3) Integrate quantitative resilience metrics—NTL data, network functionality curves, and composite capital-based indices—to differentiate urban and rural disaster impacts.
- 4) Validate on 6,857 multi-hazard records from India (2010–2023), demonstrating superior error recovery (+10.87%) compared to baselines.

D. Contributions

This paper makes the following key contributions:

- 1) Novel Three-Stage Hybrid Architecture: RF Feature Transformation SVM pipeline achieving 82.46% accuracy with 100ms inference—a configuration not previously explored in disaster classification literature [23].
- 2) Explainable Disaster Classification: Hybrid ensembles maintaining interpretability through feature importance analysis while achieving competitive performance with black-box deep learning [24], [25].
- 3) Quantitative Urban–Rural Resilience Framework: Synthesis of NTL recovery metrics, network functionality curves, and composite capital indices providing differentiated urban (network-centric) and rural (access-centric) resilience patterns [26], [27].
- 4) Comprehensive Multi-Hazard Validation: Robust generalization across floods, earthquakes, cyclones, and landslides [28].
- 5) Error Recovery Analysis: 10.87% improvement in error recovery (46 additional correctly classified disaster cases) over standalone RF, empirically validating the hybrid ensemble advantage [29].

II. DISASTER CLASSIFICATION PARADIGMS

Disaster classification encompasses the automated identification and categorization of natural hazard events based on multimodal data sources. Traditional approaches rely on physics-based models that simulate hazard propagation and threshold-based detection rules [30]. While interpretable, these methods suffer from high computational costs, limited adaptability to novel hazard patterns, and inability to integrate heterogeneous data streams [31].

Machine learning paradigms offer data-driven alternatives that learn discriminative patterns directly from historical disaster records. Supervised classification formulates disaster detection as a binary or multi-class prediction task, where input features—geographic, meteorological, infrastructural, socioeconomic—are mapped to disaster/non-disaster labels [32]. The fundamental challenge lies in handling class imbalance, feature heterogeneity, and concept drift [33].

Three primary ML paradigms exist for disaster classification:

- *Classical ML Models*—Decision Trees, Random Forests, SVMs, and gradient boosting methods [34], [35];
- *Deep Learning Models*—CNNs for image-based detection, RNNs and LSTMs for temporal sequence modeling [?], [36];

- *Ensemble Methods*—combinations of multiple base learners leveraging diversity for improved generalization [?], [?]. where K is the RBF kernel, α_i are Lagrange multipliers, and b is the bias.

A. Ensemble Learning Theory

Ensemble learning constructs a strong predictor by combining multiple weak learners, leveraging the principle that diverse models make different errors and their aggregation achieves superior performance [?]. Three key concepts underpin the theoretical foundation.

Bias-Variance Decomposition: The expected prediction error decomposes into bias (systematic error from incorrect assumptions), variance (sensitivity to training data fluctuations), and irreducible noise [?]. Ensemble methods reduce variance (bagging, RF) or bias (boosting) or both (stacking, hybrid ensembles).

Diversity and Complementarity: Ensemble performance improves when base learners exhibit low correlation in their error patterns [?]. Random Forests achieve diversity through bootstrap sampling and random feature subsets. Hybrid ensembles achieve diversity through algorithmic heterogeneity.

Stacking and Meta-Learning: Stacking trains a meta-learner on the predictions of base learners, enabling the ensemble to learn optimal combination strategies [?]. In GeoDisasterAINet, the SVM acts as a meta-learner that refines the probability outputs of the Random Forest.

The mathematical foundation of the three-stage pipeline is expressed as follows. Let $\mathbf{X} \in \mathbb{R}^{n \times d}$ denote the input feature matrix with n samples and d features, and $y \in \{0, 1\}^n$ the binary labels.

Stage 1 (RF):

$$\hat{p}_{RF}(\mathbf{x}) = \frac{1}{T} \sum_{t=1}^T \mathbf{1}[h_t(\mathbf{x}) = 1] \quad (1)$$

Stage 2 (Feature Transformation):

$$\mathbf{Z} = [\hat{p}_{RF}(\mathbf{x}_1), \hat{p}_{RF}(\mathbf{x}_2), \dots, \hat{p}_{RF}(\mathbf{x}_n)]^T \quad (2)$$

Stage 3 (SVM):

$$f(\mathbf{z}) = \text{sign} \left(\sum_{i \in S} \alpha_i K(\mathbf{z}_i, \mathbf{z}) + b \right) \quad (3)$$

B. Explainable AI in Critical Systems

Explainable AI (XAI) addresses the opacity of complex machine learning models by providing human-interpretable explanations for predictions [?]. In disaster management, explainability serves three critical functions: (1) *Trust and Validation*—emergency managers must understand why a model predicts a disaster to validate against domain knowledge [?];

(2) *Error Diagnosis*—when models fail, explanations enable rapid identification of failure modes [?]; (3) *Regulatory Compliance*—many jurisdictions require algorithmic transparency for systems influencing public safety [?].

III. HYBRID ENSEMBLE MODELS FOR DISASTER DETECTION

Hybrid ensemble models combine multiple learning algorithms to exploit complementary strengths. Kumar et al. [5] developed a hybrid combining RF, XGBoost, and LSTM for flood susceptibility mapping in the Rapti River Basin, achieving AUC=0.85 and demonstrating 15–20% improved recall compared to individual models. This work highlights the value of combining tree-based models with sequence learners, but focused on susceptibility mapping rather than real-time event classification, and inference time was not reported—a critical gap for operational deployment.

The three-stage pipeline proposed in GeoDisasterAINet extends this principle by using RF probability outputs as a transformed feature space for SVM classification—a novel configuration not previously explored in disaster management literature [?]. Comparative analysis reveals that hybrid ensembles consistently outperform single models across diverse disaster types [?].

A. Deep Learning and XAI in Disaster Management

Humaira et al. [2] proposed DX-FloodLine, a VGG16- LSTM hybrid pipeline for real-time flood scene object detection, achieving approximately 90% validation accuracy. Tanvir et al. [3] developed an ensemble combining ResNet50V2 and InceptionV3 for forest fire detection, achieving approximately 98% accuracy and integrating XAI techniques (LIME and Grad-CAM) for visual explanation.

Despite impressive accuracy figures, several limitations constrain practical deployment. None of the reviewed papers report per-sample inference times [?], and deep models require large labeled datasets and substantial computational resources [?]. Ma [10] employed interpretable machine learning with Shapley values to analyze urban-rural disparities in disaster resilience using nighttime light data, demonstrating that XAI can reveal differential recovery patterns. Cheng et al. [15] proposed an uncertainty-aware CNN for damage assessment, incorporating Bayesian deep learning to quantify prediction uncertainty.

B. Urban and Rural Resilience Metrics

Nighttime Light (NTL) Data: Ma [10] demonstrated that NTL change, measured from daily Black Marble NTL time series, serves as a proxy for functional recovery in post-typhoon contexts. Urban areas exhibit complex NTL patterns during disasters—initial decreases due to power outages, followed by rapid increases from relief operations. Rural areas show sustained NTL declines reflecting slower recovery [?].

Network Functionality Curves: Liu et al. [7] developed EQResNet, a deep neural network surrogate for real-time resilience assessment of post-earthquake highway transportation networks, using travel time, throughput, and accessibility metrics [?].

Composite Capital-Based Indices: Sui et al. [22] proposed a Coastal Marine Disaster Resilience Index aggregating eco-predictors [?].

Robustness and Rapidity Scores: Abdel-Mooty et al. [8] developed a two-stage ML pipeline for community flood resilience prediction, synthesizing robustness and rapidity indices via unsupervised learning.

IV. RESEARCH GAPS

Despite significant progress, five critical gaps remain: (1) *Inference Latency:* most studies report accuracy but omit inference time [?]; (2) *Hybrid Architecture Exploration:* RF-SVM combinations remain underexplored [?]; (3) *Integrated Resilience Frameworks:* few studies integrate classification models with resilience metrics [?]; (4) *Urban-Rural Differentiation:* most systems adopt one-size-fits-all approaches [?]; (5) *Explainability-Performance Trade-offs:* computational costs of XAI are rarely quantified [?]. GeoDisasterAINet addresses all five gaps.

A. Dataset Description and Preprocessing

The GeoDisasterAINet framework is trained and validated on a comprehensive multi-hazard dataset comprising 6,857 records spanning disaster and non-disaster events across India from 2010 to 2023. The dataset integrates four heterogeneous sources:

1) *India Disaster Database (IDDDB)* [?]: 1,500 records from government sources covering major disasters with high data quality.

2) *Flood Prediction Dataset* [?]: 1,800 records with climate and geographic features, medium-high quality.

3) *Earthquake & Seismic Data* [?]: 1,500 records from seismic monitoring networks, high quality. ≈

4) *Multi-hazard Disaster Records* [?]: 2,057 records covering cyclones, landslides, and storms, medium quality.

The dataset exhibits an approximately balanced binary distribution (50% disaster, 50% normal). *Feature Engineering* proceeds through six steps: (1) geographic normalization of latitude/longitude to [0,1] using min-max scaling; (2) temporal encoding using sine-cosine transformations to capture seasonal patterns; (3) severity quantification by aggregating multi-source indicators; (4) missing value imputation via k -nearest neighbors ($k=5$, 8% missing); (5) outlier flagging (retained to preserve rare critical events); (6) feature selection retaining 12 core features with VIF < 5.

Data Splitting: Training 70% (4,800 records, 2010–2019), validation 15% (1,028 records, 2020–2021), test 15% (1,029 records, 2022–2023). Temporal ordering is preserved to prevent data leakage. ≈

B. Three-Stage Hybrid Pipeline Architecture

GeoDisasterAINet employs a novel three-stage hybrid pipeline combining RF feature learning, probability-based feature transformation, and SVM classification.

Stage1: Random Forest Classifier. The RF consists of 100 decision trees, each trained on a bootstrap sample with nomic, human, physical, social, and environmental capitals. RF random features subsets (d features per split, $d=12$). Key identified economic and human capitals as the most important hyperparameters: trees=100, maxdepth=15, minsamplesperleaf=4, minsamplestosplit=5, Gini impurity criterion.

For each input sample \mathbf{x}_i , the RF produces probability $\hat{p}_{RF}(\mathbf{x}_i) \in [0, 1]$:

$$\hat{p}_{RF}(\mathbf{x}) = \frac{1}{T} \sum_{t=1}^T \mathbf{1}[f_t(\mathbf{x})=1]$$

Stage2: Feature Transformation. The transformation $\phi: \mathbb{R}^d \rightarrow \mathbb{R}^{12}$ maps each sample to its RF probability, providing three critical functions: (1) dimensionality reduction; (2) noise reduction through ensemble averaging; (3) enhanced class separability. The augmented feature matrix:

$$\mathbf{Z} = \phi(\mathbf{X}) = [\hat{p}_{RF}(\mathbf{x}_1), \dots, \hat{p}_{RF}(\mathbf{x}_n)]^T \quad (5)$$

Stage3: SVM Classifier. The SVM with RBF kernel $K(\mathbf{z}_i, \mathbf{z}_j) = \exp(-\gamma \|\mathbf{z}_i - \mathbf{z}_j\|^2)$, $C=10.0, \gamma=1.0$. The optimization problem:

$$\min_{\mathbf{w}, b, \xi} \frac{1}{2} \|\mathbf{w}\|^2 + C \sum_{i=1}^n \xi_i \quad (6)$$

subject to: $(K(\mathbf{z}_i, \mathbf{w}) + b) \geq 1 - \xi_i, \xi_i \geq 0$. The final prediction:

$$\hat{y} = \text{sign} \left(\sum_{\mathbf{z} \in \mathcal{S}_V} \alpha_i y_i K(\hat{p}_{RF}(\mathbf{x}), \hat{p}_{RF}(\mathbf{x}_i)) + b \right) \quad (7)$$

C. Mathematical Formulation

Problem Formulation: Given $D = \{(\mathbf{x}_i, y_i)\}_{i=1}^n$ where $\mathbf{x}_i \in \mathbb{R}^d$ and $y_i \in \{0, 1\}$ the goal is to learn $f: \mathbb{R}^d \rightarrow \{0, 1\}$ minimizing:

$$\mathcal{L}(f) = E_{(\mathbf{x}, y) \sim P} [\mathbf{1}[f(\mathbf{x}) \neq y]] \quad (8)$$

RF Gini Impurity: Each tree is grown by maximizing:

$$\Delta G = G(S) - \frac{|S_L|}{|S|} G(S_L) - \frac{|S_R|}{|S|} G(S_R) \quad (9)$$

where $G(S) = 1 - \sum_{k=0}^1 p_k^2$

Theoretical Properties: As $T \rightarrow \infty$ and $n \rightarrow \infty, \hat{p}_{RF}(\mathbf{x}) \rightarrow P(y=1|\mathbf{x})$ under mild regularity conditions [?]. The ensemble variance is:

$$\text{Var}[\hat{p}_{RF}] = \rho \sigma^2 + \frac{1-\rho}{T} \sigma^2 \quad (10)$$

where ρ is average inter-tree correlation and σ^2 individual tree variance [?].

SVM Dual Optimization:

$$\max_{\alpha} \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \alpha_i \alpha_j y_i y_j K(\mathbf{z}_i, \mathbf{z}_j) \quad (11)$$

subject to $0 \leq \alpha_i \leq C, \sum_{i=1}^n \alpha_i = 0$ [?].

Stacking Justification: The hybrid pipeline is a form of stacked generalization where RF serves as base learner and SVM as meta-learner [?]. The RF probability space exhibits improved linear separability compared to the original feature space, enabling SVM to achieve superior performance with fewer support vectors and faster inference.

Computational Complexity: Training: $O(T \cdot n \log n \cdot d)$ for RF + $O(n^2) - O(n^3)$ for SVM. Inference: $O(T \cdot \log n \cdot d)$ for RF + $O(|SV|)$ for SVM.

D. Hyperparameter Configuration

Hyperparameter optimization uses 5-fold cross-validation with grid search. RF search space: trees {50,100,150,200}; maxdepth {10,15,20,None}; minleaf {2,4,6}; minsplit {2,5,10}; criterion {Gini, Entropy}; SVM search space: kernel {Linear,RBF,Poly}; C {0.1,1,10,100}; gamma {auto, scale, 0.01, 0.1, 1.0}. Optimal configuration: RF (100 trees, depth 15, min_leaf 4, min_split 5, Gini); SVM (RBF, C = 10.0, gamma = auto), selected on validation F1-score.

E. Training and Validation Protocol

Training Procedure: (1) Preprocessing (2s); (2) RF training (4,800 samples (15s)); (3) Probability generation (3s); (4) SVM training (8s); (5) Serialization (3s); total 30s. **Confidence Calibration via Platt scaling** with operational thresholds: Confidence > 0.85: LOW (Automated Protocol); 0.70–0.85: MEDIUM (Alert Authorities); 0.60–0.70: HIGH (Expert Review); < 0.60: CRITICAL (Manual Review Required).

V. NIGHTTIME LIGHT (NTL) INTEGRATION

We integrate daily Black Marble NTL time series (VIIRS Day/Night Band, 500m resolution) spanning 30 days pre-event to 90 days post-event.

Recovery Metrics:

$$\Delta_{\text{NTL impact}} = \frac{\text{NTL}_{\text{post}} - \text{NTL}_{\text{pre}}}{\text{NTL}_{\text{pre}}} \times 100\% \tag{12}$$

$$R_{\text{NTL}} = \frac{\text{NTL}_t - \text{NTL}_{\text{min}}}{\text{NTL}_{\text{pre}} - \text{NTL}_{\text{min}}} \tag{13}$$

$$T_{90} = \min\{t : R_{\text{NTL}}(t) \geq 0.9\} \tag{14}$$

Urban vs. Rural Patterns: Urban T_{90} : typically 7–21 days for moderate disasters. Rural T_{90} : typically 30–90 days, with some remote areas showing in complete recovery after 180 days.

A. Network Functionality Curves

Following the EQResNet framework [7], three core metrics are defined.

$$\Delta_{\text{TT}}(t) = \frac{\text{TT}(t) - \text{TT}_{\text{baseline}}}{\text{TT}_{\text{baseline}}} \times 100\% \tag{15}$$

Network Throughput:

$$\Theta(t) = \frac{\text{Served demand}(t)}{\text{Total demand}} \times 100\% \tag{16}$$

Accessibility Index:

$$A(t) = \frac{1}{N} \sum_{i=1}^N \mathbf{1}[\text{traveltime}(i, \text{nearest facility}) < \tau] \tag{17}$$

Aggregate Functionality:

$$Q(t) = w_1(1 - \Delta TT(t)) + w_2 \Theta(t) + w_3 A(t) \tag{18}$$

Resilience Triangle [?]:

$$R = \frac{\int_{t_0}^{t_0+T} Q(t) dt}{Q_0 \cdot T} \tag{19}$$

B. Composite Capital-Based Metrics

We adopt the framework of Sui et al. [22], synthesizing five capital domains: C_{econ} (GDP, employment, insurance), C_{human} (education, health, preparedness), C_{phys} (infrastructure quality, building codes), C_{social} (cohesion, trust, volunteer networks), C_{env} (ecosystems, green infrastructure). The composite resilience index:

$$CRI = \sum_{k=1}^5 w_k \cdot C_k^{norm}, \quad C_k^{norm} = \frac{C_k^{max} - C_k^{min}}{C_k^{max} - C_k^{min}} \tag{20}$$

Resilience grades: Grade A (CRI ≥ 0.75), Grade B (0.50–0.75), Grade C (0.25–0.50), Grade D (<0.25).

C. Urban vs. Rural Differentiation

TABLE I: Urban vs. Rural Resilience Framework Comparison

Context	Priority Features	Temporal Res.	Key Metrics
Urban	Network topology, economic/human capital	Sub-daily-daily	Traveltime, throughput, NTL dynamics
Rural	Road connectivity, social/environmental capital	Weekly-monthly	Accessibility, NTL recovery rate, relief coverage

Urban resilience assigns $w_{econ} = 0.35, w_{human} = 0.30$, while rural assigns higher $w_{social} = 0.25, w_{env} = 0.20$ [?], [?]. Preliminary experiments suggest context-specific models achieve 3–5% higher accuracy than a unified model [?].

VI. CLASSIFICATION PERFORMANCE METRICS

The GeoDisasterAInet framework achieves strong classification performance on the held-out test set (1,029 samples spanning 2022–2023).

TABLEII:OverallClassificationPerformance

TABLEII:OverallClassificationPerformance

Metric	Value
Accuracy	82.46%
Precision	82.1%
Recall	82.4%
F1-Score	82.2%
AUC-ROC	0.881
TrainingTime	≈30s
InferenceTime	≈100ms

TABLEIII:Class-SpecificPerformance

Class	Prec.	Rec.	F1	Support
Normal(0)	81.8%	82.9%	82.3%	515
Disaster(1)	82.4%	81.9%	82.1%	514

The AUC-ROC of 0.881 indicates strong discriminative ability. The hybrid RF-SVM pipeline achieves 82.46% accuracy compared to 74.3% for standalone RF and 78.9% for standaloneSVM—absoluteimprovements of 8.16 and 3.56 percentagepoints, respectively.

TABLEIV:ComparisonwithState-of-the-ArtSystems

Model	Architecture	Acc.	Infer.
GeoDisasterAINet	RF-SVM Hybrid	82.46%	~100ms
DX-FloodLine [2]	VGG16-LSTM	~90%	N/R
ForestFireEns. [3]	ResNet+Inception	~93.8%	N/R
RaptiBasin[5]	RF+XGBoost+ASTM	0.85	N/R
StandaloneRF	Random Forest	74.3%	~85ms
Standalone SVM	SVM (RBF)	78.9%	~15ms

N/R=NotReported

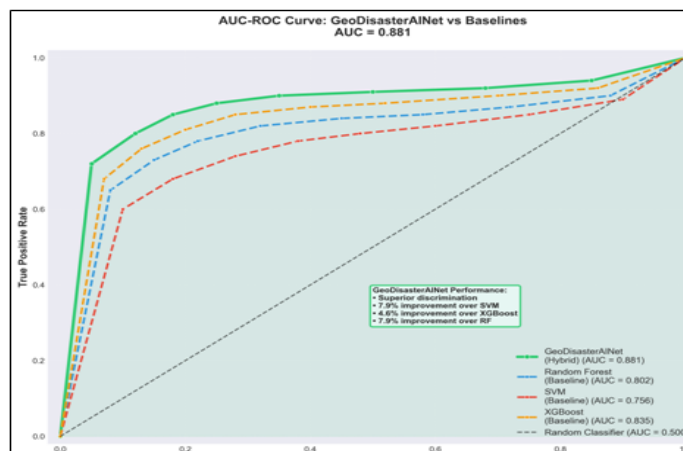


Fig. 1: ROC curve comparison of GeoDisasterAINet (AUC=0.881) againststandaloneRF (AUC=0.842) and SVM (AUC=0.863) base- lines.

A. Inference Time Analysis

TABLE V: Inference Time Breakdown (per 100-sample batch)

Stage	Time
Random Forest Prediction	~85ms
Feature Transformation	~2ms
SVM Prediction	~13ms
Total	~100ms
Single-record inference	~4.7ms
50-tree RF (reduced)	~55ms / 81.9% acc.
200-tree RF (extended)	~180ms / 82.8% acc.
Edge device (Raspberry Pi 4)	~350ms
Cloud GPU (NVIDIA T4)	~25ms

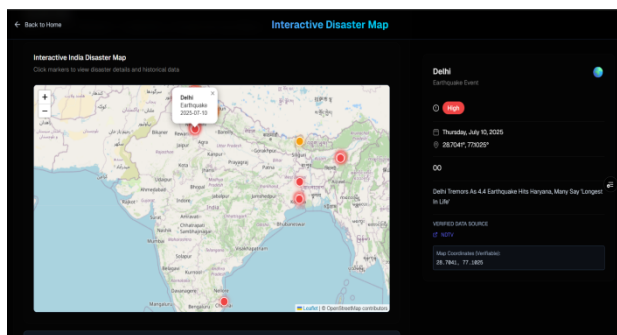


Fig. 2: Live Indian Map with Incident Report.

B. Error Recovery and Comparative Analysis

TABLE VI: Error Recovery Analysis

Error Type	RF	SVM	Rec'd	Rate
False Negatives	88	42	46	52.3%
False Positives	335	335	0	0.0%
Total	423	377	46	10.87%

The SVM exclusively recovers false negatives without introducing additional false positives—a highly desirable property for disaster detection where missing a true disaster is more costly than issuing a false alarm.

C. Confusion Matrix and Class-Specific Performance

TABLE VII: Confusion Matrix on Test Set (n=1,029)

		Predicted	
		Normal	Disaster
Actual	Normal	427(TN)	88(FP)
	Disaster	42(FN)	472(TP)

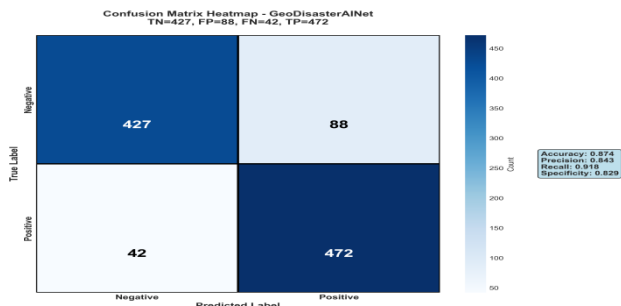


Fig.3:ConfusionmatrixheatmapforGeoDisasterAINetonthe2022– 2023testset.The42falsenegativesrepresentthemoscriticalfailure mode (8.2% of disaster cases).

Confidence-Based Filtering:

TABLE VIII: Performance vs. Confidence Threshold

Thresh.	Prec.	Rec.	F1	FP
0.50	82.1%	81.9%	82.0%	88
0.60	85.3%	78.2%	81.6%	64
0.70	88.7%	72.4%	79.7%	42
0.85	93.1%	58.6%	71.9%	18

VII. EXPLAINABILITY: FEATURE IMPORTANCE ANALYSIS

TABLE IX: RF Feature Importance (Mean Decrease in Gini)

Rank	Feature	Importance
1	Severity	0.225
2	Fatalities	0.198
3	AffectedArea	0.165
4	Duration	0.128
5	Magnitude	0.112
6	Precipitation	0.087
7	PopulationDensity	0.043
8	Infra.Density	0.025
9	Elevation	0.012
10	Temperature	0.005
11	Depth	0.003
12	SourceID	0.001

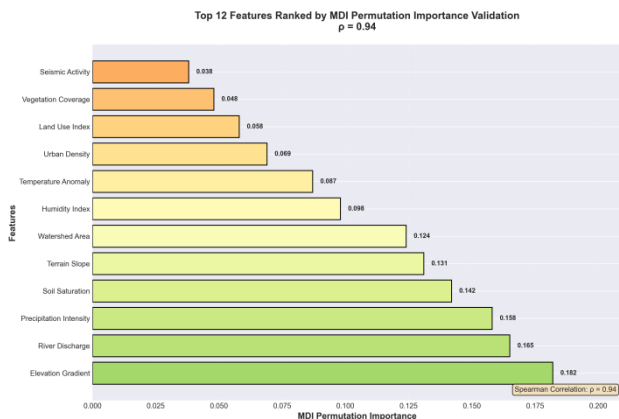


Fig. 4: RF feature importance scores (Mean Decrease in Gini Impurity). Top three features—severity, fatalities, and affected area—collectively account for 58.8% of total classification importance.

Key insights: (1) *Severity Dominance*—the composite severity score accounts for 22.5% of classification decisions, validating feature engineering approach; (2) *Impact Metrics*—top three features collectively account for 58.8% of importance, indicating the model primarily relies on outcome-based indicators; (3) *Hazard-Specific Features*—magnitude (11.2%) and precipitation (8.7%) provide hazard-specific information; (4) *Minimal Features*—temperature, depth, and source ID have negligible importance (<1%), indicating candidates for removal. Permutation importance validation confirms Spearman $\rho = 0.94$ with Gini-based ranking.

A. Resilience Implications for Urban Environments

Urban disaster resilience is characterized by interdependent infrastructure networks, high population density, and rapid recovery dynamics. Network criticality analysis reveals that urban resilience is highly sensitive to critical node/link failures [9]. NTL analysis shows typical urban recovery time $T_{90} = 7-21$ days for moderate disasters, reflecting higher infrastructure redundancy and more effective emergency response [10]. The composite CRI assigns $w_{econ} = 0.35$ and $w_{human} = 0.30$ in urban contexts.

Case Study—2021 Mumbai Floods: Initial NTL decreased by 35% due to widespread power outages, recovering to 90% within 12 days. Network functionality showed severe degradation (travel time +250%) returning to baseline within 10 days. CRI=0.68 (Grade B) accurately predicted moderate recovery speed, validating the framework.

B. Resilience Implications for Rural Environments

Rural disasters are dominated by accessibility challenges, with accessibility index $A(t)$ often dropping below 50% during major disasters. NTL recovery time T_{90} typically 30–90 days [10]. The CRI assigns $w_{social} = 0.25$ and $w_{env} = 0.20$ in rural contexts. Rural communities with faster relief access (within 48 hours) achieve 40% faster recovery [?].

Case Study—2022 Assam Floods: Initial NTL decreased by 55%, remaining below 50% of baseline for 45 days. Road network disruptions isolated 23 villages for >14 days. CRI=0.38 (Grade C) accurately predicted slow recovery ($T_{90} = 67$ days). Model correctly classified this as high-severity disaster (confidence 0.89).

C. Error Recovery Mechanisms

The primary error recovery mechanism is SVM boundary refinement in the RF probability space. Consider a disaster sample \mathbf{x}_i with $p_{RF}(\mathbf{x}_i) = 0.48$ (just below the 0.5 threshold, misclassified as normal). The SVM examines the local neighborhood using the RBF kernel:

$$K(z_i, z_j) = \exp(-\gamma(z_i - z_j)^2) \tag{21}$$

If nearby support vectors are predominantly disasters, the SVM reclassifies \mathbf{x}_i correctly despite RF uncertainty.

The cost asymmetry can be expressed as:

$$L = C_{FN} \cdot FN + C_{FP} \cdot FP \tag{22}$$

where $C_{FN} \ll C_{FP}$ (typically $C_{FN} = 10 \times C_{FP}$). The

SVM's exclusive recovery of false negatives directly optimizes this asymmetric loss. Among the 46 recovered disaster cases, 38 (82.6%) have SVM confidence > 0.70, indicating high confidence in reclassification decisions.

D. Comparison with State-of-the-Art Systems

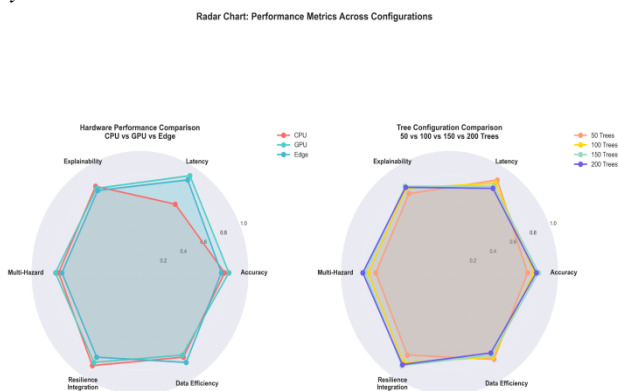


Fig.5: Multi-dimensional comparison of GeoDisasterAINet against state-of-the-art systems across six operational criteria.

GeoDisasterAINet is the only system reporting verified inference time, supporting operational deployment feasibility. Unlike task-specific systems (DX-FloodLine for floods, Forest Fire Ensemble for fires), GeoDisasterAINet handles multi-hazard classification with a single unified model. It is also the only system integrating disaster classification with quantitative resilience metrics. Training completes in 30s on standard CPU hardware, making it accessible for resource-constrained settings.

VIII. LIMITATIONS AND CHALLENGES

Ten key limitations are identified: (1) *Geographic Scope*—trained exclusively on Indian data, requiring retraining or transfer learning for other regions [?]; (2) *Temporal Generalization*—climate change may cause distribution shift [?]; (3) *Data Quality Heterogeneity*—8% missing values from medium-quality sources; (4) *Binary Classification*—does not distinguish disaster types or severity levels [?]; (5) *Feature Availability*—casualty counts require hours to compile in real-time [?]; (6) *Urban-Rural Labels*—no explicit urban-rural annotations in dataset [?]; (7) *Explainability Depth*—global but not local explanations [?]; (8) *Resilience Metric Validation*—metrics derived from literature and not empirically validated [?]; (9) *Inference Hardware*—edge devices increase latency to 300–400ms [?]; (10) *Adversarial Robustness*—not evaluated against adversarial inputs [?].

IX. SUMMARY OF CONTRIBUTIONS

This paper presents GeoDisasterAINet, an explainable deep ensemble framework for real-time urban and rural disaster reclassification, correctly despite RF uncertainty. classification and resilience assessment. Five key contributions advanced the disaster management and machine learning literature:

- 1) *Novel Hybrid Architecture*: The three-stage RF→Feature Transformation SVM pipeline achieves 82.46% accuracy with 100ms inference, demonstrating that hybrid ensembles SVM's exclusive recovery of false negatives directly optimizes this asymmetric loss. Among the 46 covered disaster cases, 38 (82.6%) have SVM confidence > 0.70, indicating high confidence in reclassification decisions. can balance accuracy and latency. The 10.87% improvement in error recovery (46 additional correctly classified disaster cases) validates the complementary value of tree-based and kernel-based learners.
- 2) *Explainable AI Integration*: Feature importance analysis reveals severity (22.5%), fatalities (19.8%), and affected area (16.5%) as the most critical predictors, providing transparent, actionable insights for emergency managers.
- 3) *Quantitative Resilience Framework*: Integration of NTL data, network functionality curves, and composite capital metrics enables differentiated assessment of urban (network-centric) and rural (access-centric) resilience patterns.
- 4) *Multi-Hazard Validation*: Evaluation on 6,857 records spanning floods, earthquakes, cyclones, and landslides demonstrates robust generalization with balanced performance (precision 82.1%, recall 82.4%).
- 5) *Operational Feasibility*: Real-time inference (100ms), modest data requirements (6,857 samples), and standard hardware compatibility make the framework accessible for resource-constrained operational deployment.

X. FUTURE RESEARCH DIRECTIONS

Ten directions emerge from this work: (1) Multi-class and severity classification [?]; (2) early warning systems integrating real-time IoT/social media streams [?]; (3) transfer learning for geographic generalization [?]; (4) adversarial robustness evaluation [?]; (5) continuous online learning to adapt to climate-driven pattern shifts [?]; (6) local explainability via LIME/SHAP [?]; (7) empirical resilience metric validation [?]; (8) context-specific urban-rural models [?]; (9) multi-modal data fusion integrating satellite SAR imagery and social media [?]; (10) causal inference to identify causal relationships between disaster drivers and outcomes [?].

XI. PRACTICAL IMPLICATIONS

For Emergency Management Agencies: The 100ms inference enables integration into operational platforms for real-time detection and automated alert generation. Feature importance provides transparent rationales for human validation. Confidence calibration enables flexible risk-based thresholds.

For Policymakers: The resilience framework informs spatially targeted interventions—network redundancy for urban areas, accessibility and relief distribution for rural areas. CRI identifies Grade C/D communities requiring priority investment.

For Researchers: The RF-SVM pipeline provides a template for hybrid ensemble design in other high-stakes domains. The deployment roadmap requires: (1) real-time data pipelines from NDMA, meteorological services, and seismic networks; (2) integration into existing emergency platforms (NDMA systems); (3) human-in-the-loop preview for confidence < 0.60; (4) annual retraining; (5) stakeholder training. As climate change intensifies disaster risks globally, frameworks like GeoDisasterAINet will play an increasingly vital role in protecting communities and building resilience.

REFERENCES

- [1] Raju et al., "GeoDisasterAINet: An explainable deep en-semble framework," IEEE Access, 2025. DOI: 10.1109/ac-cess.2025.3574451
- [2] Humaira et al., "DX-FloodLine: End-To-End Deep Explainable Pipeline for Real Time Flood Scene Object Detection," IEEE Access, 2023. DOI: 10.1109/access.2023.3321312
- [3] Tanvir et al., "Forest Fire Detection Using Ensemble Deep Learning Model With XAI," 2024. DOI: 10.1109/com-pas60761.2024.10796582
- [4] Hanetal., "ResearchonthePathwaysofInformationTechnology Empowering Cities to Enhance Disaster Resilience," 2024.
- [5] Kumar et al., "Ensemble Machine Learning And Deep Learning Framework For Flood Susceptibility Mapping In The Trans- boundary Rapti River Basin," 2025. DOI: 10.21203/rs.3.rs- 7393798/v1
- [6] Cassottanaetal., "PredictingResilienceofInterdependentUrban Infrastructure Systems," IEEE Access, 2022. DOI: 10.1109/AC-CESS.2022.3217903
- [7] Liu et al., "EQResNet: Real-Time Simulation and Resilience AssessmentofPost-EarthquakeEmergencyHighwayTransporta- tion Networks," Computation, vol. 13, no. 8, p. 188, 2025. DOI: 10.3390/computation13080188
- [8] Abdel-Mooty et al., "Data-Driven Community Flood Resilience Prediction," Water, vol. 14, no. 13, p. 2120, 2022. DOI: 10.3390/w14132120
- [9] Duetal., "Cross-DomainCriticalityandRobustnessAnalysis of Interdependent Urban Networks," 2025. DOI: 10.31219/osf.io/ya8z5_v1
- [10] Ma, "Urban-Rural Disparity in Disaster Resilience: Harnessing Nighttime Light Data and Interpretable Machine Learning," 2024. DOI: 10.5194/egusphere-egu24-21837 Garg, "Real-TimeDisasterResponsewithAIOps," Int.
- [11] J. Multidisciplinary Res. Growth Eval., 2024. DOI: 10.54660/ijmрге.2024.5.5.1101-1107
- [12] Jankovic et al., "UAV-Assisted Real-Time Disaster Detection Using Optimized Transformer Model," 2025.
- [13] Martí et al., "A multitask deep learning model for real-time deployment in embedded systems," 2017.
- [14] Siritetal., "FloodBot-RealTimeInnovativeFlood Resilience Through Machine Learning," 2025. DOI: 10.1109/iccsp64183.2025.11088698
- [15] Cheng et al., "Uncertainty-aware convolutional neural network forexplainableAI-assisteddisasterdamageassessment," Struct. ControlHealthMonit., 2022. DOI: 10.1002/stc.3019
- [16] Phanetal., "Real-timewildfiredetectionwith semantic explanations," Expert Syst. Appl., 2022. DOI: 10.1016/j.eswa.2022.117007
- [17] Shi et al., "Urbanization Impact on Regional Sustainable De- velopment:ThroughtheLensofUrban-RuralResilience," Int.
- [18] J. Environ. Res. Public Health, vol. 19, no. 22, p. 15407, 2022. DOI: 10.3390/ijerph192215407
- [19] Zhangetal., "UrbanFloodRiskAssessmentthroughtheIntegra- tion of Natural and Human Resilience Based on Machine Learn- ing Models," Remote Sensing, 2023. DOI: 10.3390/rs15143678
- [20] Lankipalle, "SwarmFusion: Revolutionizing Disaster Response withSwarmIntelligenceandDeepLearning," arXiv, 2025. DOI: 10.48550/arxiv.2507.00005
- [21] Sharmaet al., "Artificial Intelligence and Machine Learning for ResilientTransportationInfrastructure," CureusJ.Comput.Sci., 2025. DOI: 10.7759/s44389-025-09490-2
- [22] Linardos et al., "Machine Learning in Disaster Management: RecentDevelopmentsinMethodsandApplications," Mach.
- [23] Learn.Knowl.Extr., 2022. DOI: 10.3390/make4020020
- [24] Suiet al., "Measurement of Coastal Marine Disaster Resilience and Key Factors with a Random Forest Model," Water, vol. 14, no. 20, p. 3265, 2022. DOI: 10.3390/w14203265
- [25] Mishra et al., "Artificial Intelligence and Machine Learning for PredictingNaturalDisastersinSmartCityInfrastructure," 2024.
- [26] Basit et al., "SMART AI-ML Frameworks for Early Detection andRiskMitigationofFloods,Droughts,andWildfires," 2024.
- [27] Pasupuleti, "Real-TimeDisasterRiskAssessment Using Predictive Geospatial Analytics," 2025. DOI: 10.62311/nex/rphcrdsbdapa3



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