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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:** Naturaldisastersposeescalating threatstobothurban andruralcommunities,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 in- frastructural losses globally. The increasing frequency and intensity of extreme weather events, driven by climate change, demandintelligentsystemscapableofreal-timedisasterdetec- tion and classification to enable rapid emergency response [1], [2]. Traditional disaster management approaches rely heavily on manual reporting, satellite imagery analysis, and physics-basedsimulationmodels,whichsufferfromsignificantlatency, limited scalability, and inability to process heterogeneous multi-source data streams [4], [5].

Current machine learning approaches for disaster classifica- tion face three critical challenges. First, standalone models— whether classical algorithms or deep neural networks—often exhibit suboptimal performance when confronted with imbal- anced, noisy, and multi-hazard datasets [5], [21]. Second, the “black-box” nature of many high-performing models under- mines 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 highaccuracyandlowlatencyremainsafundamentaltrade-off in machine learning system design [13].

B. Motivation

ThemotivationforGeoDisasterAINetstemsfromthreeconvergingimperatives.First,operationalrequirementsofdisastermanagementagenciesdemandsystemsthat canprocessincom- ing data streams—from IoT sensors, social media, satellite feeds, and ground reports—and deliver actionable classifica- tions within milliseconds [14]. Second, the growing emphasis on explainable AI in high-stakes domains necessitates frame- works 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].

Recentadvancesinhybridensemblelearningofferapromis- ing pathway to address these challenges. By combining the complementarystrengthsoftree-basedmodels(whichexcel at capturing non-linear feature interactions) and kernel-based classifiers (which specialize in boundary refinement), hybrid architectures can achieve superior generalization while main- taining computational efficiency [19], [20]. The urban–rural resiliencedimensionaddsacriticallayerofpracticalrelevance. 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

Thisresearchpursuesfourprimaryobjectives:

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 in- ference.
2) Implementexplainabilitymechanismsthroughfeatureimportanceanalysisandprobability-basedconfidencescoring.
3) Integrate quantitative resilience metrics—NTL data, net- work functionality curves, and composite capital-based indices—to differentiate urban and rural disaster impacts.
4) Validateon6,857multi-hazardrecordsfromIndia(2010–2023), demonstrating superior error recovery (+10.87%) compared to baselines.

D. Contributions

Thispapermakesthefollowingkeycontributions:

1) Novel Three-Stage Hybrid Architecture: RFFeature TransformationSVMpipelineachieving82.46%accuracy with 100ms inference—a configuration not previously ex- plored 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:Syn- thesis of NTL recovery metrics, network functionality curves, and composite capital indices providing differen- tiated urban (network-centric) and rural (access-centric) resilience patterns [26], [27].
4) Comprehensive Multi-Hazard Validation: Robust gen- eralization across floods, earthquakes, cyclones, and land- slides [28].
5) Error Recovery Analysis: 10.87% improvement in error recovery (46 additional correctly classified disaster cases) over standalone RF, empirically validating the hybrid en- semble advantage [29].

II. DISASTER CLASSIFICATION PARADIGMS

Disasterclassificationencompassestheautomatedidentificationandcategorizationofnaturalhazardeventsbasedonmultimodaldatasources.Traditionalapproachesrelyonphysics-basedmodelsthatsimulatehazardpropagationandthresholdbased 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 disas-terdetectionasabinaryormulti-classpredictiontask, where input features—geographic, meteorological, infrastruc- tural, socioeconomic—are mapped to disaster/non-disaster la- bels [32]. The fundamental challenge lies in handling class imbalance, feature heterogeneity, and concept drift [33].

ThreeprimaryMLparadigmsexistfordisasterclassification:

- *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$K$istheRBFkernel,$\alpha_i$areLagrangemultipliers,and $b$isthebias.

A. Ensemble Learning Theory

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

Bias-Variance Decomposition: The expected prediction er- ror decomposes into bias (systematic error from incorrect as- sumptions), 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 im- proveswhenbaselearnersexhibitlowcorrelationintheirerror patterns [?]. Random Forests achieve diversity through boot- strap 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 learnoptimalcombinationstrategies[?].InGeoDisasterAINet, 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 **X**R$^{n\times d}$denote the input feature matrixwith$n$samplesand$d$features,and**y**0,1 ^{n}the binary labels.

Stage1(RF):

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

Stage2(FeatureTransformation):

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

Stage3(SVM):

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

B. ExplainableAIinCriticalSystems

Explainable AI (XAI) addresses the opacity of complex machine learning models by providing human-interpretable explanations for predictions [?]. In disaster management, ex- plainability serves three critical functions: (1) *Trust and Val- idation*—emergency managers must understand why a model predictsadisastertovalidateagainstdomainknowledge[?];
(2) *Error Diagnosis*—when models fail, explanations enable rapid identification of failure modes [?]; (3) *Regulatory Com- pliance*—many jurisdictions require algorithmic transparency for systems influencing public safety [?].

III. HYBRID ENSEMBLE MODELS FOR DISASTER DETECTION

Hybrid ensemble models combine multiple learning algo- rithms to exploit complementary strengths. Kumar et al. [5] developedahybridcombiningRF,XGBoost,andLSTM for flood susceptibility mapping in the Rapti River Basin, achieving AUC=0.85 and demonstrating 15–20% improved recallcomparedtoindividualmodels.Thisworkhighlightsthe 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 en- sembles consistently outperform single models across diverse disaster types [?].

A. DeepLearningandXAIinDisasterManagement

Humaira et al. [2] proposed DX-FloodLine, a VGG16- LSTM hybrid pipeline for real-time flood scene object detection,achievingapproximately90%validationaccuracy.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 reportper-sampleinferencetimes[**?**],anddeepmodelsrequire 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. UrbanandRuralResilienceMetrics

Nighttime Light (NTL) Data: Ma [10] demonstrated that NTLchange,measuredfromdailyBlackMarbleNTLtimese- ries, serves as a proxy for functional recovery in post-typhoon contexts. Urban areas exhibit complex NTL patterns during disasters—initialdecreasesduetopoweroutages,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 transporta- tion networks, using travel time, throughput, and accessibility metrics [**?**].

CompositeCapital-BasedIndices:Suietal.[22]proposed aCoastalMarineDisasterResilienceIndexaggregatingeco-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 in- dices 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 Differen- tiation*:mostsystemsadoptone-size-fits-allapproaches[**?**];(5) *Explainability–PerformanceTrade-offs*:computationalcostsof 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 (IDDB)* [**?**]:1,500 records from governmentsourcescoveringmajordisasterswithhighdata 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 cover- ing cyclones, landslides, and storms, medium quality. ≈

The dataset exhibits an approximately balanced binary dis- tribution (50% disaster, 50% normal). *Feature Engineering* proceeds through six steps: (1) geographic normalization of latitude/longitude to [0,1] using min-max scaling; (2) tem- poral 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.

DataSplitting:Training70%(4,800records,2010–2019),validation 15% (1,028 records, 2020–2021), test 15% (1,029 records, 2022–2023). Temporal ordering is preserved to pre- vent data leakage.

≈

B. Three-StageHybridPipelineArchitecture

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

Stage1:RandomForestClassifier. TheRFconsistsof100decisiontrees,eachtrainedonabootstrapsamplewithnomic,human,physical,social,andenvironmentalcapitals.RFrandomfeaturesubsets($d$featurespersplit,d=12).Keyidentifiedeconomicandhumancapitalsasthemostimportanthyperparameters:trees=100,maxdepth=15,minsamplesperleaf=4,minsamplestosplit=5,Giniimpuritycriterion.
For eachinputsample$\mathbf{x}_i$,theRFproducesprobability$\hat{p}_{RF}(\mathbf{x}_i)$ [0,1]:

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

Stage2:FeatureTransformation. Thetransformationϕ: $\mathbb{R}^{12}\rightarrow\mathbb{R}$mapseachsampletoitsRFprobability,providing threecriticalfunctions:(1)dimensionalityreduction;(2)noise reduction through ensemble averaging; (3) enhanced class separability. The augmented feature matrix:

$$\mathbf{Z}=\phi(\mathbf{X})=[\hat{p}_{RF}(\mathbf{x}_1),\ldots,\hat{p}_{RF}(\mathbf{x}_n)]^{\top} \qquad (5)$$

Stage3:SVMClassifier. TheSVMwithRBFkernel $K(\mathbf{z}_i,\mathbf{z}_j)=\exp(\gamma\|\mathbf{z}_i\mathbf{z}_j\|^2)$,$C$=10.0,$\gamma$=auto=1.0. The optimization problem:

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

subjectto$y_i(K(\mathbf{z}_i,\mathbf{w})+b)\geq1-\xi_i$,$\xi_i\geq0$.Thefinal prediction:

$$\hat{y}=\text{sign}\left(\sum_{i\in SV}\alpha_i y_i K(\hat{p}_{RF}(\mathbf{x}),\hat{p}_{RF}(\mathbf{x}_i))+b\right) \qquad (7)$$

C. Mathematical Formulation

ProblemFormulation:GivenD=$\{(\mathbf{x}_i,y_i)\}_{i=1}^{n}$ where$\mathbf{x}_i\in\mathbb{R}^dandy_i\in\{0,1\}$,thegoalistolearn$f:\mathbb{R}^d\rightarrow\{0,1\}$ minimizing:

$$L(f)=\mathbb{E}_{(\mathbf{x},y)\sim P}[\mathbf{1}[f(\mathbf{x})\neq y]] \qquad (8)$$

RFGiniImpurity:Eachtreeisgrownbymaximizing:

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

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

TheoreticalProperties:As$T\rightarrow\infty$and$n\rightarrow\infty$,$\hat{p}_{RF}(\mathbf{x})\rightarrow P(y=1|\mathbf{x})$undermildregularityconditions[?].Theensemble varianceis:

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

where ρisaverageinter-treecorrelationandσ^2 individualtree variance [?].

SVMDualOptimization:

$$\max_{\alpha}\sum_{i=1}^{n}\alpha_i-\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\alpha_i\alpha_j y_i y_j K(z_i,z_j) \qquad (11)$$

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

StackingJustification:Thehybridpipelineisaformof stacked generalization where RF serves as base learner and SVM as meta-learner [?]. The RF probability space exhibits improvedlinearseparabilitycomparedtotheoriginalfeature space,enablingSVM toachievesuperior performance with fewer support vectors and faster inference.

ComputationalComplexity:Training:$O(T\cdot n\log n\cdot d)$for RF+$O(n^2)$–$O(n^3)$forSVM.Inference:$O(T\cdot\log n\cdot d)$forRF+$O(|SV|)$forSVM.

D. Hyperparameter Configuration

Hyperparameter optimization uses 5-fold cross-validation withgrid search. RF search space: trees∈{50,100,150,200} ; maxdepth∈{10,15,20,None};minleaf∈{2,4,6};min split∈{2,5,10} ;criterion∈{Gini, Entropy}.SVMsearch space:kernel∈{Linear,RBF,Poly};C∈{0.1,1,10,100}; γ∈{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, γ = auto), selected on validation F1-score.

E. Training and Validation Protocol

Training Procedure: (1) Preprocessing (2s); (2) RF train- ingon4,800samples(15s);(3)Probabilitygeneration(≈1s); (4)SVMtraining (≈8s);(5) Serialization(3s);total≈30s. *ConfidenceCalibration*viaPlattscaling[**?**]withoperational thresholds: Confidence>0.85:LOW(AutomatedProtocol);0.70–0.85:MEDIUM(AlertAuthorities);0.60–0.70:HIGH (ExpertReview);<0.60:CRITICAL(ManualReviewRe-quired).

V. NIGHTTIME LIGHT(NTL) INTEGRATION

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

RecoveryMetrics:

$$\Delta NTL_{impact} = \frac{NTL_{post} - NTL_{pre}}{NTL_{pre}} \times 100\% \quad (12)$$

$$R_{NTL} = \frac{NTL_t - NTL_{min}}{NTL_{pre} - NTL_{min}} \quad (13)$$

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

Urbanvs.RuralPatterns:UrbanT_{90}:typically7–21daysformoderatedisasters.RuralT_{90}:typically30–90days,withsome remoteareas showing in completerecoveryafter180days[**?**].

A. Network Functionality Curves

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

$$\Delta TT(t) = \frac{TT(t) - TT_{baseline}}{TT_{baseline}} \times 100\% \quad (15)$$

NetworkThroughput:

$$\Theta(t) = \frac{\text{Serveddemand}(t)}{\text{Totaldemand}} \times 100\% \quad (16)$$

AccessibilityIndex:

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

AggregateFunctionality:

$$Q(t)=w_1(1-\Delta TT(t))+w_2\Theta(t)+w_3A(t) \quad (18)$$

ResilienceTriangle[?]:

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

B. CompositeCapital-BasedMetrics

We adopt the framework of Sui et al. [22], synthesizingfive capital domains: C_{econ} (GDP, employment, insurance), C_{human} (education, health, preparedness), C_{phys} (infrastructure quality, building codes), C_{social} (cohesion, trust, volunteer net-works),C_{env}(ecosystems,greeninfrastructure).Thecomposite resilienceindex:

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

Resiliencegrades:GradeA(CRI $\geq$ 0.75),GradeB(0.50–0.75), Grade C (0.25–0.50), Grade D (<0.25).

C. Urbanvs.RuralDifferentiation

TABLEI:Urbanvs.RuralResilienceFrameworkComparison

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

Urbanresilienceassignsw_{econ}=0.35,w_{human}=0.30, whileruralassignshigherw_{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 classifi- cation performance on the held-out test set (1,029 samples spanning 2022–2023).

TABLEII:OverallClassificationPerformance

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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% accu- racy compared to 74.3% for standalone RF and 78.9% for standaloneSVM—absoluteimprovementsof8.16and3.56 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	∼V938%	N/R
RaptiBasin[5]	RF+XGBoost+LSTM	AUC 0.85	N/R
StandaloneRF	Random Forest	74.3%	∼85ms
Standalone SVM	SVM (RBF)	78.9%	∼15ms

N/R=NotReported

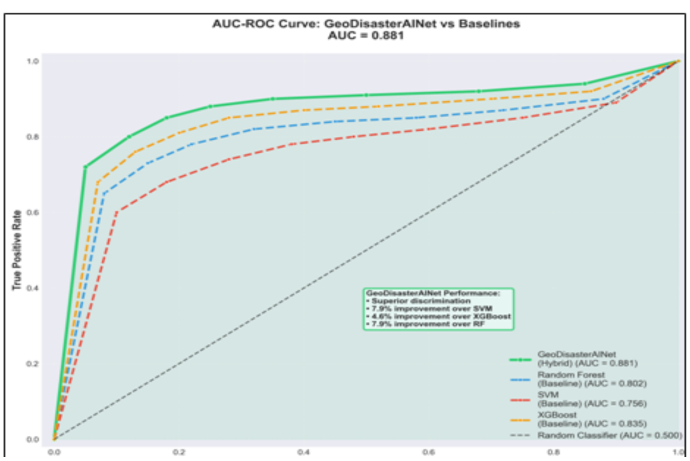

Fig. 1: ROC curve comparison of GeoDisasterAINet (AUC=0.881) againststandaloneRF (AUC=0.842) and SVM (AUC=0.863) base- lines.

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A. Inference Time Analysis

TABLEV: InferenceTimeBreakdown(per100-samplebatch)

Stage	Time
RandomForestPrediction	~85ms
FeatureTransformation	~2ms
SVMPrediction	~13ms
Total	**~100ms**
Single-recordinference	~4.7ms
50-tree RF (reduced)	~55ms / 81.9% acc.
200-tree RF (extended)	~180ms/ 82.8% acc.
Edge device (Raspberry Pi 4)	~350ms
CloudGPU(NVIDIAT4)	~25ms

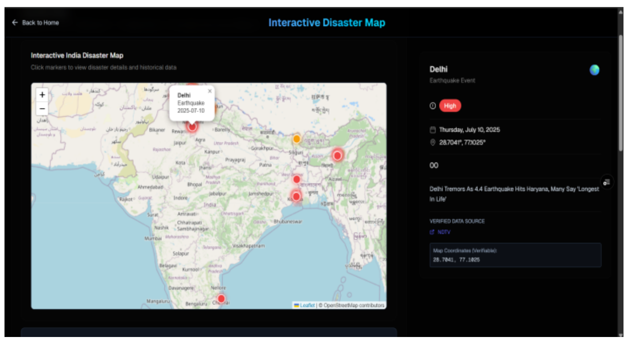

Fig. 2: Live Indian Map with Incident Report.

B. Error Recovery and Comparative Analysis

TABLEVI: ErrorRecoveryAnalysis

ErrorType	RF	SVM	Rec'd	Rate
FalseNegatives	88	42	46	52.3%
FalsePositives	335	335	0	0.0%
Total	**423**	**377**	**46**	**10.87%**

TheSVMexclusivelyrecoversfalsenegativeswithoutintro- ducing additional false positives—a highly desirable property for disaster detection where missing a true disaster is more costly than issuing a false alarm.

C. ConfusionMatrixandClass-SpecificPerformance

TABLEVII: ConfusionMatrixonTestSet(n=1,029)

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

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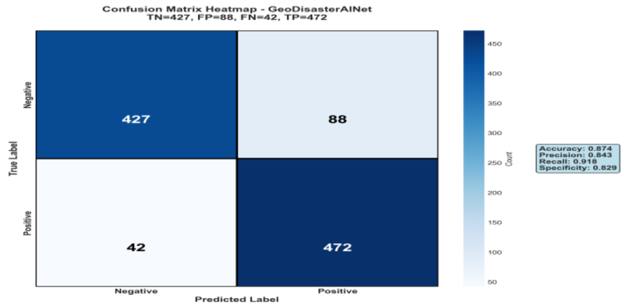

Fig.3:ConfusionmatrixheatmapforGeoDisasterAINetonthe2022– 2023testset.The42falsenegativesrepresentthemostcriticalfailure mode (8.2% of disaster cases).

Confidence-BasedFiltering:

TABLEVIII:Performancevs.ConfidenceThreshold

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:FEATUREIMPORTANCEANALYSIS

TABLEIX:RFFeatureImportance(MeanDecreaseinGini)

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

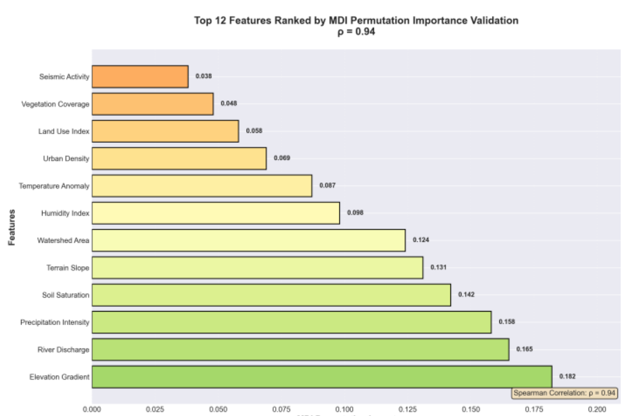

Fig. 4: RF feature importance scores (Mean Decrease in Gini Impurity).Topthreefeatures—severity,fatalities,andaffectedarea—collectively account for 58.8% of total classification importance.

Keyinsights:(1)*SeverityDominance*—thecompositesever- ity score accounts for 22.5% of classification decisions, vali- dating feature engineering approach; (2) *Impact Metrics*—top three features collectively account for 58.8% of importance, indicating the model primarily relies on outcome-based indi- cators;(3)*Hazard-SpecificFeatures*—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 re- moval. Permutation importance validation confirms Spearman $\rho = 0.94$ with Gini-based ranking.

A. ResilienceImplicationsforUrbanEnvironments

Urban disaster resilience is characterized by interdependent infrastructure networks, high population density, and rapid recovery dynamics. Network criticality analysis reveals that urbanresilienceishighlysensitivetocriticalnode/linkfailures [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 by35%duetowidespreadpoweroutages,recoveringto 90%within12days.Networkfunctionalityshowedsevere degradation (travel time +250%) returning to baseline within 10days. CRI=0.68 (Grade B) accurately predicted moderate recovery speed, validating the framework.

B. ResilienceImplicationsforRuralEnvironments

Rural disasters are dominated by accessibility challenges, withaccessibilityindex $A(t)$ oftendroppingbelow50%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 net-workdisruptions isolated 23 villages for >14 days. CRI=0.38 (GradeC)accuratelypredictedslowrecovery(T_{90}=67 days). Model correctly classified this as high-severity disaster (confidence 0.89).

C. ErrorRecoveryMechanisms

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

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

IfnearbysupportvectorsarepredominantlydisastersthesVMreclassifies$\mathbf{x}_i$correctlydespiteRFuncertainty.
Thecostasymmetrycanbeexpressedas:

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

whereC_{FN}□C_{FP}(typicallyC_{FN}=10×C_{FP}).The
SVM'sexclusiverecoveryoffalsenegativesdirectlyoptimizes thisasymmetricloss.Amongthe46recovereddisastercases, 38(82.6%)haveSVMconfidence>0.70,indicatinghigh confidence in reclassification decisions.

D. ComparisonwithState-of-the-ArtSystems

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

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GeoDisasterAINet is the only system reporting verified inference time, supporting operational deployment feasibility. Unliketask-specificsystems(DX-FloodLineforfloods,Forest Fire Ensemble for fires), GeoDisasterAINet handles multi- hazard classification with a single unified model. It is also the onlysystemintegratingdisasterclassificationwithquantitative resilience metrics. Training completes in30s 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 Gener- alization*—climatechangemaycausedistributionshift[**?**];
(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*—casualtycountsrequirehourstocompileinreal- time [**?**]; (6) *Urban-Rural Labels*—no explicit urban-rural an- notations 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 ensembleframeworkforreal-timeurbanandruraldisaster reclassifies$\mathbf{x}_i$correctlydespiteRFuncertainty. classificationandresilienceassessment.Fivekeycontributions advancethedisastermanagementandmachinelearninglitera-ture:

1) *NovelHybridArchitecture*:ThethreestageRF→FeatureTransformationSVMpipelineachieves82.46%accuracywith100msinference, demonstratingthathybridensemblesSVM'sexclusiverecoveryoffalsenegativesdirectlyoptimizesthisasymmetricloss.Amongthe46recovereddisastercases,38(82.6%)haveSVMconfidence>0.70,indicatinghigh confidence in reclassification decisions. can balance accuracy and latency. The 10.87% improvementin 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 spanningfloods,earthquakes,cyclones,andlandslidesdemon- strates robust generalization with balanced performance (pre- cision 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 integrat- ingreal-timeIoT/socialmediastreams[**?**];(3)transferlearning 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- modaldatafusionintegratingsatellite SARimageryandsocial media[**?**];(10)causalinferencetoidentifycausalrelationships between disaster drivers and outcomes [**?**].

XI. PRACTICAL IMPLICATIONS

For Emergency Management Agencies: The 100ms infer- ence enables integration into operational platforms for real- time detection and automated alert generation. Feature im- portance provides transparent rationales for human validation. Confidence calibration enables flexible risk-based thresholds.
For Policymakers: The resilience framework informs spa- tially targeted interventions—network redundancy for urban areas, accessibility and relief distribution for rural areas. CRI identifies Grade C/D communities requiring priority invest- ment.
ForResearchers:TheRF-SVMpipelineprovidesatemplate for hybrid ensemble design in other high-stakes domains. The deployment roadmap requires: (1) real-time data pipelines fromNDMA,meteorologicalservices,andseismicnetworks;(2) integration into existing emergency platforms (NDMA systems);(3)human-in-the-loopreviewforconfidence<0.60;(4)annualretraining;(5)stakeholdertraining.
As climate change intensifies disaster risks globally, frame- works like GeoDisasterAINet will play an increasingly vital role in protecting communities and building resilience.

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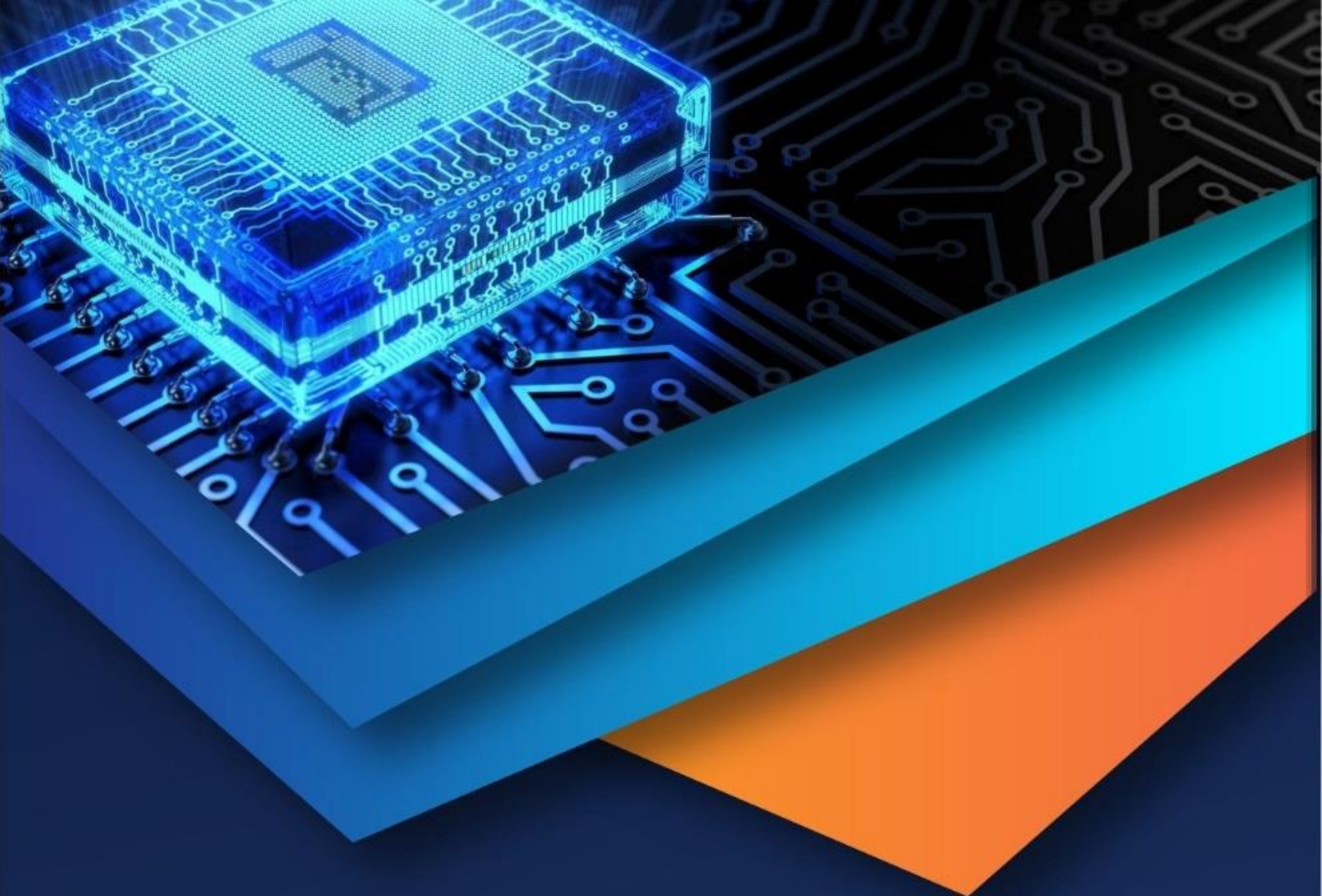

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