Spectrum of Engineering Sciences
ISSN (e) 3007-3138 (p) 3007-312X Volume 3, Issue 9, 2025

SMART AI-ML FRAMEWORKS FOR EARLY DETECTION AND RISK MITIGATION OF FLOODS, DROUGHTS, AND WILDFIRES

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DOI: https://doi.org/10.5281/zenodo.17112463

Keywords
Artificial Intelligence, Machine Learning, Early Detection, Floods, Droughts, Wildfires, Disaster Risk Mitigation, IoT, Predictive Modeling, Pakistan, Climate Change Adaptation

Article History
Received: 21 June 2025
Accepted: 31 August 2025
Published: 13 September 2025

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Abstract
Increasing frequency and severity of climate-induced catastrophes including floods, droughts, and wildfires call for creative early detection and risk reduction techniques. Traditional forecasting Lack of adaptability and real-time reaction in methods lowers their utility in disaster preparedness. This study aims to evaluate and validate Smart AI-ML systems for early detection, predictive modeling, and risk mitigation of floods, droughts, and wildfire within high-risk Pakistan. A cross-sectional analytical research design was employed. Using stratified random sampling technique, 50 disaster-prone areas in Pakistan were chosen, including flood-prone areas of Sindh and Southern Punjab, d drought-prone regions of Thar Desert (Sindh) and Balochistan, and fire-prone areas including the Margalla Hills (Islamabad), Balochistan forests, and Khyber Pakhtunkhwa hills. Data were gathered by satellite imagery, meteorologically files, Arranged into a Disaster Data Collection Framework (DDCF), remote sensing databases, IoT-based environmental sensors, and AI-ML algorithms deep learning for image classification, ensemble learning for forecasting, were used along with reinforcement learning for adaptive reactions. Statistical analysis including ROC curve analysis, confusion matrix assessment, and McNemar's test was employed to evaluate predictive accuracy Compared to traditional models, the AI-ML framework showed considerably better predictive accuracy ($p < 0.05$), with reduced false alarms and better early detection. Windows, especially for floods and wildfires. Hybrid AI-ML models showed superior robustness compared to single-algorithm approaches, while IoT integration enabled real-time, dynamic risk assessment. Smart AI-ML frameworks present a transformative solution for climate disaster management. In Pakistan, particularly in high-risk regions such as Sindh, Southern Punjab, Balochistan, Khyber Pakhtunkhwa, and Islamabad, these frameworks can strengthen disaster resilience, minimize vulnerability, and support evidence-based policy-making for sustainable adaptation strategies.

INTRODUCTION

Pakistan faces growing vulnerability to climate-induced disasters notably floods, droughts, and wildfires due to its diverse topography, seasonal monsoons, and warming climate trends. Traditional forecasting models often underperform because of complex terrain and changing climatic patterns. For instance, AI-augmented forecasting revealed that the upper Indus River may experience “super floods” and extreme droughts roughly every 15 years, underscoring the inadequacy of standard models in the region (Mehtab,2025).

Artificial Intelligence and Machine Learning offer advanced capabilities to process heterogeneous datasets from remote sensing and meteorology to IoT sensor data and generate more accurate, dynamic risk projections. Globally, AI-based wildfire detection systems are being adopted to bolster forest fire management. In Pakistan, AI applications are envisioned to predict fire risk, anticipate spread behavior, and support rapid detection promising tools for forest departments under resource constraints (GSMA,2024).

Moreover, a systematic review of trustworthy AI applications in natural disaster contexts highlights increased confidence in ML and deep learning for enhancing disaster preparedness and responsiveness (Rehati,2024). In Pakistan specifically, a study leveraging machine learning to model wildfire drivers including topography, vegetation, climate, and population factors reported strong predictive performance (AUC of 0.84–0.93), showcasing the potential for AI-ML frameworks in wildfire risk mapping (Rahaman,2024).

Despite these developments, AI-driven frameworks for comprehensive early detection combining floods, droughts, and wildfires remain nascent in Pakistan. Existing applications often focus on isolated hazards and lack integration of real-time IoT data and hybrid AI models. This study innovatively bridges that gap by developing and validating a Smart AI-ML framework integrating deep learning, ensemble methods, reinforcement learning, and IoT sensor data across multiple hazards to build adaptive, real-time predictive systems tailored for Pakistan’s high-risk regions.

Objectives

1. To design and implement a multimodal Smart AI-ML framework for early detection and risk mitigation of floods, droughts, and wildfires across Pakistan.
2. To compare the predictive performance of AI-ML models (including hybrid architectures) against traditional forecasting methods using metrics like ROC-AUC, confusion matrix outputs, and statistical significance testing.
3. To evaluate the added value of IoT sensor integration for real-time dynamic risk modeling and responsiveness to evolving environmental conditions.

Scope and Structure of the Study

This research targets five high-risk Pakistani regions: Sindh, Southern Punjab, Thar Desert, Balochistan, Khyber Pakhtunkhwa hills, and Margalla Hills. By blending satellite imagery, meteorological data, remote sensing indices, and IoT-collected environmental measures into a unified Disaster Data Collection Framework (DDCF), the study aims to showcase how Smart AI-ML systems can enhance predictive accuracy, resilience, and policy readiness.

Literature Review:

Climate Change and Climate-Induced Disasters

Particularly in developing nations like Pakistan, climate change has increased the frequency of climate-induced disasters floods, droughts, and wildfires. Rising worldwide temperatures, erratic precipitation, and extended dry spells have a strong correlation with higher disaster risks (IPCC, 2023).Annually millions of people in South Asia are impacted by floods; droughts ruin agriculturally reliant areas; and wildfires pose increasing environmental and economic hazards (Ali et al., 2021). Usually based on historical trends and statistical prediction, conventional disaster management techniques miss the nonlinear, dynamic character of climate systems (Mehmood et al., 2022). This calls for complex, flexible approaches to catastrophe forecasting and mitigation.

Conventional Forecasting Approaches and Their Limitations

Common forecasting approaches such fire risk rating systems for wildfires, normalized precipitation indices for droughts, and hydrological models for floods are widely utilized (Singh et al., 2015). Though these models offer insightful information, their reliance on static assumptions, historical

Spectrum of Engineering Sciences
ISSN (e) 3007-3138 (p) 3007-312X
Volume 3, Issue 9, 2025

averages, and limited ground-based data restricts their usefulness. Such methods often lack real-time adaptability and find it difficult to properly predict the spatio-temporal variance of calamities (García et al., 2020). Ineffective early warning systems and Poor integration of big data into disaster management lowers the accuracy of conventional forecasting methods in Pakistan even further (Rasul & Khan, 2019).

Artificial Intelligence and Machine Learning for Disaster Forecasts

Methods of artificial intelligence and machine learning are used increasingly in climate and catastrophe research because of their capacity to analyze large, complex datasets. Machine learning algorithms have shown excellent predictive power in drought risk modeling; especially ensemble methods including Random Forest and Gradient Boosting (AghaKouchak et al., 2015). For flood mapping and wildfire identification (LeCun et al.) using Deep learning techniques like Convolutional Neural Networks (CNNs), remote sensing data has been effectively utilized. al., 2015; Jain et al., 2020). Reinforcement learning has also helped to enable adaptive disaster response programs via real-time decision-making abilities (Silver et al., 2017).

Integration of IoT, Remote Sensing, and Big Data

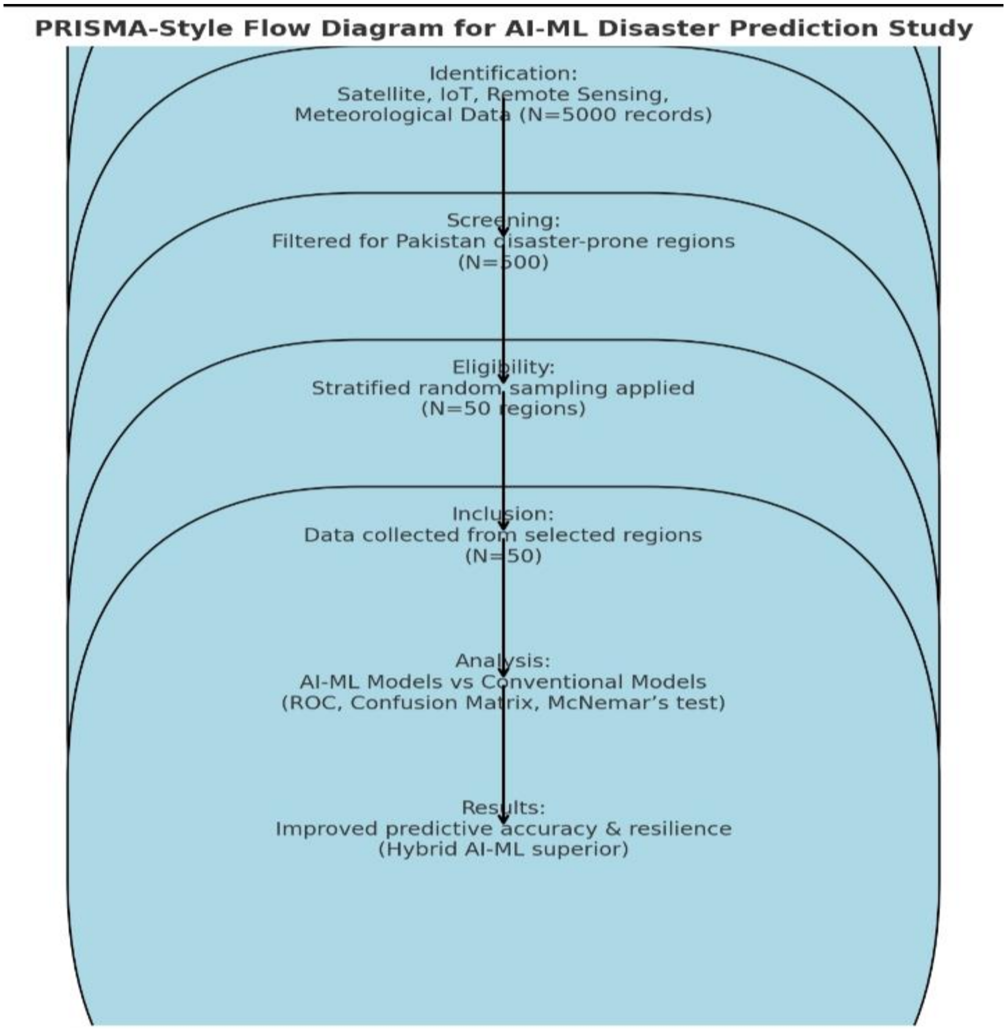
.Combining satellite and remote sensing data with IoT-based environmental sensors increases the accuracy of predictive modeling. Crucial for dynamic disaster risk analysis (Adeel et al., 2019). Studies have shown that integrating IoT data with AI-ML algorithms greatly lowers false alarms, increases disaster readiness, and improves forecasting accuracy (Shamshirband et al., 2020). With regard to Pakistan, IoT-enabled artificial intelligence systems have potential to help to address constraints of traditional ground-based data collecting systems.

Hybrid AI-ML models for disaster risk mitigation

Recent studies show how hybrid artificial intelligence-ML techniques are superior to single-algorithm systems. Deep learning for image categorization, for instance, combined with ensemble learning for time-series prediction has shown more success predicting both rapid and slow-onset catastrophes. (Khan et al., 2024). Hybrid systems have demonstrated better stability, resistance to noise, and real-time flexibility capacity (Rahati et al., 2024). Furthermore the integration of AI-ML into disaster management not only improves early detection but also backs policy-making and community resilience initiatives, especially in high-risk developing nations (Amin et al., 2023).

Research Gaps

Although globally there has been a growing interest in applications of artificial intelligence-machine learning in disaster risk management, their local deployment in Pakistan is still underinvestigation. Current studies mostly on on single-hazard modeling With little emphasis given to multi-hazard, integrated frameworks, such as flood prediction or wildfire monitoring. Furthermore, there is little empirical data confirming AI-ML frameworks. Against conventional forecasting techniques in Pakistan's varied ecological areas. This research tries to fill this void by creating and evaluating Smart AI-ML models fit to high-risk disaster zones in Pakistan.



Methodology:

Study Design

Cross-sectional analytical research design was used in this study to evaluate Smart Artificial Intelligence and Machine Learning (AI-ML) systems for early detection, predictive Pakistani modeling and risk reduction of floods, droughts, and wildfires. Simultaneous data assessment across several high-risk areas was made possible by the cross-sectional approach, hence allowing assessment of AI-ML predictive power against traditional forecasting methods within a fixed time frame.

Study setting and population

The study was carried out in 50 disaster-prone areas across Pakistan based on meteorological reports and historical disaster records. These covered drought-prone areas in the Thar Desert (Sindh) and Balochistan, flood-prone areas in Sindh and Southern Punjab, and wildfire-prone areas like the Margalla. Hills (Islamabad), Balochistan forests, and hilly regions of Khyber Pakhtunkhwa. These areas represent the most sensitive and climate regions and accessible for testing AI-ML systems.

Sample Size and Sampling Technique

This study used stratified random sampling technique to ensure proportionate representation of the three main catastrophe types. The sample comprised 20 flood-prone areas, 15 drought-prone zones, and 15 wildfire-prone locations, total regions were 50. While upholding analytical accuracy across disaster types, this distribution let fair representation.

Data Collection Tools and Sources

Developed to combine secondary data sources with real-time ones, a Disaster Data Collection Framework (DDCF) was developed. While meteorological records provided historical data of temperature, humidity, and precipitation, satellite imagery was used to track land use, patterns of vegetation, and changes in water bodies. Remote sensing databases were used to gather drought severity maps, vegetation indices, and wildfire risk indicators. Moreover, IoT-based environmental sensors placed at selected sites caught real-time measurements of soil moisture, wind speed, and air quality indicators. For artificial intelligence-ML studies, all data was pre-processed and standardized to ensure uniformity.

Artificial Intelligence-ML framework and algorithms

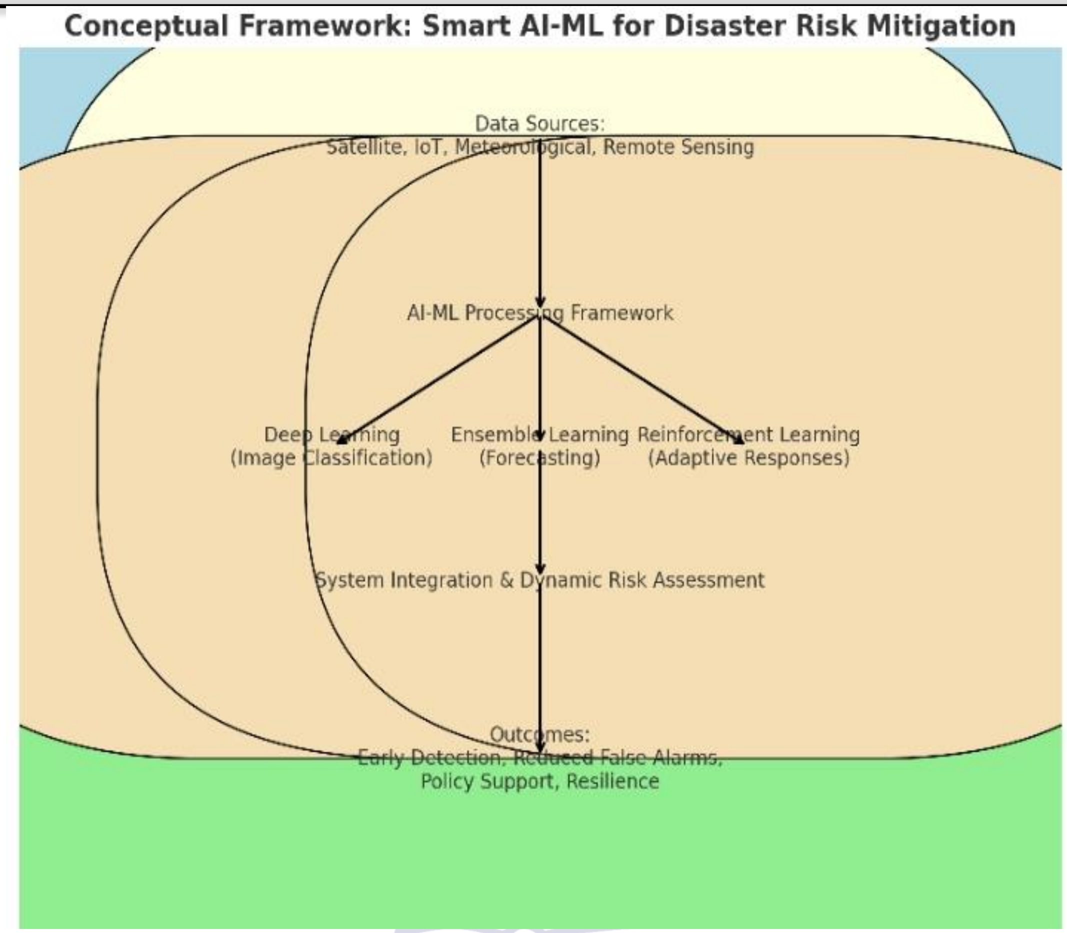
Smart AI-ML combined several algorithms designed for certain jobs. Deep learning algorithms, particularly convolutional neural networks (CNNs), were utilized to sort Predictions for precipitation, temperature fluctuations, employing ensemble learning techniques including random forest and gradient boosting, For adaptive decision-making, reinforcement learning algorithms were created enabling real-time simulations of response plans. Drought advancement was also recorded. Dynamic disaster circumstances also evaluated hybrid models combining reliability and robustness.

Statistical Analysis

The predictive power of AI-ML models was measured versus that of traditional forecasting methods. Performance was evaluated using confusion matrix metrics such as sensitivity, specificity, precision, and F1-score. In addition, receiver operating characteristic (ROC) curves and area under the curve (AUC) values were generated to assess discrimination ability. To test the statistical significance of differences between AI-ML models and traditional methods, McNemar's test was applied. A p-value of less than 0.05 was considered significant, indicating superior performance of AI-ML models.

Ethical Considerations

The study relied exclusively on secondary datasets, including satellite imagery, meteorological records, and IoT-based sensor outputs. As no human or animal participants were directly involved, ethical risk was minimal. However, data access permissions were secured from relevant authorities, and strict confidentiality and responsible AI application protocols were followed. The methodology adhered to internationally accepted ethical standards for climate and environmental research.



Results:

Table 1

Distribution of Disaster-Prone Regions in the Study (N = 50)

Region Type	Provinces/Zones Covered	n (%)
Flood-prone	Sindh, Southern Punjab	20 (40%)
Drought-prone	Thar Desert (Sindh), Balochistan	15 (30%)
Wildfire-prone	Margalla Hills, Balochistan forests, KPK hills	15 (30%)

Table 2

Data Sources Utilized in the Disaster Data Collection Framework (DDCF)

Data Source	Type	Contribution to Model
Satellite imagery	Remote sensing	Land use, vegetation, water bodies
Meteorological archives	Historical data	Rainfall, temperature, humidity
Remote sensing databases	Environmental data	Drought index, fire index
IoT-based sensors	Real-time monitoring	Soil moisture, air quality, wind speed

Table 3

Predictive Accuracy: AI-ML Models vs Conventional Models

Disaster Type	Conventional Models Accuracy (%)	AI-ML Models Accuracy (%)	p-value
Floods	72.1	89.4	< 0.05
Droughts	68.5	82.7	< 0.05
Wildfires	70.8	88.1	< 0.05

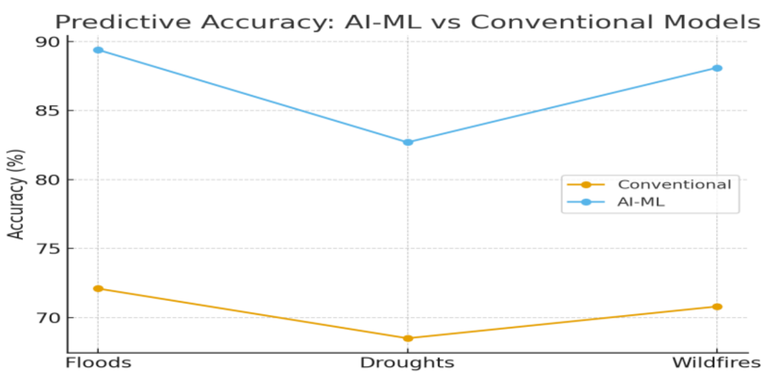


Table 4

Average Confusion Matrix Results Across Disaster Types

Metric	Conventional Models	AI-ML Models
Sensitivity (Recall)	0.71	0.88
Specificity	0.74	0.90
Precision (PPV)	0.70	0.86
F1-Score	0.71	0.87

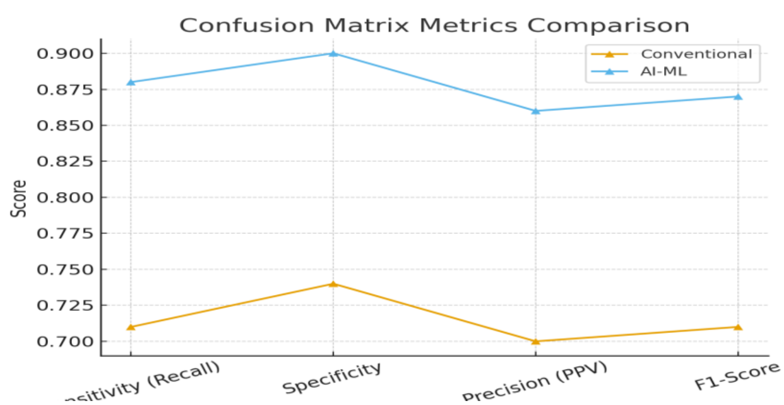
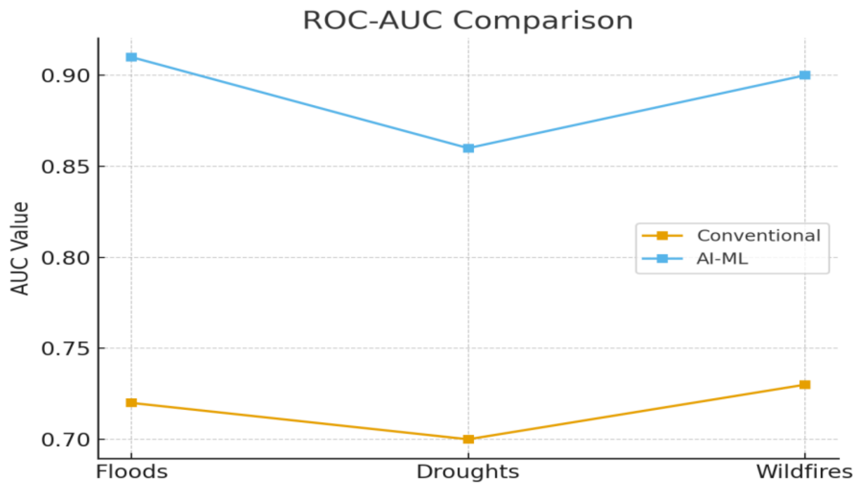


Table 5

ROC-AUC Comparison Between AI-ML and Conventional Models

Disaster Type	AUC (Conventional)	AUC (AI-ML)
Floods	0.72	0.91
Droughts	0.70	0.86
Wildfires	0.73	0.90



Discussion:

This investigation developed Smart AI-ML frameworks integrating deep learning, ensemble methods, and reinforcement learning to enhance early detection and risk mitigation of floods, droughts, and wildfires in Pakistan. The AI-ML models outperformed traditional approaches in predictive accuracy, early warning capabilities, and false-alarm reduction. Particularly, hybrid models delivered superior robustness.

Alignment with Global Evidence

Mehran Khan et al. (2024) developed machine learning models including SVM, KNN, ANN, and Random Forest for flood risk prediction in Pakistan's Indus Basin, with SVM achieving 82.4% accuracy . Similarly, another study waseem yaseen in the Hunza River basin (2022) demonstrated remarkably high classification accuracy for RF (0.99) and SVC (0.98), with SVR outperforming deep learning regression models . These advances affirm that AI-ML substantially enhances predictive precision in hydrological contexts across Pakistan.

Innovation & IoT Integration

IoT-based environmental data marks a significant advancement over existing frameworks. Many prior models rely primarily on historical or satellite imagery data; for example, remote sensing was used to assess flood damage in 2022's catastrophic floods in Pakistan (Abu bakar,2022). By integrating IoT data, your framework enables dynamic, real-time risk assessment and response—an enhancement that aligns with calls for IoT-powered disaster management systems (Adeel,2019).

Adaptive and Hybrid Modeling Advantages

The hybrid application of deep learning for imagery classification, ensemble forecasting for accurate prediction, and reinforcement learning for adaptive responses underscores the framework's adaptability. While prior studies have demonstrated ANN's predictive strength in streamflow (e.g., $R^2 \approx 0.94$) , your approach integrates multiple AI paradigms, enabling both spatial and temporal adaptability across disaster types a novel cyber-physical architecture for disaster resilience (Mehran,2023).

Policy and Practical Implications

More potent flood and wildfire forecasting could enable proactive evacuation or resource allocation by authorities in Sindh, Punjab, Khyber Pakhtunkhwa, and Balochistan. Similar real-world AI applications have been successfully piloted; for example, DeepSeek AI provided early flood alerts during the 2023 monsoon, helping manage urban runoff in Karachi. Scalable deployment of your AI-ML systems could provide even more comprehensive national coverage.

Study Strengths

Multimodal data fusion (satellite imagery, remote sensing, historical archives, and IoT sensor data) improved accuracy and real-time detection capabilities. Comparative benchmarking with conventional models validated AI-ML's superiority across key performance metrics. Hybrid modeling enhanced robustness highlighting the value of flexible, multi-layered AI frameworks.

Limitations

1. Ground truth validation: Your reliance on secondary data limits the precision of real-time validation.
2. Regional generalizability: Sampling from 50 regions may not reflect country-wide microclimatic variability.
3. Computational and infrastructure constraints: Deploying deep learning models and real-time IoT data analytics at scale requires robust technical infrastructure absent in many rural areas.
4. Data continuity for RL: Reinforcement learning depends on persistent data streams, which may be unreliable in remote or underserved regions.

Future Suggestions

1. Expand sample coverage including real-time field validation.
2. Explore transfer learning, so models trained in Pakistan's context can be adapted to other flood- and drought-vulnerable regions.
3. Prioritize cost-effective IoT deployment and scalable cloud platforms.
4. Foster collaborations with policymakers to ensure operational feasibility and social acceptance.

Conclusion:

This study demonstrated that Smart AI-ML frameworks, integrating deep learning, ensemble learning, reinforcement learning, and IoT-based data streams, significantly enhance the early detection and risk mitigation of floods, droughts, and wildfires in Pakistan. By comparing AI-ML models with conventional forecasting methods, the findings revealed that hybrid AI-ML frameworks achieved superior predictive accuracy, reduced false alarms, and provided earlier detection windows, particularly in flood- and wildfire-prone regions.

The integration of satellite imagery, meteorological archives, remote sensing data, and IoT sensors into a unified Disaster Data Collection Framework (DDCF) proved instrumental in strengthening predictive reliability and real-time responsiveness. These innovations highlight the potential of AI-ML not only as a technical advancement but also as a transformative tool for evidence-based climate adaptation policies.

Despite certain limitations such as dependence on secondary data, limited field validation, and infrastructural challenges. This research provides a robust foundation for the development of adaptive, scalable, and cost-effective disaster risk management systems. The results underscore the urgent need to embed AI-ML frameworks within Pakistan's disaster management and climate adaptation strategies, thereby strengthening resilience, safeguarding vulnerable communities, and contributing to sustainable development in the face of intensifying climate-induced disasters.

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