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Artificial Intelligence In Disaster Prediction: A Review Of Flood, Earthquake And Wildfire Forecasting With Machine Learning And Early Warning Dashboards

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Abstract—Natural disasters such as floods, earthquakes, cyclones, landslides and forest fires cause severe loss of life, property and environment. Conventional disaster prediction depends on historical records, weather bulletins and expert analysis, and delayed or incomplete information makes response difficult. This paper reviews artificial intelligence and machine learning for disaster prediction and early warning. It examines flood prediction with machine learning and deep learning on rainfall, river level and catchment data, including rainfall–runoff modelling with recurrent networks and global flood forecasting in ungauged basins; precipitation nowcasting with convolutional recurrent and generative models on radar data; earthquake detection and phase picking with deep networks and the scientific limits of earthquake early warning; wildfire risk prediction; and satellite and aerial damage assessment with social-media analysis for post-disaster situational awareness. It discusses data sources, from meteorological services and river gauges to satellite imagery and IoT sensors, and the design of risk dashboards and alerting that follow people-centred early warning principles and India's disaster management framework. A five-layer architecture comprising data acquisition, integration, risk modelling, warning and dissemination, and response support is proposed, with research gaps, objectives, a comparison of hazards and challenges such as data scarcity, rare events, false alarms and last-mile communication. The review stresses that AI predictions supplement, never replace, official warnings.

Index Terms—Disaster prediction, machine learning, flood forecasting, precipitation nowcasting, earthquake detection, wildfire risk, early warning systems, risk dashboard

I. INTRODUCTION

In India, the monsoon brings both agriculture and disaster. A single night of extreme rainfall can flood a city, and landslides can cut off hill districts. Earthquakes give no useful notice, while cyclones can be tracked for days. Each hazard therefore needs a different prediction approach and a different warning lead time.

AI can help because the relevant data are abundant and the relationships are complex: rainfall, river levels, soil moisture, terrain, land use, satellite imagery and historical disaster records. Rolnick *et al.* [1] described many such applications within climate and disaster resilience, and Basher [2] argued that early warning systems must be both scientifically sound and people-centred to save lives.

This paper reviews AI methods for predicting major hazards and proposes a warning-oriented architecture aligned with disaster management practice.

II. BACKGROUND AND RELATED WORK

1. Hazards And Prediction Horizons

Fig. 1 organizes hazards by the type of prediction possible: nowcasting for rainfall, hours-to-days forecasting for floods and cyclones, seasonal risk mapping for wildfires and landslides, and seconds-scale warning for earthquakes.

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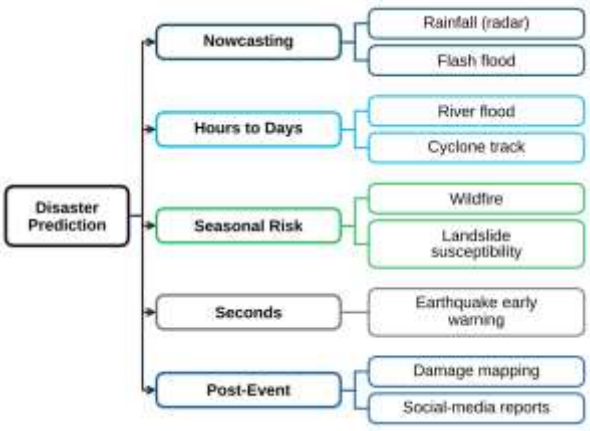


Fig. 1. Hazards and the prediction horizons that AI can support.

2. Disaster Management Cycle

Prediction supports the preparedness and early warning phases of the cycle described in the Sendai Framework [3] and India's National Disaster Management Plan [4], which also covers response, recovery and mitigation.

3. Review Of Related Studies

Floods. Mosavi *et al.* [5] reviewed machine learning models for flood prediction and found ensembles and hybrid models most effective. Kratzert *et al.* [6] used LSTM networks for rainfall–runoff modelling and matched or exceeded calibrated hydrological models. Nearing *et al.* [7] reported global prediction of extreme floods in ungauged watersheds, extending reliable lead times in data-poor regions. Bentivoglio *et al.* [8] reviewed deep learning for flood mapping.

Rainfall nowcasting. Shi *et al.* [9] introduced ConvLSTM for precipitation nowcasting from radar sequences, and Ravuri *et al.* [10] used deep generative models of radar to produce skilful, realistic nowcasts preferred by forecasters.

Earthquakes. Perol *et al.* [11] applied convolutional networks to detect and locate small earthquakes, and Mousavi *et al.* [12] proposed Earthquake Transformer for simultaneous detection and phase picking. Allen and Melgar [13] reviewed earthquake early warning, emphasizing that warning comes from detecting an ongoing rupture rather than predicting a future quake.

Wildfires and damage assessment. Jain *et al.* [14] reviewed machine learning in wildfire science and management. Gupta *et al.* [15] released xBD for building damage assessment from satellite imagery, Rahnemoonfar *et al.* [16] released FloodNet for post-flood aerial scene understanding, and Imran *et al.* [17] surveyed processing of social media messages during mass emergencies. Table I summarizes these works.

TABLE I Summary of Literature Survey

Ref.	Authors	Year	Technique Used	Merits	Demerits
[17]	Imran et al.	2015	Social media in emergencies	Situational awareness methods	Noisy data
[9]	Shi et al.	2015	ConvLSTM nowcasting	Spatio-temporal rainfall forecast	Short horizon
[6]	Kratzert et al.	2018	LSTM rainfall–runoff	Matches calibrated models	Needs gauge data
[5]	Mosavi et al.	2018	ML flood prediction review	Ensembles most effective	Review only
[11]	Perol et al.	2018	CNN earthquake detection	Detects small events	Detection, not prediction
[15]	Gupta et al.	2019	xBD damage dataset	Building damage benchmark	Post-event only
[12]	Mousavi et al.	2020	Earthquake Transformer	Detection and phase picking	No prediction
[10]	Ravuri et al.	2021	Generative radar nowcasting	Skilful, realistic forecasts	Radar coverage
[7]	Nearing et al.	2024	Global flood prediction	Works in ungauged basins	Extreme events hard

III. RESEARCH GAP AND OBJECTIVES

1. Identified Research Gaps

1. 1) Dense, quality-controlled gauge and sensor data are lacking in many basins.

2. 2) Extreme events are rare, so models have few training examples.

3. 3) Models trained in one region transfer poorly to different terrain and climate.

4. 4) False alarms erode public trust in warnings.

5. 5) Warnings often fail to reach vulnerable communities in time.

2. Objectives Of The Review

1. 1) To review AI methods for flood, rainfall, earthquake and wildfire prediction.

2. 2) To examine satellite and social-media analysis for situational awareness.

3. 3) To design a risk dashboard and alerting approach for authorities and the public.

4. 4) To propose a five-layer disaster prediction and warning architecture.

5. 5) To identify challenges in data, reliability and last-mile communication.

I. IV. Design of the Proposed System

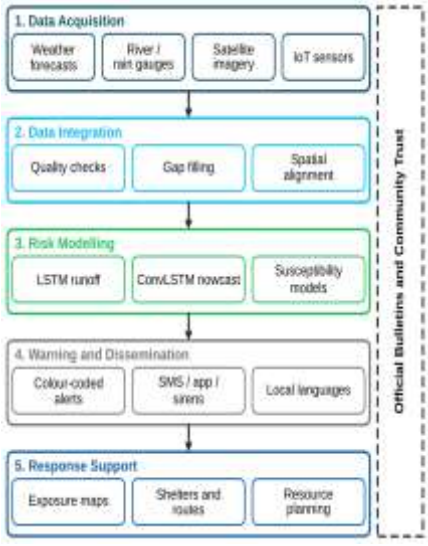


Fig. 2 shows the proposed architecture.

Fig. 2. Proposed five-layer AI-based disaster prediction and warning architecture.

3. Data Acquisition Layer

Weather service forecasts, rainfall and river-level gauges, soil moisture and IoT sensors, satellite imagery, terrain and land-use maps, and historical disaster records are collected.

4. Data Integration Layer

Observations are quality-checked, gap-filled and aligned in space and time onto a grid of administrative units and river reaches.

5. Risk Modelling Layer

Hazard-specific models run: LSTM rainfall–runoff for river levels, ConvLSTM nowcasting for rainfall, gradient-boosted models for landslide and wildfire susceptibility, and change detection on satellite imagery for damage.

6. Warning And Dissemination Layer

Risk levels are mapped to colour-coded alerts; messages are issued in local languages through SMS, app notifications, sirens and community volunteers, always referencing official bulletins.

7. Response Support Layer

Dashboards show at-risk populations, shelters, roads and resources to assist authorities in evacuation and relief planning.

8. Methodology

Fig. 3 describes the workflow. Risk is expressed as the product of hazard probability, exposure and vulnerability,

$$Risk = P(hazard) \times Exposure \times Vulnerability \quad (1)$$

and model skill for continuous forecasts such as river level is measured with the Nash–Sutcliffe efficiency,

$$NSE = 1 - \Sigma(Q_o - Q_s)^2 / \Sigma(Q_o - \bar{Q}_o)^2 \quad (2)$$

while warning performance is reported with probability of detection and false alarm ratio.

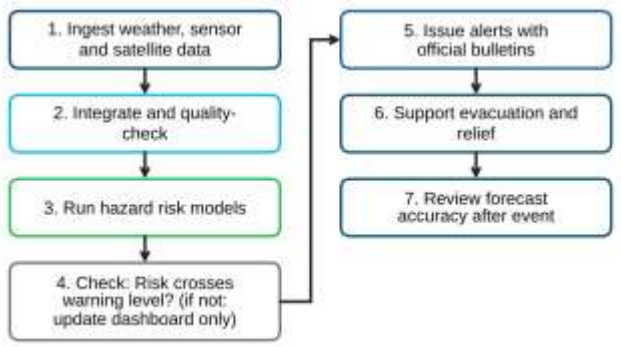


Fig. 3. Disaster prediction and early warning workflow.

IV. DISCUSSION AND COMPARISON

Table II compares hazards by typical lead time, main data sources and AI maturity.

Hazard	Lead Time	Main Data	AI Maturity
Heavy rainfall	Minutes–hours	Radar, satellite	High
River flood	Hours–days	Rainfall, gauges	High
Cyclone	Days	Satellite, models	Medium–High
Landslide	Seasonal / event	Rainfall, terrain	Medium
Earthquake	Seconds (warning)	Seismic waveforms	Detection only

TABLE II Comparison of Hazards and AI Prediction

V. CHALLENGES AND FUTURE DIRECTIONS

Table III summarizes challenges. Future directions include foundation models for weather, low-cost sensor networks on rivers, impact-based forecasting that predicts consequences rather than only hazard levels, and community-based warning dissemination.

Challenge	Mitigation
Sparse data	Low-cost sensors; satellite inputs
Rare extreme events	Transfer learning; physics-informed models
False alarms	Probabilistic, tiered warnings
Last-mile reach	Local languages; sirens; volunteers
Over-reliance on AI	Always pair with official warnings

TABLE III Challenges and Mitigation

VI. CONCLUSIONS

AI can strengthen disaster risk assessment and early warning by learning from large volumes of meteorological, hydrological, seismic and satellite data. The reviewed literature shows strong results in flood forecasting, rainfall nowcasting and earthquake detection, with wildfire and landslide risk mapping advancing. Because predictions are uncertain, AI outputs should be used together with official warnings and local knowledge to help communities and authorities prepare and respond.

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