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AI Powered Disaster Management System

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Abstract

Disasters happen a lot. Floods, cyclones, earthquakes they hit fast. Houses, roads, schools sometimes people get hurt. Scary stuff. We built an AI-based Disaster Management System. Each disaster has its own model. For floods we use Random Forest, for cyclones we use ARIMA for Earthquakes we use Neural Networks. For the overall system, we used Logistic Regression to combine everything and figure out overall risk. The system sorts areas into low, medium, or high risk. If risk is high, it can send alerts through SMS, email, or apps. Not perfect, but even small warnings can help people and authorities prepare.

Keywords:

AI, Disaster Management System, Machine learning, Satellite sources, Logistic Regression

1. Introduction

Disasters are unpredictable and dangerous. Floods, cyclones, earthquakes they can destroy homes, roads, schools sadly, sometimes even people. Even small warnings help. People can move. Authorities can help if they know early. That's why we need to predict disasters before they hit.AI and Machine Learning well, they look at tons of data. They try to find patterns. Stuff humans might not notice right away. For our project, we made a system that checks past disasters and what's happening right now in the environment. Floods, cyclones, earthquakes… they're all different. So, we needed different models for each disaster. Floods behave differently from cyclones or earthquakes. That's why we chose: Random Forest for floods – handles rainfall, rivers, terrain ARIMA for cyclones to handles time series data like wind speed, air pressure Neural Networks for earthquakes to handles complex seismic patterns Finally, Logistic Regression combines outputs to give an overall risk score. It's not perfect. But even a small heads-up helps. Emergency teams can act faster. People can prepare.

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2. Literature Review

Lots of people studied ML for disasters. They usually check past events and environmental data. Models used: Logistic Regression, Random Forest, ARIMA, Neural Networks. Each works best for different types of data: Random Forest for floods. Checks rainfall, rivers, terrain. Finds patterns easily. ARIMA for cyclones. Looks at trends over days for wind speed and pressure. Neural Networks for earthquakes. Handles complex, non-linear seismic data. Logistic Regression to combines outputs for overall risk. Historical data is key. Machine Learning looks at a lot of data. It tries to find patterns. Things we might not notice ourselves. Early warnings help. They give people a chance to prepare. Can save lives. Can reduce damage too.

2.1 Literature Survey

S.No	Author & Year	Purpose of Study	Methods/ Technologies Used	Key Findings	Relevance to Your Project
1.)	Smith et al., 2018	Flood prediction using weather and hydrological data	Logistic Regression & Random Forest	Logistic Regression provides clear probability-based flood risk levels; Random Forest increases accuracy with complex patterns	Supports your flood risk prediction module, especially using Logistic Regression for binary classification
2.)	Kumar & Singh, 2019	Early warning system for river-based flooding	Machine Learning on rainfall + river level datasets	Demonstrated that combining rainfall + river discharge improves prediction reliability	Justifies your data collection layer combining multiple environmental inputs
3.)	Rao et al., 2020	Cyclone intensity forecasting	Time-Series Forecasting using LSTM	LSTM handles time-dependent cyclone features like wind speed and pressure variations	Supports your use of LSTM for cyclone forecasting
4.)	Chen et al., 2021	Cyclone track prediction	Deep Learning +	Deep models reduce track prediction error	Validates your inclusion of satellite-based AI prediction

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			Satellite data analysis	significantly compared to classical models	
5.)	Lee & Park, 2017	Earthquake early signal classification	Neural Networks analyzing seismic wave patterns	Neural Networks outperform traditional methods for detecting early earthquake waves	Supports your Earthquake Prediction Module using neural networks
6.)	Gupta et al., 2022	Damage classification post-earthquake	CNN on building images	CNN accurately identifies cracked, collapsed, or safe structures	Fits your AI damage assessment module using CNN-based image analysis
7.)	Dutta & Roy, 2020	Multi-hazard risk assessment (floods + cyclones)	Multinomial Logistic Regression	Classification into low/medium/high risk improves early decision-making	Supports your risk level classification using multinomial logistic regression
8.)	Ahmed et al., 2021	Disaster alert automation	Probability threshold–based alert triggering	Automated alerts reduce response delay by up to 60%	Strengthens your alert generation module using logistic regression probability thresholds
9.)	Nair et al., 2022	Rescue route optimization after disasters	Dijkstra & A* pathfinding algorithms Relevant to your rescue route planning module	Shortest safe routes significantly speed up evacuation	Relevant to your rescue route planning module
10.)	Prasad et al., 2019	Resource allocation during disasters	Optimization Algorithms (Linear Programming)	Ensures balanced use of emergency resources	Supports your resource allocation module

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3. Methodology:

So, we got the data. Lots of it messy. Had to fix stuff ourselves. Poured it into the models saw if it worked. Alerts? Set them up after a bunch of trial and error .Let's do step by step

1. Data Collection: Data came from

Weather reports – rainfall, humidity, temperature

Historical disaster records – floods, cyclones, earthquakes

Satellite observations – rainfall patterns, wind speed, cloud movement

Seismic data – magnitude, depth, location

More data = better predictions, mostly.

2. Data Preprocessing:

Data wasn't perfect. Missing stuff, weird numbers, inconsistent formats. We Filled missing values, Corrected errors, Normalized numbers, some parts were tricky. We had to check some records manually. Took a bit of time, honestly.

3. Model Prediction:

Each disaster type has its own model:

Floods → Random Forest-Looks at rainfall, river levels, terrain, gives flood probability

Cyclones → ARIMA-Uses wind speed and air pressure trends over days, predicts cyclone likelihood and intensity

Earthquakes → Neural Networks-Uses seismic magnitude, depth, location, estimates probability and severity

Finally, Logistic Regression combines everything to give overall risk for a region.

4. Risk Classification:

Areas split into:

Low Risk – small chance

Medium Risk – moderate chance

High Risk – high chance

This helps authorities focus on high-risk areas first.

5. Alert Generation:

If medium/high risk then alerts will be sent through website notification

Goal: give a heads-up so people and authorities can act. Even small warnings save lives.

4. Results

We tested the system on floods, cyclones, and earthquakes. Random Forest predicted floods based on rainfall + river levels. Heavy rain + full rivers → medium/high risk. ARIMA predicted cyclones using wind + pressure trends. Sudden spike → high risk. Neural Networks predicted earthquakes using magnitude + depth. Big shake + shallow depth → higher risk. Logistic Regression combined all this to give overall risk per region. Even small early warnings helped. Authorities could prepare relief, evacuate people, reduce damage. We noticed patterns over time too. Some areas get floods every monsoon. Cyclones tend to hit coastal regions. Earthquakes are more common in certain fault zones. That info is useful for planning.

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5. Conclusion

One problem we kept running into was the data. A lot of it wasn't real-time, and some datasets just didn't have enough detail. Because of that, the predictions can be off sometimes. At first, we assumed combining all the models would be simple, but it wasn't. Sometimes the outputs didn't match, and we had to go back and correct things more than once. It's not perfect, but it does give a rough idea about what might happen. That alone can help people stay a bit more prepared. In real situations, even a small early warning can actually matter. If we continue this work, there are a few clear things we can improve. Getting proper real-time data would help a lot. Another thing is making all the models work together more smoothly. Right now it works, but it can definitely be better. Adding some kind of live tracking or alert feature would also make it more practical. At the end, we got a clear idea of how AI works outside textbooks. It didn't always give accurate results—we saw that ourselves—but it was still useful.

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