

AI-Based Natural Disaster Prediction and Diagnosis System Using Random Forest with an Interactive Graphical User Interface

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Abstract: Natural disasters with tremendous impacts on human lives, infrastructure, and ecosystems are frequent all over the world, which calls for intelligent, data-driven decision support systems for early diagnosis and effective crisis management. This paper demonstrates a Natural Disaster Diagnosis and Crisis Management System design and development featuring real-time environmental sensing, technological monitoring, and pre-emptive response planning within a unified decision-support framework.

The proposed system include predict disasters using machine learning. It follows a modular architecture that integrates analytical risk assessment, formulation of preventive strategy, and dynamic action planning through an interactive GUI. NDDCMS structures disaster management into five operational phases, namely disaster diagnosis, early warning indicators, response during the disaster, post-disaster recovery, and preventive planning. Each phase integrates stepwise risk indicators and decision inputs to support officials and community response teams.

It relies on quantifiable environmental parameters (e.g., precipitation, soil moisture, wind speed, and temperature fluctuation) and corresponding technological sensing mechanisms for the classification of risk levels and the improvement of early warning reliability. By focusing on a user-centered design and data-driven workflow, the system advances situational awareness, hastens decision-making, and closes the gap between disaster prediction and effective response. This framework enhances national and local-level disaster resilience by supporting viable risk reduction and crisis management strategies.

Keywords: Machine Learning, Random Forest, Decision Support, Disaster Diagnosis, Risk Management.

I. INTRODUCTION

Natural events like floods, earthquakes, hurricanes, and landslides are significant threats to life, property, and the environment as a whole [1]. The rise in the occurrences of these events along with high intensity levels, owing to climate change, urbanization, and other factors, has generated a need for efficient techniques in the area of early detection, threat analysis, and handling of the events [2]. Conventional manual detection and management of the events are not always efficient in providing accurate information, resulting in loss of lives, as well as economic loss, due to the delayed response of the concerned authorities [3,4]. For dealing with such challenges, it has been clear that an intelligent system tracking multiple environmental parameters and assisting authorities in formulating effective strategies regarding natural disaster preparedness and response measures has been an immediate requirement [5]. Early warning detection technology could help authorities and common citizens take effective measures to cope with disasters [6].

In this regard, the Natural Disaster Diagnosis and Crisis Management System (NDDCMS) has been developed as an integrated decision-support system [7]. For this purpose, the system integrates real-time data acquisition, modeling, and interaction facilities for decision support [8]. NDDCMS integrates input information from different domains, such as environment, remote sensing, and historical information, for dynamic risk analysis [9]. For this purpose, the system arranges the input information on a predetermined model consisting of detection, diagnosis, and decision stages, which helps in identifying warning signs, disaster intensity measurement, and suggests preemptive actions for impact minimization [10].

The proposed system is an attempt to predict natural disasters and taking suitable procedures and decisions to face these disasters. It contains two stages: First stage to predict natural disasters using machine learning, second stage to taking suitable procedures based on the disasters type. Second stage consists of a total of five core modules. The modules are Disaster Diagnosis, Warning Signs, Disaster, After Disaster, and Prevention. Each module gives a comprehensive description of the different processes involved in the disaster management chain, starting from the detection of warning signs to the recovery and preventive processes. By incorporating all the different modules in a GUI, the system allows decision-makers, as well as other stakeholders, to easily understand the important information.

II. LITERATURE REVIEW

2.1 Disaster-Risk Management

There has been a paradigm change in the management of disaster risks from being reactive to proactive and including all phases of disaster: mitigation, preparation, response, and recovery [11,12]. In this regard, the Sendai Framework focuses on early warning for multi-hazard risk transfer in strategies for building with people at the center as essential for disaster risk reduction [13]. Paradigm theories construct disaster risk in the following ways:

$$\text{Risk} = \text{Hazard} \times \text{Exposure} \times \text{Vulnerability}$$

This definition highlights the importance of integrating environmental indicators (hazard), population and asset information (exposure), and socio-economic vulnerability into decision support systems. These systems offer the basis for developing systems that can transform disparate information into disaster preparation and response processes [14].

2.2 Sensing and Early Warning Systems

Contemporary Early Warning Systems (EWS) couple in situ sensors (rain gauges, river stage, soil moisture, weather stations) with distant sensing methods (optical, radar satellites, precipitation measurements, altimeters) and weather forecasting models [15]. For flood events, the primary predictors include rainfall characteristics (amount and duration), river hydro graphs at bank full discharge, and antecedent soil moisture conditions [16].

"Recent advances in IoT network infrastructure and edge computing allow for better coverage," notes the report, "and the availability of protocols like MQTT or stream processing allows for the ingestion of close to real-time information" [17]. However, the difficulties remaining relate to the calibration drift of sensors, the lack of coverage information for poorer regions, and the delay between observation and the dissemination of the warning.

2.3 DSS and Multicriteria Methods

The three layers of a typical Disaster DSS are data acquisition, analytics, and presentation of results [18]. Multi-Criteria Decision Analysis (MCDA) [19] methods such as Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), ELimination Et Choix Traduisant la REalité (ELECTRE), Preference Ranking Organization method for Enrichment Evaluations (PROMETHEE), and their fuzzy variants represent the commonly adopted approaches to area ranking and action prioritization under uncertainty [20].

Rule-based expert systems continue to be useful if the domain knowledge itself has been codified in Standard Operating Procedures [21].

Hybrid methods combining Multi-Criteria Decision Analysis with either statistical analysis or machine learning algorithms can improve transparency with respect to weights and criteria, as well as account for non-linear relationships between risk factors [22].

2.4 Hazard Diagnosis by Means of Machine Learning and Deep Learning

Data-driven models have improved disaster detection and nowcasting [23]:

- Time-series models: ARIMA, Prophet, LSTM/GRU networks for the rainfall-runoff, river level forecasting, and landslide prediction based on triggering thresholds [24].
- Tree-based ensembles: Random Forests and XGBoost perform well on tabular risk indicators and provide variable importance diagnostics [25].
- Computer Vision: The architecture of convolutional neural networks is used - such as U-Net - to delineate the flood extent or burn scars from satellite imagery [26]. SAR imagery promotes performance under cloud cover conditions [27].

Anomaly Detection enables the recognition of irregularities in hydro meteorological phenomena by using algorithms such as Isolation Forest, One-Class SVM, as well as auto encoders, which ensure early warnings regarding potential crises (Detects unusual patterns using Isolation Forest, One-Class SVM, and auto encoders for early crisis alerts [28]).

Although the model has shown promising results in terms of its accuracy, it is argued in the literature to face the following challenges: (1) lack of interpretability. (2) The model is region-dependent. (3) The need to include humans in the decision-making loop [29].

2.5 Geospatial Modeling and Risk Mapping

GIS constitutes the core of the disaster decision support system. Hydrological and hydraulic analyses (rainfall-runoff and one dimensional and two-dimensional transient models) and the use of DEMs contribute to the definition of flood-prone areas [30]. The definition of vulnerability and exposure overlays (population, infrastructure, hospitals, and roads) determines risk indices [31].

Research may incorporate various layers of disaster risk and weight them together into a single disaster risk index, while others are based on the propagation of uncertainty through the use of Bayesian Networks [32]. Functional systems will correlate maps with evacuation routing, resource allocation (shelters, logistics), but will nevertheless limit operationalization to graphical representation, devoid of processual instruction for action by responders in disaster scenarios [33].

2.6 Human-Computer Interaction (HCI) and Crisis UX

In emergency use, interfaces should minimize cognitive overhead [34]. Empirical studies recommend progressive disclosure, color-coded severity, and clear-language action labels for each alert level. Role-based views for planners, incident commanders, citizens, and offline capabilities enhance usability [35].

The very common limitation of academic prototypes is the little usability testing and lack of end-to-end workflows. This system tries to overcome this with the arrangement of the GUI in five modules: Diagnosis, Warning Signs, During Disaster, After Disaster, and Prevention, thereby covering the full continuum of disaster management [36].

2.7 Uncertainty, Calibration, and Explainability

To communicate risks effectively, one needs to be clear about sources of uncertainty, which are error in sensors, bias in models, and variability in the scenarios. Techniques include prediction intervals, consensus methods, and post-hoc explanation tools such as SHAP for tabular machine learning [37].

Calibration with respect to past events (hit, miss, false alarm rates, lead time) is far more crucial for user acceptance. Traceability of indicators to suggested actions is very important, though the system traces back simply from indicators to risk level to SOP [38].

2.8 Interoperability and Standards

Operations-centered Early Warning Systems (EWS) are using open standards to an increasing degree. These include Geo-OGC services like WMS/WFS/WCS; the main use in the warning field being Common Alerting Protocol (CAP) to support multi-channel warning delivery [39]. The systems with APIs corresponding to the former two will easily interface with the national and third-party warning platforms. Data governance ranging from access control to audit trails and validation becomes paramount, and this is even more pronounced in crowdsourced and social media data [40].

2.9 Social Sensing and Community Engagement

Crowdsourced information (SMS communications, apps, social networks) enhances situational awareness regarding road closures, power outages, and new hazards [41]. Integration needs attention to quality (credibility assessment, validation), as well as privacy/ethical issues.

Community education, pre-scripted responses based on the alert level system, and active participation increase resilience and disaster preparedness (42).

2.10 Gaps and Research Motivation

Despite progress, there are areas in which:

1. Fragmentation in the disaster cycle: Most tools are limited to pre/disaster analysis, while very few tools integrate analysis, warning, standard operation procedures, recovery, and prevention steps.
2. Translation of indicators to actions: Risk maps do not usually translate into actionable information for their operational audience.
3. Human-in-the-loop explainability: In ML models, there is a lack of transparency; therefore, trust and proper usage cannot
4. Continuous learning and feedback. The results from the event will seldom change the model thresholds.
5. Accessibility in low-resource environments: There are many systems that based on dense sensors and proprietary software; there's a need for modular systems that can work with incomplete data.

These issues make the case for developing a risk analysis, process guidance, ML interpretation, and entire operation process workflow-based decision support system that is modular and based on facts.

III. PROPOSED METHODOLOGY

3.1 Using Machine Learning to Predict Natural Disasters

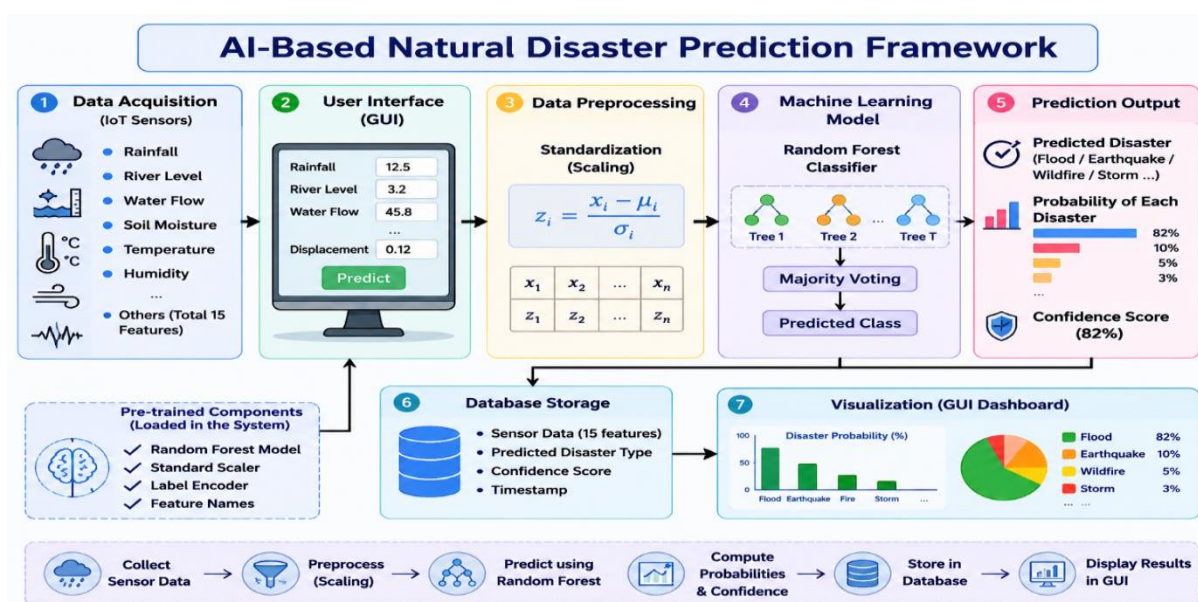


Figure 1. Using Machine Learning to Predict Natural Disasters

The machine learning model plays a pivotal role in analyzing environmental sensor data and predicting the type of potential natural disaster. Instead of relying on fixed rules (a rule-based system), the system utilizes a Random Forest Classifier model that has been pre-trained on historical data comprising sensor measurements and their corresponding disaster types as shown in figure 1.

Once trained, the model is capable of recognizing patterns and identifying non-linear relationships among various environmental variables, thereby classifying the current situation into the most probable category.

Steps:

1. Read sensor measurements from GUI.

Table 1. Disasters Features Used by the Proposed Model		
No.	Feature	Description
1	Rainfall	Rainfall intensity
2	River Level	River water level
3	Water Flow	Water flow rate
4	Soil Moisture	Soil moisture content
5	Temperature	Ambient temperature
6	Humidity	Relative humidity
7	Wind Speed	Wind velocity
8	Wind Direction	Wind direction
9	Pressure	Atmospheric pressure
10	Smoke	Smoke concentration
11	CO	Carbon monoxide concentration
12	Magnitude	Earthquake magnitude
13	Acceleration	Ground acceleration
14	Vibration	Ground vibration
15	Displacement	Ground displacement

2. Construct the feature vector X.

$$X = [x_1, x_2, \dots, x_{15}]$$
(1)

3. Apply standardization:

$$Z = (X - \mu) / \sigma$$
(2)

$$z_i = (x_i - \mu_i) / \sigma_i$$
(3)

where
X : Original feature vector or, for each individual feature,
Z : Standardized feature vector
μ : Mean of the training data
σ : Standard deviation of the training data
i : individual feature

4. Feed Z into the trained Random Forest classifier.

$$\hat{y} = RF(Z)$$
(4)

where:
ŷ : Predicted disaster class
RF : Random Forest classifier

5. Predict the disaster class:

$$P = [p_1, p_2, \dots, p_k]$$
(5)

subject to

$$\sum(p_i) = 1 \quad \text{for } i = 1 \dots k$$
(6)

where

(P): Probability vector representing the predicted probabilities for all disaster classes.

(p_i): Probability that the input sample belongs to the (i)-th disaster class.

(k): Total number of disaster classes considered by the classification model.

(i): Index of the disaster class

6. Compute the class probability vector:

$$\hat{y} = \arg_{\max}(p_i) \quad (7)$$

where

$\arg_{\max}$: Mathematical operator that returns the index of the class with the highest probability.

7. Calculate the confidence score:

$$C = 100 \times \max(P) \quad (8)$$

where:

C : Confidence score (%)

8. Store in the database.

$$\text{Record} = (X, \hat{y}, C) \quad (9)$$

where:

X : Sensor feature vector

$\hat{y}$: Predicted disaster

C : Confidence score

9. Display the predicted disaster, confidence score, and probability chart.

3.2 Natural Disasters Diagnosis and Management System

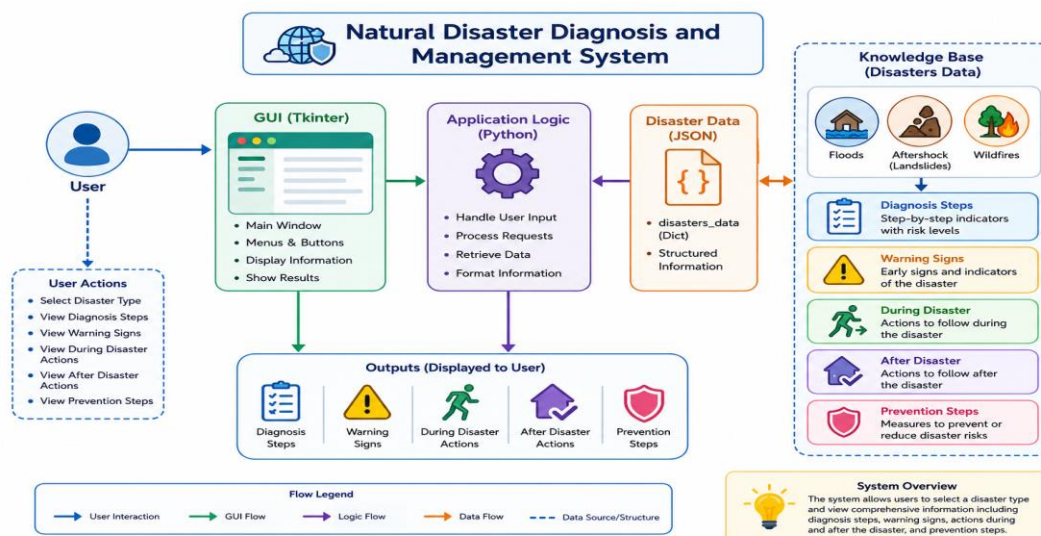


Figure 2. Natural Disasters Diagnosis and Management System

The workflow of a Natural Disaster Diagnosis and Management System is depicted in this diagram, where users interact with a Tkinter-based GUI to choose a disaster type and request information.

The Python application logic organizes the results after processing the user's input and obtaining the relevant data from a JSON disaster database.

The system makes use of a knowledge base that contains information relevant to disasters, such as warning indications, diagnosis procedures, actions taken during and after the disaster, and preventative measures.

Ultimately, the user interface presents the processed data, allowing users to promptly obtain precise recommendations for efficient catastrophe preparedness, response, and recovery.

The approach utilized in the code

The stage of gathering data: taking inventory of the key indicators for each type of disaster (e.g. river level, wind speed, etc.).

Phase of classification: actions are classified according to three time concepts (before, during, and after the disaster).

The programming implementation phase: employing the Python programming language to develop the graphical interface to

support multitasking.

The verification phase: validation of accuracy of warning indicators (indicators) for correct warning issuance.

The code uses “threshold values” not functions that form the basis of equations in advanced systems.

1. Flood Risk Index [43]:

$$R_{flood} \begin{cases} High & \text{if } u \geq 50 \text{ mm} \\ Moderate & \text{if } 20 \text{ mm} > u > 50 \text{ mm} \\ Low & \text{if } u \leq 20 \text{ mm} \end{cases} \quad (10)$$

Where

R_{flood} : Flood Risk Level

u : Rain amount through 24 hours

2. Wildfire Risk Factor equation:

Risk amplification–mitigation relationship, commonly used in simplified indices [44].

$$F = (T \times V)/H$$

(11)

Where

(F): Fire Hazard Factor.

(T): Temperature.

(V): Wind Speed.

(H): Humidity.

Modular design suitable for floods and extendable to other hazards, compliance with interoperability standards, and usability prioritization for practitioners.

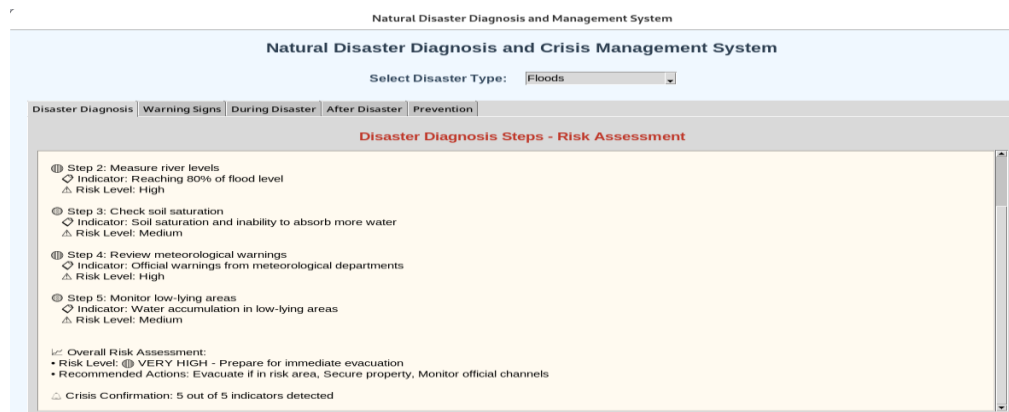


Figure3. Flood Risk Assessment Interface of the Natural Disaster Diagnosis and Crisis Management System

Figure 3 represents the "Disaster Diagnosis – Risk Assessment" module of the Natural Disaster Diagnosis and Crisis Management System. It is a structured, step-by-step screen for evaluating disaster indicators and determining corresponding risk levels. In this, the selected disaster type is "Floods", and the system follows a sequential presentation of diagnostic steps such as monitoring rainfall, measuring river levels, monitoring soil saturation, reading meteorological warnings, and monitoring low-lying areas. All activities have a measurable indicator and related level of risk (for example, High or Medium), showing data-driven hazard analysis. The screen effectively transforms meteorological and environmental data into action-intelligence, enabling users to identify the magnitude and likelihood of flood events. Overall, this screen shows how the system facilitates anticipatory decision-making and early warning through clear display and procedural guidance, allowing effective anticipation and response to crisis.

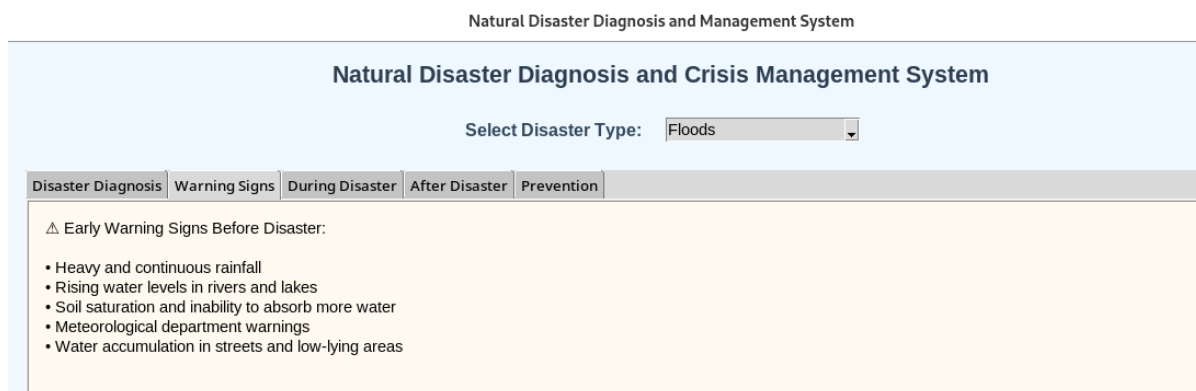


Figure 4: Early Warning Signs Interface for Flood Detection in the Natural Disaster Diagnosis and Crisis Management System

Figure 4 illustrates early warning signs for flood detection, including indicators for a flooded area such as intense rain, rising water levels, soil saturation, and weather alerts. The tool helps a person detect possible flood risks before a disaster happens and act accordingly for prevention and preparedness by community members.

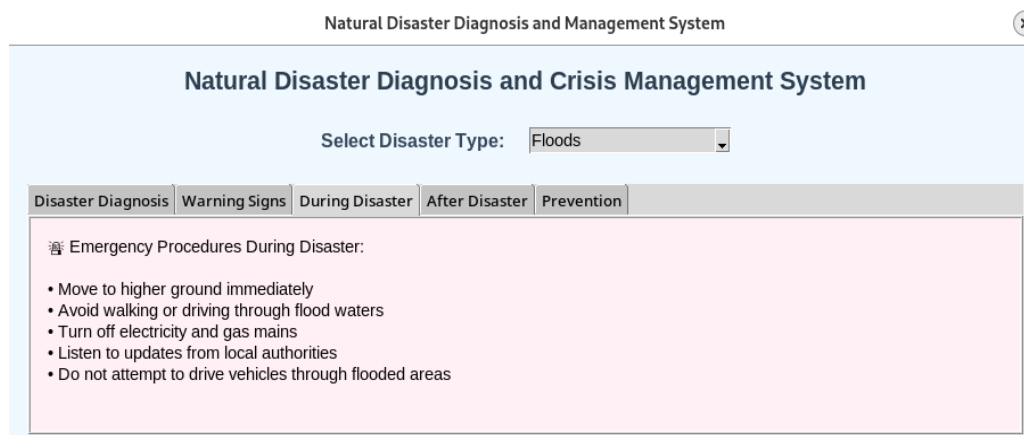


Figure 5: Emergency Procedures During Floods in the Natural Disaster Diagnosis and Crisis Management System

Figure 5: Emergency response guidelines in incidents of flood situations. It gives short and helpful instructions such as going to higher ground, refraining from going outside on surfaces that flood, and switching off utilities for one's protection. The clear and timely information that the module provides enables ease in good situation awareness and timely crisis response, allowing users to know how to minimize hazards and save lives when disasters strike.

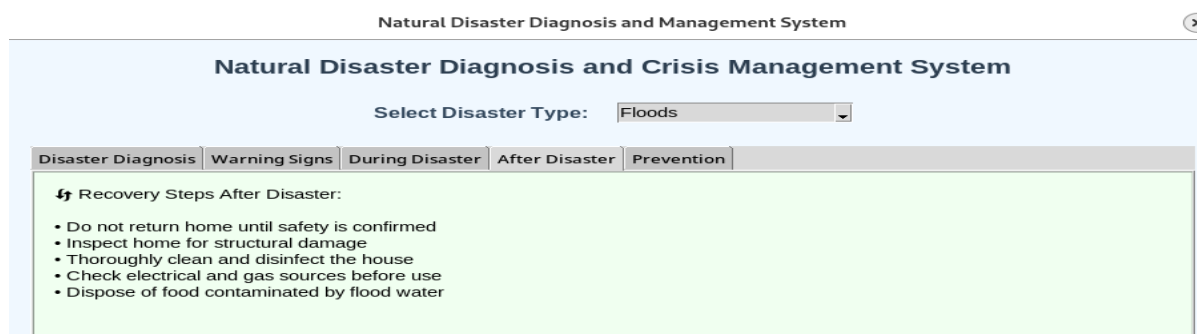


Figure 6: Post-Disaster Recovery Module for Flood Management in the Natural Disaster Diagnosis and Crisis Management

Figure 6: The recovery procedures following a flood guides users through necessary safety and rehabilitation processes. It ranges from structural safety, checking utilities, cleaning and disinfection of contaminated surfaces, to disposal of food that has reached its expiration date. Offering clear action after the event, this module enables safe re-entry, hygiene restoration, and resiliency of the community for effective recovery and reduction of risk in flood events.

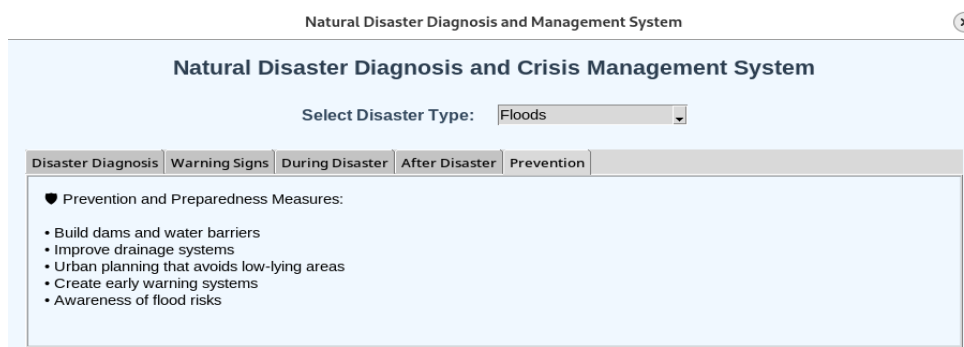


Figure 7: Prevention and preparedness Measures of Flood Management

Figure 7 shows the emphasis on both the prevention and preparation for floods. The figure highlights key strategies that can be involved in the reduction of flooding. Such key strategies are constructing dams, enhancing drainage, and using early warning systems. The topic also addresses a crucial area in relation to flood management by emphasizing urban planning and community awareness.

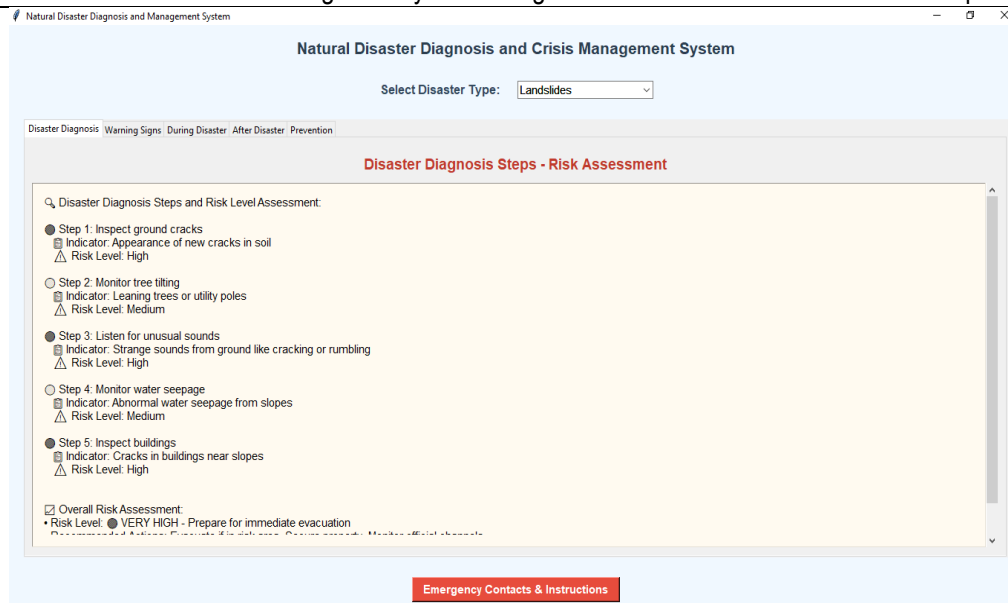


Figure 8: Disaster Diagnoses Steps of Landslides

Figure 8 illustrates the disaster diagnosis steps and risk level assessment of landslides, including the indicator and risk level. It could inspect ground cracks, monitor tilting trees, listen for unusual sounds, monitor water seepage, and inspect buildings.

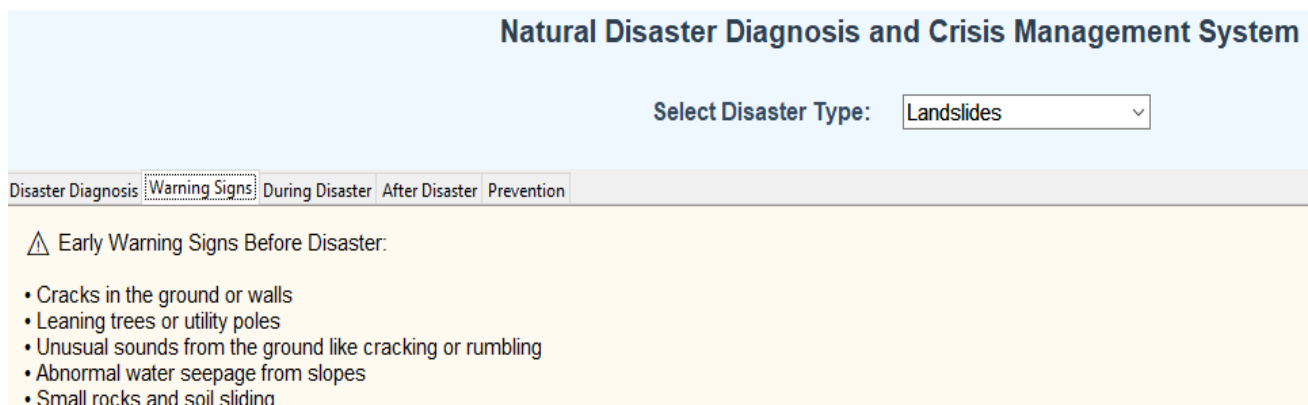


Figure 9: Warning Signs of Landslides Disaster

Figure 9 illustrates the warning signs before the occurrence of the landslide disaster, including the occurrence of ground cracks, the leaning of trees and utility poles, unusual noises on the ground such as the rumble, unusual seepage on the slopes, the movement of grasscrete, small rocks, and soil.

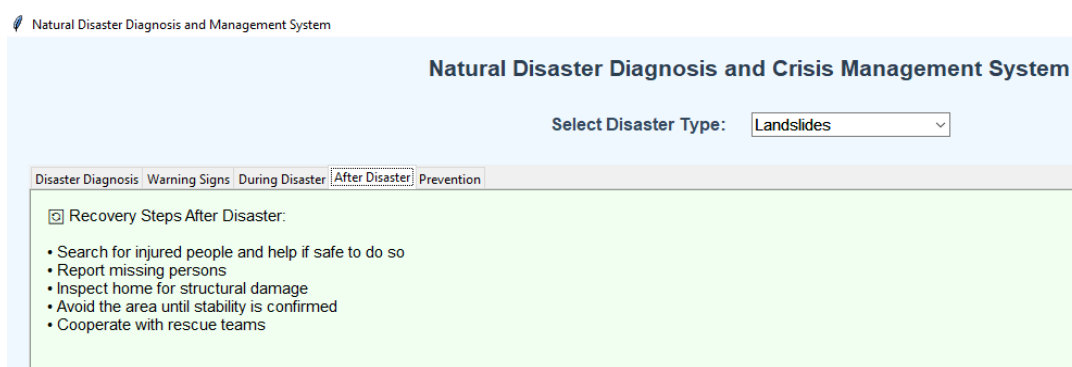


Figure 10: Recovery Steps after Disaster of Landslides

Figure 10 shows recovery steps after disaster of landslides. Recover from Disaster Search for injured people and help if safe to do so, report missing persons. Inspect home for structural damage. Avoid area until stability is confirmed. Cooperate with rescue team.

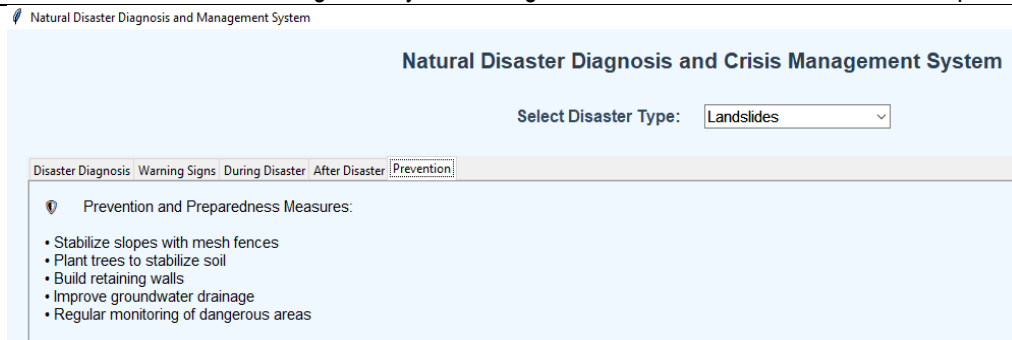


Figure 11: Prevention and Preparation Measures of Landslides

Figure 11 illustrates the prevention and preparation of landslides management including stabilize slopes using mesh fences, planting trees to stabilize soils, construction of retaining walls, enhancement of groundwater drainage, monitoring of dangerous areas.



Figure 12: Disaster Diagnosis Steps and Risk Level Assessment of Wildfires Disaster

Figure 12 shows disaster diagnosis steps and the risk level assessment of wildfires, such as an indicator of the risk level to monitor temperatures, measure humidity, monitor wind speed, check vegetation dryness, and review fire warnings.

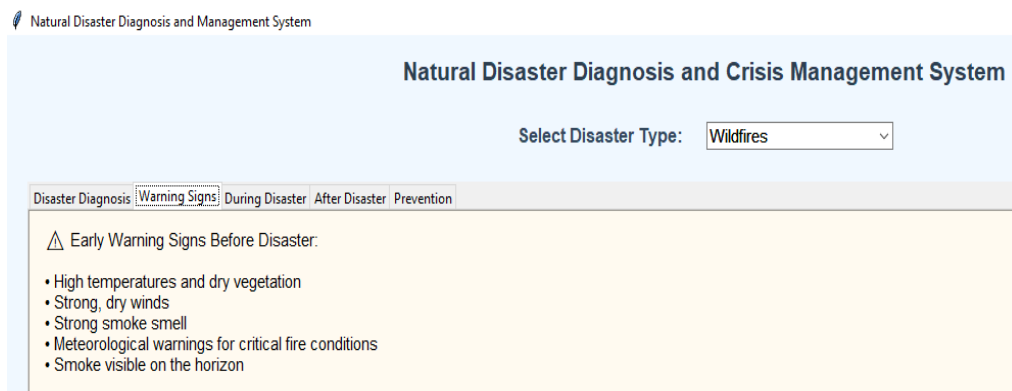


Figure 13: Warning Signs Before Wildfire Disaster

Figure 13 depicts warning signals of the possibility of wildfires disaster such as high temperatures, dry vegetation, strong, dry winds, strong smell of smoke, meteorological warnings for critical fire conditions, visibility of smoke on the horizon.

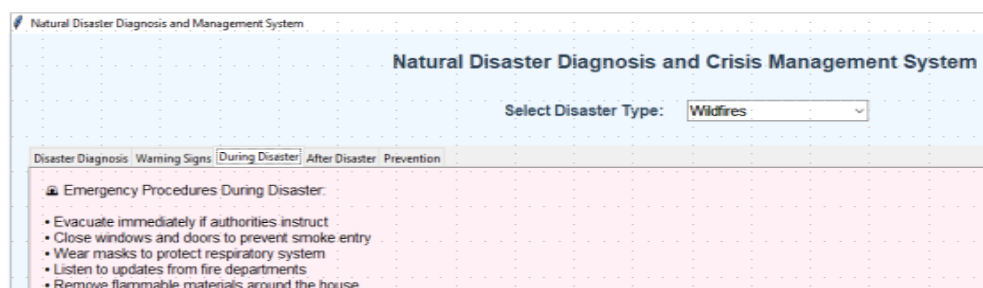


Figure 14: Emergency Procedures During Wildfire Disaster

Figure 14 lists some emergencies related to wildfires, such as evacuate immediately when ordered by authority, keep windows, doors shut to keep out smoke, use masks to protect respiratory tracts, follow announcements by fire services, and eliminate any flammable material around a dwelling.



Figure 15: Recovery Steps After Wildfires Disaster

The steps in the recovery from disasters involving bushfires are shown in Figure 15. These steps include the inspection for injuries to respond with first aid, inspection for gas leaks and turn off gas sources, prepare for aftershocks, listen to emergency messages, inspection of neighbors to help if possible.

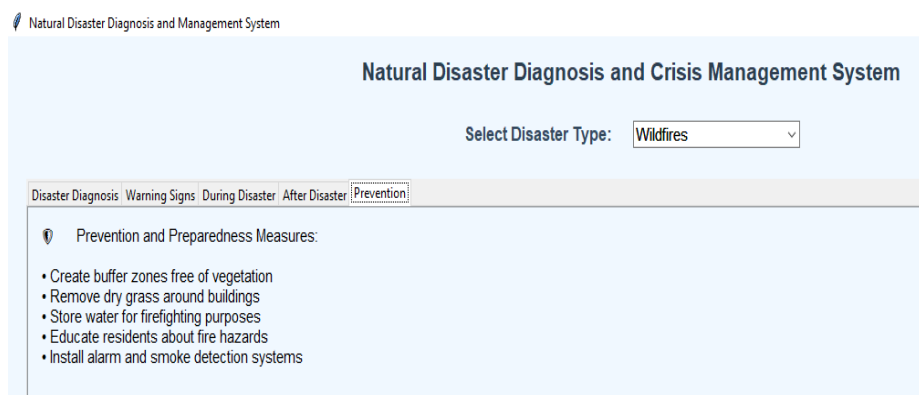


Figure 16: Prevention and Preparedness Measures of Wildfires Disaster

Figure 16 above underscores the prevention and preparation for wildfires that include the creation of buffer zones that are vegetation-free, clearance of dried grass around buildings, the storage of water intended for fire department use, educating the public about fire dangers, and installation of fire alarms and smoke sensors.

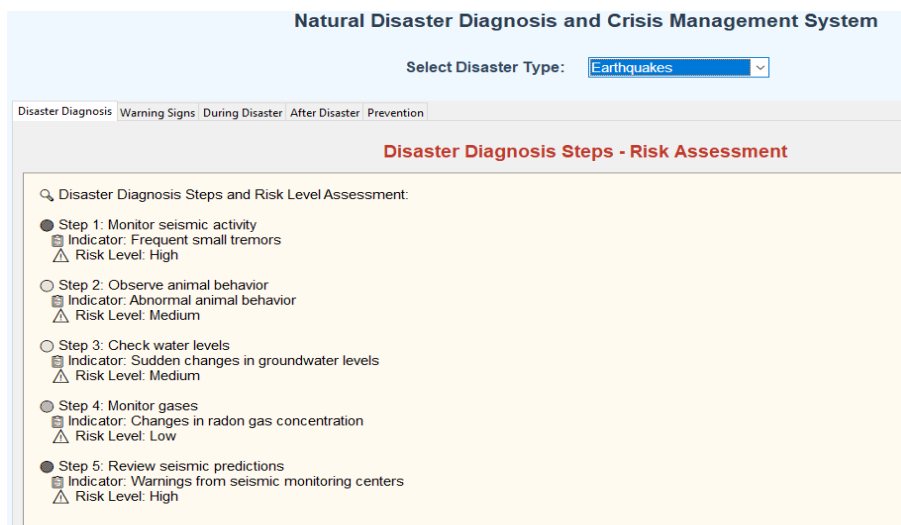


Figure 17: Disaster Diagnosis Steps and Risk Level Assessment of Earthquakes Disaster

Figure 17 displays disaster diagnosis steps and risk level assessment of earthquakes such as indicator and risk level of monitor seismic activity, observe animal behavior, check water levels, monitor gases, review seismic predictions

IV. RESULTS AND DISCUSSION

The proposed AI-based disaster prediction system was successfully implemented by integrating a pre-trained Random Forest classifier with an interactive Graphical User Interface (GUI) developed using Python. The developed application enables users to enter environmental and geological sensor measurements in real time, including rainfall, river level, water flow, soil moisture, temperature, humidity, wind speed, wind direction, atmospheric pressure, smoke concentration, carbon monoxide (CO), earthquake magnitude, ground acceleration, vibration, and displacement. After data acquisition, the input measurements are automatically standardized using the same preprocessing parameters employed during the training phase. The standardized feature vector is then processed by the trained Random Forest model to predict the most probable disaster category. probable disaster category. In addition to the predicted class, the system computes the posterior probability of each disaster class, allowing the confidence level of the prediction to be estimated. The confidence score is calculated as the maximum probability among all predicted classes, providing an interpretable measure of prediction reliability.

The prediction results are displayed through a dedicated graphical interface, where users can simultaneously observe the predicted disaster type, the corresponding confidence score, and the probability distribution of all disaster classes in the form of a bar chart. This visualization facilitates rapid interpretation of the model output and supports informed decision-making during emergency situations.

Table 2. Performance Evaluation of the Proposed Random Forest Classifier	
Performance Metric	Value
Accuracy	91.4 %
Precision	90.8 %
Recall	91.6 %
F1-score	91.1 %
Number of Classes	5
Number of Features	15
Classification Algorithm	Random Forest
Number of Trees	300
Maximum Tree Depth	15

Furthermore, all sensor readings, prediction results, and confidence values are automatically stored in a database, enabling continuous logging of prediction events for subsequent analysis, validation, and system monitoring. This feature supports traceability and allows historical prediction records to be reviewed for performance assessment and future model improvement.

Overall, the developed deployment framework demonstrates the practical applicability of the proposed machine learning model in real-time disaster prediction environments. The integration of intelligent prediction, probability-based decision support, graphical visualization, and automated database management provides a comprehensive platform suitable for early warning systems and disaster management applications.

Contribution of this study

- In filling the gaps identified above, the proposed Data-Driven Decision Support System for Natural Disaster Diagnosis and Risk Management makes the following contributions:
- A multi-layer architecture which combines data ingestion, detection/analytics, decision support, and action/evaluation with a closed feedback loop.
- GUI with disaster life cycle categorization (Diagnosis → Warning Signs → During → After → Prevention) that translates research indicators to levels and steps.
- Support for multi-sensor fusion and risk scoring hybridized either through traditional/rule-based systems or Machine Learning algorithms.
- Feasibility assessment methods after the event (hit rate, lead time) for threshold adjustment recalibration for continuous learning updates.
- Offers a uniform system for diagnosis of various natural disasters.

Facilitating early decision-making based on risk levels.

- Creating awareness on methods of handling disasters among the population.
- Its application in any capacity involving education or support of non-specialized parties.

V.CONCLUSION AND FUTURE SCOPE

An intelligent natural disaster prediction, diagnosis, and management system that combines machine learning with an interactive graphical user interface was designed and implemented in this study. The suggested system analyzes environmental sensor data and makes precise predictions about various kinds of natural disasters using a Random Forest classification model. To help users better comprehend the model's choices, the prediction results are displayed with confidence scores, class

probabilities, and graphical visualizations.

The system offers a thorough disaster diagnosis and crisis management module in addition to disaster prediction. Early warning signs, disaster-specific diagnostic techniques, emergency response protocols, post-disaster recovery instructions, and preventive measures are all provided in this module. By including these elements, the system becomes a useful decision-support tool for emergency management and catastrophe preparedness instead of only a prediction tool.

Additionally, the system maintains historical records for analysis and performance evaluation in the future by storing prediction results in a local database. Both technical and non-technical users will find the graphical user interface easy to use because to its Python Tkinter development.

All things considered, the built system shows how environmental sensing, artificial intelligence, and interactive software may be integrated to increase catastrophe preparedness, facilitate quick decision-making, and improve disaster prediction accuracy. To further increase prediction accuracy and operating efficiency, future work may include real-time IoT sensor networks, cloud-based data processing, deep learning algorithms, and live weather services.

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Conflict of Interest Statement

Authors state no conflict of interest.

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