

REAL-TIME DISASTER PREDICTION & ALERT SYSTEM

INNOVATION LAB PROJECT

(PH49201)

GROUP-11

UNDER THE SUPERVISION OF

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INTRODUCTION:

Natural disasters, including cyclones, floods, and heat waves, constantly threaten life and infrastructure. Accurate and timely predictions are essential for minimizing damage and ensuring preparedness. This project introduces a real-time, AI-driven disaster prediction and alert system that combines historical weather data, machine learning, and IoT sensors to monitor environmental conditions and foresee potential disasters.

An IoT-based Cyclone Prediction System is a project that uses sensors, cloud computing, and machine learning to predict cyclones and provide early warnings. This system collects real-time environmental data (temperature, humidity, pressure, wind speed, etc.), processes it using an algorithm (machine learning or threshold-based analysis), and alerts if cyclone conditions are detected.

MOTIVATION:

India, with its diverse geography and climate, is highly vulnerable to natural disasters such as cyclones, floods, and heat waves. These events not only disrupt daily life but also lead to severe economic and human losses. Despite advancements in weather forecasting, there exists a significant gap in localized, real-time disaster detection and alerting systems, especially in smaller towns and rural areas.

This project was motivated by the need to bridge that gap through an affordable, scalable, and intelligent solution. By leveraging historical weather patterns, real-time environmental sensing, and machine learning, we aim to create a system that can predict potential disasters before they escalate. The use of IoT further enables on-the-ground monitoring and instant alerting, making the solution practical for deployment in vulnerable areas.

Our goal is to empower communities and authorities with early warnings, enabling faster response times and potentially saving lives. In an era where climate extremes are becoming increasingly common, such proactive disaster management tools are not just valuable — they are essential.

SYSTEM ARCHITECTURE:

1. DHT22 SENSOR:

Measures and sends Temperature and Humidity readings every 5 seconds to the ESP32 microcontroller.

2. BMP180 SENSOR:

Measures Atmospheric Pressure, sending a reading to the microcontroller every 5 seconds.

3. BUZZER :

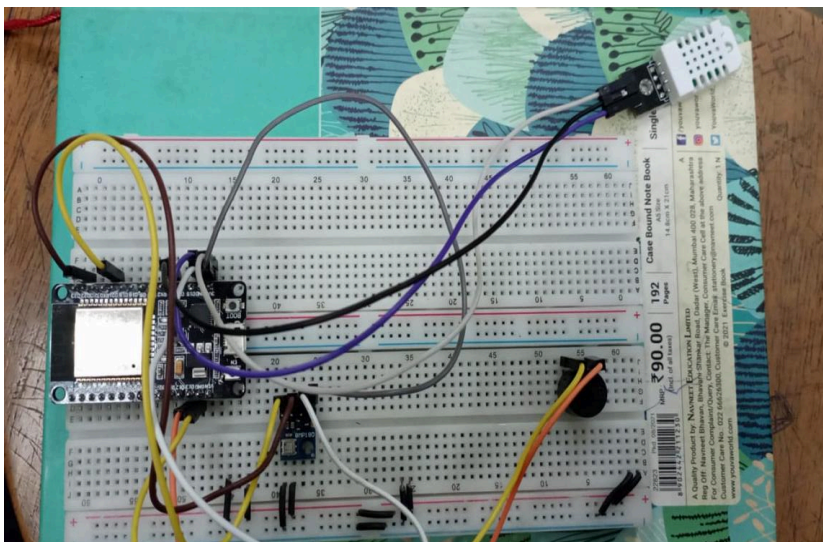
If the Temperature and Pressure values cross a certain threshold, a local alert is issued as the buzzer buzzes.

4. MODEL:

A Random Forest classifier trained on labeled disaster data.

5. IOT DEPLOYMENT:

An ESP32-based device integrated with sensors and connected to a Blynk dashboard for real-time alerts and monitoring.



DATA PIPELINE:

The foundational component in this project is the creation of this data pipeline, where historical data is processed to be fed into the model to train it.

Extraction:

The historical weather data of the Kharagpur region was acquired from the Open-Meteo API and NASA POWER platform, covering the years 2014 to 2024. These APIs provided hourly resolution data on temperature, humidity, pressure, wind speed, and rainfall for Kharagpur. The Disaster Labels of Cyclone, flood, and heatwave events were annotated using records from the Indian Meteorological Department (IMD) and verified through news sources such as Hindustan Times and Times of India.

Handling & Cleaning:

Data Merging:

Combined weather features (temperature, humidity, pressure, rainfall, wind speed) across different APIs and labeled with corresponding disaster events. Datasets from various APIs were joined based on datetime fields. Invalid or malformed datetime entries were identified (e.g., 43,834 rows without valid datetime values) and removed to ensure temporal alignment.

Missing Data Handling:

Removed all rows with missing or malformed datetime entries. Inspected and removed rows with incomplete weather. `Kharagpur_weather_with_additional_disasters.csv` was curated with cleaned and labeled data, ready for training.

- Explored but rejected interpolation techniques due to the high sensitivity of disaster prediction; interpolated data might smooth over critical changes.
- Opted to drop rows with essential missing features (e.g., temperature, pressure) during training.
- For real-time sensor input, fallback values (e.g., -1) were assigned when sensors failed, preserving pipeline stability.

MODEL BUILDING:

A Random Forest classifier was trained on labeled disaster data. Random Forest was selected due to its robustness with high-dimensional, noisy, and non-linear datasets typical of meteorological readings. It creates multiple decision trees and combines their outputs for improved prediction accuracy.

How does it work in This Project?

Training Phase (Model Building)

1. Historical weather data (Temperature, Humidity, Pressure, windfall, rainfall) is used as training data.
2. The model learns patterns of past disasters with the help of labelled data of Output Labels: Disaster types such as Cyclone Amphan, Cyclone Dana, Flood, and Heatwave.

Prediction Phase (Real-time Data)

1. Live sensor data from IoT devices is fed into the trained Random Forest model.
2. The model classifies whether the conditions indicate a disastrous condition.

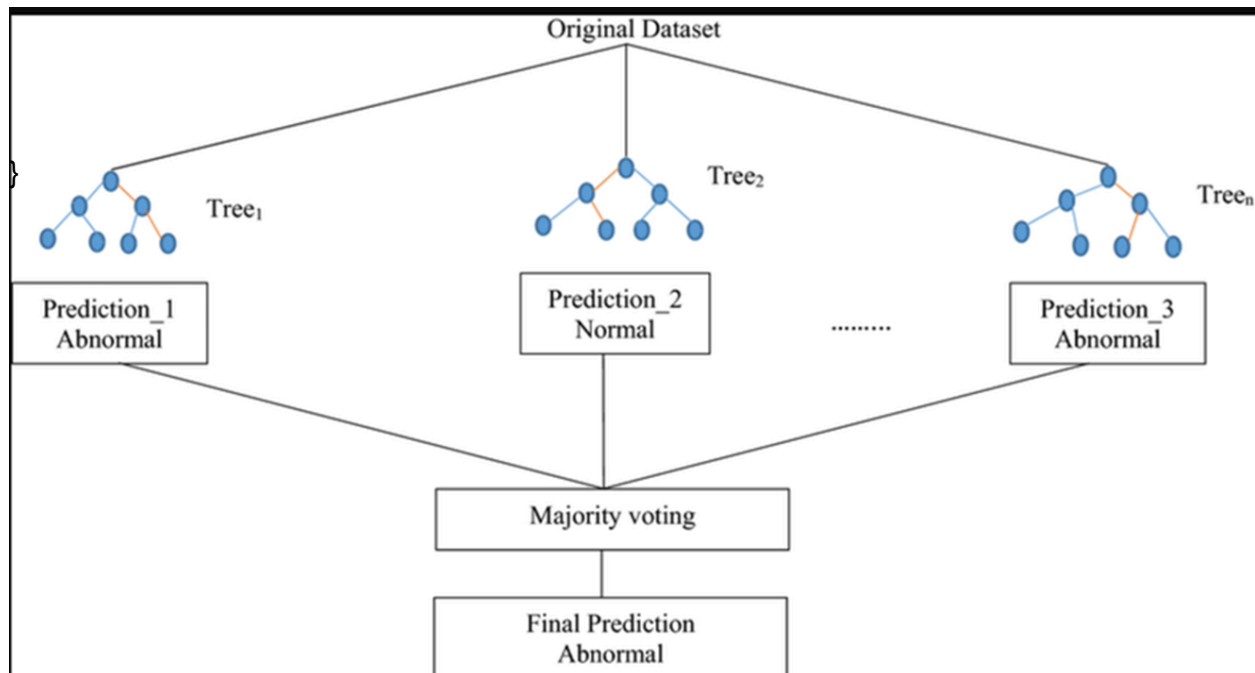
Alert Mechanism

1. If the model predicts a disaster cyclone, an **SMS or Email Alert** is sent to authorities and user, and the buzzer goes off locally.

Advantages :

- Handles both numerical and categorical data well.
- Reduces the risk of overfitting compared to a single decision tree.
- Provides feature importance metrics for interpretability.

MODEL ARCHITECTURE :



TRAINING :

```
: import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.ensemble import RandomForestClassifier
import pickle
df = pd.read_csv("kharagpur_weather_cleaned.csv", parse_dates=["datetime"])
# Select features and target
features = ["temperature", "humidity", "pressure", "rainfall", "wind_speed"]
target = "additional_disaster_event"
df = df.dropna(subset=features + [target])
# Encode target labels
le = LabelEncoder()
df[target] = le.fit_transform(df[target])
# Split into training and testing
X = df[features]
y = df[target]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Train the model
clf = RandomForestClassifier(n_estimators=200, random_state=42)
clf.fit(X_train, y_train)
# Save the model and Label encoder
with open("disaster_model.pkl", "wb") as f:
    pickle.dump(clf, f)
with open("label_encoder.pkl", "wb") as f:
    pickle.dump(le, f)
print("✅ Model trained and saved as 'disaster_model.pkl'")
```

WORKING :

1. Data is read every 5 seconds, and sensor anomalies are flagged by substituting -1 when readings fail.

```
if (isDisaster && temp != -1 && pressure != -1) {  
    digitalWrite(BUZZER_PIN, HIGH);  
    delay(500);  
    digitalWrite(BUZZER_PIN, LOW);  
}
```

2. The data is uploaded to the Blynk dashboard via virtual pins:


```
Blynk.virtualWrite(V1, temp);  
Blynk.virtualWrite(V2, humidity);  
Blynk.virtualWrite(V3, pressure);  
Blynk.virtualWrite(V4, isDisaster ? 1 : 0);
```

3. These readings are passed to the trained Random Forest model. These readings are passed to the trained Random Forest model.

Dashboard Visualization

The Blynk dashboard offers real-time visibility:

- **V1:** Displays live temperature.
- **V2:** Displays humidity.
- **V3:** Shows atmospheric pressure.
- **V4:** Indicates disaster alert status (1 = alert, 0 = safe).



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Edit

Live

1h

6h

1d

1w

1mo

3mo

6mo

1y

🔍

Pressure

1,007.93 hPa

Temperature

32.4 °C


050

Humidity

66.8 %

0100


Alarm and Sound



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Messages used: 4k of 30k





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Edit

Live

1h

6h

1d

1w

1mo

3mo

6mo

1y

🔍

Pressure

900 hPa

Temperature

28.5 °C


050

Humidity

57.8 %

0100

Alarm and Sound

Sound permission req. 

SENSOR DATA

1	day	time	temp	pressure	humidity
2	#####	0:00	25	1007.8	74
3	#####	0:15	25	1008.11	69.3
4	#####	0:30	25	1007.69	71.3
5	#####	0:45	25	1008.44	72.2
6	#####	1:00	25	1008.13	72.5
7	#####	1:15	25	1007.99	74.7
8	#####	1:30	25	1008	72.5
9	#####	1:45	25	1008.6	75.3
10	#####	2:00	25	1007.74	73.3
11	#####	2:15	25	1007.99	73.1
12	#####	2:30	25	1008.22	80
13	#####	2:45	25	1007.81	77.5
14	#####	3:00	25	1008.31	78.4
15	#####	3:15	25	1007.45	78.6
16	#####	3:30	25	1008.73	79
17	#####	3:45	25	1008.19	76.1
18	#####	4:00	25.6	1007.7	78.6
19	#####	4:15	25.4	1008.78	76.8
20	#####	4:30	25	1008.17	79.4
21	#####	4:45	25.7	1007.63	80
22	#####	5:00	25.9	1008.1	80
23	#####	5:15	26.6	1008.56	76.3
24	#####	5:30	26.6	1008.27	80
25	#####	5:45	26.6	1007.76	80
26	#####	6:00	27.1	1008	76.7
27	#####	6:15	28.3	1007.81	80
28	#####	6:30	27.7	1008.1	78.5
29	#####	6:45	28.4	1007.59	79.2
30	#####	7:00	28.6	1007.48	79.3

RESULTS:


The disaster prediction model achieved high accuracy (97%) across cyclone, flood, and heatwave categories. Testing on known disaster periods validated its predictive capability. The cleaned dataset ensured data integrity, and the system's fallback mechanisms made it resilient to real-time sensor issues. These outcomes indicate that the system is both accurate and robust in its mission.

This project successfully demonstrates a scalable real-time disaster detection system that integrates AI and IoT. By harnessing machine learning for classification and an ESP32-based network of sensors for real-time data collection, the system provides reliable predictions and timely alerts. The use of fallback strategies ensures robustness in sensor-dependent environments.

FUTURE ENHANCEMENTS

1. The system is ready for future enhancements such as:
 - Cloud-based model deployment
 - Automated alert delivery via SMS or email
2. Adding sensors for rainfall and wind speed will complete the real-time detection suite.
3. Expanding the training dataset to include decades of weather data across multiple regions (from city-level to state and national scales) will enhance the model's robustness and disaster prediction accuracy.
4. The final goal is to build a comprehensive software application that:
 - Visualizes live and historical weather data
 - Issues real-time alerts
 - Provides safety instructions for disaster-prone areas
 - Supports decision-making for authorities and communities

REFERENCES:

- [Open-Meteo Historical Weather API](#)
- [NASA POWER Climate Data](#)
- [IMD Cyclone Archive](#)
- [Hindustan Times - Cyclone News](#)
- [Times of India - Disaster Reports](#)
-  [sensor data.pdf](#)