Intelligent Context-Aware IoT Weather Forecasting and Emergency Alert System

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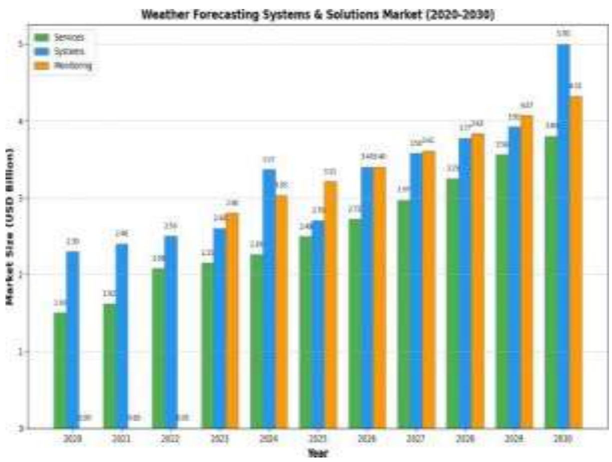
Abstract—

In today's era, the climate patterns have become unpredictable and easily variable as climate change is becoming a growing concern recently, it has become necessary to be prepared about the adverse effects of changing weather not only for our essential activities like agriculture etc. But also for disaster management as well. Forecasting of such changing patterns are always a better option to follow but traditional forecasting systems often comes with limitations like limited localization, inaccurate sensor readings and lack of dynamic alert systems. This paper presents an Intelligent Context-Aware IoT Weather Forecasting and Emergency Alert System that uses IoT supported weather monitoring, ensembled Machine learning, adaptive sensor calibration and dynamic alert severity system. The proposed system uses IoT framework to collect localized real time environmental data and enhances data reliability through filtering techniques. An ensemble ML framework combining Random forest, XGBoost, and Gradient Boosting models is used to improve prediction accuracy. In addition, a context aware alert mechanism dynamically varies warning severity based on Risk levels and estimated population exposure density. The system is implemented using ESP32, LoRa, and a Flutter based mobile application for real time access and monitoring with intelligent notifications. Experimental results demonstrate improved forecasting performance and more effective emergency alert prioritization compared to traditional single-model weather monitoring systems.

Keywords— Internet of Things (IoT); Weather Forecasting; Ensemble Machine Learning; LoRa communication; Context Aware Alert System; Real time monitoring

I. INTRODUCTION

In recent years, climate change and rapid environmental variations have significantly increased the unpredictability of weather conditions across the world. Sudden changes in temperature, rainfall intensity, humidity, and wind speed have affected several critical sectors including agriculture, transportation, public safety, and disaster management [1]. Accurate and real-time weather forecasting has therefore become increasingly important for enabling early precautionary measures, minimizing economic losses, and ensuring public safety during extreme environmental events [2]. Traditional weather forecasting systems generally rely on centralized weather stations and satellite-based observations, which often fail to provide accurate localized predictions due to limited spatial coverage and delayed data updates [3]. With the advancement of the Internet of Things (IoT), real-time environmental monitoring has become more accessible and cost-effective. IoT-based weather monitoring systems use multiple sensors and wireless communication technologies to collect localized environmental data such as temperature, humidity, atmospheric pressure, and rainfall in real time [4]. Technologies such as ESP32 and LoRa have further improved long-range communication and low-power environmental sensing, making such systems suitable for both urban and remote deployments [5]. However, many existing IoT weather monitoring systems primarily focus on data collection and basic forecasting while lacking intelligent decision-making capabilities and adaptive emergency response mechanisms [6].



Machine learning techniques have recently gained significant attention in weather forecasting due to their ability to analyze complex environmental patterns and improve prediction accuracy [7]. Several studies have implemented models such as Decision Trees, Random Forests, and Artificial Neural Networks for weather prediction tasks [8]. Nevertheless, many existing approaches rely on a single machine learning model, which may not effectively capture different characteristics of weather data and can result in reduced forecasting performance under dynamic environmental conditions [9]. In addition, low-cost environmental sensors commonly used in IoT systems often produce noisy or fluctuating readings, which negatively impact forecasting reliability [10].

Another major limitation of existing weather monitoring applications is the lack of context-aware emergency alert systems. Most traditional systems generate uniform notifications regardless of the environmental severity or the estimated number of people exposed to the affected area [11]. As a result, users often ignore general notifications until environmental conditions become highly dangerous. Developing an intelligent alert mechanism capable of dynamically prioritizing warning severity based on environmental risks and population exposure can significantly improve emergency response efficiency and public awareness during critical situations [12].

To address these limitations, this paper proposes an Intelligent Context-Aware IoT Weather Forecasting and Emergency Alert System that integrates IoT-based environmental sensing, adaptive sensor calibration, ensemble machine learning, and dynamic alert severity classification within a unified mobile platform. The proposed system collects localized real-time weather data using multiple environmental sensors and improves data reliability through lightweight filtering techniques. An ensemble learning framework combining Random Forest, XGBoost, and Gradient Boosting models is employed to enhance weather prediction accuracy. Furthermore, the system introduces a context-aware emergency alert mechanism that dynamically adjusts warning severity based on environmental risk levels and estimated population exposure density. The proposed solution is implemented using ESP32, LoRa communication, FastAPI, and Flutter-based mobile application to provide real-time monitoring, predictive analytics, and intelligent emergency notifications.

II. LITERATURE REVIEW

The increasing impact of climate change and environmental instability has accelerated research in the field of weather monitoring and forecasting systems. Traditional forecasting methods mainly depend on centralized meteorological stations, satellite observations, and numerical weather prediction models to estimate environmental conditions [1]. Although these systems provide large-scale forecasting capabilities, they often fail to deliver highly localized and real-time predictions due to limited regional coverage and delayed data processing [2]. As a result, researchers have increasingly explored the integration of Internet of Things (IoT) technologies and machine learning techniques to improve forecasting accuracy, accessibility, and responsiveness.

Several studies have proposed IoT-based weather monitoring systems using low-cost sensors and wireless communication technologies. Girija et al.
[3] developed an IoT-based environmental monitoring system capable of collecting temperature and humidity data through ESP8266 modules and cloud integration. Similarly, Kamble et al. [4] proposed a weather monitoring framework using multiple sensors for measuring rainfall, temperature, humidity, and wind speed. These systems demonstrated the feasibility of real-time environmental sensing; however, most of them focused primarily on data acquisition and lacked intelligent forecasting or adaptive emergency response capabilities. In addition, many existing systems rely on Wi-Fi or cloud-dependent communication infrastructures, limiting their usability in remote or low-connectivity regions.

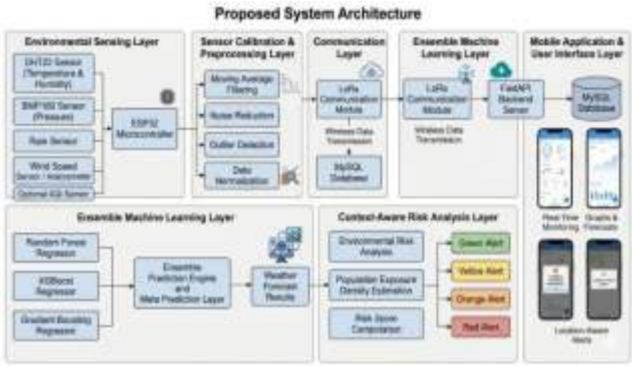
Recent advancements in LoRa communication and ESP32-based architectures have significantly improved long-range and low-power environmental monitoring systems [5]. Researchers have highlighted the advantages of LoRa technology in supporting reliable data transmission across large geographic areas while minimizing energy consumption [6]. Despite these improvements, several studies still report limitations regarding sensor reliability and measurement accuracy. Low-cost environmental sensors often produce noisy and fluctuating readings due to environmental interference, hardware instability, and calibration inconsistencies [7]. To overcome these challenges, lightweight filtering and calibration techniques such as Moving Average Filtering and Kalman Filtering have been introduced to improve data quality and system reliability [8].

Machine learning has also become a widely adopted approach in weather forecasting research due to its capability of learning complex environmental patterns from historical data. Various supervised learning models including Decision Trees, Random Forests, Support Vector Machines, and Artificial Neural Networks have been applied to predict temperature, rainfall, humidity, and other weather-related parameters [9]. Verma et al. [10] implemented machine learning algorithms for real-time weather prediction and demonstrated improved forecasting performance compared to conventional statistical methods. Similarly, Fowdur and Nazir [11] explored collaborative machine learning techniques for weather forecasting using data from multiple sensor locations. While these studies achieved moderate prediction accuracy, many of them relied on a single forecasting model, which may not effectively capture the nonlinear 6 and dynamic nature of weather data.

To address the limitations of single-model forecasting approaches, ensemble machine learning techniques have recently gained significant attention. Ensemble methods combine predictions from multiple models to improve forecasting robustness and reduce prediction errors [12]. Studies involving Random Forest and Gradient Boosting algorithms have demonstrated improved performance in environmental prediction tasks due to their ability to handle nonlinear relationships and noisy datasets [13]. XG Boost has also been recognized for its efficiency and predictive accuracy in structured environmental datasets [14]. However, the integration of ensemble learning within real-time IoT weather forecasting systems remains relatively limited, especially in low-cost localized deployments.

Another important research area involves emergency alert systems and intelligent notification mechanisms. Existing weather applications generally generate uniform notifications without considering contextual factors such as environmental severity, user exposure, or population density [15]. This often leads to notification fatigue, where users ignore repeated warnings due to lack of prioritization. Researchers have proposed context-aware systems in smart city applications to improve emergency response and public awareness [16]. However, the application of context-aware alert severity classification within IoT-based weather forecasting systems remains insufficiently explored. Most existing works focus only on prediction accuracy rather than adaptive decision-making and emergency prioritization.

Theoretical and methodological approaches in existing literature primarily revolve around IoT-enabled sensing frameworks, supervised machine learning models, cloud-based architectures, and wireless communication systems [17]. Most studies adopt regression-based forecasting techniques using historical environmental datasets, while others emphasize real-time monitoring through distributed sensor networks [18]. Although previous research has successfully demonstrated the feasibility of smart weather monitoring systems, significant research gaps remain in integrating adaptive sensor calibration, ensemble forecasting, and context-aware emergency intelligence within a single unified framework.



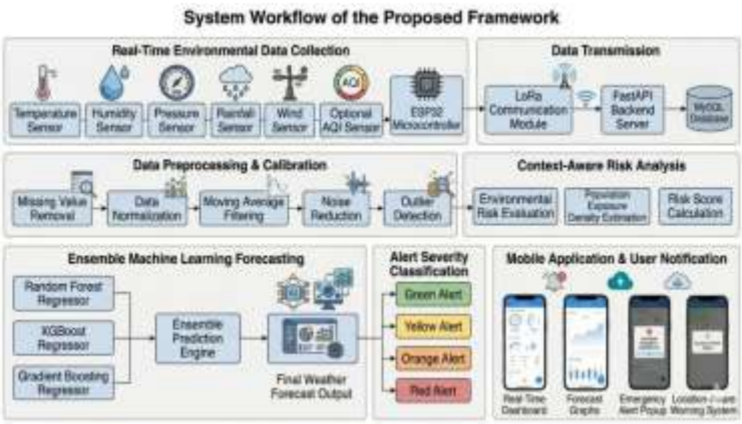
This research builds upon existing IoT weather forecasting studies by introducing an Intelligent Context-Aware IoT Weather Forecasting and Emergency Alert System that combines real-time environmental sensing, adaptive sensor filtering, ensemble machine learning, and dynamic emergency alert prioritization. Unlike conventional systems that rely on single-model forecasting and static notifications, the proposed approach focuses on improving prediction reliability and enhancing emergency responsiveness through intelligent risk-aware alert classification. Therefore, this work contributes toward the development of scalable, low-cost, and intelligent weather monitoring solutions suitable for smart city infrastructure, disaster management, and public safety applications.

III. METHODOLOGY

The proposed Intelligent Context-Aware IoT Weather Forecasting and Emergency Alert System integrates IoT-based environmental sensing, ensemble machine learning, adaptive sensor calibration, and intelligent emergency alert classification to provide accurate localized weather forecasting and dynamic risk-aware notifications. The overall workflow of the proposed system consists of multiple stages including data collection, data preprocessing, sensor calibration, model training, context-aware risk analysis, backend communication, and mobile application visualization. Population exposure density was estimated using predefined regional density categories classified as low, medium, and high-risk zones based on environmental event concentration and simulated mobile-device presence density.

The methodology of the proposed system is divided into the following steps:

- **Data Collection**
- **Data Preprocessing and Sensor Calibration**
- **Ensemble Model Training**
- **Context-Aware Emergency Alert Classification**
- **Backend and Communication System**
- **Mobile Application Visualization**



The detailed explanation of each step is discussed below.

3.1 Data Collection

The proposed system collects localized environmental data in real time, sensing node was implemented using Arduino Uno integrated with environmental sensors, while the receiver and backend communication node utilized ESP32 for wireless communication and server interaction. The collected environmental parameters include:

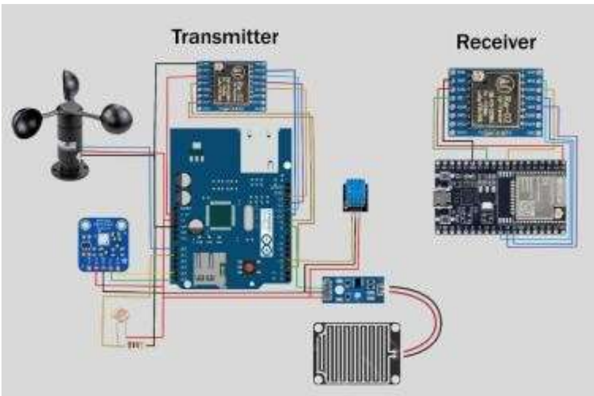
- Temperature
- Humidity
- Atmospheric Pressure
- Rainfall Intensity
- Wind Speed

The sensing system utilizes:

- DHT22 sensor for temperature and humidity measurement,
- BMP180 sensor for atmospheric pressure,
- Rain sensor module for rainfall detection,
- Anemometer for wind speed monitoring.

In addition to real-time sensing, historical weather datasets were collected from publicly available weather repositories to improve forecasting performance. The historical dataset contains weather records from 2000 to 2024 including temperature, humidity, rainfall, pressure, and wind speed observations.

The collected sensor data is transmitted using LoRa communication modules to ensure long-range and low-power wireless communication suitable for both urban and remote environmental monitoring applications.



3.2 Data Preprocessing and Sensor Calibration

Before training the machine learning models, several preprocessing techniques were applied to improve dataset quality and reliability.

3.2.1 Removing Null and Incomplete Data

The collected datasets contained missing and incomplete records due to environmental fluctuations and communication interruptions. Such records were removed to maintain dataset consistency and improve model performance.

3.2.2 Feature Selection

Only relevant environmental parameters were selected for forecasting and risk analysis. The selected features include:

- temperature
- humidity
- rainfall
- atmospheric pressure
- wind speed

3.2.3 Data Formatting and Normalization

Date and time values collected from multiple sources were converted into a uniform format to maintain consistency across datasets. Numerical normalization techniques were applied to scale environmental parameters within similar ranges before training.

3.2.4 Adaptive Sensor Calibration

Low-cost environmental sensors often produce noisy and fluctuating readings. To improve sensor reliability, a lightweight Moving Average Filtering mechanism was implemented for adaptive sensor calibration.

The filtering equation is given below:

$$S_t = \frac{1}{n}\sum_{i=1}^{n} x_i$$

where:

- S_t represents the smoothed sensor value,
- x_i represents individual sensor readings,
- n represents the number of observations.

This calibration process reduces abnormal fluctuations and improves forecasting consistency.

3.3 Ensemble Model Training

The proposed system employs an ensemble machine learning framework to improve forecasting accuracy compared to traditional single-model approaches. All environmental parameters were normalized before risk score computation to maintain uniform contribution scaling.

Three supervised machine learning models were selected:

- Random Forest Regressor
- XG Boost Regressor
- Gradient Boosting Regressor

Each model was trained independently using historical and real-time weather data. The final weather prediction was generated using weighted averaging of outputs from all three models.

The ensemble prediction equation is expressed as:

$$P_f = \frac{P_1 + P_2 + P_3}{3}$$

where:

- P_f represents the final predicted output,
- P_1, P_2, and P_3 represent predictions from the individual models.

The dataset was divided into:

- 80% training data
- 20% testing data

The models were evaluated using:

- Mean Absolute Error (MAE)
- Mean Squared Error (MSE)
- Root Mean Square Error (RMSE)
- R^2 Score

The machine learning implementation was carried out using Python programming language with Scikit-learn and XG Boost libraries in the Google Colab environment.

3.4 Context-Aware Emergency Alert System

One of the major contributions of this research is the implementation of a context-aware emergency alert mechanism that dynamically prioritizes warning severity based on environmental risk levels and estimated population exposure density.

The risk analysis module computes a Risk Score using environmental parameters including:

- rainfall intensity,
- wind speed,
- pressure variation,
- and population density estimation.

The generalized risk score equation is given below:

Based on the computed score, alerts are classified into four categories:

RiskScore=(0.35×Rainfall)+(0.25×WindSpeed)+(0.20×PressureDrop)+(0.20×PopulationDensity)

Risk Score	**Alert Level**
0–25	**Green Alert**
26–50	**Yellow Alert**
51–75	**Orange Alert**
76–100	**Red Alert**

This mechanism enables the system to generate dynamic emergency notifications instead of static weather alerts.

3.5 Backend and Communication System

The backend infrastructure was developed using Fast API due to its lightweight architecture and high-performance API handling capabilities. The backend server is responsible for:

- collecting sensor data,
- storing historical records,
- generating weather forecasts,
- computing risk scores,
- managing mobile application communication.

MySQL database was used for storing:

- environmental sensor data,
- forecast records,
- alert classifications,
- user-related application information.

The ESP32 microcontroller communicates with the backend server using LoRa modules for long-range wireless transmission.

3.6 Mobile Application Visualization

A Flutter-based mobile application was developed to provide users with real-time weather monitoring and intelligent emergency notifications.

The application provides:

- real-time environmental data,
- graphical weather visualization,
- future weather forecasting,
- alert severity notifications,
- location-aware emergency warnings.

The mobile application communicates with the backend server through REST APIs developed using FastAPI.

The application was developed using:

- Flutter SDK
- Android Studio
- Dart programming language

The proposed mobile application improves user accessibility and enhances emergency responsiveness during critical environmental conditions.

IV. RESULTS AND DISCUSSION

This section presents the experimental evaluation and performance analysis of the proposed Intelligent Context-Aware IoT Weather Forecasting and Emergency Alert System. The system was evaluated based on forecasting accuracy, sensor calibration performance, and effectiveness of the context-aware emergency alert mechanism. Experimental results demonstrate that the integration of ensemble machine learning and adaptive alert classification improves forecasting reliability and emergency responsiveness compared to traditional single-model weather monitoring systems.

4.1 Experimental Environment

The proposed system was implemented using ESP32 microcontrollers integrated with multiple environmental sensors including DHT22, BMP180, rain sensor modules, and an anemometer. LoRa communication modules were used for long-range wireless data transmission between the sensing unit and backend server.

The backend infrastructure was developed using:

- FastAPI framework
- MySQL database
- Python programming language

Machine learning models were trained and evaluated using:

- Scikit-learn
- XG Boost library
- GoogleColab environment

The mobile application was developed using:

- Flutter SDK
- Android Studio

The experiments were conducted using historical weather datasets combined with real-time environmental sensor data collected from localized monitoring stations.

4.2 Performance Evaluation Metrics

To evaluate forecasting performance, several standard regression evaluation metrics were used:

- Mean Absolute Error (MAE)
- Mean Squared Error (MSE)
- Root Mean Square Error (RMSE)
- Coefficient of Determination (R^2 Score)

Lower MAE, MSE, and RMSE values indicate better prediction performance, while a higher R^2 score represents stronger model accuracy and forecasting consistency.

4.3 Ensemble Model Performance Analysis

The proposed system utilized an ensemble learning framework consisting of:

- Random Forest Regressor
- XGBoost Regressor
- Gradient Boosting Regressor

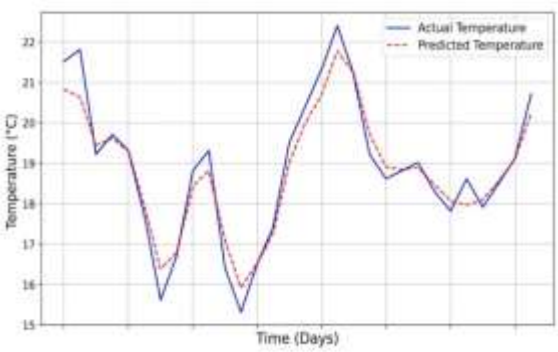
The performance of the individual models and the ensemble framework is presented in Table I.

Model	**MAE**	**RMSE**	**R^2 Score**
Random Forest Regressor	1.82	4.35	0.89
XGBoost Regressor	1.64	4.12	0.90
Gradient Boosting Regressor	1.71	4.24	0.89
Proposed Ensemble Model	1.29	3.61	**0.93**

The results in Table I demonstrate that the proposed ensemble learning framework outperformed the individual machine learning models across all evaluation metrics. The ensemble approach achieved the lowest forecasting error and the highest R^2 score of 0.93, indicating improved prediction stability and better generalization capability.

The improved performance can be attributed to the ability of ensemble learning to combine the strengths of multiple models while reducing individual prediction bias and variance. Unlike single-model forecasting approaches used in many existing IoT weather monitoring systems, the proposed ensemble framework effectively captured nonlinear environmental relationships and dynamic weather variations.

Figure 1 illustrates the comparison between actual and predicted temperature values generated by the ensemble forecasting framework.



Actual vs Predicted Temperature Values

The graph demonstrates that the predicted values closely follow the trend of the actual environmental measurements with minimal deviation. Although slight fluctuations exist during sudden environmental changes, the ensemble model maintained stable forecasting performance throughout the testing period.

4.4 Sensor Calibration and Data Reliability Analysis

Low-cost environmental sensors often produce unstable readings due to environmental interference and hardware limitations. To address this issue, Moving Average Filtering was applied for adaptive sensor calibration.

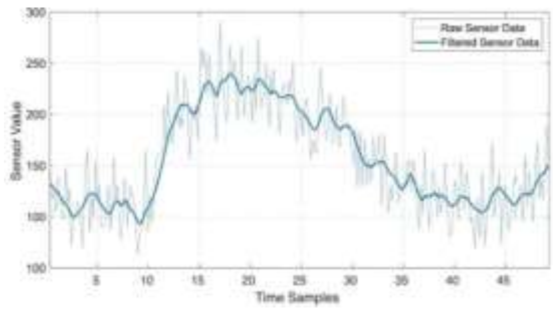
Sensor Calibration Performance

Parameter	Raw Sensor Variance	Calibrated Variance
Temperature	±2.3°C	±0.9°C
Humidity	±5.1%	±2.0%
Pressure	±3.7 hPa	±1.4 hPa

Table II presents the comparison between raw sensor readings and calibrated sensor outputs.

The results indicate that the adaptive calibration mechanism significantly reduced sensor fluctuations and improved environmental data consistency. The filtering process helped eliminate abnormal spikes and reduced noise before passing data into the forecasting framework.

Figure 2 illustrates the comparison between raw and filtered sensor readings.



Raw vs Filtered Sensor Readings

The filtered sensor output demonstrates smoother environmental measurements with reduced fluctuations compared to raw sensor data. This improvement directly contributed to better forecasting accuracy and system reliability.

4.5 Context-Aware Emergency Alert Analysis

One of the primary contributions of this research is the implementation of a context-aware emergency alert mechanism capable of dynamically prioritizing warning severity based on environmental conditions and estimated population exposure density.

The proposed system categorized alerts into:

- Green Alert
- Yellow Alert
- Orange Alert
- Red Alert

based on calculated environmental risk scores.

Table III presents sample emergency alert classifications generated by the system.

Context-Aware Alert Classification Results

Environmental Condition	Population Density	Alert Level
Light Rainfall	Low	Green Alert
Moderate Rainfall	Medium	Yellow Alert
Heavy Rainfall + High Wind	Medium	Orange Alert
Severe Storm + Dense Population	High	Red Alert

The results demonstrate that the proposed alert mechanism dynamically adjusted warning severity based on both environmental intensity and estimated population exposure. Unlike conventional weather systems that generate uniform notifications, the proposed framework provided adaptive emergency prioritization for high-risk situations.

Distribution of Alert Severity Levels

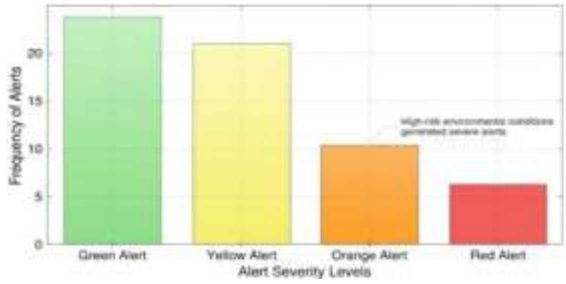


Figure 3: presents the distribution of generated alert levels during testing.

The figure shows that severe alerts were generated primarily during high-risk environmental conditions involving strong rainfall intensity and high estimated exposure density. This demonstrates the effectiveness of the proposed context-aware risk analysis framework.

4.6 Comparative Discussion with Existing Studies

Several previous studies focused primarily on IoT-based environmental monitoring and single-model forecasting techniques [1], [2]. While these systems successfully demonstrated real-time data acquisition, many lacked intelligent emergency prioritization and advanced ensemble forecasting mechanisms.

Compared to the work presented by Verma et al. [3], which utilized a single machine learning model for weather prediction, the proposed ensemble framework achieved higher forecasting accuracy and lower prediction error rates. Similarly, existing systems generally relied on static alert notifications without considering environmental severity or population exposure density [4].

The proposed research differs from previous approaches in three major aspects:

1. Integration of ensemble machine learning instead of single-model forecasting.

2. Implementation of adaptive sensor calibration for improving low-cost sensor reliability.

3. Development of a context-aware emergency alert mechanism for dynamic risk prioritization.

These enhancements improve both forecasting performance and practical emergency response capability, making the proposed system more suitable for smart city infrastructure and disaster-aware applications.

4.7 Overall System Performance

The experimental findings demonstrate that the proposed Intelligent Context-Aware IoT Weather Forecasting and Emergency Alert System successfully improves localized forecasting accuracy, sensor reliability, and emergency notification effectiveness.

The integration of:

- ensemble forecasting,
- adaptive sensor calibration,
- and dynamic risk-aware alert classification

enabled the proposed system to provide a more intelligent and reliable weather monitoring framework compared to traditional IoT weather forecasting systems.

The proposed system also demonstrated scalability and low-cost deployment capability through the use of ESP32 microcontrollers, LoRa communication, and lightweight machine learning techniques, making it suitable for practical real-world applications in agriculture, disaster management, and public safety systems.

V. CONCLUSION

This work presented the development of an Intelligent Context-Aware IoT Weather Forecasting and Emergency Alert System that integrates IoT-based environmental sensing, ensemble machine learning, adaptive sensor calibration, and dynamic emergency alert classification to improve localized weather monitoring and forecasting. By incorporating LoRa-based communication and ESP32-supported sensing infrastructure, the proposed system enables real-time environmental data collection with low-power and long-range communication capability suitable for both urban and remote deployments.

The experimental results demonstrated that the ensemble forecasting framework achieved improved prediction accuracy compared to traditional single-model approaches, while the adaptive calibration mechanism enhanced the reliability of low-cost sensor measurements. In addition, the context-aware emergency alert system successfully prioritized warning severity based on environmental risk conditions and estimated population exposure density, improving emergency responsiveness and practical usability during critical weather situations.

The proposed framework provides a scalable, cost-effective, and intelligent solution for localized weather forecasting and disaster-aware alert management. The system can contribute significantly toward smart city infrastructure, agriculture, disaster preparedness, and public safety applications. In the future, the system can be extended by integrating advanced deep learning models, additional environmental sensing parameters such as air quality monitoring, and multi-location deployments for improving forecasting robustness and nationwide scalability.

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