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Real Time Smart Weather Forecasting Using Low Cost Edge Computing

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Abstract: The project aims to develop an intelligent system that can predict weather conditions more accurately using modern technology. Traditional forecasting systems primarily rely on largescale data collected from weather stations. The proposed system, however, utilizes multi-sensor information to predict rainfall, temperature, humidity, and other climatic factors with enhanced accuracy. "Smart Weather Forecasting" builds upon existing research in numerical weather prediction (NWP), satellite data analysis, and statistical forecasting models. Traditional methods often use historical data and complex mathematical equations to simulate atmospheric behavior. However, recent studies have explored the use of machine learning and artificial intelligence (AI) to improve forecast accuracy by analyzing large volumes of real-time sensor data. Techniques such as Decision Trees, Neural Networks, and Support Vector Machines have been applied to predict weather patterns more efficiently. Furthermore, many systems incorporate Internet of Things (IoT)-enabled sensors for continuous data collection. Despite the promising results, there is still a need for more accessible, cost-effective, and localized forecasting systems. To address this need, the Smart Weather Forecasting project combines real-time sensor data collection with intelligent analysis techniques. The data is processed using microcontrollers, such as Arduino or Raspberry Pi, and transmitted to a cloud server. This methodology ensures faster and more precise weather updates, which can be particularly useful in both rural and urban areas for providing timely alerts and supporting informed decision making.

Keywords: Edge Computing, Real-Time Weather Forecasting, Low-Cost IoT Devices, Environmental Monitoring, Weather Sensors, Machine Learning, Data Analytics, Smart Agriculture, IoT, Localized Weather Prediction, Embedded Systems, Sensor Networks

I. INTRODUCTION

Weather forecasting plays a vital role in various sectors such as agriculture, disaster management, transportation, and smart city planning. Accurate and timely weather information helps in minimizing risks, improving resource utilization, and supporting informed decision-making. Traditional weather forecasting systems mainly rely on centralized cloud infrastructures and expensive meteorological stations, which often result in high deployment costs, increased latency, and limited accessibility in remote or resource-constrained areas.

With the rapid growth of the Internet of Things (IoT), low-cost sensors and embedded devices have enabled continuous monitoring of environmental parameters such as temperature, humidity, atmospheric pressure, and rainfall. However, transmitting large volumes of sensor data to the cloud for processing can lead to network congestion, higher energy consumption, and delayed responses. These limitations highlight the need for a more efficient and decentralized approach to weather data processing.

Edge computing has emerged as a promising solution by enabling data processing closer to the data source. By performing real-time analytics and lightweight machine learning inference at the edge, weather predictions can be generated with minimal latency and reduced dependency on cloud connectivity. This approach enhances system responsiveness, improves data privacy, and ensures reliable operation even in low-connectivity environments.

In this context, this paper proposes a real-time smart weather forecasting system using low-cost edge computing devices. The system integrates environmental sensors with edge-based data processing and predictive models to provide localized and timely weather forecasts. The proposed solution aims to achieve cost efficiency, scalability, and accuracy, making it suitable for applications in smart agriculture, rural monitoring, and disaster preparedness.

If you want, I can also adapt this introduction to a specific journal format (IEEE, Springer, Elsevier) or shorten it to exact word limits.

II. Literature Survey:

In [20] Forecast verification is the subject of measuring the goodness of the forecast. In atmospheric science, the current practice of weather forecast verification is to compare observed data to past forecasts from weather services. The aim of this paper is to study a situation in which probabilistic rain forecasts are verified against crowdsourced data, in addition to station data. Weather reporting tasks were outsourced to participants of a mobile social application called SWUA in Bangkok. We show that crowdsourced data are able to make biases and weaknesses of forecast services more prominent using the Reliability diagrams and the Brier scores. The results should call for further attention to the application of crowdsourced data for weather forecast verification in the future.
In [21] Short-term load forecasting is mainly utilized in control centers to explore the changing patterns of consumer loads and predict the load value at a certain time in the future. It is one of the key technologies for the smart grid implementation. The load parameters are affected by multi-dimensional factors. To sufficiently exploit the time series characteristics in load data and improve the accuracy of load forecasting, a hybrid model based on Residual Neural network (ResNet) and Long Short-Term Memory (LSTM) is proposed in this paper. First, the data with multiple feature parameters is reconstructed and input into ResNeT network for feature extraction. Second, the extracted feature vector is used as the input of LSTM for short-term load forecasting. Lastly, a practical example is used to compare this method with other models, which verifies the feasibility and superiority of input parameter feature extraction, and shows that the proposed combined method has higher prediction accuracy. In addition, this paper also carries out prediction experiments on the variables in the weather influencing factors.
In [22] Ka-band experimental validations of a radiometeorological forecast model chain are reported. Measurements from BepiColombo ESA mission to Mercury are used. An optimization of the satellite link exploiting daily weather-forecast statistics of the atmospheric channel is implemented, which defines a link-budget optimization technique. Different global-scale data are used for the model initialization, while three

ensemble methods for the computation of the daily statistics are used. In total, 54 statistics were tested over 42 sample passes characterized by different meteorological conditions. The results demonstrate superiority of the model chain with respect to other conventional techniques.

In [23] Air temperature is closely related to daily life, and accurate temperature forecast can improve efficient production and convenient living. Currently, in terms of temperature forecast by machine learning, academic research is mostly based on the performance of a single or a few models on the same dataset, and there is a slight lack of research on comparing the performance of multiple models under the same conditions. This article uses real-world datasets to evaluate and compare 19 popular machine learning models based on 7 evaluation metrics under the same conditions, which helps with in-depth exploration, analysis, and improvement of machine learning models. The experiments show that CatBoost achieved the best performance on all metrics except for the training time.

In [24] In this paper, we develop a data-driven methodology to characterize the likelihood of orographic precipitation enhancement using sequences of weather radar images and a digital elevation model (DEM). Geographical locations with topographic characteristics favorable to enforce repeatable and persistent orographic precipitation such as stationary cells, upslope rainfall enhancement, and repeated convective initiation are detected by analyzing the spatial distribution of a set of precipitation cells extracted from radar imagery. Topographic features such as terrain convexity and gradients computed from the DEM at multiple spatial scales as well as velocity fields estimated from sequences of weather radar images are used as explanatory factors to describe the occurrence of localized precipitation enhancement. The latter is represented as a binary process by defining a threshold on the number of cell occurrences at particular locations. Both two-class and one-class support vector machine classifiers are tested to separate the presumed orographic cells from the nonorographic ones in the space of contributing topographic and flow features. Site-based validation is carried out to estimate realistic generalization skills of the obtained spatial prediction models. Due to the high class separability, the decision function of the classifiers can be interpreted as a likelihood or susceptibility of orographic precipitation enhancement. The developed approach can serve as a basis for refining radar-based quantitative precipitation estimates and short-term forecasts or for generating stochastic precipitation ensembles conditioned on the local topography.

In [25] Weather uncertainty poses significant challenges to industries, including construction, major events (e.g., Wimbledon, IPL), and public health (e.g., heat events) this paper addresses these challenges by a new solution that introduces an "automated weather forecast station". Leverages IoT) technology The system uses advanced forecasting techniques such as ARIMA (Auto Regressive Integrated Moving Average) and deep learning to provide real-time weather data These by continuously collecting data from resources controlling the environmental sensors that have been deployed within a specific area It meets objectives and then the collected data is processed and made available through a user-friendly interface. While the concept of IoT-based weather forecasting is not new, this research goes beyond traditional applications. It extends its utility to smart cities and diverse industries, making it a valuable resource for individuals, organizations and government departments. By addressing climate-related challenges first, the program ensures safety and resilience in the face of climate change. The paper highlights the potential of these new solutions to improve decision-making processes, reduce climate-related problems, and enhance overall quality of life in urban and industrial settings as the world faces climate uncertainty increasing emphasis.

In [26] Weather prediction is gaining up ubiquity quickly in the current period of Machine learning and Technologies. It is fundamental to foresee the temperature of the climate for quite a while. Decision trees, K-NN, Random Forest algorithms are an integral asset which has been utilized in several prediction works for instance, flood prediction, storm detection etc. In this paper, a simple approach for weather prediction of future years by utilizing the past data analysis is proposed by the decision tree, K-NN and random forest algorithm calculations and showing the best accuracy result of these three algorithms. Weather prediction plays a significant job in everyday applications and in this paper the prediction is done based on the temperature changes of the certain area. All these algorithms calculate the mean values, median, confidence values, probability and show the difference between plots of all the three algorithms etc. Finally, using these algorithms in this work we can predict whether the temperature increases or decreases, is it a rainy day or not. The dataset is completely based on the weather of certain area including few objects like year, month, and temperature, predicted values and so on.

III.EXISTING SYSTEM:

Existing weather forecasting systems are mainly based on centralized, cloud-driven architectures that rely on data from traditional meteorological stations and satellites. Sensor data is transmitted to remote cloud servers, where complex numerical and statistical models generate forecasts.Although these systems provide large-scale predictions, they involve high deployment and maintenance costs and offer limited coverage in rural or remote areas. Continuous data transmission to the cloud also requires reliable internet connectivity, leading to increased latency and bandwidth usage. As a result, real-time forecasting and rapid response to sudden weather changes are often delayed.Additionally, centralized systems raise concerns related to data privacy, security, and reliability during network failures. These limitations highlight the need for a low-cost, decentralized, and real-time weather forecasting approach.

IV.PROPOSED SYSTEM AND WORKING METHODOLOGY:

The proposed methodology describes the systematic approach adopted for designing and implementing a **real-time smart weather forecasting system** using **low-cost edge computing** and **environmental sensors**. The methodology focuses on real-time data acquisition, edge-based processing, and localized weather prediction with minimal dependence on cloud infrastructure.

AUDIO DATABASE: Audio database creation is gathering different kinds of audio, for example, stand-up comedy sessions, stadium speeches and other relevant sources. Additionally, this consists of CSV files that indicate that each mat file is classified as time domain features, Statistical and informative Features, MFCC Features computation. Such all Audio recordings metadata like labels or tags are carefully annotated to provide useful information about what they contain and in which contexts they were recorded. About 90% of the audios are used as training data. This part of the database is a major resource for developing and refining models/ algorithms / analytical techniques.

A) Overall System Design

The proposed system is designed as a decentralized, edge-based weather forecasting architecture that emphasizes real-time data processing, low latency, and cost efficiency. The system integrates environmental sensors with embedded controllers and an edge computing platform to enable localized weather monitoring and prediction. Unlike conventional cloud-centric systems, the proposed architecture minimizes reliance on continuous internet connectivity by performing data analysis and forecasting directly at the edge.

B) Environmental Sensing and Data Generation

Environmental data is generated using a set of low-cost sensors deployed in the target area to measure critical weather parameters such as temperature, humidity, atmospheric pressure, rainfall, wind speed, air quality, and ultraviolet radiation. These sensors operate continuously and produce time-stamped readings that reflect real-time environmental conditions. The use of multiple sensors enables a comprehensive understanding of localized weather behavior.

C) Embedded Controller-Based Data Acquisition

An embedded controller such as Arduino or ESP32 is used to interface with the environmental sensors. The controller is responsible for periodically sampling sensor data and converting analog signals into digital values. Basic preprocessing operations, including sensor calibration and noise filtering, are performed at this stage to enhance data quality. The embedded controller acts as a reliable bridge between the physical sensing layer and the digital processing layer.

D) Edge Communication and Data Transfer

The digitized sensor data is transmitted from the embedded controller to the edge computing unit using a wired communication protocol. This communication approach ensures stable and low-latency data transfer, which is essential for real-time forecasting applications. The continuous flow of sensor data allows the edge device to maintain up-to-date environmental information for accurate analysis.

E) Edge-Level Data Management and Preprocessing

At the edge computing layer, the Raspberry Pi manages incoming sensor data and performs advanced preprocessing operations. These operations include data normalization, handling of missing or inconsistent readings, and structuring of data into suitable formats for machine learning models. Preprocessing at the edge ensures that the prediction algorithms receive clean and standardized input, improving forecasting accuracy and robustness.

F) Machine Learning-Based Weather Forecasting

The core forecasting functionality is implemented using lightweight machine learning models deployed directly on the Raspberry Pi. These models are trained using historical weather data combined with real-time sensor inputs to predict short-term weather conditions. The edge-based execution of machine learning algorithms reduces response time and eliminates the need for frequent data transmission to cloud servers, making the system efficient and scalable.

G) Real-Time Visualization and User Interaction

To enable effective monitoring, the system provides real-time visualization of both live sensor readings and predicted weather parameters. A Streamlit-based dashboard is developed on the edge device to display numerical data, graphical trends, and forecast summaries. Remote access to the visualization interface is facilitated using RealVNC Viewer, allowing users to monitor the system from any location.

H) Optional Cloud Integration and Data Storage

While the system primarily operates at the edge, optional cloud integration is included to support long-term data storage, historical analysis, and system diagnostics. The cloud is not involved in real-time prediction, ensuring that the system remains operational even in the absence of internet connectivity. This hybrid approach balances local processing efficiency with the benefits of centralized data storage.

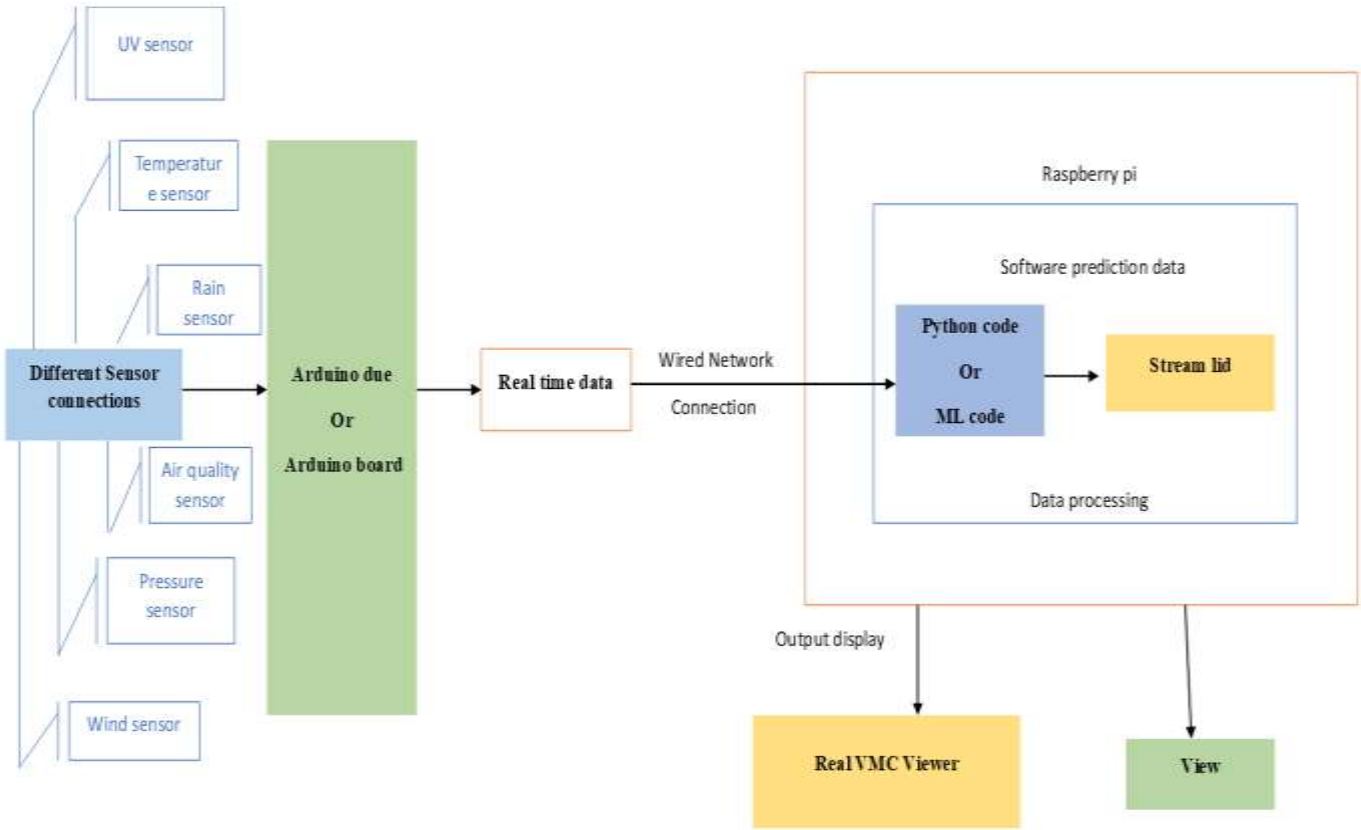
I) System Scalability and Reliability

The modular design of the proposed system allows additional sensors or edge nodes to be integrated with minimal modification. The decentralized nature of the architecture improves system reliability by eliminating single points of failure. Furthermore, local data processing enhances privacy and reduces bandwidth consumption, making the system suitable for deployment in rural and resource-constrained environments.

J) Application Suitability

The proposed methodology supports a wide range of applications, including smart agriculture, localized weather monitoring in rural regions, and early warning systems for adverse weather conditions. By providing accurate and timely weather forecasts, the system aids decision-making processes and contributes to improved environmental awareness and disaster preparedness.

V.BLOCK DIAGRAM FOR THE PROPOSED MODEL:



VI. RESULT:

Present Live Data With Sensor Comparing With Google
Location - 17.016300, 81.773435
Date: 17-12-2025 Time: 11:28:00 AM

Serial No	Sensor	Live Sensors Data	Live Google Data
1	Temperature	26.9°C	26°C-27°C
2	Humidity	70%	67%
3	Pressure	1014 hpa	1014 hpa
4	Wind Speed	3.2 km/h	4-7 km/h
5	UV Index	7.7	7
6	Air Quality	171	150-200
7	Precipitation	0	0
8	Weather status	Partly Cloudy	Haze (or) Cloudy

Present Live Data With Sensor Comparing With Google
Location - 17.016300, 81.773435
Date: 18-12-2025 Time: 12:55:00 PM

Serial No	Sensor	Live Sensors Data	Live Google Data
1	Temperature	26°C - 28°C	29°C-27°C
2	Humidity	63%-70%	55% - 64%
3	Pressure	1012 hpa	1014 hpa
4	Wind Speed	3.2 km/h - 11.06 km/h	5 km/h -12 km/h
5	UV Index	3.8 - 4.6	05-Apr
6	Air Quality	172	150-200
7	Precipitation	0	0
8	Weather status	Partly Cloudy	Haze Sunsine(or) Partly Cloudy

System Implementation and Output Results

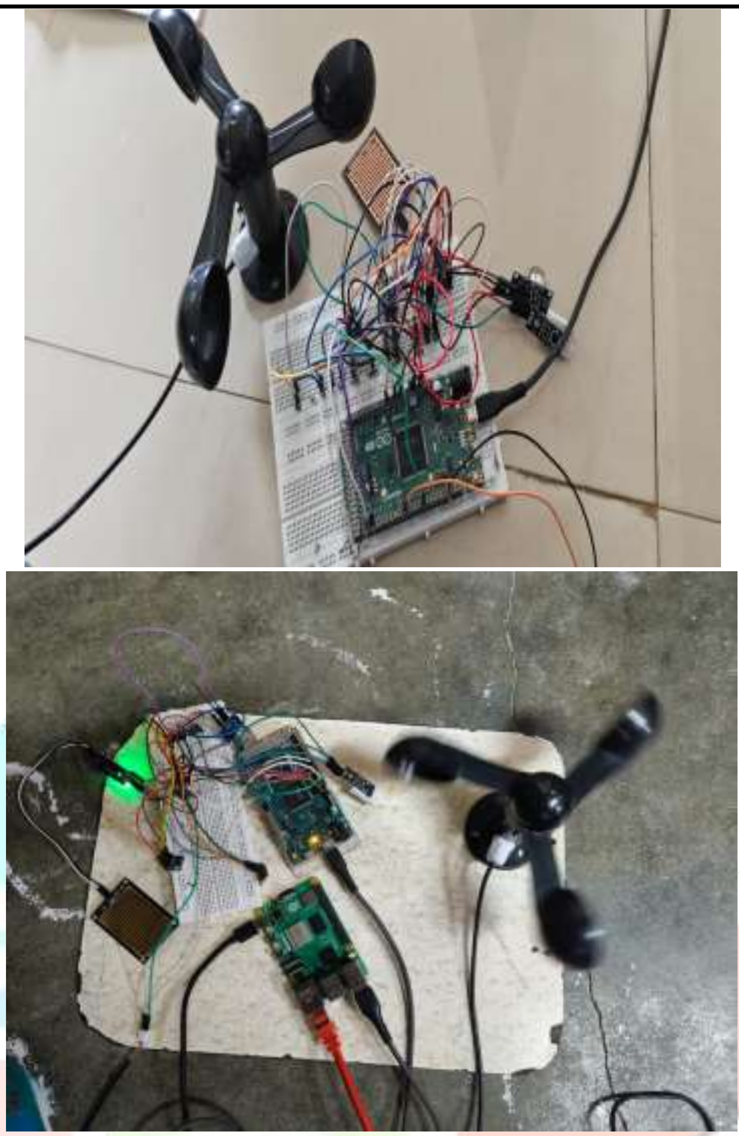


FIGURE – 1: Experimental Hardware Setup of the Proposed Weather Station.

```
==============================================
    WEATHER STATION — ARDUINO DUE
==============================================
BMP280 Connected Successfully!
==================== WEATHER DATA ====================
Temperature: 26.5 °C (Fahrenheit: 79.7 °F)
Humidity: 70.5 %

Air Quality Index: 88 - Moderate
  [0-50: Good | 51-100: Moderate | 101-150: Poor]
  [151-200: Unhealthy | 201-300: Severe | 301+: Hazardous]

Rain Sensor Raw: 3209
Rain State: Light Drops
Precipitation: 0.00 mm/h

UV Index: 6.78 - High
  [0-2: Low | 3-5: Moderate | 6-7: High]
  [8-10: Very High | 11+: Extreme]

Wind Speed: 0.00 km/h

Atmospheric Pressure: 1012.95 hPa
  (1 hPa = 100 Pascals)
BMP Temperature: 27.7 °C
Altitude: 2.5 m

>>> WEATHER STATUS: Partly Cloudy <<<
```

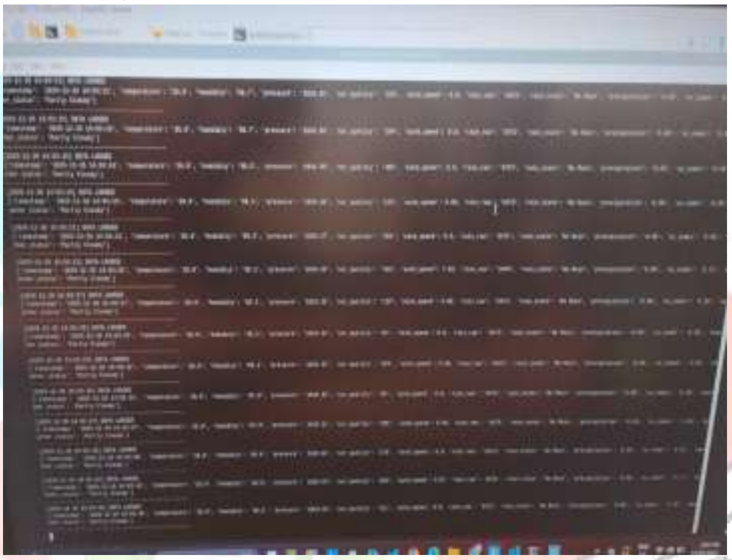


FIGURE - 2: Live Sensor Data Displayed on the Arduino Serial Monitor.

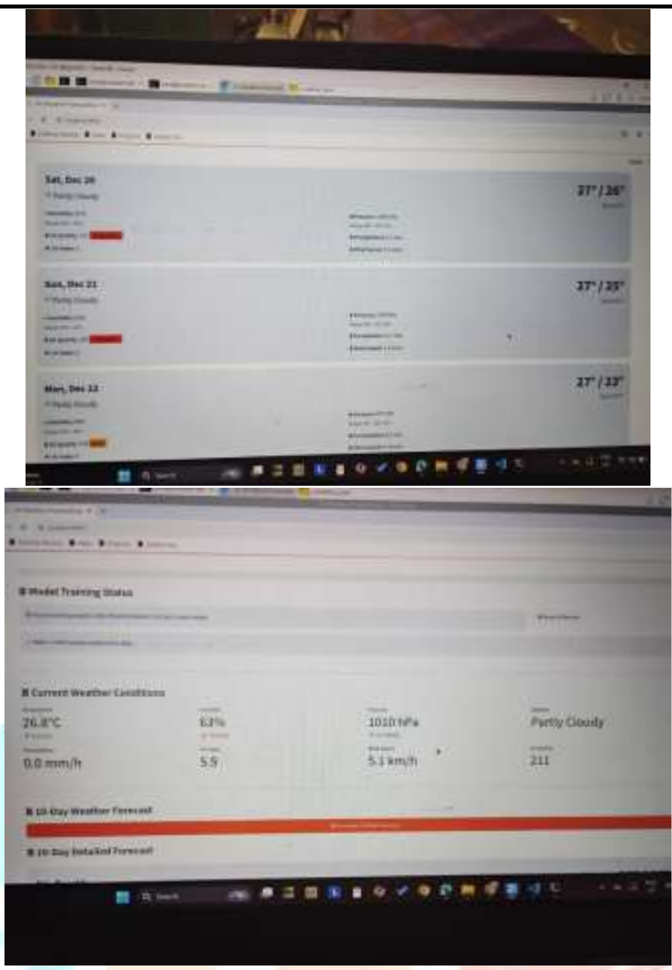


FIGURE-3: Web Dashboard Showing Weather Forecast and Environmental Data.

VII. CONCLUSION:

This paper presented a real-time smart weather forecasting system using low-cost edge computing to overcome the limitations of traditional cloud-based approaches. By processing sensor data locally at the edge, the system achieves low-latency, cost-efficient, and privacy-preserving weather prediction. The use of lightweight machine learning models enables accurate short-term forecasting, making the system suitable for smart agriculture, rural monitoring, and disaster management. Its scalability and reliable operation in low-connectivity environments highlight its practical effectiveness. Overall, the proposed system offers an efficient and economical alternative to conventional weather forecasting solutions, with scope for further enhancement using advanced learning models and collaborative edge intelligence.

VIII. FUTURE SCOPE:

The proposed edge-based smart weather forecasting system can be further enhanced to improve accuracy and scalability. Advanced machine learning and deep learning models, such as LSTM and hybrid forecasting techniques, can be deployed using optimized edge frameworks to better capture complex weather patterns. Adaptive and self-learning models can enable continuous performance improvement with new data.

The system can be expanded by integrating additional sensors such as air quality, soil moisture, and solar radiation sensors for comprehensive environmental monitoring. Collaboration among multiple edge nodes can support regional-level forecasting through distributed intelligence. Additionally, integrating 5G and edge–cloud hybrid architectures, along with improved visualization dashboards and alert systems, can enhance real-time performance and usability, making the system suitable for smart cities and precision agriculture.

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