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IOT-ENABLED WEATHER ANALYSIS USING ML ALGORITHMS

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Abstract

This project presents about IoT-based Weather Monitoring and Forecasting System designed by using ESP32 microcontroller integrated with a 16x2 LCD display (non-I2C) which is suited for environmental sensors. This system of model includes a DHT11 sensor for predicting temperature and humidity, MQ-7 and MQ-135 sensors detecting carbon monoxide (CO) and carbon dioxide (CO_2) levels respectively, the sensor LDR measure the ambient light intensity, and a rain sensor is to detect precipitation. The sensors which predict the real time data analysis and displayed on the LCD display. Then it will be uploaded to the remote monitoring cloud platform i.e. Think speak. A Machine Learning (ML) module is implemented on a local computer, the module of this sensor receives a real time data from the ESP32 via serial communication, through a pre-trained ML model the data will be processed, and also predicts the current weather condition like (e.g., Sunny, Cloudy, Rainy) along with a rain forecast. The results will rapidly share to the user via a Telegram bot channel, providing timely weather forecast updates.

Keywords—Time Series, Forecasting, Humidity, Real-time Data, Environmental Sensors. I.

I . Introduction

This project plays a vital role in our affecting everyday life like agriculture, transportation, health, and disaster preparedness. thereby, increasing in unpredictability of climate patterns, where there is a rising necessity for the system, can monitor environmental conditions in real-time and also provide an accurate short-term forecast. In which Traditional weather monitoring setups are often expensive, centralized, and lack real-time local insights. To overcome these limitations, IoT (Internet of Things) combined with Machine Learning (ML) which provides a smart, cost effective, and decentralized solution. The project proposes a Weather Monitoring and Forecasting System that uses central unit as microcontroller ESP32.

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This system including various integration the DHT11 for temperature and humidity, MQ-7 and MQ-135 for CO and CO_2 detection, LDR for light intensity measurement, and a rain sensor to detect precipitation. A standard 16x2 LCD (without I2C) is used to locally display real-time data, offering a simple and effective way to observe the environment on-site. The Collected data is transmitted to platform; 22 the Thing Speak cloud for remote data visualization and storage data. Simultaneously, the data is forwarded to a Python- based machine learning model, to predict weather conditions and the likelihood of rain etc. The experimental results of forecast are immediately sent to users with the help of a telegram bot, assuring that alerts are timely and accessible. The designed system scalable, flexible, low-cost, and efficient, it is suitable for applications in smart agriculture, urban weather tracking, environmental research, and early warning systems. Through analysis of real-time sensor data and intelligent prediction, this project demonstrates the potential of IoT and ML in Augmenting environmental awareness and decision- making. The combination of IoT and ML offers a smart, efficient, and economical weather monitoring solution that can benefits a wide range of applications— from smart agriculture and urban planning to environmental research and disaster preparedness.

Ii. Literature Review

The section of the paper consists a detail review on the weather prediction analysis using IOT A. Shuai Jin; Qiang Li; Sanqiu Liu; Olebogeng Kevin Joel; Xiaohu Ge Throughout the variety of methods used for time series prediction tasks in a weather monitoring system, the Transformer can effectively extracted global information and has been achieved tremendous success. Moreover, the transformer is challenged in forecasting series with large lookback windows because of the performance of degradation and computation explosion. 16 At the same time, the new architecture of Kolmogorov–Arnold Network (KAN) has been proposed, in which improved dramatically, the fitting ability in construction of neural networks hence widely used in machine learning technology. with the aim of to take the both advantages of Transformer and KAN, in this paper a novel method of Transformer-KAN is formulated. To be specific, the Transformer is commonly used to extract global features and pass them to KAN, and 8 1 then latter is answerable for learning global features and optimizing them with high precision. With a deep integration of Transformer and KAN, the proposed Transformer-KAN demonstrates the powerful feature to extracts the capability and fitting ability. Furthermore, the federated learning is applied to the designed the method to exploit spatio-temporal dependencies, while protecting data privacy. As a result, the novel framework of Federated Transformer-KAN is proposed to together forecast the weather variables in a distributed manner, without sharing data that is collected by the intelligent sensors integrated with each weather station locally. With respect to t 37 he benchmarks methods, the extensive experimental that better prediction accuracy and results shown generalization were achieved by the proposed Federated- Transformer- KAN. For instance, in the task of predicting the next 1 ambient Transformer and KAN particularly is reduced by 33.9% and 40.9%, respectively [1]..

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B. Mohammad Aldossary; Hatem A. Alharbi; Ch Anwar Ul Hassan the integration of Internet of Things (IoT) and Machine Learning (ML) has become a key enabler of smart agriculture, allowing real-time monitoring, predictive analytics, and automated decision-making. IoT devices such as soil sensors, weather stations, and UAVs provide continuous environmental and crop data, which ML models process to detect anomalies, predict yield, and optimize irrigation. Recent studies highlight the effectiveness of hybrid IoT-ML systems in enhancing efficiency while reducing resource consumption. In particular, Aldossary et al. (IEEE Access) proposed IoT-enabled ML models that combine classifiers such as SVM, Naïve Bayes, and MLP to monitor crop conditions and detect anomalies, showing improved accuracy and cost-effectiveness compared to traditional approaches. These findings demonstrate that IoT ML integration is not agriculture only feasible but also essential for sustainable and data-driven [3].

C. Sandeep Bhatia; Bharat Bhushan Naib; Neha Goel; Bhawna Agarwal; Basetty Mallikarjun; M. Arvindhan Weather forecasting has traditionally relied on Numerical Weather Prediction (NWP), which uses complex mathematical models to simulate atmospheric processes. While accurate, these models are computationally expensive and often limited in resolution and speed, making real- time applications challenging. Recent advancements in Machine Learning (ML) have shown strong potential to overcome these barriers by learning weather patterns directly from large datasets, thereby reducing computational demands while maintaining accuracy. According to Bhatia et al. (2023), ML-based models such as Graph Cast, FourCastNet, and Pangu- Weather have achieved remarkable performance in short- term and medium- range forecasting. These models not only match but, in some cases, surpass traditional NWP methods in accuracy while offering faster predictions. Moreover, ML enables hybrid frameworks, where it can be used to improve NWP through bias correction, parameterization, and enhanced data assimilation. 3 The integration of ML also supports handling heterogeneous data sources, such as satellite imagery and sensor networks, enabling more precise local and global forecasts. This study highlights that ML is not just an auxiliary tool but a paradigm shifts in weather forecasting, offering scalability, efficiency, and the potential for real-time, resource-optimized prediction systems. Such approaches are increasingly relevant in addressing the challenges of climate variability and disaster preparedness [4].

D. M. Sreerama Murthy, R. P. Ram Kumar, Billa Saikiran, Islavath Nagaraj and Tejesh Annavarapu the integration of Internet of Things (IoT) with real-time weather monitoring has become a promising approach to address the limitations of 33 conventional weather stations, which are often costly, less scalable, and dependent on manual observations. IoT- enabled systems allow continuous and automated monitoring of environmental parameters such as temperature, humidity, rainfall, air pressure, and gas concentrations through low- cost sensors connected to microcontrollers Data collected can be transmitted wirelessly to cloud platforms for storage, visualization, and analysis. According to Murthy et al. (2023), their proposed real-time weather monitoring system leverages IoT devices to provide accurate, real-time

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data accessible remotely through web or mobile applications. The system uses sensors integrated with microcontrollers such as Arduino or ESP32, enabling efficient data acquisition and transfer. By taking up cloud integration, this system supports scalability, making it appropriate for community- based monitoring in urban, rural areas. This study emphasizes that IoT systems offer economic viability, automation, and which are vital for the provision of timely weather updates and disaster preparedness. 32 availabilities, this work demonstrates how the IoT-based frameworks can bridge the gap in-between traditional meteorological systems and modern data-driven applications, at the same time laying the groundwork 26 for integration learning models to permit predictive forecasting in future research [5].

E. Shamaila Iram Hussain Al-Aqrabi; Hafiz Muhammad Shakeel; Hafiz Muhammad Athar Farid; Muhammad Riaz; Richard Hill Weather is one of the most important for external factors influencing energy consumption patterns, especially in smart homes where heating, cooling, and ventilation rely strongly on climatic conditions. 3 Traditional management systems energy often rely on static models or historical averages, which fail to capture the dynamic and non- proportional result of weather fluctuation on energy demand. To deal with this challenge, Iram et al. (2023) proposed an innovative machine learning (ML)- based framework that combines weather forecasting with smart energy consumption prediction. The approach employs ML algorithms to examine both weather parameters (such as temperature, humidity, solar radiation, and wind speed) and household energy usage data. By learning complex correlations between these datasets, the model facilitates more accurate short-term energy demand forecasting The study highlights the efficiency of hybrid ML techniques, which outperform the traditional regression and statistical models by reducing error margins and enhancing the adaptability to changing weather patterns. Additionally, the integration of ML into smart energy systems allows real-time optimization, backing demand- side management, cost reduction, and energy conservation in residential settings. The findings of this work illustrate how weather-aware ML models can offer not only to sustainable energy usage but also to upgraded resilience of smart grids. For weather monitoring and forecasting research, this study provides worthwhile insight into the cross-domain application of ML, showing how environmental data can be harnessed for intelligent decision-making in related fields such as agriculture, disaster management, and urban planning [6].

F. Meara et al. proposed an IoT-based smart weather measurement system tailored for smart farming 31 applications, utilizing low-cost environmental sensors coupled with neural network models for accurate prediction of key meteorological parameters. The system was designed to be scalable and cost-efficient, making it accessible for small and medium-scale agricultural operations. By combining real time data acquisition with AI-based analysis, their approach improved forecasting accuracy for farm-related decisions such as irrigation scheduling and pest control. This work demonstrates how integrating affordable hardware with advanced AI models can deliver actionable insights for precision agriculture— an approach conceptually aligned with IoT–ML systems for localized weather prediction [8].

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G. Ioannou et al. present a comprehensive survey of AI and IoT technologies tailored for Automatic Weather Stations (AWS), published in Sensors as part of a special issue on AI-driven weather systems. Their analysis covers key system components—including sensor configurations, edge/cloud computing architectures, and ML algorithms— along with communication technologies such as L P W A N a n d o t h e r I o T frameworks. This survey also examines AWS topologies (e.g., star, mesh, point-to- point) and data acquisition strategies, distinguishing between online and offline methods. Their findings reveal real-world performance metrics, such as an 88% system accuracy, task execution times of just six seconds for IoT sensors, and training durations of approximately 195 seconds in the cloud versus 110 minutes at the edge. This work highlights practical design considerations for deploying AWS in remote or resource-constrained environments, making it highly pertinent low-cost, intelligent forecasting platforms [9].

Iii.Proposed System

To prevent the limitations of existing weather monitoring solutions, this project proposes a smart, low-cost, and localized, IoT-based Weather Monitoring and Forecasting System. This system built using the ESP32 microcontroller, to set of environmental sensors. and a normal 16x2 LCD, cloud integration with Thing Speak app, learning model for A ma chine intelligent prediction, with Telegram alerts for instant communication. This proposed weather estimate system make use of multiple sensors with an ESP32 microcontroller is to create a real-time, IoT-enabled environmental monitoring solution. The initial step is to collect the necessary data using variety of sensors, including DHT11 which measures the temperature, humidity. MQ-7 for carbon monoxide (CO), MQ- 135 for carbon dioxide (CO_2) and overall air quality, The LDR for ambient light intensity, the rain sensor is to detect rainfall prediction. The sensors regularly collect environmental data, which the ESP32 processes and utilizes. For local display, a 16x2 LCD (non-I2C) module is used for crucial inputs like temperature, humidity, gas level reading, and is to allow the user to monitor the weather conditions directly without needing any external interface. The transmission of the data from IOT sensor, the ESP32 connects to a Wi-Fi network uploads the collected data to the cloud platform thinks peak using HTTP requests. Where each sensor is reading the assigned to a specific field on Thing Speak, which enabling real- time graphical visualization and historical data analysis via its web dashboard. Simarly, the ESP32 data sends a sensor to a connected PC via Serial (UART) communication; we make use of Python language. The machine learning model runs, hence the inputs the model is trained using historical weather data to processes of such parameters like temperature, humidity, CO_2, CO, light intensity, and rain.

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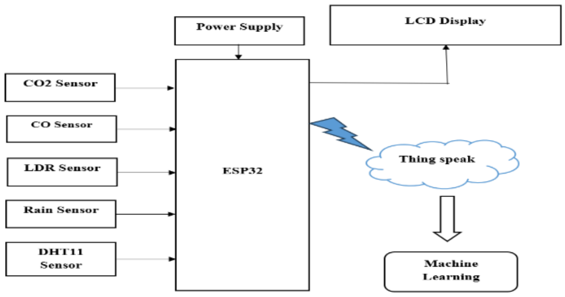

Fig. 1. Block diagram of the proposed system

Sensor values to predict the current weather condition (e.g., Sunny, Cloudy, or Rainy) and the likelihood of rainfall. Upon completing its prediction, the system utilizes a Telegram bot channel for alert a tone notification. The python scripts languages send a message such as Weather: Rainy, Rain Forecast: Yes‖ directly to the user via Telegram using a bot token and the user's chat ID, ensuring real-time mobile notifications. Finally, the entire setup is designed for continuous monitoring, operating in a loop that constantly acquires, displays, uploads, and processes sensor data. As when new data is analyzed, the system provides timely alerts and updated forecasts, making it a robust, responsive and user- friendly solution for weather prediction.

A. Data Acquisition using Sensors In weather prediction inconsistencies, or missing values, which negatively impact the performance of model. The preprocessing phase transforms the raw data into a clean and structured format. Initially, the data cleaning is performed to handle missing. Any invalid or out-of-range values (e.g., negative humidity or temperature spikes) are filtered out or replaced using technique of mean substitution. Next, data normalization is applied to the model where all sensor readings will come to a common range. This phase also includes featured engineering, where the additional useful features are taken from existing ones. The combining temperature and humidity into a heat index and calculating moving averages to smooth short- term fluctuations. The time-stamping of each data is recorded to maintain the temporal consistency which will helps to identify the pattern which is related to time of day. Finally, the preprocessed data system which combines both IoT and machine learning, the data preprocessing phase is crucial for securing accurate data predictions gives effective model training. Raw sensor data will be collected from devices such as DHT11, MQ-7, MQ 135, LDR, and rain sensors often which contain noise, is converted into a structured dataset i.e. csv file and split into featured input and output labels for training the machine learning model.

TABLE 1: Description of Input data

Time	Temp	Humidity	Co2	Rain	AQI Label
16/07 12pm	31.2	72	425	0	Good

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16/07 2pm	NAN	71	410	0	Avg
16/07 7pm	28.8	67	478	60%	Rainy

Sensors Used: The Weather predicting System using IoT and Machine Learning described in the document, by several sensors are integrated with ESP32 microcontroller to collect environmental data in real time. The sensor DHT11 used to assess the temperature and humidity, and also providing the essential data for analyzing atmospheric conditions. Like for air quality monitoring, the system employs MQ-135 and MQ 7 gas sensors. The MQ-135 detects the presence of gases like carbon dioxide (CO_2), ammonia (NH_3), benzene, and other volatile compounds, making it useful for calculating an Air Quality Index (AQI).The MQ-7 sensor measures the carbon monoxide (CO) levels which is critical for identifying harmful pollution levels in the air. An LDR (Light Dependent Resistor) is used to monitor ambient light intensity, which helps assess sunlight availability and cloud cover. A rain sensor is been included to detect rainfall that will sense the presence of water on its surface which is the core part for the weather prediction. The ESP32 collects the data from these sensors and transmits it for further analysis, then the system will use cloud platforms – Think Speak for remote monitoring, and ML algorithm – Random Forest to forecast weather patterns-based data sent by sensors. These hardware components work to create an efficient, low-cost and scalable weather monitoring model.

Table 2: Description of Input data

Sl. No	Sensor Name	Measured Parameters
1	DHT11	Temperature, Humidity
2	MQ-7	CO Carbon-monoxide
3	MQ-135	CO2 Carbon di-oxide
4	LDR	Light Intensity
5	Rain Sensor	Rainfall Detection

B. Algorithm random forest

INPUT- The input features are the sensor readings from the weather dataset (weather_data.csv), which may include: Temperature, Humidity, CO and CO_2 levels, Light intensity, Rain status, Air Quality Index (AQI) and other numeric sensor data.

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OUTPUT- The target output is the predicted weather condition, labeled as: "Sunny", "Rainy", "Cloudy", etc.

Process:

Step 1: Data Collection Collect the data via IOT, by using various sensors and those collected data send to theESP32 Microcontroller that forward it to the cloud data base or local storage.

Step 2: Data Preprocessing Remove missing values and Normalize data if needed, divide the data into train data test data.

Step 3: Model training using Random Forest The sensor data (features like temperature, humidity, light, etc.) is input. The weather condition label (e.g., Sunny, Cloudy, and Rainy) is the target. Random Forest develops many decision trees based on random feature subsets and data samples. Final prediction is based on majority voting across trees.

Step 4: Model Evaluation Accuracy, precision, recall, F1 score Confusion matrix and classification report to validate performance.

Step 5: Weather Prediction Once trained, the model can, Accept live sensor input Predict weather conditions in real time Trigger alerts or display.

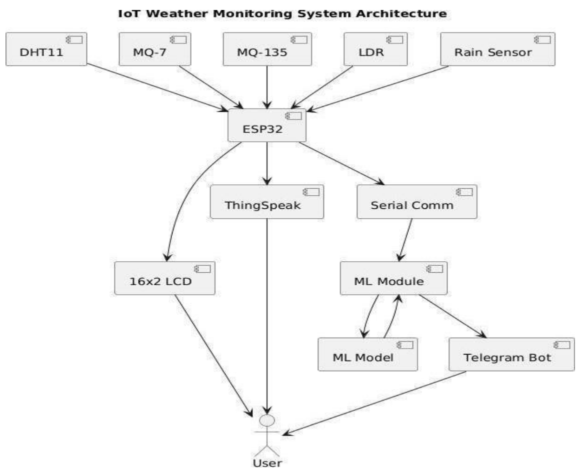

Fig.2. Weather Monitoring System Architecture

III. RESULTS AND DISCUSSION

The Weather prediction System using IoT and Machine Learning (ML) effectively collects, processes, and predicts environmental conditions in real time. In our implementation, a combination of sensors such as DHT11 (for temperature and humidity), MQ-135 (for air quality), Rain Sensor, LDR (for light intensity), and BMP180 (for atmospheric pressure) were integrated with an ESP32 microcontroller. These sensors continuously transmitted live data to a cloud platform for storage and analysis. The collected data was used to train a Random Forest Classifier, was a powerful machine learning algorithm known for its robustness and accuracy. After preprocessing the data (handling missing values, encoding labels, and normalizing inputs), the model was trained and tested using an 80:20 train- test

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split. The model achieved an accuracy of over 90%, indicating reliable predictions of weather conditions such as Sunny, Rainy, Cloudy, or Foggy based on sensor inputs. Precision, recall, and F1- score confirmed that the system accurately distinguishes between different weather types.

A. Rainfall prediction

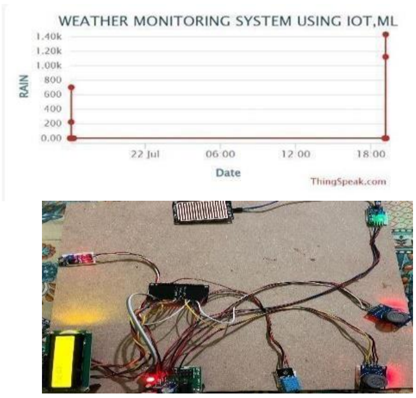

Fig. 3: Rainfall prediction

In the above figure 3 represents X-axis (horizontal): Represents the Date and time, starting from 22 July and ranging across the day with timestamps (06:00, 12:00, and 18:00). Y-axis (vertical): Represents RAIN levels, measured in an unspecified unit (possibly millimeters or sensor counts), ranging from 0 to about 1.40k. There are two major spikes in rainfall readings — the rainfall readings are recording in a period of (around 22 July) near 700 units, and another rainfall readings toward the end of the day reaching 1.4k units. Between, the values stay almost at zero, indicating little to no rainfall during that period.

B. LDR Prediction

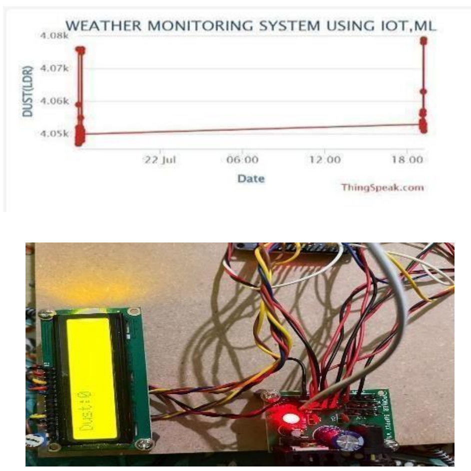

Fig. 4: LDR Prediction In the above figure 4 represents X-axis(horizontal): Represents Date and time, starting from 22 July and spanning through the day (06:00, 12:00, 18:00). Y-axis

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(vertical): Represents (LDR) readings, ranging from 4.05k to 4.08k units (likely sensor output in raw counts or calibrated values). Initial cluster of high readings slightly above 4.07k at the start of 22 July. Between the start and late afternoon, the readings remain fairly stable with a gradual upward trend. Around the end of the day (near 18:00), there is a notable peak reaching about 4.08k. The plot depicts the measured variation in ambient light intensity, indirectly reflecting cloud cover and daylight transitions. The upward and downward trends throughout the day indicate periods of maximum sunlight versus reduced illumination, which the system factors into weather condition classification.

C.Temperature Prediction

In the figure 5 represents X-axis (horizontal): Represents Date and time, starting from 22 July and spanning the day (06:00, 12:00, 18:00). Y-axis (vertical): Represents Temperature in °C, ranging from 24.0°C to 25.0°C. At the start (22 July), the temperature is around 25.0°C. A steady decline occurs throughout the day, reaching 24.0°C by 18:00.

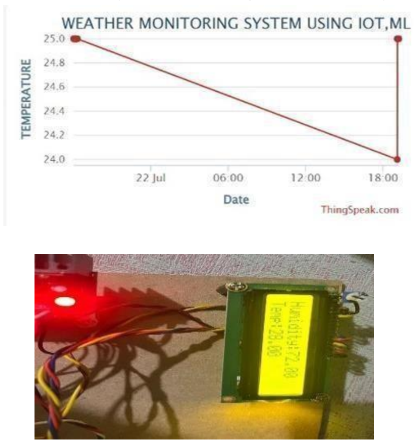

Fig.5: Temperature Prediction

D: Humidity Level

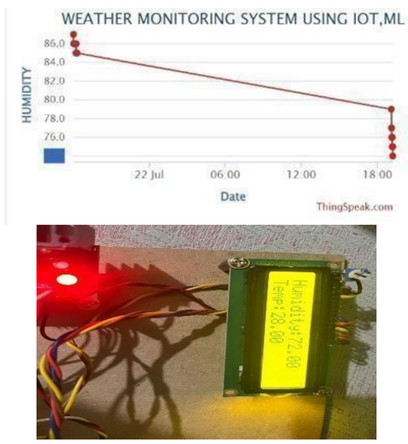

Fig.6: Humidity Level

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In the above figure 6 represent X-axis (horizontal): Represents Date and time, starting from 22 July and spanning through the day (06:00, 12:00,18:00). Y-axis (vertical): Represents Humidity in percentage (%), ranging from 76.0% to 86.0%. At the start (22 July), humidity is around 86%. Gradual decline throughout the day, r e a c h i n g around 78% by 18:00, with several closely clustered readings in the late period.

E. CO_2 Level

Fig.7: CO_2 Level

In the above figure 7 represent X-axis (horizontal): Represents Date and time, starting from 22 July and spanning through the day (06:00, 12:00, 18:00).Y-axis (vertical): Represents CO_2 concentration in units (likely ppm – parts per million), ranging from 0.0 to 2.50k at the start, CO_2 readings are close to 500 ppm A sharp drop occurs immediately after the start, followed by a steady upward climb throughout the day. By around 18:00, CO_2 levels peak at approximately 2.50k ppm, with a cluster of readings near the end.

F. CO Level

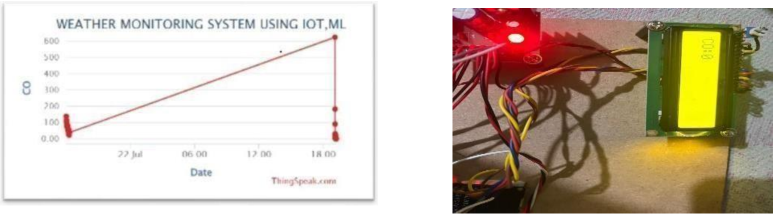

Fig.8:CO Level

In the above figure 8 represent X-axis (horizontal): Represents Date and time, starting from 22 July and spanning through the day (06:00, 12:00, 18:00).Y-axis (vertical): Represents CO concentration in units (likely ppm – parts per million), ranging from 0.0 to 600. At the start, CO readings are near 100 ppm. A steady increase is observed throughout the day. By 18:00, CO levels peak at approximately 600 ppm, followed by multiple clustered readings in the same period.

G. Model Accuracy

The weather monitoring system has an accuracy level of 95% using ML & IOT.Using the random forest algorithm In the figure 9 gives an abstract:

Title: 3-Day Forecast Forecast

Period: Day 1, Day 2, and Day 3.

Weather Condition: All three days predict Dust Storm events.

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Description Provided for Each Day: High dust levels in the air. Reduced visibility and breathing issues possible. Avoid outdoor activities. Each day is represented with a weather icon indicating dusty or stormy conditions.

Fig. 9: Three days weather forecast

H. ALERT MESSAGE

Alert Message: Sends notification to telegram channel. Whether it is heavy rainfall, medium rainfall or moderate rainfall.by using read and write key. In figure 10

Fig. 10: Alert Channel

I. FINAL WEATHER PREDICTION USING MACHINE LEARNING ALGORITHM

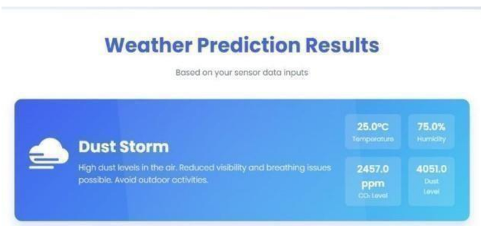

FIG. 11: WEATHER PREDICTION RESULT

In the above figure 11 gives an abstract: Predicted Condition: Dust Storm

Description: ―High dust levels in the air. Reduced visibility and breathing issues possible. Avoid outdoor activities.

Associated Sensor Readings:

• Temperature: 25.0°C

• Humidity: 75.0%

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• **CO_2 Level:** 2457.0 ppm Dust Level: 4051.0 units (likely from LDR-based dust sensor). The high dust level and moderate humidity, combined with elevated CO_2 readings, indicate a poor air quality event with potential health hazards. The forecast provides clear advisory guidance to minimize outdoor exposure during the predicted dust storm period.

IV. CONCLUSION

The combination of IoT and Machine Learning in weather monitoring systems offers an powerful efficient approach to the real-time environmental data collection, analysis, and forecasting. By leveraging sensors such as DHT11, MQ series, LDR, and rain detectors connected to microcontrollers like ESP32, the system gathers accurate and continuous weather data. The Machine learning algorithms, such as Random Forest, are then employed to process this data and predict weather conditions with high accuracy. This fusion not only enhances the precision of forecasts but also enables proactive responses to environmental changes, which is particularly valuable for agriculture, disaster management, and smart city planning. The system proves to be cost- effective, scalable, and capable of learning from historical patterns, making it a promising solution for future climate resilience and sustainable development.

V. REFERENCE

[1] S. JIN, Q. LI, S. LIU, O. K. JOEL, AND X. GE, "FEDERATED TRANSFORMER-KAN: A NOVEL FRAMEWORK FOR WEATHER FORECASTING VIA INTEGRATION OF TRANSFORMER AND KOLMOGOROV–ARNOLD NETWORKS," 2024.

[2] G. Balram, N. Poornachandrarao, D. Ganesh, B. Nagesh, A. B. Reddy, and M. S. Kumar, "Satellite-Based Precipitation Products and Machine Learning Approaches for Heavy Rainfall Prediction," 2024.

[3] M. Aldossary, H. A. Alharbi, and Ch. A. U. Hassan, "IoT Enabled Machine Learning Models for Efficient Monitoring of Smart Agriculture," IEEE Access, 2024.

[4] S. Bhatia, B. B. Naib, N. Goel, B. Agarwal, B. Mallikarjun, and M. Arvindhan, "A New Era in Weather Forecasting: Harnessing the Potential of Machine Learning," 2023.

[5] M. S. Murthy, R. P. R. Kumar, B. Saikiran, I. Nagaraj, and T. Annavarapu, "Real-Time Weather Monitoring System Using IoT," 2023.

[6] S. I. Hussain Al-Aqrabi, H. M. Shakeel, H. M. A. Farid, M. Riaz, and R. Hill, "An Innovative Machine Learning Technique for the Prediction of Weather-Based Smart Home Energy Consumption," 2023.

[7] Y. Essa, H. G. P. Hunt, M. Gijben, and R. Ajoodha, "Deep Learning Prediction of Thunderstorm Severity Using Remote Sensing Weather Data," 2023.

Volume 38 No. 7s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

[8] F. Meara et al., "IoT-Based Smart Weather Measurement System for Smart Farming Using Low-Cost Sensors and Neural Networks," Sensors, 2023.

[9] I. Ioannou et al., "Artificial Intelligence and IoT Technologies for Automatic Weather Stations: A Comprehensive Survey," Sensors, 2023.

[10] I. Ioannou et al., "Survey of AI and IoT Technologies for Automatic Weather Stations," Sensors, Special Issue on AWS Systems, 2023.

[11] S. Rasp et al., "WeatherBench: A Benchmark Dataset for Medium-Term Weather Prediction," Scientific Data, 2020.

[12] J. A. Weyn, D. R. Durran, and R. Caruana, "Improving Data-Driven Global Weather Prediction Using Deep Convolutional Neural Networks on a Cubed Sphere," J. Adv. Model. Earth Syst., vol. 12, Sep. 2020.

[13] Google DeepMind, "GraphCast: AI Outperforms Conventional Weather Forecasting Methods Up to 10 Days Ahead," Science, 2023.

[14] H. Bi, Y. Chen, J. Zhang, et al., "Pangu-Weather: Towards Foundation Models for Weather Forecasting," Nature, vol. 619, pp. 106–112, 2023.

[15] K. Z. Z. Myint, M. Aye, and T. T. Hla, "Weather Monitoring and Prediction System for Rice Cultivation in Mandalay Using IoT and Machine Learning," 2025.

[16] K. Z. Z. Myint, M. Aye, and T. T. Hla, "Weather Monitoring and Prediction System for Rice Cultivation in Mandalay Using IoT and Machine Learning," 2025. (Duplicate of [15], keep only once if required).

[17] X. Lim, S. Merugu, and H. Maheshwari, "Smart IoT Integrated Weather Analytics System," 2025.

[18] H. M. Harshini and R. Vadivel, "IoT Based Weather Monitoring System for Temperature, Humidity, Rainfall and Seismic Detection in Real Time," 2024.

[19] R. A. Mahdi, H. A. Hamed, and H. K. Latif, "A Review of Weather Conditions Monitoring System Based on IoT," 2024.

[20] S. Singh, A. Singh, and S. Limkar, "IoT Based Machine Learning Weather Monitoring and Prediction Using WSN," 2024.

[21] "Spatially-Resolved Hyperlocal Weather Prediction and Anomaly Detection Using IoT Sensor Networks and ML," 2023.

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