A Smart IoT–AI Integrated System for Accurate Rainfall Prediction

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Abstract: This paper describes a new IoT-based system that can keep an eye on the weather in real time. The system uses the internet to connect many sensors so that it can give you constant weather updates. All of the data that is collected is sent to the cloud, where users can get to it from anywhere.

This makes it easier to keep an eye on the weather, especially in rural or agricultural areas. When the weather is bad, traditional wired and analog devices often don't work. The system uses wireless sensors to collect data reliably to fix this problem. These sensors keep track of important things like light, temperature, humidity, and rainfall. The wireless setup makes monitoring easier and more accurate by cutting down on manual work.

The system is very helpful for farmers who need to know about the weather right away. It also backs ideas like vertical farming, which is when crops are grown in small spaces. Keeping an eye on the environment all the time helps keep farming conditions perfect. The answer is cheap, easy to use, and works well in rural areas. It helps people make better choices by giving them real-time data.

In general, the IoT-enabled approach makes it easier to plan for farming and keep an eye on the weather. It shows a modern and effective way to watch the environment.

Keywords: GSM technology, an IOT webpage, a rain sensor, a humidity sensor, an LDR, and a temperature sensor.

I. INTRODUCTION

With the rise of high-speed Internet, people all over the world are becoming increasingly linked. The growing Internet of Things (IoT) goes even further through connecting not just people but also electronic devices that may communicate to each other [1]. The pattern will only get greater as the prices of Wifi-enabled devices go down. The Internet of Things (IoT) is all about linking multiple gadgets through a link and then getting the data from those devices (sensors). This data can be transmitted in any way, submitted to any cloud service, and subsequently evaluated and processed. In the cloud service, you can use this data to let people know in various manners, like by sending them an email, SMS, or buzzing them.

The foremost objective of this paper is to generate and put into place an effective monitoring system that lets you remotely check the necessary parameters over the internet, maintain the data from the sensors in the cloud, and show the predicted trend in a web browser. The values in the cloud are always changing. The soil is tested, mostly to see what moisture content it is, and the crops are grown. So, we can grow different crops in the identical place. Vertical farming is a new way to farm that involves stacking produce vertically.

II. LITERATURE REVIEW

This section examines the current weather forecasting techniques that exist in the literature. Undeviating Reversion is the greatest straightforward and often utilized second-hand a prescient classical for the study. Reversion evaluations are primarily utilized to represent statistics and show the connection among at least one autonomous and one helpless variable. Graphically, direct recession discoveries the greatest fit concluded the opinions. The regression line is the route that fits best through the focuses.

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The route can be traditional or rounded here, provisional on the statistics. The best-fit track can also be a quadratic or polynomial, which benefits we find improved answers to our questions.

This research employs Decision Tree and Time Series Analysis as two of its algorithms. From the beginning, predicting the weather has been a big problem. Every day, new method come out that replace the old ones. Investigations in literature have established that machine learning methods overtake conservative numerical approaches. Computing's next big thing will be something other than the traditional workstation. The Things on the Internet is a way of thinking about how many of the things surrounding us will be connected to the internet in some way. Machine learning is very comparable to the internet of things.

Rainfall prediction plays a crucial role in agriculture, disaster management, water resource planning, and environmental monitoring. Traditional weather forecasting methods rely on numerical weather prediction models and statistical approaches; however, these methods often require extensive computational resources and large-scale meteorological data. Recent advancements in the Internet of Things (IoT) and Artificial Intelligence (AI) have enabled the development of cost-effective and real-time rainfall prediction systems.

Rahman et al. (2022) proposed a machine learning fusion framework for rainfall prediction in smart cities using environmental sensor data. Their study demonstrated that combining multiple machine learning models improved forecasting accuracy compared to individual models. However, the framework primarily focused on urban environments and required significant computational resources.

Nithyashri et al. (2023) developed an IoT-based rainfall forecasting system for coastal regions using a deep reinforcement learning model. The proposed system utilized environmental sensor data to predict rainfall patterns and achieved improved forecasting performance. Nevertheless, the complexity of the deep learning architecture increased computational requirements and limited deployment on low-cost hardware.

Jagadeesan and Nagarajan (2025) introduced an IoT-driven federated learning framework employing an Attention-based Convolution Recurrent Neural Network (A-CRNN) optimized using the Golden Jackal Optimization algorithm. Their approach enhanced prediction accuracy while preserving data privacy. However, the system required distributed computational infrastructure, making it less suitable for small-scale agricultural applications.

Kukre et al. (2025) proposed an integrated IoT-based weather monitoring and machine learning prediction system that collected environmental data using multiple sensors and applied machine learning algorithms for weather forecasting. The study demonstrated the effectiveness of combining IoT sensing and AI techniques but focused primarily on general weather prediction rather than localized rainfall forecasting.

Recent studies have also highlighted the growing importance of AI-enabled local weather forecasting systems. The IoT-AI Powered Local Weather Forecasting framework (2025) demonstrated that low-cost IoT sensors combined with machine learning algorithms can provide reliable localized weather predictions. The study emphasized the potential of integrating cloud computing, IoT, and AI technologies for precision agriculture and smart environmental monitoring.

Machine learning algorithms such as Decision Trees, Random Forests, Support Vector Machines (SVM), Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), and ARIMA models have been extensively used for rainfall prediction. Among these methods, Decision Trees provide interpretable prediction rules and low computational complexity, while ARIMA effectively models temporal patterns and seasonal weather variations. These characteristics make them suitable for deployment in resource-constrained IoT environments.

1. Research Gap

Although considerable research has been conducted on IoT-based weather monitoring and AI-based rainfall forecasting, several limitations remain. Most existing studies focus either on environmental data collection using IoT devices or on advanced machine learning models for prediction. Furthermore, many proposed systems rely on expensive infrastructure, large datasets, cloud-intensive processing, or computationally complex deep learning models that are difficult to deploy in rural agricultural environments.

There is a lack of low-cost, real-time, and easily deployable systems that integrate IoT-based environmental sensing with machine learning-based rainfall prediction using lightweight algorithms. Additionally, limited attention has been given to developing solutions suitable for small-scale farmers who require localized weather information for agricultural decision-making.

To address these challenges, the proposed work integrates IoT sensors, cloud-based monitoring, and AI-driven rainfall prediction within a unified framework. The system employs affordable sensors and lightweight machine learning techniques, enabling real-time rainfall forecasting and environmental monitoring suitable for smart agriculture and rural deployments.

TABLE I

DIFFERENT TECHNICQUE

Author	Year	Technique	Limitation
Rahman et al.	2022	ML Fusion Models	High computational requirements
Nithyashri et al.	2023	Deep Reinforcement Learning	Complex architecture
Jagadeesan & Nagarajan	2025	Federated Learning + A-CRNN	Requires distributed infrastructure
Kukre et al.	2025	IoT + Machine Learning	Focused on general weather prediction
Proposed Work	2026	IoT + Decision Tree + ARIMA	Low-cost real-time rainfall prediction

III. METHODOLOGY

1. Suggested System

In this, we talk about the theory behind using the Internet of Things (IoT) to predict rain. This suggested block diagram displays the way several sensors (LDR sensor, humidity sensor, temperature sensor, and rain sensor) link to our controller. A controller is getting the sensor values, processing them, displaying them on an LCD display, and submitting them to a website server. All of the sensors are linked to the controller. A wireless networks module gets the latest readings and transforms them into graphs and statistics.

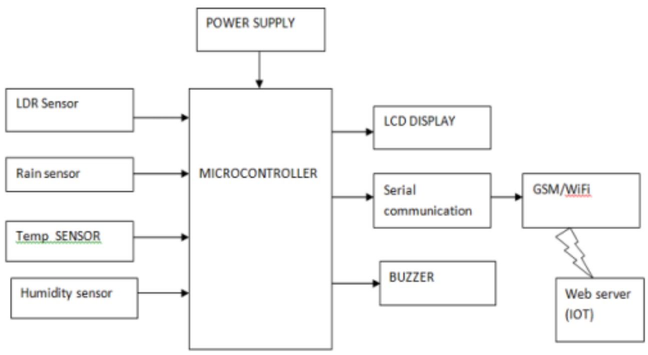

Fig. 1. Block Illustration of the Framework

A. PIC 18f4520 chip: 4k bytes of data memory Data register map: 000-FFF 12-bit address bus

Separated into banks of 256 bytes ,The total number of F banks is a virtual (or access) bank is generated by half of bank 0 and half of bank 15, and it is accessible with regard to whatever bank has been selected; this selection is made using 8-bits.

Within the PIC18, a distinct program data bus and address bus are used to access software memory, which is 16 bits wide. The system's program and static data are conserved in program memory. External on-chip Either PROM or EEPROM are types of on-chip software memory. The Once-only programmable, or OTP, is the name of the PROM version (PIC18C). The Flash memory (PIC18F) is the EEPROM variant. The maximum size of program memory is 2 million bytes. The 21-bit program memory addresses begin at point 0x000000.

B. Rain Sensor

Fig 2. PIC18F452

This device determines when it is raining. It can also be used to determine how much rain is dropping. Its output is both analog and in addition to digital output. This module uses a single analog pin to measure moisture, and it produces an analog signal when the moisture threshold is achieved. Lower output voltage occurs by either more water or less impedance. On the other hand, less water results in greater obstacle or a higher output voltage on the sensor pin.

Fig. 3.Rain Sensor

C. Humidity Sensor:

The DHT11 is a humidity and temperature sensor that sends out calibrated digital signals. DHT11 can be connected to with any microcontroller, such as PIC, Arduino, or Raspberry Pi, and get results right away. The DHT11 is a cheap sensor for moisture and temperature that is very reliable and stable over time. It has a sensor for humidity that works with capacitance and measures the air around it and sends a digital signal to the data pin. It's informal to use, and there are libraries and example codes for both Arduino and Raspberry Pi.

Fig. 4. Humanity sensor

D. LM35 Disease Sensor:

The LM35 series is a set of precise disease sensors using integrated circuits. Their production energy is linearly. In relation to the Celsius (Centigrade) illness. The LM35 is better than linear temperature sensors that are calibrated in ° Kelvin because the user doesn't have to deduct an enormous persistent energy from its production to get easy Centigrade scaling.

The LM35 doesn't need some external correction or decoration to give classic exactitudes of ±¼°C at room fever and ±¾°C over a full disease range of -55 to +150°C. Decoration and standard is action at the cracker level make sure that the cost is truncated. The LM35 is informal to attach to display or regulator motherboard because it has a squat production impedance, a direct output, and precise built-in calibration.

TEMP Sensor:

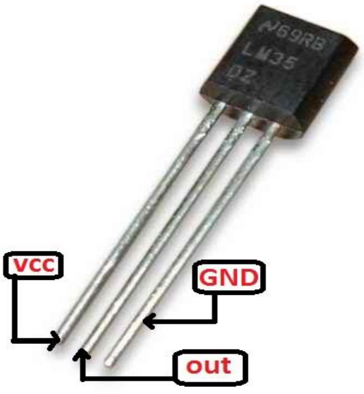

Fig. 5. LM35

E. LCD demonstration:

A 16x2 LCD can show 16 charms per streak, and here are two lines like this. This LCD displays both charms. In a 5x7 pixel grid. This LCD has two registers: Command and Data. The appreciation register keeps track of the requests that the LCD has been given. A facility is an training assumed to the LCD to do a specific job, for example starting it up, dissipating its display, moving the indicator, or regulatory the presentation. The data register keeps any records that will be shown on the LCD.

Fig. 6. LCD Display

F. GSM module:

This cellular mode has a SIM800A chip and an RS232 interface. It can easily connect to a processor using the USB to Sequential connector or to a microchip using the TTL converter. After you attach the modem with the USB to RS232 connector, you need to look for the right COM port in the Device Manager of the USB to Serial Adapter. You can then use other computer software to connect to that COM anchorage at 9600 baud degree, which is the modem’s avoidance byte per second amount.

Fig 7.GSM Module

G. AI-Based Rainfall Prediction Module

The proposed system integrates Internet of Things (IoT) technology with Artificial Intelligence (AI) to provide accurate rainfall prediction for agricultural and environmental monitoring applications. Environmental parameters collected through multiple sensors are continuously transmitted to the cloud platform, where machine learning algorithms analyze historical and real-time data to forecast rainfall conditions.

1. Data Collection

The IoT node consists of multiple sensors including:

- DHT11 Humidity Sensor – measures relative humidity (%).
- LM35 Temperature Sensor – measures ambient temperature (°C).
- Rain Sensor – detects rainfall intensity and precipitation occurrence.
- LDR Sensor – measures light intensity and atmospheric brightness.

The sensors are connected to the PIC18F4520 microcontroller, which collects data at regular intervals. The collected data are transmitted through the GSM communication module and stored in a cloud database for further processing.

2. Dataset Preparation

The dataset consists of environmental observations collected from the deployed sensor network. Each record contains:

TABLE II

FEATURE

Feature	Description
Temperature	Ambient temperature in °C
Humidity	Relative humidity (%)
Rainfall Sensor Value	Rain intensity measurement
Light Intensity	LDR sensor reading
Timestamp	Date and time of observation
Rainfall Status	Target variable (Rain/No Rain)

Before model training, the collected data undergo preprocessing to improve prediction accuracy.

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3. Data Preprocessing

The preprocessing stage includes:

- Removal of incomplete or corrupted records.
- Noise filtering to eliminate abnormal sensor readings.
- Handling missing values through interpolation techniques.
- Feature normalization to bring sensor values into a comparable range.
- Conversion of categorical rainfall labels into machine-readable numerical values.

These preprocessing steps improve data quality and reduce prediction errors.

4. Feature Engineering

Feature engineering is performed to identify the most influential environmental parameters affecting rainfall prediction. Statistical analysis shows that humidity, temperature variation, and rainfall sensor readings have significant influence on rainfall occurrence.

Additional derived features include:

- Average temperature over a specific time window.
- Humidity trend variation.
- Rainfall intensity changes.
- Daytime and nighttime environmental patterns.

These engineered features help the machine learning model capture complex weather relationships.

5. Machine Learning Model

The proposed system utilizes a hybrid AI approach combining Decision Tree Classification and ARIMA Time-Series Analysis.

Decision Tree Model

Decision Tree is a supervised machine learning algorithm used to classify whether rainfall is likely to occur. The model creates decision rules based on environmental conditions such as humidity, temperature, and rainfall sensor values.

Advantages include:

- Easy interpretation of prediction results.
- Fast training and prediction.
- Ability to handle nonlinear relationships.
- Suitable for resource-constrained IoT environments.

The Decision Tree model learns from historical weather observations and generates rainfall predictions based on learned decision paths.

ARIMA Model

Autoregressive Integrated Moving Average (ARIMA) is employed for time-series forecasting of weather parameters.

The ARIMA model captures:

- Historical weather trends.
- Seasonal variations.
- Temporal dependencies among observations.

ARIMA provides short-term rainfall forecasting by analyzing sequential sensor data collected over time.

6. Model Training Process

The prepared dataset is divided into:

- 80% Training Data
- 20% Testing Data

The training phase includes:

1. Input sensor data acquisition.
2. Feature extraction and preprocessing.
3. Model training using historical observations.
4. Hyper parameter optimization.
5. Model validation using testing data.

Cross-validation techniques are applied to reduce over fitting and improve model generalization.7. Performance Evaluation

The trained model is evaluated using standard machine learning metrics:

- Accuracy
- Precision
- Recall
- F1-Score
- Mean Absolute Error (MAE)
- Root Mean Square Error (RMSE)

These metrics assess both classification performance and forecasting accuracy.

8. Real-Time Prediction Workflow

The real-time prediction process follows the steps below:

1. Sensors collect environmental data.
2. Data are transmitted to the cloud server through the GSM module.
3. Preprocessing and feature extraction are performed.
4. The trained AI model analyzes current weather conditions.
5. Rainfall probability is calculated.
6. Prediction results are displayed on the IoT web dashboard.
7. Alerts can be generated when rainfall probability exceeds a predefined threshold.

9. Advantages of the Proposed AI-IoT Framework

The proposed AI-integrated framework offers several advantages:

- Real-time weather monitoring.
- Early rainfall prediction for agricultural planning.
- Low-cost deployment using affordable sensors.
- Reduced manual observation effort.
- Improved decision-making for farmers.

IV. CONCLUSION

Keeping devices that are embedded in the environment for monitoring makes the environment safer through facilitating self-protection (i.e., a smart environment). To meet this requirement, the sensor devices must be set up in the environment to collect and analyze the data. The main goal was to build the most accurate system possible using cheap parts. This system could monitor the weather in real time on farms and use machine learning algorithms to make better predictions about the weather in the future. ARIMA can better capture how the temperature changes over time than the Decision Tree. This makes the Rain information in the weather profile more compact and natural.

It has always been hard to predict the weather, and new methods are being developed every day to replace the old ones. The next big thing in computers will be something other than the traditional desktop. In the Internet of Things (IoT) model, a lot of the things around us will be connected to the internet in some way. Machine Learning and the Internet of Things are very similar. A perfect mix of them can speed up the modernization of agriculture, make smart agriculture a reality, and solve problems with farmers, agriculture, and the countryside. The user will formerly be able to contact the data and investigation results

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