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Rainfall Measurement And Prediction Using IOT And Artificial Intelligence

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Abstract: Rain is an essential part of the water cycle that transfers water from the atmosphere to the surface, sustaining life. For many human activities, including irrigation management, hydrological monitoring, water resource management, and flood prevention, accurate rainfall data is crucial. Traditional approaches to monitoring rainfall data, however, can be inefficient and time-consuming. A reliable system for predicting rainfall is necessary because global climate change has also altered rainfall patterns. Effective sensors for measuring rainfall are rain gauges. However, it can be difficult to accurately predict when it will rain. Unexpected or significant rainfall can harm crops and property, which has an impact on the economy. Therefore, early warning systems and reducing risks to life and property, particularly in agriculture, depend on improved forecasting models. The goal of this project is to create a system for predicting rainfall using machine learning and artificial intelligence. The system aims to make machine learning techniques easy to use for non-experts in the field and to compare them. For increased accuracy, the project makes use of a sizable dataset of historical weather information. The system can forecast rainfall amounts and provide advance warnings to lower the risk of loss. Since the people of this country are primarily dependent on agriculture, this prediction system is crucial to managing agricultural farms and utilizing water resources efficiently.

Index Terms **- Tipping Bucket Rain Gauge, ESP32, Reed Switch, Rain Fall Prediction.**

I. INTRODUCTION

Rain is an essential part of the Earth's water cycle because it makes it easier for water to move from the atmosphere to the ground, sustaining life and supporting a variety of human activities. Precise estimation and expectation of precipitation are fundamental for various applications, including water system executives, hydrological checking, water asset the board, flood avoidance, and barometrical and hydrological gauging. Conventional strategies for checking precipitation, for example, depending on actual downpour measure stations, frequently experience the ill effects of impediments, blocking the expected regular and extensive observing essential for exact applications. Rain gauges have been effective sensors for measuring rainfall for a long time [1]. However, timely and accurate rainfall forecasting is just as important because severe and erratic rainfall can cause crop damage, property destruction, and financial losses. An improved forecasting model can reduce risks to life, property, and livelihoods by enabling better agricultural management and early warnings. Customary techniques that depend exclusively on atmospheric conditions like temperature, stickiness, and strain have constraints in creating productive and precise precipitation forecasts [4]. The integration of machine learning and artificial intelligence (AI) techniques offers promising solutions for overcoming these obstacles. Utilizing vast datasets, these advanced methods are able to identify intricate patterns that would otherwise be difficult to discern with conventional methods. The creation of a rainfall prediction system that makes use of AI and machine learning to provide timely forecasts is the primary objective of this project. The expectation is to make these methods available to non-specialists by offering a simple to-utilize stage. In addition, the goal of this research is to compare various machine learning algorithms to ascertain how well they work for forecasting precipitation [6][7]. Potential losses can be minimized, particularly for farmers whose livelihoods are heavily dependent on agriculture, by accurately predicting the amount of rainfall and providing advance notice.

II. RELATED WORK

Researchers have set up networks of rain gauges and weather sensors for comprehensive and real-time data collection in the field of rainfall measurement by utilizing IoT technologies. When compared to traditional manual measurements, the study emphasized the advantages of real-time data transmission, extensive coverage, and lower costs. As to forecast, AI procedures have been broadly investigated. A support vector machine (SVM) model for rain prediction was trained using historical rainfall data and meteorological variables like temperature, humidity, and wind speed in the study. This demonstrated that SVM can accurately forecast short-term rainfall [12]. In addition, ensemble methods that combined multiple machine learning algorithms, such as random forest, gradient boosting, and deep learning, to predict rainfall have been used to improve the accuracy of rainfall predictions [7]. The outcomes demonstrated that the gathering approach outflanked individual calculations, displaying the potential for further developed precision through the model.

III. METHODOLOGY

A. Block Diagram

This project was mainly focused to design and develop a model of a tipping bucket Rain Gauge and to develop a system to forecast the probability of rain using Machine Learning.

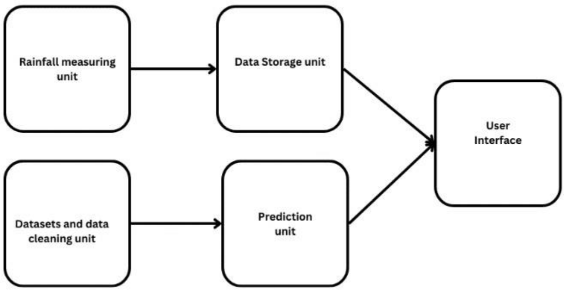

Fig. 1. General Block Diagram

Fig. 1 depicts the main block diagram for the whole project. Rainfall measurement is done in the upper row, while rainfall forecasting is done in the lower row. The system is made up of one user interface unit and four functional units. The four operating units are the Rainfall measuring unit, Data storage unit, Datasets and data cleaning unit, and Prediction unit, as shown in Fig. 1.

i. Rainfall Measuring Unit: This unit must compute the acquired rainfall and communicate it to the following unit.

ii. Data Storage Unit: This unit provides data storage for the obtained rainfall data.

iii. Datasets and Data Cleaning Unit: This unit helps in obtaining the past dataset and cleaning them before they are let into the prediction unit for further operations [5].

iv. Prediction unit: This section predicts the probability of rainfall for the next day based on the previously obtained data [7].

v. User Interface: The amount of rainfall and prediction output are displayed by this unit.

B. Working

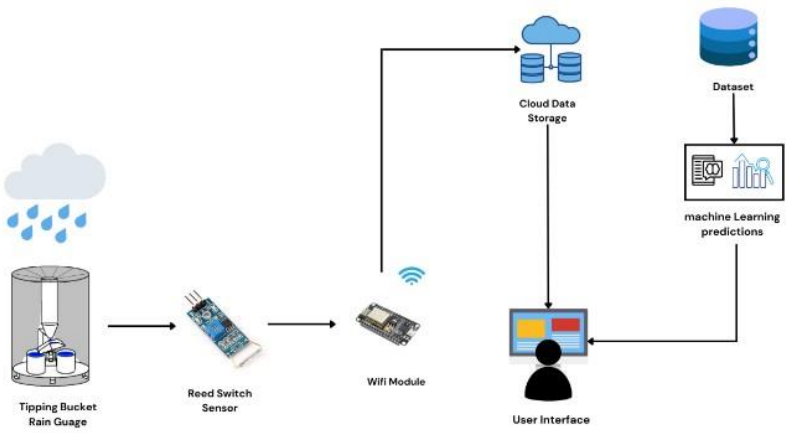

Fig. 2. System Diagram

The tipping bucket first receives rainwater. A funnel and an inlet are used to fill the bucket with water. A see-saw mechanism and a reed switch are both inside the bucket. When the seesaw's two sides are uneven, this reed switch will be an open circuit. When one side is full, the filled side descends, and the empty side ascends. At some point in this, when both sides are equal, the reed switch will be closed, allowing current to pass through the circuit. Logic 1 will then be sent to the output as a result [3]. The microcontroller in the station receives these signals via a Wi-Fi module. At the microcontroller, the input will be gathered. The microcontroller will be the one to receive this input. The microcontroller's code will be used to analyze these inputs, and the appropriate amount of rainfall is calculated in millimeters. The data is transferred to the data storage unit once more via the Wi-Fi module. Both historical data and recently acquired data are available in the data storage unit. The user can access the present data or any other data at any moment by gaining access to the data storage unit. These data are forwarded to the machine learning and prediction section, where both historical and current data are analyzed [6]. Future projections are based on this. The user receives future predictions via the user interface unit. Present, past, and future data are presented to the user via the user interface unit in the form of text, graphs, and statistical charts.

IV. Implementation

The hardware for this project was implemented first, followed by the software, including IoT. The mechanical components of the tipping bucket rain gauge were designed using solid works and 3D printed.

A. Model Design

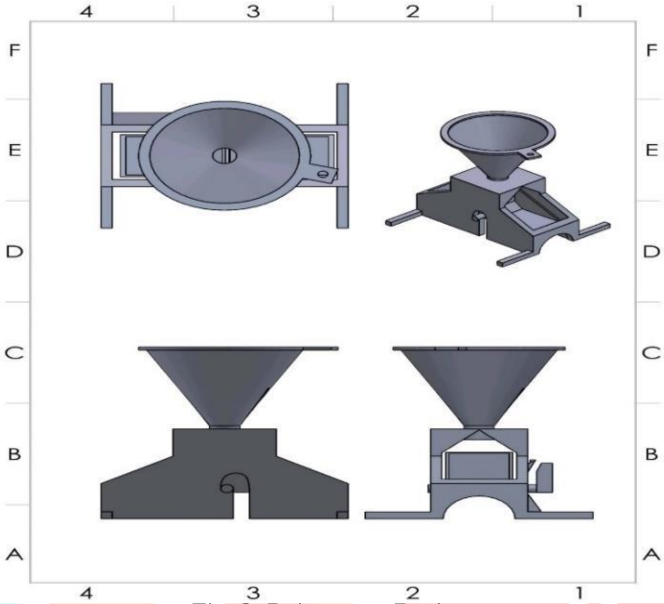

Fig. 3. Rain gauge Design

The Rain gauge 3D model consists of three components: the base, the funnel, and the structure [1].

Compartment: The portion of the rain gauge called the compartment is where the tipping buckets are kept. Typically, it is a box-shaped structure with a top opening where rainwater can enter. The tipping buckets and the funnel can fit inside the compartment because it is big enough. Typically, PLA+ filament is used to create the compartment in order to shield the internal mechanisms from the outside elements.

Funnel: The funnel is the top part of the rain gauge that collects rainwater and directs it into the compartment. It is usually a cone-shaped structure that is positioned above the compartment opening. The funnel is typically made of plastic or metal and is attached to the structure at an angle that allows rainwater to flow smoothly into the compartment.

Structure: The parts holding the funnel and the compartments together make up the structure of a tipping bucket rain gauge. To ensure precise measurements of rainfall, it offers a stable base for the rain gauge. The structure typically consists of a base that can be fastened to the ground with bolts and an upward-extending support column that holds the funnel. The compartments are typically fastened to the sides of the support column so that rainwater can be funneled into them [3]. Each compartment contains a tipping bucket mechanism that measures rainfall and records those readings.

B. Hardware Implementation

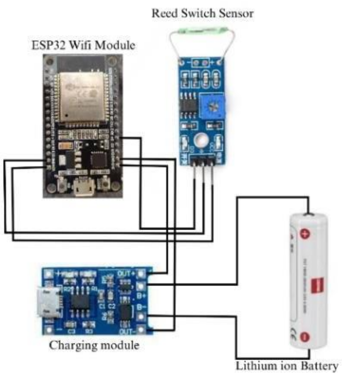

Fig. 4. Hardware Setup

The ESP32 receives the signal from the reed switch and processes the information to determine how much rain fell. The microcontroller is also powered by a lithium-ion battery attached to the ESP32. The charging module is connected to the lithium-ion battery to maintain its charge and ensure that the ESP32 has sufficient power to function. The charging module, reed switch, ESP32, and lithium-ion battery all work together to measure the amount of precipitation and supply power to the microcontroller. The ESP32 examines the information while the reed switch tracks the turn of the tipping pail downpour measure, which is utilized to decide how much precipitation [2]. For the ESP32 to have the option to run persistently, a reliable power source is given by the lithium-particle battery and charging module.

C. Software Implementation

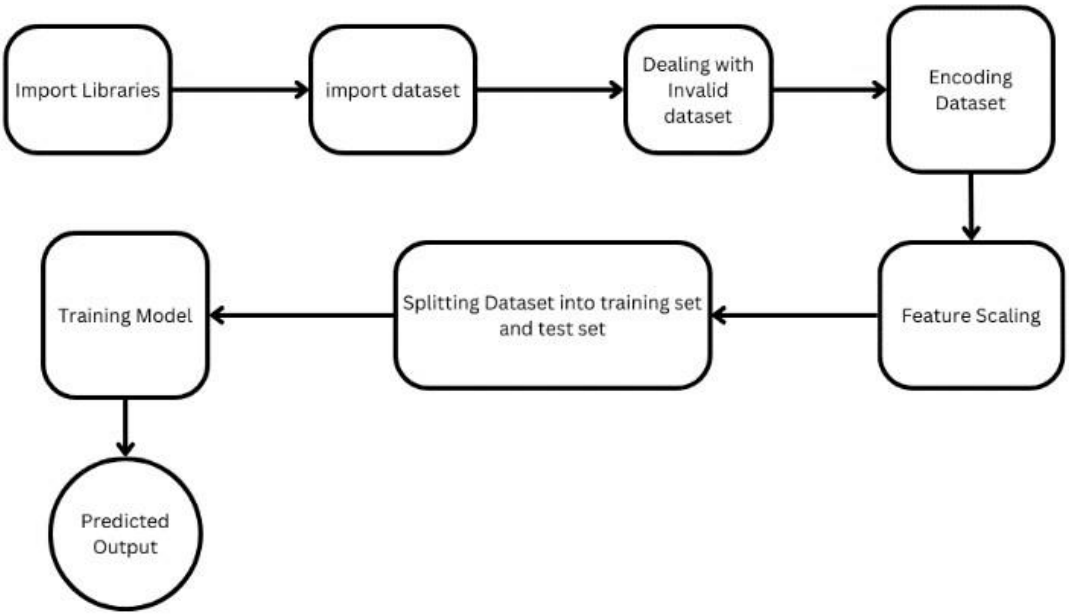

Fig. 5. Prediction Block Diagram

In Fig. 5, The code scrap imports the essential libraries like NumPy and Pandas for information control and examination. Using Pandas, it reads a CSV file, selects particular columns as input features, and makes the last column the target variable. The "SimpleImputer" class is used to handle missing values in the dataset, and the "LabelEncoder" class is used to encode categorical variables. The "StandardScaler" class is used to standardize the input features. After that, the dataset is divided into testing and training sets. On the training data, a Random Forest classifier is trained, and its accuracy is evaluated. A data frame for comparison is created by concatenating the actual values with the predicted output. The "accuracy_score" function is used to determine the model's accuracy.

D. Rainfall Measurement Formula

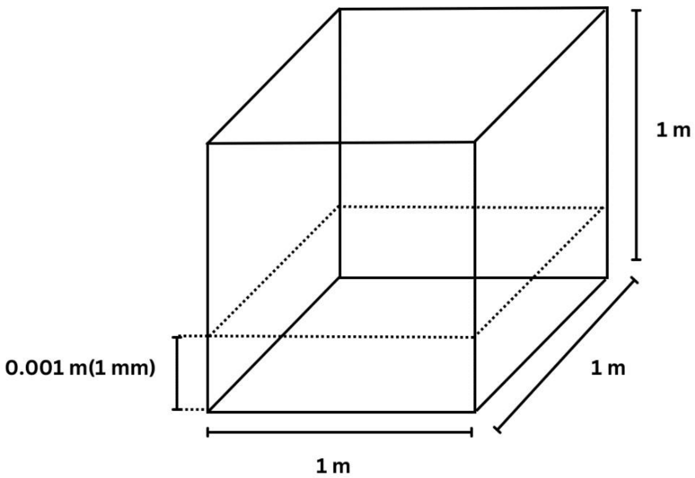

Fig. 6. Measuring Block

Imagine an open square container, 1 m wide, 1 m long and 1 m high. This container is placed horizontally on an open area in a field. During a rain shower, the container collects the water. Suppose that when the rain stops, the depth of water contained in the pan is 1 mm.

The volume of water collected in the pan is:

V (m^3) = l (m) x w (m) x d (m) = 1 m x 1 m x 0.001 m = 0.001 m^3 or 1 liters (1 liter = 0.001 m^3).

It can be assumed that the surrounding field has also received a uniform water depth of 1 mm. In terms of volume, with a rainfall of 1 mm, every square meter of the field receives 0.001 m, or 1 liter, of rainwater. With a rainfall of 1 mm, every square meter receives 1 liter of rainwater. A rainfall of 1 mm supplies 0.001 m3, or 1 liter of water to each square meter of the field.

Hence,
1 mm = 1000 ml (1 liter).

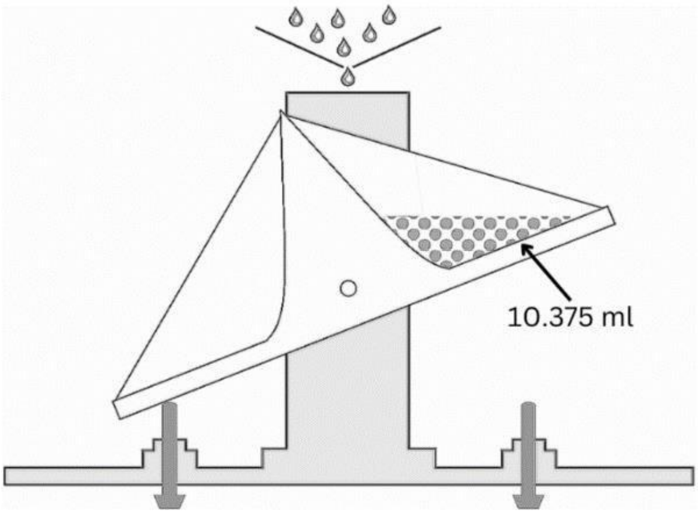

Fig. 7. Tipping Bucket

From the experiment done in the laboratory with the tipping bucket, the bucket used to tip at every 10.375 ml. Hence converting ml to mm, one tip will be 0.01075 mm.

Therefore,

1 tip of the bucket = 0.010375 mm.

V. Results and Discussion

A prototype model was originally developed and modeled. 3D printing was used to create the model. The model's dimensions were scaled up after the concept was put to the test.

Fig. 8. Rain gauge

Practical calculations were made after the bucket's construction to determine how much rain would descend at the tip. Calculated for the tip is the quantity of rainwater. 10.375 ml is the measured quantity of rainwater for one tip. As mm are used to quantify rainfall. 0.01075 mm of rainwater is represented by the number 10.375 ml, given that 1 millimeter of rainfall equals 1 liter. Consequently, all the calculations and planning work was completed.

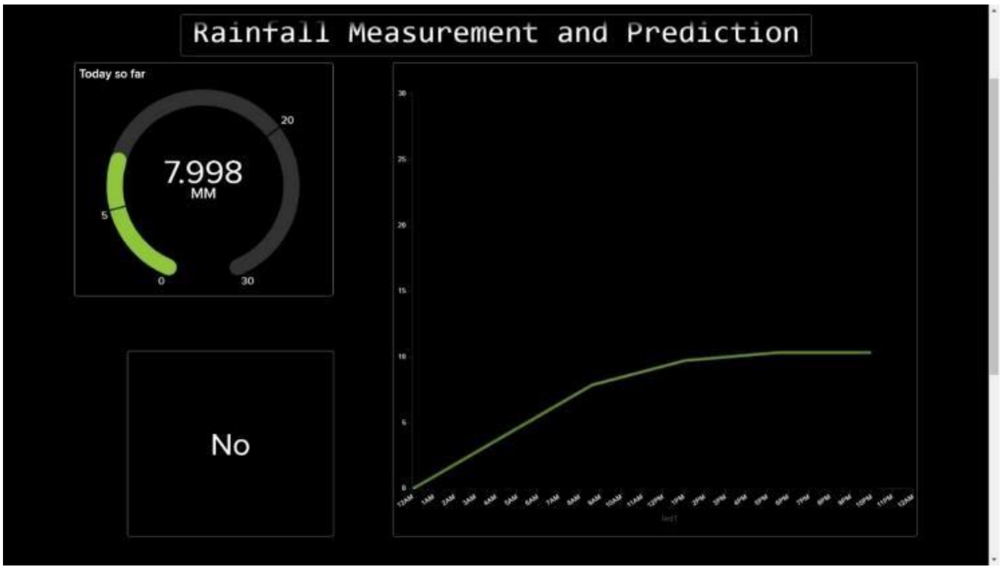

Fig. 9. Adafruit Interface

The above fig shows the sensor's value was connected to the Adafruit IO interface via Esp32 and the Arduino IDE [14]. The above Interface shows the Amount of rainfall in mm, the timing graph of the rainfall amount and the Prediction.

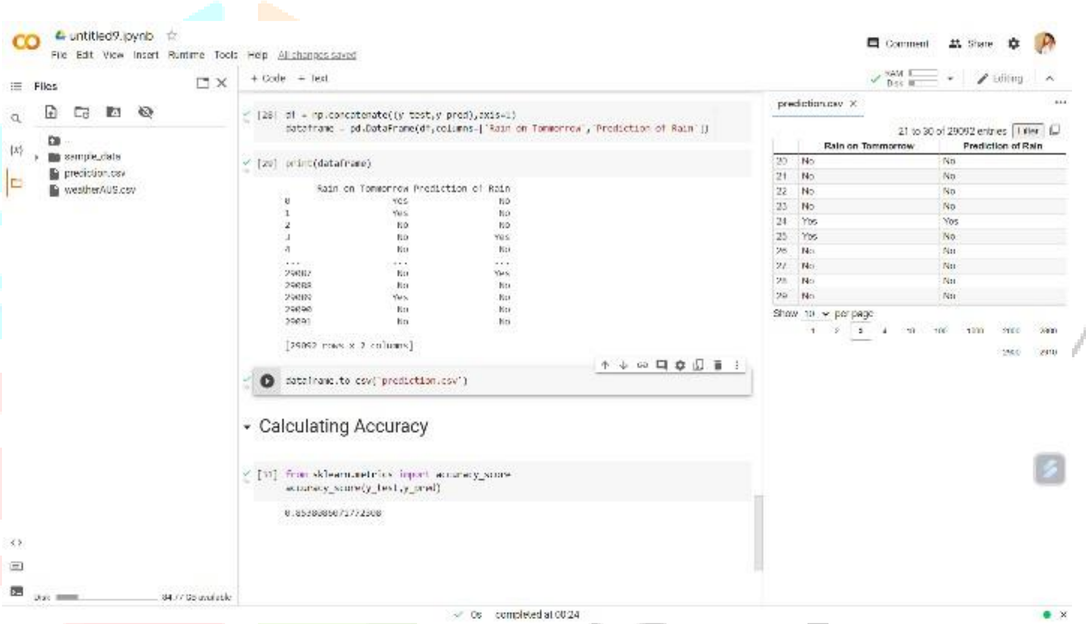

Fig. 10. Accuracy of the Prediction

Initially, 30000 data points from the single-day rainfall datasets of several cities were used to test the model [5]. To isolate the information, test, and train information was utilized. The RandomForestClassifier used 20% of the data as test data while training on 80% of the data. The calculation was thusly educated to gauge the probability of precipitation [11]. The above Fig. 10 shows us the accuracy of the system. The sklearn metrics "accuracy_score" were used to measure accuracy. The accuracy was compared to predicted and previously obtained data. The precision was viewed as 0.85, which is 85%

VI. Conclusion and Future Work

The utilization of a tipping pail and reed switch component guarantees exact precipitation estimation, making it significant for different applications. Users can access current and future rainfall data thanks to real-time data collection, analysis, and machine learning capabilities. Its cost-effectiveness and low maintenance requirements make it accessible to a broader audience, while its user-friendly interface and easy access to data improve usability. However, the system's reliance on a Wi-Fi network and limited power supply may present difficulties, and it should be considered the possibility of obstructions affecting accuracy. This rainfall measurement system has many advantages, but it also has some drawbacks. Later on, headways in precipitation estimation frameworks could incorporate the usage of refined sensors to improve accuracy and screen extra ecological variables. It is possible to create mobile applications that give smartphone users easy access to rainfall data. The system's sustainability can be enhanced by incorporating renewable energy sources like solar power. Flood mitigation and early detection are made possible by the system's compatibility with flood monitoring systems. By providing detailed information about the weather and the environment, integrating the system with smart city infrastructure can also help build resilient and sustainable communities. Rainfall measurement technology's ongoing progress and potential for further improvement are demonstrated by these potential advancements.

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