Smart Irrigation Using ML and IoT

Project Report Submitted in Partial Fulfilment of the Requirements for the Degree of

BACHELOR OF TECHNOLOGY

by

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November 2022

CERTIFICATE

This is to certify that this project report **“Smart Irrigation using ML and IOT”** is submitted by **Apoorv Jain, Karan Singh Khati and N Vikranth Choudary** who have carried out the project work under the supervision of **Dr. Sonam Jain**.

We approve this project for submission of the BTECH Project, IIT (BHU) Varanasi.

Signature of Supervisor

Dr. Sonam Jain

Department of Electronics Engineering

IIT BHU Varanasi

DECLARATION BY THE CANDIDATE

We hereby declare that the project report entitled ”*Smart Irrigation Using ML*” submitted by Apoorv Jain (19095017), Karan Singh Khati (19095051) and N Vikranth Choudary (19095068) to Indian Institute of Technology (BHU), Varanasi, in partial fulfillment of the requirement for the award of the degree of B.Tech in Electronics Engineering is a record of bonafide project work carried out by us under the guidance of Dr. Sonam Jain. I further declare that the work reported in this project has not been submitted and will not be submitted, either in part or in full, for the award of any other degree in this institute or any other institute or university.

Made by:

Apoorv Jain (19095017)

Karan Singh Khati (19095051)

N Vikranth Choudary (19095068)

CERTIFICATE BY THE SUPERVISOR

I certify that the thesis entitled "**Smart Irrigation using ML and IOT**" submitted for the degree of B. Tech in Electronics Engineering by **Apoorv Jain (19095017), Karan Singh Khati (19095051) and N Vikranth Choudary (19095068)** is the record of the work carried out by them during the period from January 2022 to December 2022 under my guidance, and this work has not formed the basis of the award of any other Degree, Diploma, Associateship and Fellowship or any other Titles in the University or any other University or institution of Higher Learning.

ABSTRACT

Farms can be upgraded with electronic technology that continuously monitors crop and soil conditions, so crops can be watered as needed. All of these can be controlled and monitored online using IoT applications. Create a device that connects to a water pump controlled by an Arduino UNO R3 microcontroller. The water pump automatically controls based on the values of various environmental factors such as temperature, humidity, soil moisture and light intensity, which can be measured via sensors such as DHT-11 temperature and humidity sensor, humidity sensor, LDR sensor Throughout our research work, we try to make the model intelligent by storing previously scanned values in a database and performing pre-recognition based on the stored historical values during the training phase of the working model. increase. Train the model using the PLSR algorithm.

Agriculture plays an important role in the economy and its contribution is based on quantifiable crop yields that are heavily dependent on irrigation. In countries like India, where agriculture is largely based on an unorganized sector, irrigation techniques and patterns are inefficient and often lead to unnecessary water wastage. You need a system that can provide a deployable solution. This article presents an automated irrigation system based on artificial vision and the Internet of Things that can autonomously irrigate fields using soil moisture data. The system is based on forecasting algorithms that use historical weather data to identify and forecast precipitation patterns and climate change. This creates a sophisticated system that selectively irrigates crop fields only when needed at the right time based on weather and soil moisture conditions. The system has been tested with 80% accuracy in a controlled environment and offers an efficient solution to your dilemma.

INTRODUCTION

As for irrigation, India follows traditional agricultural methods. Irrigation is a major determinant of crop yield and varies greatly with geographical, climatic and topographical factors. Farmers rely primarily on personal supervision and experience in irrigating the fields, making irrigation highly inefficient and quaint. India therefore has the ability to ensure that farmers are indefinitely reliable, able to adapt to local climatic conditions, and timely and accurately determine the amount of water their crops need to ensure wise use of water resources, I need a better and simpler irrigation solution. yield. The main concern in India is not water scarcity but water waste and poor use of resources due to lack of precautions, facilities and infrastructure. Due to water wastage, the country is already suffering enormous economic losses from massive drought conditions, variable rainfall patterns, and crop eradication.

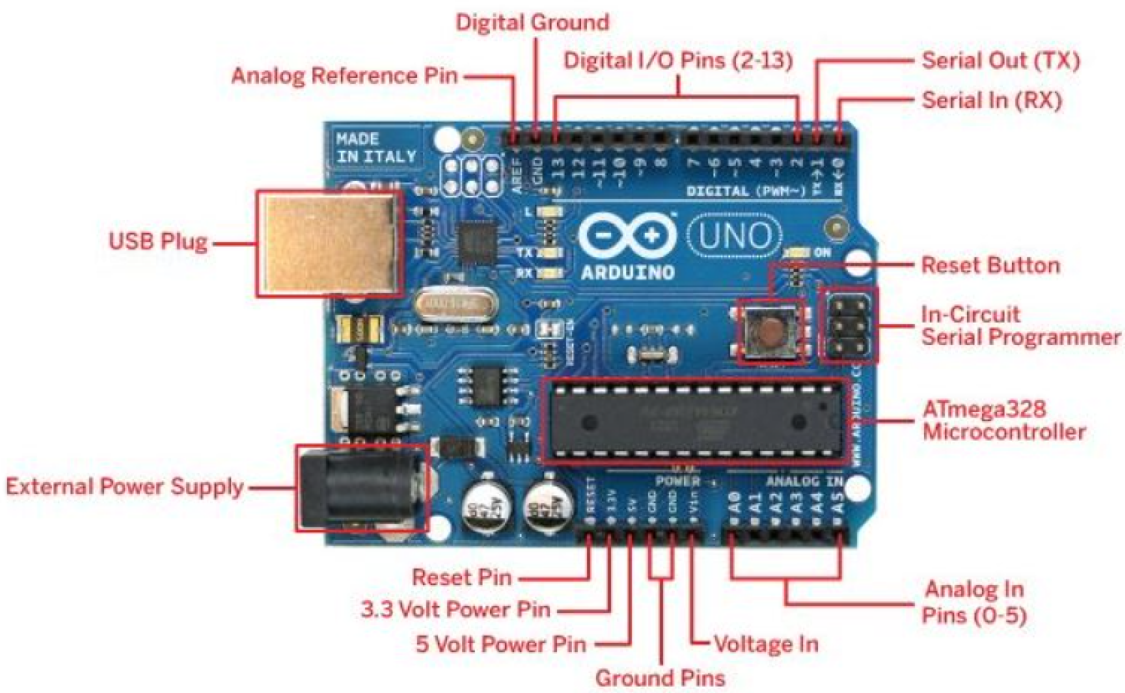
Traditional automated irrigation systems are not suitable for India as they cannot adapt to changing rainfall patterns and respond well to geographical changes. So we can study local rainfall patterns and realistic weather conditions to adapt to geography, predict how much water is needed for irrigation, minimize waste, and increase yields. Developed a unique system. To achieve this, it uses microcontrollers and soil moisture sensors placed in waterproof boxes and evenly distributed over the area to be irrigated. All of these nodes are connected to the cloud via Wi-Fi connections. The system analyzes soil moisture levels via deployed sensors. Sensors are used to determine the amount of water needed to irrigate an area with great accuracy. It is a highly autonomous system that requires little to no human intervention once deployed. The developed system uses Desultory Forest Regressor to estimate weather. Uses conventional data for precipitation patterns and weather data. It has the ability to gradually acclimate to the specific climatic conditions of the region, and its accuracy varies from forecast to forecast. The system is designed to update continuously. At each such traditional interval, update the data set according to the initial sensor data provided. The system turns on motors or pumps when the sensed soil moisture content is insufficient and is based on sensor data used using a Partial Least Squares Regression (PLSR) algorithm to predict moisture requirements. This will allow you to calculate the time interval for the motor to pump water. Also, if the system detects sufficient soil moisture or rain is forecast, the pump will not turn on while the sensor is measuring soil moisture capacity after rainfall. The developed system is energy efficient, water efficient and low maintenance. Systems are scattered throughout the farm grounds. This allows the drip or sprinkler to be turned on for specific areas rather than the entire operation, increasing efficiency. This is to minimize water wastage and to better understand the water capacity of plants and the patterns required for efficient watering.In addition, the nodes work with a replication prediction system, which makes failure easier. can be identified. Node status can be monitored via a mobile app based on the mapping of farms and areas designated for irrigation. The system therefore promotes low maintenance and has proven to be effective.

COMPONENTS AND TECHNOLOGY USED

- ### Arduino Uno R3:

  Arduino Uno R3 is one kind of ATmega328P based microcontroller board. It includes the whole thing required to hold up the microcontroller; just attach it to a PC with the help of a USB cable, and give the supply using AC-DC adapter or a battery to get started. The term Uno means “one” in the language of “Italian” and was selected for marking the release of Arduino’s IDE 1.0 software. The R3 Arduino Uno is the 3rd as well as most recent modification of the Arduino Uno. Arduino board and IDE software are the reference versions of Arduino and currently progressed to new releases. The Uno-board is the primary in a sequence of USB-Arduino boards, & the reference model designed for the Arduino platform.

Arduino Uno R3 configuration:

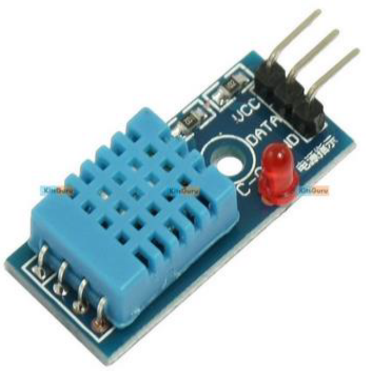


The Arduino Uno R3 board includes the following specifications.

- It is an ATmega328P based Microcontroller
- The Operating Voltage of the Arduino is 5V
- The recommended input voltage ranges from 7V to 12V
- The i/p voltage (limit) is 6V to 20V
- Digital input and output pins-14
- Digital input & output pins (PWM)-6
- Analog i/p pins are 6
- DC Current for each I/O Pin is 20 mA
- DC Current used for 3.3V Pin is 50 mA
- Flash Memory -32 KB, and 0.5 KB memory is used by the boot loader
- SRAM is 2 KB
- EEPROM is 1 KB
- The speed of the CLK is 16 MHz
- In Built LED

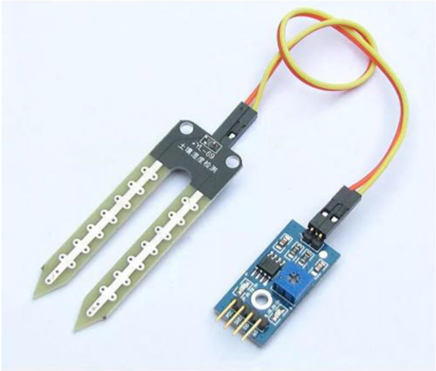
- Length and width of the Arduino are 68.6 mm X 53.4 mm
- The weight of the Arduino board is 25 g

- **DHT11 Sensor**



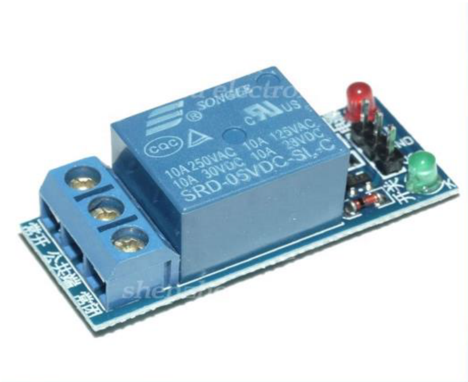
The digital temperature and humidity sensor DHT11 is a composite sensor that contains a calibrated digital signal output of temperature and humidity. The technology of a dedicated digital modules collection and the temperature and humidity sensing technology are applied to ensure that the product has high reliability and excellent long-term stability. The sensor includes a resistive sense of wet component and an NTC temperature measurement device, and is connected with a high-performance 8-bit microcontroller.

- **Soil moisture sensor**



Soil moisture sensors measure the volumetric water content in soil. Since the direct gravimetric measurement of free soil moisture requires removing, drying, and weighing of a sample, soil moisture sensors measure the volumetric water content indirectly by using some other property of the soil, such as electrical resistance, dielectric constant, or interaction with neutrons, as a proxy for the moisture content. The relation between the measured property and soil moisture must be calibrated and may vary depending on environmental factors such as soil type, temperature, or electric conductivity. Reflected microwave radiation is affected by the soil moisture and is used for remote sensing in hydrology and agriculture. Portable probe instruments can be used by farmers or gardeners. Soil moisture sensors typically refer to sensors that estimate volumetric water content. Another class of sensors measure another property of moisture in soils called water potential; these sensors are usually referred to as soil water potential sensors and include tensiometers and gypsum blocks.

- **Relay Module**



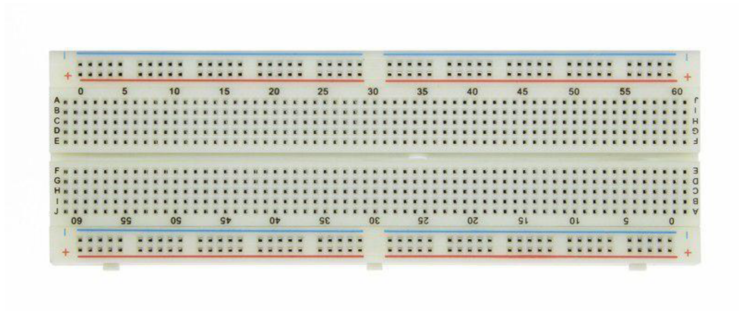
A relay is an electrically operated device. It has a control system and (also called input circuit or input contactor) and controlled system (also called output circuit or output cont actor). It is frequently used in automatic control circuit. To put it simply, it is an automatic switch to controlling a high-current circuit with a low-current signal.

The advantages of a relay lie in its lower inertia of the moving, stability, long-term reliability and small volume. It is widely adopted in devices of power protection, automation technology, sport, remote control, reconnaissance and communication, as well as in devices of electro mechanics and power electronics. Generally speaking, a relay contains an induction part which can reflect input variable like current, voltage, power, resistance, frequency, temperature, pressure, speed and light etc. It also contains an actuator module (output) which can energize or de-energize the connection of controlled circuit. There is an intermediary part between input part and output part that is used to coupling and isolate input current, as well as actuate the output. When the rated value of input (voltage, current and temperature etc.) is above the critical value, the controlled output circuit of relay will be energized or de-energized.

- **Motor Pump (DC 12V)**

A DC motor is any of a class of rotary electrical motors that converts direct current electrical energy into mechanical energy. The most common types rely on the forces produced by magnetic fields. Nearly all types of DC motors have some internal mechanism, either electromechanical or electronic, to periodically change the direction of current in part of the motor. DC motors were the first form of motor widely used, as they could be powered from existing direct-current lighting power distribution systems. A DC motor's speed can be controlled over a wide range, using either a variable supply voltage or by changing the strength of current in its field windings. Small DC motors are used in tools, toys, and appliances. The universal motor can operate on direct current but is a lightweight brushed motor used for portable power tools and appliances. Larger DC motors are currently used in propulsion of electric vehicles, elevator and hoists, and in drives for steel rolling mills. The advent of power electronics has made replacement of DC motors with AC motors possible in many applications.

- **Breadboard**

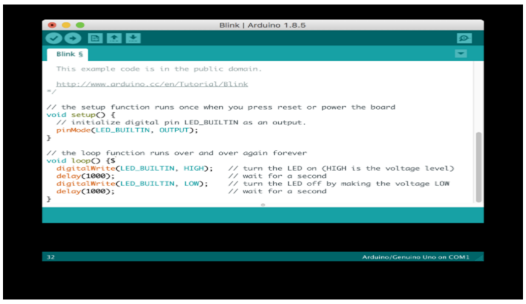


A breadboard is a construction base for prototyping of electronics. Originally the word referred to a literal bread board, a polished piece of wood used for slicing bread. In the 1970s the solderless breadboard (a.k.a. plugboard, a terminal array board) became available and nowadays the term "breadboard" is commonly used to refer to these. Because the solderless breadboard does not require soldering, it is reusable. This makes it easy to use for creating temporary prototypes and experimenting with circuit design. For this reason, solderless breadboards are also popular with students and in technological education. Older breadboard types did not have this property. A stripboard (Veroboard) and similar prototyping printed circuit boards, which are used to build semi-permanent soldered prototypes or one-offs, cannot easily be reused. A variety of electronic systems may be prototyped by using breadboards, from small analog and digital circuits to complete central processing units (CPUs).

- **Connecting wires**

A jump wire (also known as jumper wire, or jumper) is an electrical wire, or group of them in a cable, with a connector or pin at each end (or sometimes without them – simply "tinned"), which is normally used to interconnect the components of a breadboard or other prototype or test circuit, internally or with other equipment or components, without soldering. Individual jump wires are fitted by inserting their "end connectors" into the slots provided in a breadboard, the header connector of a circuit board, or a piece of test equipment. Jumper wires typically come in three versions: male-to-male, male-to-female and female-to-female. The difference between each is in the end point of the wire. Male ends have a pin protruding and can plug into things, while female ends do not and are used to plug things into. Male-to-male jumper wires are the most common and what you likely will use most often. When connecting two ports on a breadboard, a male-to-male wire is what you'll need.

- ## Arduino IDE



The Arduino Integrated Development Environment (IDE) is a cross-platform application (for Windows, macOS, Linux) that is written in functions from C and C++ . It is used to write and upload programs to Arduino compatible boards, but also, with the help of 3rd party cores, other vendor development boards.

METHODOLOGY

- ## Rainfall Prediction using Artificial Intelligence

The rainfall presage involved a two-phase solution:

- Prediction of Probability of Rainfall in the next 30 minutes
- Estimation of the Amplitude of Rainfall

The first phase is to avail the network to realize whether there is a chance of rainfall to occur in the next 30 minutes or not and the contrivance keeps checking the status at customary intervals of time when it is switched on periodically.

The amplitude of rainfall depends on multiple parameters including mean of temperature, pressure, maximum and minimum sultriness as well as the mean dew associated with the air. The dataset used is accountable for local areas and regions since it contained parameters which can be generalized to presage the rainfall and had desultory values of all the parameters. The data used is taken from the rainfall data available on the Regime of India Portal for local regions.

The data was divided into three sets, namely, training, validation and testing, with a percentage of 70, 15 and 15 respectively. The values of the dataset were facilely accountable with Arbitrary Forest Relegation and Regression.

Once it has been determined that the rainfall would occur or not the next challenge is to presage the amplitude of rainfall which would occur. This majorly deals with the historic precipitation data available for different regions and the model has to acclimate to a plethora of such historic data spread over a wide duration.

- ## Estimation of Soil Moisture Content required

The decision system takes into account the water level content required by the crop to calculate its irrigation requisites. In traditional applications, these decisions are taken by the farmer predicated on their experience or an expert agricultural expert. Information from sundry sources is accumulated; these include weather statistics, crop and soil properties, moisture content data accumulated from soil sensors deployed in the fields, and moisture influencing factors such as evapotranspiration. An agricultural expert analyses this data to decide an estimate of the quantity of water that the crop would require on a particular day. Predicated on this conception, our autonomous irrigation system is developed. We accumulate historical data which consists of decisions taken by an agricultural expert for the water content required by a crop predicated on available information and current crop condition. The accumulated information is analysed utilizing machine learning to presage the water requisites for the crop in authentic-time. Decision history by an agricultural expert is utilized to evaluate our system's performance. The decisions taken by the machine learning model are evaluated against those taken by the agricultural expert. The machine learning system is to be trained with historical data and decision reports of the agricultural expert, taking into account the kenned water level requisite of the particular crop and sundry authentic-time factors mentioned anteriorly. The aim of the machine learning model is to be as proximate as possible to the decisions taken by an agronomist, which are utilized as ground truth for evaluation.

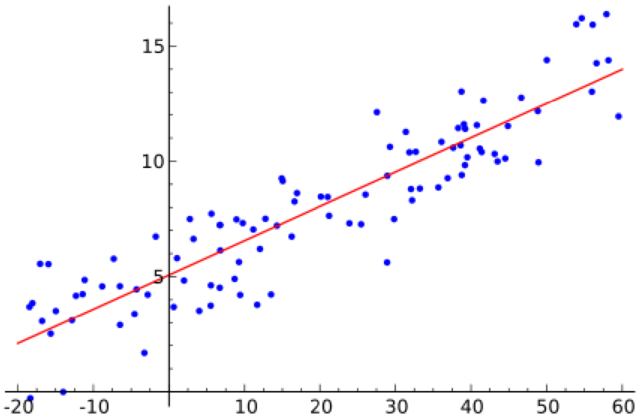
Evapotranspiration is derived from the words “evaporation” and “transpiration”. It refers to the process of moisture eluding from the soil and crop to the atmosphere.The FAO Penman-Monteith formula can be used to calculate the reference crop evapotranspiration (ET0) on a daily basis, using information from weather stations or alternatively weather sensors.

We've utilized the Partial Least Square Regression (PLSR) algorithm to design the machine learning decision model. It is a statistical algorithm that identifies fundamental cognations between input and output variables. Predictor (input) variables, denoted by X, are defined as the visually examined variables that are quantified for providing input to the decision model. Replication variables, denoted by Y, are the outputs that must be estimated provided the input.

We utilize the PLSR technique among other regression algorithms since it efficiently tackles cases when the number of inputs is much higher than the number of output variables, the outputs are strepitous and there subsists a high probability of having multicollinearity among the input variables. The multicollinearity quandary occurs when input variables are highly correlated, due to redundancy between meteorological factors and soil sensors data. We ascertain that all of these factors appear in our irrigation decision system.

The trained PLSR model takes the predictor matrix as input which contains the soil and weather information for a particular day, and predicts the soil moisture percentage required for the crop. This soil moisture percentage helps us to calculate the minutes of irrigation required as a function of the area of the crop field and the power of the electric motor being used.

A PLS regression algorithm:



The properties of pls regression can be analyzed from a sketch of the original algorithm. The first step is to create two matrices: E = X and F = Y. These matrices are then column centered and normalized (i.e., transformed into Zscores). The sum of squares of these matrices are denoted SSX and SSY . Before starting the iteration process, the vector u is initialized with random 2 values. (in what follows the symbol ∝ means "to normalize the result of the operation").

Formula used:

With one independent variable, we may write the regression equation as:

$$Y = a + bX + e$$

Where Y is an observed score on the dependent variable, a is the intercept, b is the slope, X is the observed score on the independent variable, and e is an error or residual.

We can extend this to any number of independent variables:

$$Y = a + b_1 X_1 + b_2 X_2 + \ldots + b_k X_k + e$$

Note that we have k independent variables and a slope for each. We still have one error and one intercept. Again we want to choose the estimates of a and b so as to minimize the sum of squared errors of prediction. The prediction equation is:

$$Y' = a + b_1 X_1 + b_2 X_2 + \ldots + b_k X_k$$

For the one variable case, the calculation of b and a was:

$$b = \frac{\sum xy}{\sum x^2}$$

$$a = \overline{Y} - b\overline{X}$$

For the two variable case:

$$b_1 = \frac{(\sum x_2^2)(\sum x_1 y) - (\sum x_1 x_2)(\sum x_2 y)}{(\sum x_1^2)(\sum x_2^2) - (\sum x_1 x_2)^2} \quad , \quad b_2 = \frac{(\sum x_1^2)(\sum x_2 y) - (\sum x_1 x_2)(\sum x_1 y)}{(\sum x_1^2)(\sum x_2^2) - (\sum x_1 x_2)^2}$$

The equation for a with two independent variables is:

$$a = \overline{Y} - b_1 \overline{X}_1 - b_2 \overline{X}_2$$

Equation used to calculate Soil Moisture by crop at given instance:

$$ET_o = \frac{0.408\Delta\,(R_n - G) + \gamma \frac{900}{T + 273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34\,u_2)}$$

The FAO Penman-Monteith method to estimate ETo can be derived [Eq. 1]:

Where,

ET_o = reference evapotranspiration, mm day-^{1};

R_n = net radiation at the crop surface, MJ m-^{2} d-^{1};

G = soil heat flux density, MJ m-^{2} d-^{1};

T = mean daily air temperature at 2 m height, °C;

u_2 = wind speed at 2 m height, m s-^{1};

e_s = saturation vapor pressure, kPa;

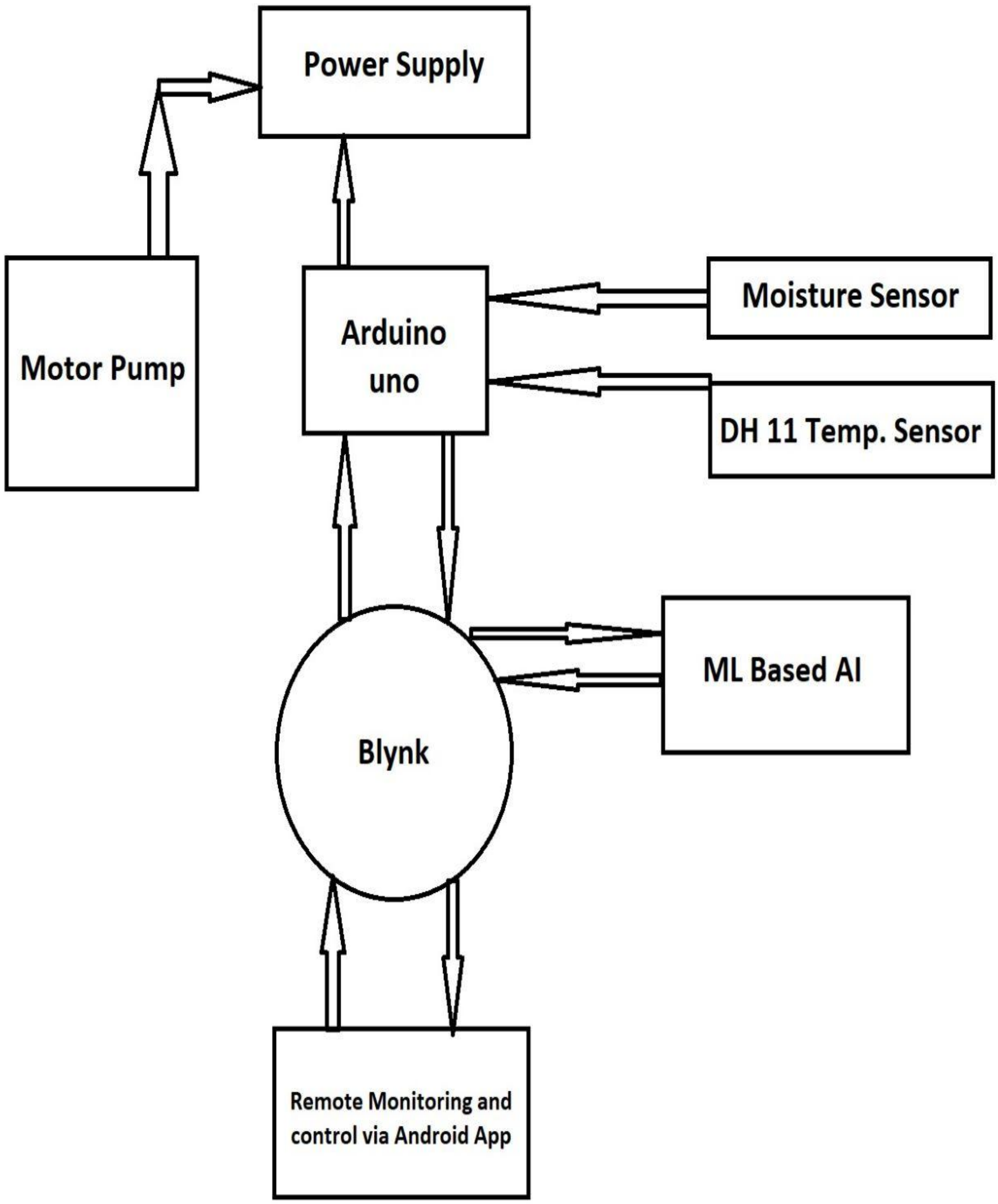
e_a = actual vapor pressure, kPa;

e_s-e_a = saturation vapor pressure deficit, kPa;

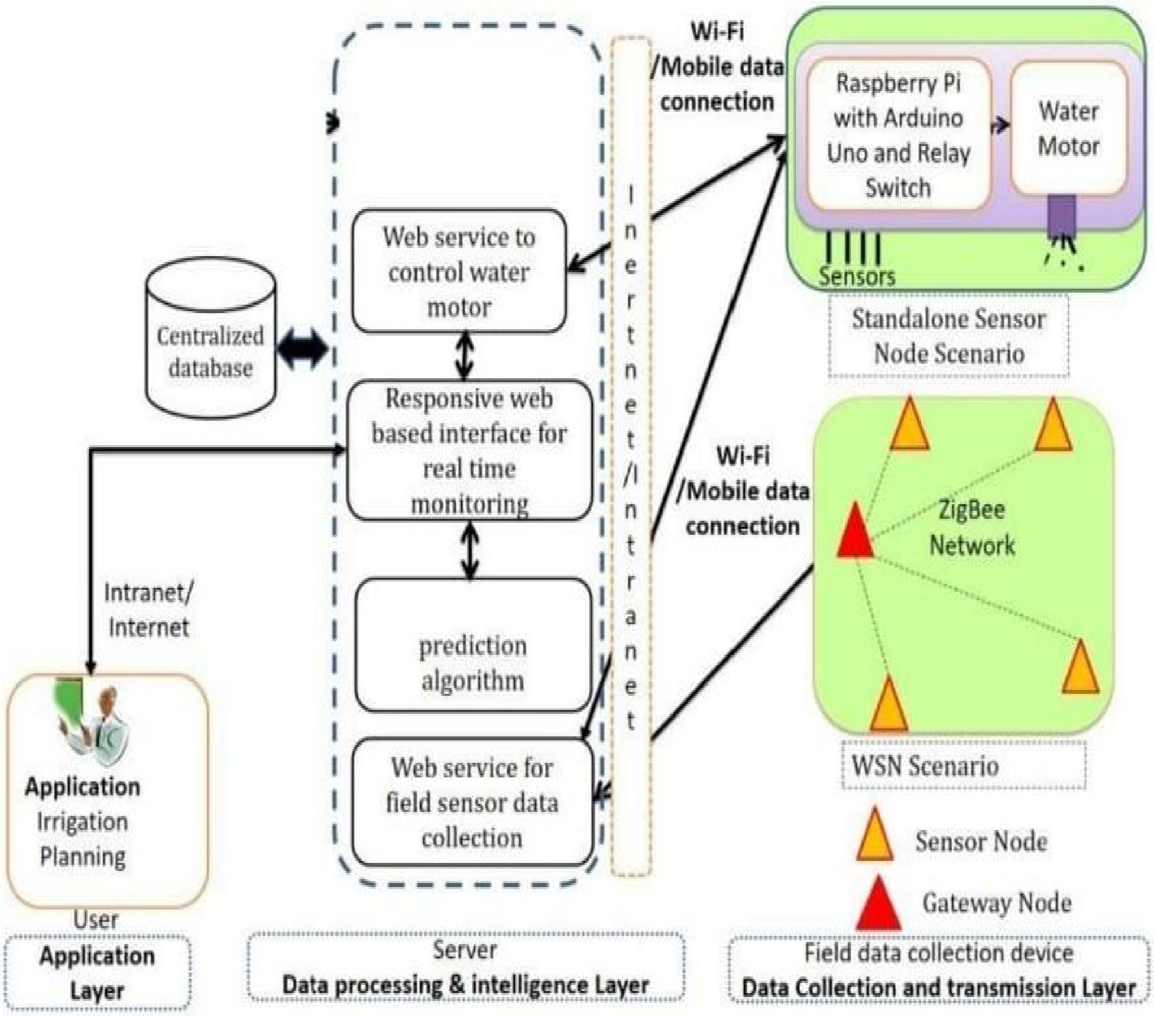
î = slope of the vapor pressure curve, kPa °C-^{1};

³ = psychrometric constant, kPa °C-^{1}.

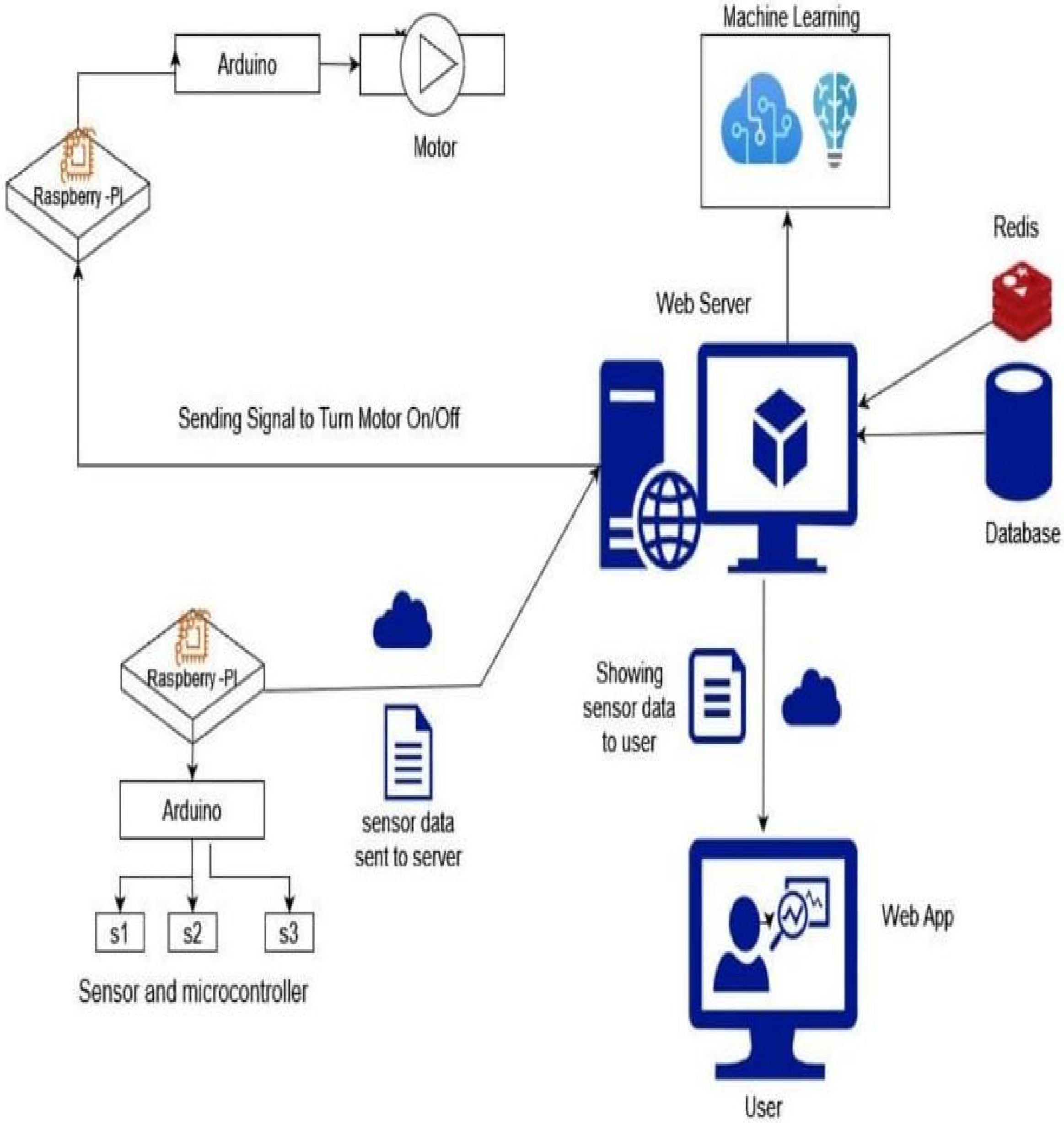
FLOWCHART OF MODEL METHODOLOGY:



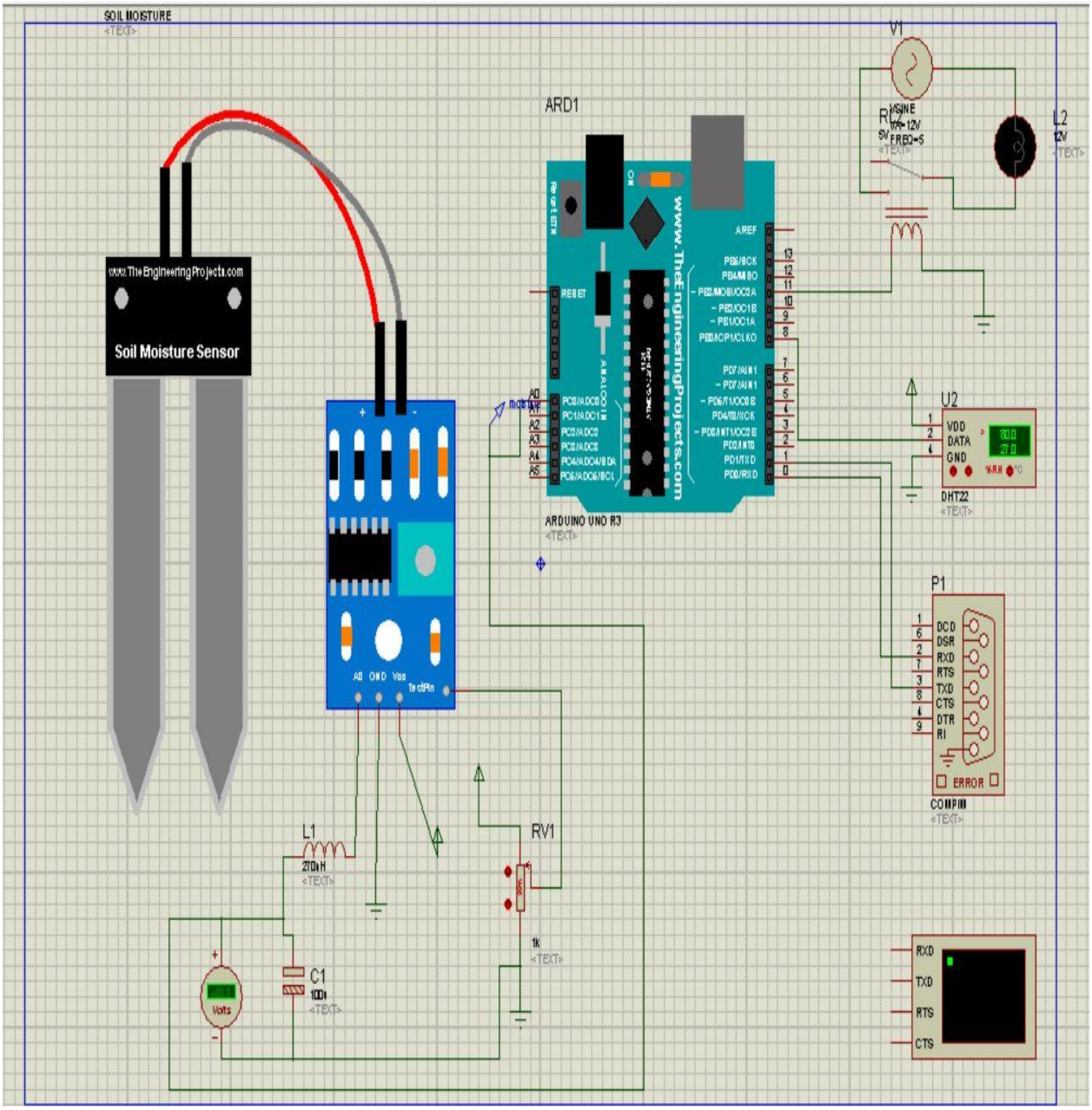
PROCESS FLOW



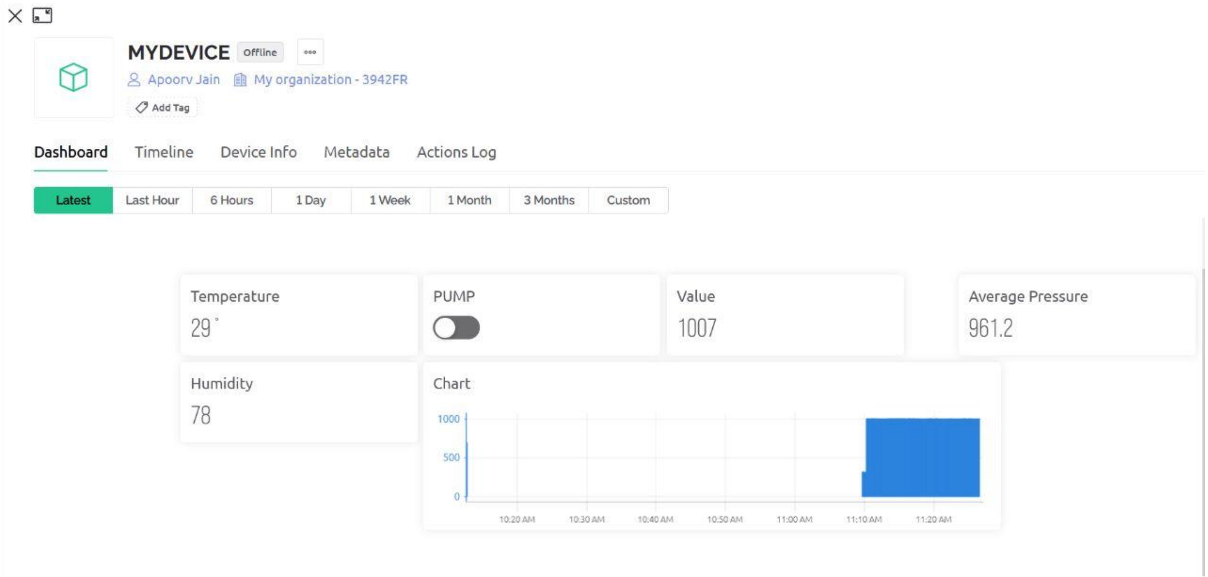
FLOWCHART OF THE PROCESS



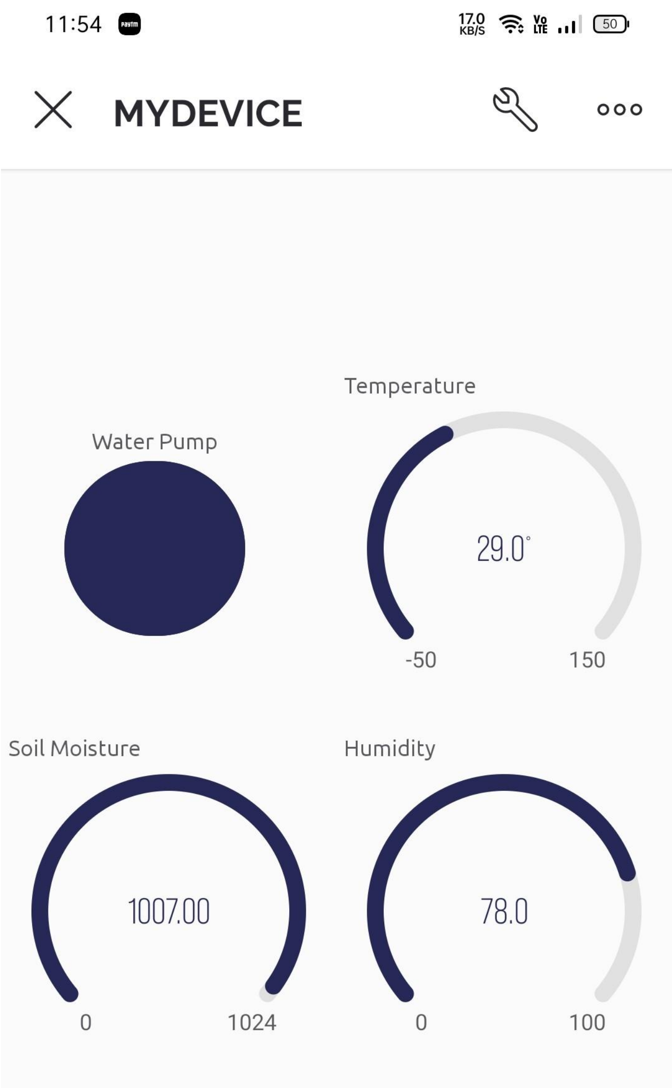
ARCHITECTURE OF THE MODEL:



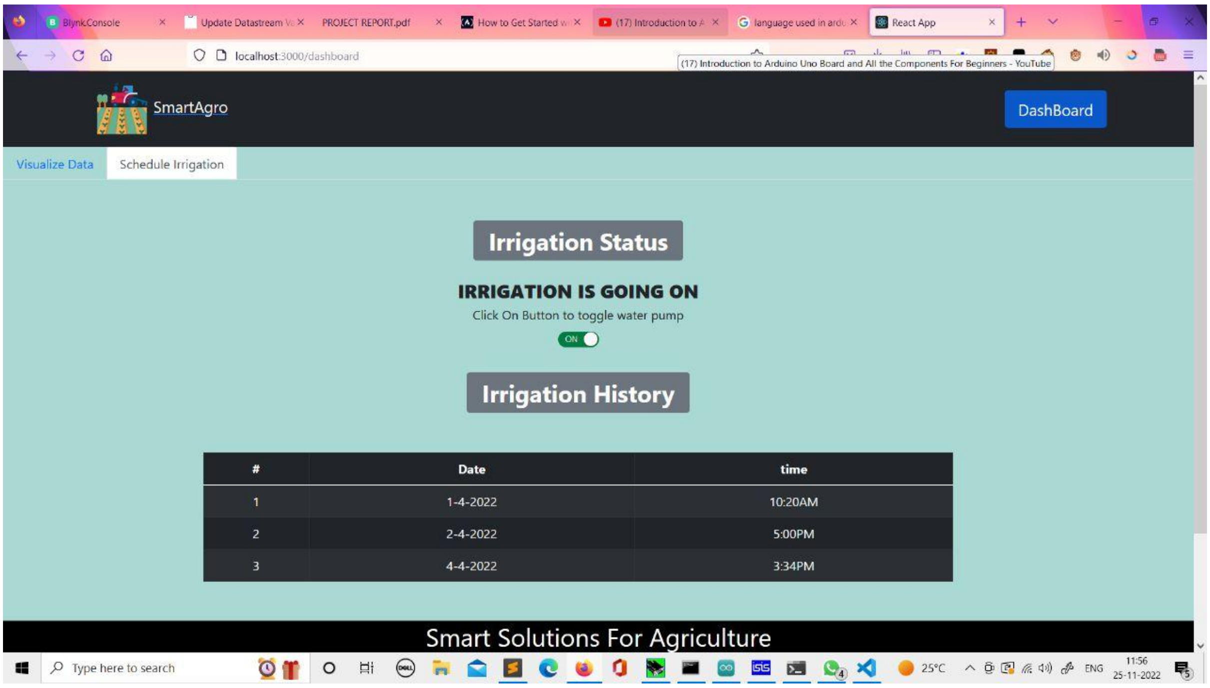
BLYNK WEB USER INTERFACE:

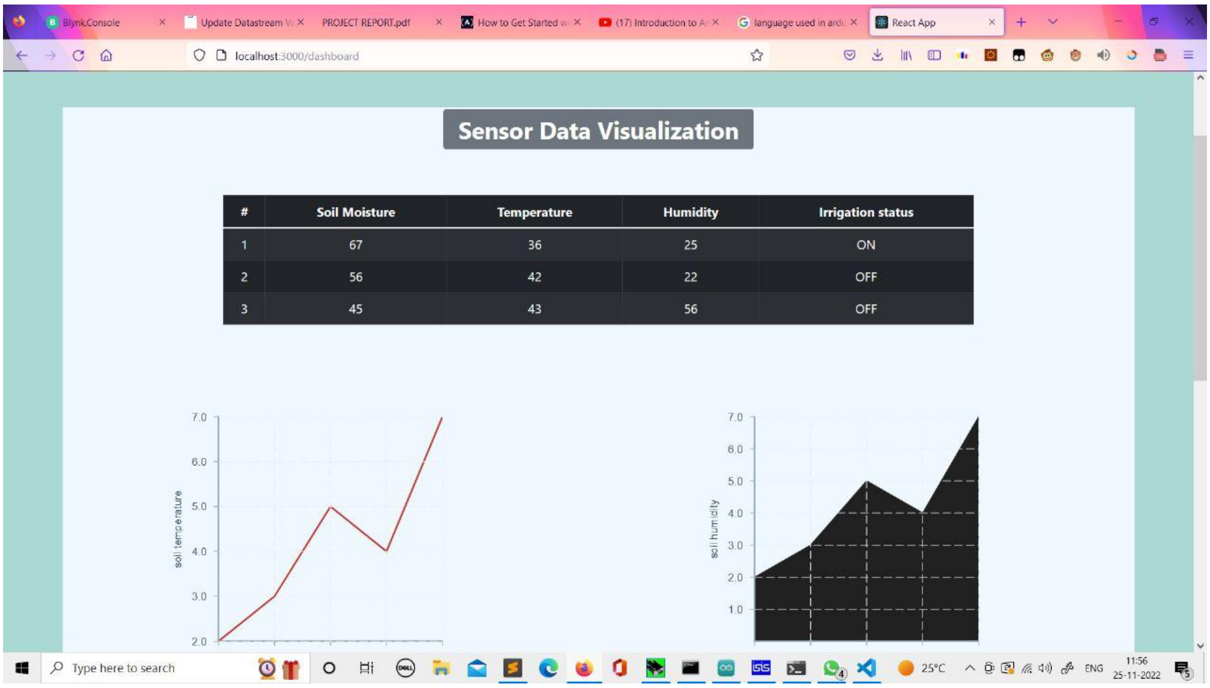


ANDROID APP INTERFACE



USER WEB INTERFACE

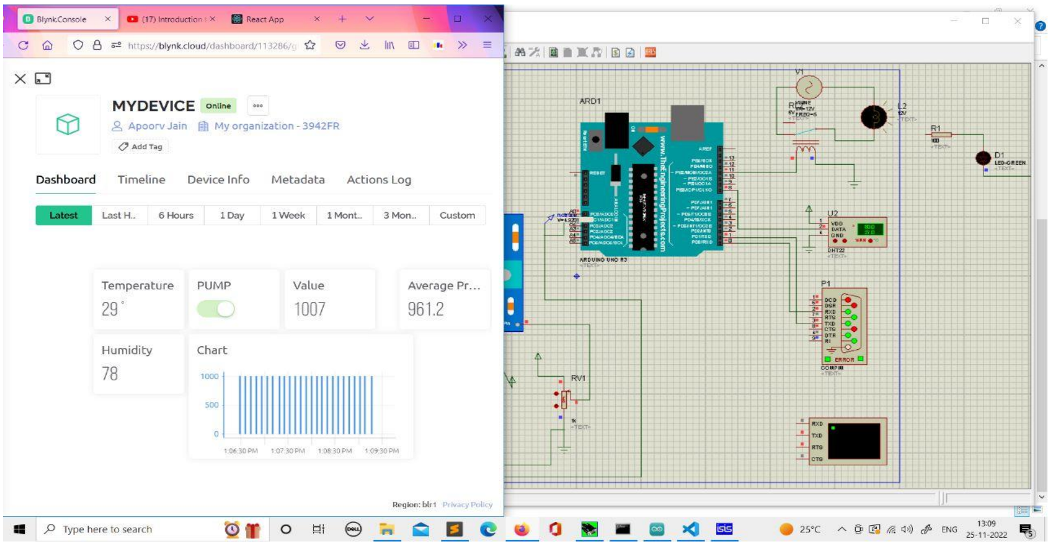




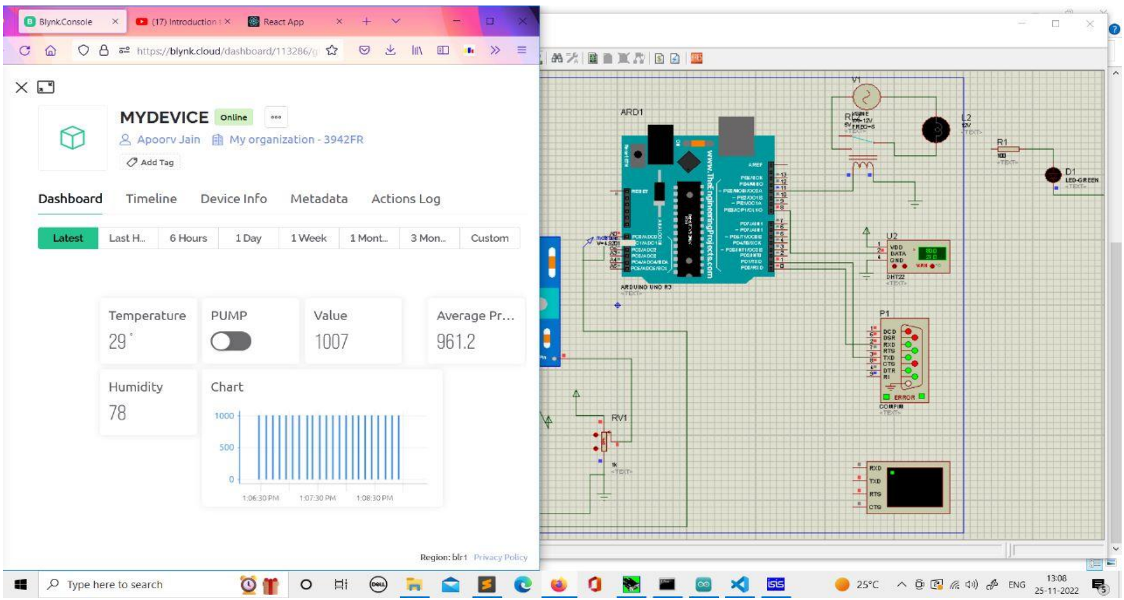
RESULTS

The system designed is an astute irrigation solution predicated on artificial astuteness which makes utilization of the soil moisture content and the moisture requisites of the crop to make the entire process of irrigation automatic Its core benefit is its efficiency and economic feasibility The main conception abaft the rainfall estimation proposed is to get the virtually correct estimation of the rainfall of a concrete local region as well as the annual rainfall to get data for future estimation of the rainfall in states.

The model will turn on the motor pump for irrigation of the crops when the soil moisture measured is lower than the needed threshold value and there is no rain predicted by the ML algorithm:



when irrigation is needed, the circuit is on ans we can seeLED is on .



When irrigation is not needed, the circuit is on as we can see the LED is off.

CONCLUSION

The autonomous irrigation system we developed uses Artificial Intelligence learning and predictive algorithms to integrate perspicacity to subsisting concept of automatic irrigation systems The methods discussed in this paper can avail increase irrigation efficiency while decrementing effort required and avails water conservation compared to current irrigation methods The system currently depends on weather station information for its calculation This dependency can be superseded with on premise sensors for deployment in rural areas widely found in the Indian subcontinent and arid regions where water is available in constrained quantity.

SOURCE CODE:

Arduino code:

```
#include <DHT.h>

/* Fill-in your Template ID (only if using Blynk.Cloud) */
#define BLYNK_TEMPLATE_ID "TMPLYXtOg0jT"
#define BLYNK_DEVICE_NAME "BTPPROJECT"
#define BLYNK_AUTH_TOKEN
"IIBPUqiLkEt3R0kDt0cMn3p5X5suse_k"

// You could use a spare Hardware Serial on boards that have it
(like Mega)
#include <SoftwareSerial.h>
//SoftwareSerial DebugSerial(2, 3); // RX, TX

#include <BlynkSimpleStream.h>
#define PUMP 11
#define SENSOR V1
// You should get Auth Token in the Blynk App.
// Go to the Project Settings (nut icon).
char auth[] = BLYNK_AUTH_TOKEN;
float soilMoisture;
float temperature;
float humidity;
int var;
int cnt=0;
// BlynkTimer timer;
```

```
void syncValues()
{
  humidity=80+random(6)-3;
  temperature=27+random(6)-3;
}

BLYNK_WRITE(V0){
  var=param.asInt();
  if(var==0)
  {
    digitalWrite(PUMP,LOW);
  }
  else
  {
    digitalWrite(PUMP,HIGH);
  }
}

void myTimer()
{
  Serial.println(soilMoisture);
  Blynk.virtualWrite(V1, soilMoisture);
}

#define DHTPIN 8     // Digital pin connected to the DHT sensor
#define DHTTYPE DHT22
DHT dht(DHTPIN, DHTTYPE);
```

```
void setup()
{
  cnt=0;
  analogReference(DEFAULT);
  //DebugSerial.begin(9600);
  pinMode(PUMP,OUTPUT);
  Serial.begin(9600);
  Blynk.begin(Serial, auth);
  dht.begin();
  //timer.setInterval(1000L, myTimer);
}

void loop() {
  soilMoisture = analogRead(A0);
  humidity = dht.readHumidity();
  temperature = dht.readTemperature();
  Blynk.run();
  // Serial.println(soilMoisture);
  // Serial.println(temperature);
  // Serial.println(humidity);
  syncValues();
  Blynk.virtualWrite(V1, soilMoisture);
  //Blynk.virtualWrite(V2, temperature);
  // Blynk.virtualWrite(V3, humidity);
  cnt++;
  delay(1000);
 //timer.run();    }
```

Backend code:

```
# importing the requests library
import requests
import time
import pickle;

token="lIBPUqiLkEt3R0kDt0cMn3p5X5suse_k"
pumpPin="v0";
soilPin="v1"
temperaturePin="v2"
humidityPin="v3";

weather_api="http://api.weatherbit.io/v2.0/forecast/agweather?lat=23.2756&lon=77.4560&key=c0cebec5f6594632acdfc4b8347014f9";
loaded_model=pickle.load(open("finalized_model.sav", 'rb'));

def required_soilMoisture(temperature,humidity,avg_pres,evapotranspiration):
    return loaded_model.predict([[temperature,humidity,avg_pres,evapotranspiration]])[0][0]+50;

def isThePumpNeedsToBeOn(curSoilMoisture,requiredSoilMoisture):
    if(curSoilMoisture/10>requiredSoilMoisture):
        return False
    else:
        return True
```

```
while True:

URL =
"https://blynk.cloud/external/api/get?token="+token+"&"+pumpPin+
"&"+soilPin+"&"+temperaturePin+"&"+humidityPin;

URLupdate="https://blynk.cloud/external/api/update?token="+toke
n+"&"

# sending get request and saving the response as response object

        r = requests.get(url = URL)

        u=requests.get(url=weather_api);

        # extracting data in json format

        data = r.json()

        data2=u.json();

        evapotranspiration=data2['data'][0]['evapotranspiration'];

        avg_pres=data2['data'][0]['pres_avg'];

        print(avg_pres);

        requests.get(url=URLupdate+"V4="+str(avg_pres));

        requests.get(url=URLupdate+"V5="+str(evapotranspiration));

        print(data);

        print(required_soilMoisture(data['v2'], data['v3'], avg_pres,
        evapotranspiration))

        time.sleep(10);
```

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