IMPLEMENTATION OF PRECISION SOIL AND WATER CONSERVATION AGRICULTURE (PSWCA) THROUGH MACHINE LEARNING, CLOUD ENABLED IOT INTEGRATION AND WIRELESS SENSOR NETWORK

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ABSTRACT

Precision Agriculture (PA) is a trending research area since it provides a solution for increasing the productivity of farmlands using Internet of Things (IoT). This technique ensures that the farmland receives optimum amount of resources for maximum sustainability and profit using Information Technology. In this research, a novel methodology cloud enabled Internet of Things (IoT) integration and wireless sensor network is proposed for precision soil and water conservation agriculture (PSWCA) through machine learning. WSN comprises of a network of wireless sensors like moisture, temperature, ultrasonic, light detection sensors, soil nutrition sensor, etc. These sensors are used for determining optimum amount of water and fertilizer required by the plants. The entire framework with all the sensors and irrigation system was integrated using Arduino Uno Microcontroller and Raspberry Pi module. A novel Machine Learning based Automated Irrigation System using IoT (MLAIS-IoT) algorithm is proposed for Precision Soil and Water Conservation Agriculture (PSWCA). In this scheme, the machine learning algorithm embedded in the Raspberry Pi module is used to predict the amount of water and fertilizer required by the plants for irrigation. To validate the proposed methodology, the amount of water and fertilizer required using this MLAIS-IoT method is compared with that of scheduled and automatic irrigation. It was observed that, the proposed technique required lesser amount of water and fertilizer compared to that of scheduled and automatic irrigation. In this way, water logging can be avoided. This technology also aided in saving huge quantities of water. Thus, this system achieved optimum conservation based on the soil and climatic conditions as well. This also helps in achieving healthy growth of the plants. The experimental results prove that the logistic regression provide better efficiency and accuracy than other methodologies.

Keywords: Precision Agriculture (PA), IoT, WSN, Soil and Water conservation, Arduino, Raspberry Pi.

1. Introduction

Since, in our country the backbone is agriculture, automation of various agriculture-based tasks aids in achieving better yield. One important task is irrigation. Recently, several automation techniques have replaced the traditional irrigation systems [1]. Scheduled water conservation is a technique in which the agricultural land is irrigated uniformly on a periodic basis. These techniques lead to excessive loss of water. Several systems based on wireless sensor networks (WSN) have been proposed in the literature for automating the water conservation [2]. Application of machine intelligence helps in achieving more robust irrigation results [3]. Several machine learning techniques have been used in the literature for the estimation of crop diseases and crop yield prediction [4]. Today Internet of Things (IoT) has helped the farmers to monitor their field from remote locations [5]. This has helped in achieving increased control over the field [6]. Thus, integration of machine learning, Internet of Things (IoT) and wireless sensors helps in achieving a robust irrigation automation system. To increase the crop yield people may suppose to use harmful pesticides for crop growth [7]. The good insect also killed by using pesticides and yielding also very less, as well as people are effecting by harmful pesticides [8]. This work is useful for formers to identify the beneficial and harmful pest, they can use organic pesticides for harmful pest and they can improve the quantity of yielding too [9]. The novelty of work is to identifying the beneficial and harmful pest by using Mel Frequency Cepstrum Coefficient and classifies by Deep Learning Techniques through acoustic signal of pest. Many noises where occurred in recorded acoustic signal [10]. HNM HMM wiener filter and HNM Infinite filter are used to filter pest acoustic signals. The acoustic signal is further segmented and Feature extraction has done by IMFCC (Improved Mel Frequency Cepstrum Coefficient). Finally Deep Neural Network classifies whether harmful pest or useful insects [11]. Hence, in the research, a novel methodology called Machine Learning based Automated Irrigation System using IoT (MLAIS-IoT) is proposed.

The rest of the paper is organized as follows. Section 2 includes a detailed discussion about the related works in the literature. Section 3 indicates the contributions of the paper. Section 4 shows the objectives. Section 5 indicates the problem formulation. Section 6 explains the existing system with disadvantages. Section 7 describes the proposed methodology. The results and discussion are performed in Section 8. Conclusion of the paper is presented in Section 9.

2. Related Works

A Fuzzy-based precision irrigation system was proposed in[28].Three parameters were monitored in this system namely, the temperature, humidity and the moisture. These parameters are transmitted to the microcontroller device. In this device the fuzzy algorithm is embedded using which the prediction is made regarding the operation of the valve. A precision irrigation system based on IoT and machine learning was proposed in [29]. In this paper, the weather forecast data is also being utilized for efficient utilization of water resource for water conservation. In addition, moisture, temperature, humidity sensors are also used. This system achieved a closed-loop control over the utilization of water. Raspberry Pi was used to create a precision irrigation scheme in [30]. Here, the motor valve is controlled based on the sensor values. In addition, the growth of the plants is also monitored using webcam. Using the cloud-based architecture the growth of the plants can be constantly monitored with the usage of mobile phones. IoT based precision soil and water conservation was proposed in [31]. In this paper, sensors like moisture, temperature and humidity sensors are monitored for automation of soil and water conservation. These values are also stored in the cloud using Thing Speak application. The water conservation is automatically done whenever dry conditions are observed. A system for monitoring garden was proposed in [32]. In this paper, the garden parameters are continuously monitored using mobile applications. The level of water in the water tank is monitored using an ultrasonic sensor. Also, NodeMCU is used as a hub for automating the entire process. The mobile platform used in this paper is the Firebase. Precision soil and water conservation using wireless sensor networks based on IP was presented in [33]. In this paper, protocol stacks are utilized. Also, the average power consumed by the sensors are analyzed and studied in this paper. The round-trip time and the packet loss are also studied and simulated. The radio duty cycle is also analyzed here. Design of precision water conservation system for citrus plants was presented in [34]. In this work, fault tolerance of the wireless sensors is studied and evaluated. Also, the various energy saving schemes are being discussed. An algorithm for energy saving is also proposed in this paper. The bandwidth consumption of every node is also analyzed here. A technique for water management was proposed in [35]. Here, an architecture called SWAMP was proposed. This platform has five layers. The first layer is the device communication layer. The second layer is the acquisition security layer. The third layer is the data management layer. The fourth is the water conservation model and the final layer is the application service layer. A scheme for precision drip irrigation was proposed in [36]. In this paper, the water for irrigation is determined based on the level of moisture content in the soil. This system utilizes Raspberry Pi unit. The values of the moisture sensor are amplified and are given to Analog to digital converter. This digital value is given to Raspberry Pi unit. This unit uses this value to determine the amount of water for irrigation. Precision irrigation system for green house environment was proposed in [37].Here, a star topology architecture was utilized. The scheme had two levels, namely, the sensing and control unit. Sensors like temperature sensor, humidity sensor and moisture sensors were continuously monitored to automate the irrigation process in green house. A system for the synchronization of wireless sensor nodes was proposed in [38]. In this paper, a scheme for synchronizing the clock of all the sensor nodes is proposed. This aids in achieving measurements that are highly synchronized and correlated in real-time. Olive grove was utilized for the implementation of this system. A framework for tuning the MAC parameters was proposed in [39]. Here, the traffic control problem was evaluated. In this paper, the sampling frequency used to sample the sensor values are analyzed and simulated. The energy consumption of the sensor nodes, time delay, access delay, reliability is simulated, analyzed and compared in this paper. The use of Non-Orthogonal Multiple Access (NOMA) was evaluated in [40]. In this paper, NOMA scheme was utilized to increase the lifetime of the sensor nodes employed in the precision agriculture framework. The data rate involved in the NOMA scheme is analyzed theoretically in this paper. Kalman filter was used in intelligent agriculture scheme in [41]. Soil moisture and temperature are predicted using the Kalman Filter. This scheme helps in achieving extended lifetime of the sensor nodes. Also, for each type of the crop, the sampling interval is predefined. This scheme also helps to eliminate the noise involved during data collection. Wireless moisture sensor network was used in [42] for automating the irrigation process. This system was evaluated using a greenhouse environment. Two types of irrigation were compared in this paper, namely, the scheduled and the automatic irrigation. Moisture sensors were used for monitoring the moisture content of the soil. A scheme for farm management was proposed in [43]. This research uses IoT for agriculture management. The cloud and the sensors were integrated using Raspberry Pi module. Master-slave protocol was used for automating the irrigation. The Raspberry Pi module is the master and the sensors act as the slaves.

3. Contributions of the Paper

The overall contributions of this paper are fourfold:

a) A novel methodology for Machine Learning (ML) based Automated Irrigation and water management using IoT is presented.
b) Analysis of various ML algorithms to identify the best algorithm for predicting the water conservation scheme according to environmental and soil conditions is presented.
c) A new algorithm for detecting water level label is proposed.
d) Comparison of scheduled, automatic and proposed water conservation in terms of water and fertilizer used is presented.

4. Objectives

The main objective of the research is to implement efficient PSWCA practices in real time environment by achieving water conservation and fertilization using different wireless sensors. The proposed framework is employed to incorporate ML techniques into the PSWCA system. This helps to achieve robust automation compared to conventional automation techniques. The IoT technology is integrated into PSWCA to make the farmer for accessing digital information from the agriculture field. This helps the farmer to understand all activities such as water requirements, fertilizer requirement, animal intrusion, and soil quality and moisture level at the agriculture field from remote area. This monitoring and controlling the agriculture field by from the farmer from remote help to improve the efficient agriculture production.

5. Problem Formulation

The major disadvantage of the conventional irrigation systems is the insufficient water during the extreme dry conditions and excess water during wet conditions. These problems are eradicated in the proposed framework by the usage of machine learning techniques for precision agriculture (PA). In addition to PSWCA, finding the optimum conditions for applying fertilizers to the plants is the aim of the research.

6. Existing System with its Disadvantages

The existing systems for irrigation can be categorized into two types. The first type is scheduled irrigation. In this type of irrigation, the plants are watered in a periodic basis. This does not consider environmental factors like humidity, temperature etc. Since these factors are not taken into account, the plants do not get appropriate amount of water. Also, there is a lot of water wastage in this scheme. The second type is the automatic irrigation. In this type of irrigation, instead of periodic watering, irrigation is done based on certain factors. For instance, a particular threshold is computed based on environmental factors like humidity, temperature etc. Using the computed threshold, irrigation is done. Though this type of irrigation is better than the scheduled irrigation, it does not predict the exact amount of water required by the plants.

7. Materials and Methods

The block diagram of the proposed Machine Learning based Automated Irrigation System using IoT (MLAIS-IoT) for PSWCA is shown in figure 1.The agricultural field is digitally integrated with wireless sensors such as moisture sensors, temperature sensors and nutrition sensors, rainfall sensor, intrusion detection sensor (Ultrasonic sensor). These sensors capture the real-time environmental values and transmit them to Arduino microcontroller. The Arduino microcontroller obtains values from these sensors and transfers them to Raspberry Pi 3 module using serial communication UART module. The Raspberry Pi 3 acts as the processing unit. The ML algorithm necessary for predicting the water requirement is embedded in this module. Based on the real-time data acquired by the sensors, the Raspberry Pi 3 module predicts the water and fertilizer requirements. The output of the processing unit is transmitted back to the Arduino microcontroller. This output value is used for operating the motor valve of the water tank through a relay. In addition, Liquid Crystal Display (LCD) is employed for displaying the values of the sensors and also for displaying the output of the processing unit. These sensors help to determine the amount of light available in the environment. This can be monitored by the farmers from remote places. Ultrasonic sensor is employed for estimating the amount of water available in the water tank. Whenever the machine learning algorithm predicts that water is required by the plants, the ultrasonic sensor calculates the amount of water available. If sufficient water is available, then irrigation is started. Using the Raspberry Pi module all these values are transferred to the cloud using Internet of Things (IoT). From the cloud, they are transmitted to the farmer's mobile. Thus, the farmers can monitor the complete state of the farm land from a remote location.

7.1. Advantages of Proposed Methodology

Though ML algorithms have been used in the literature for precision agriculture, they have been mainly employed for predicting crop diseases. However, in our proposed work, ML algorithm is used for predicting the water and fertilizer requirements and accordingly operates the sprinkler valve and fertilizers for watering the plants. Since, this system is connected to the cloud using IoT, remote access is also possible. In addition, in our proposed framework, real time data is collected and trained ML models for prediction. These models have been trained using various machine learning algorithms like decision tree, k-Nearest neighbor (k-NN), Support Vector Machine (SVM) And Logistic Regression (LS). The best model for prediction has been analyzed and identified. This model was then employed for prediction.

7.2. Proposed Methodology

The proposed architecture is shown in figure 2. The Arduino Microcontroller acquired data from various sensors. The moisture sensor employed is FC28. The temperature sensor employed is LM35. The soil pH is determined using Labman pH meter. The ultrasonic sensor used is HC-SR04. The LDR sensor employed is LM393. The voice IC used is APR 9301. Arduino LCD and APR 9600 are used as output devices. APR 9301 IC is used for playing the output identified by the machine learning algorithm. The Raspberry Pi 3 acts as the processing unit. Also, it transferred all the data to the cloud. Farmer can monitor all the data using his mobile that is connected to the cloud. The output data predicted by the ML algorithm that is embedded in the Raspberry Pi module is used for operating the valve of the water tank.

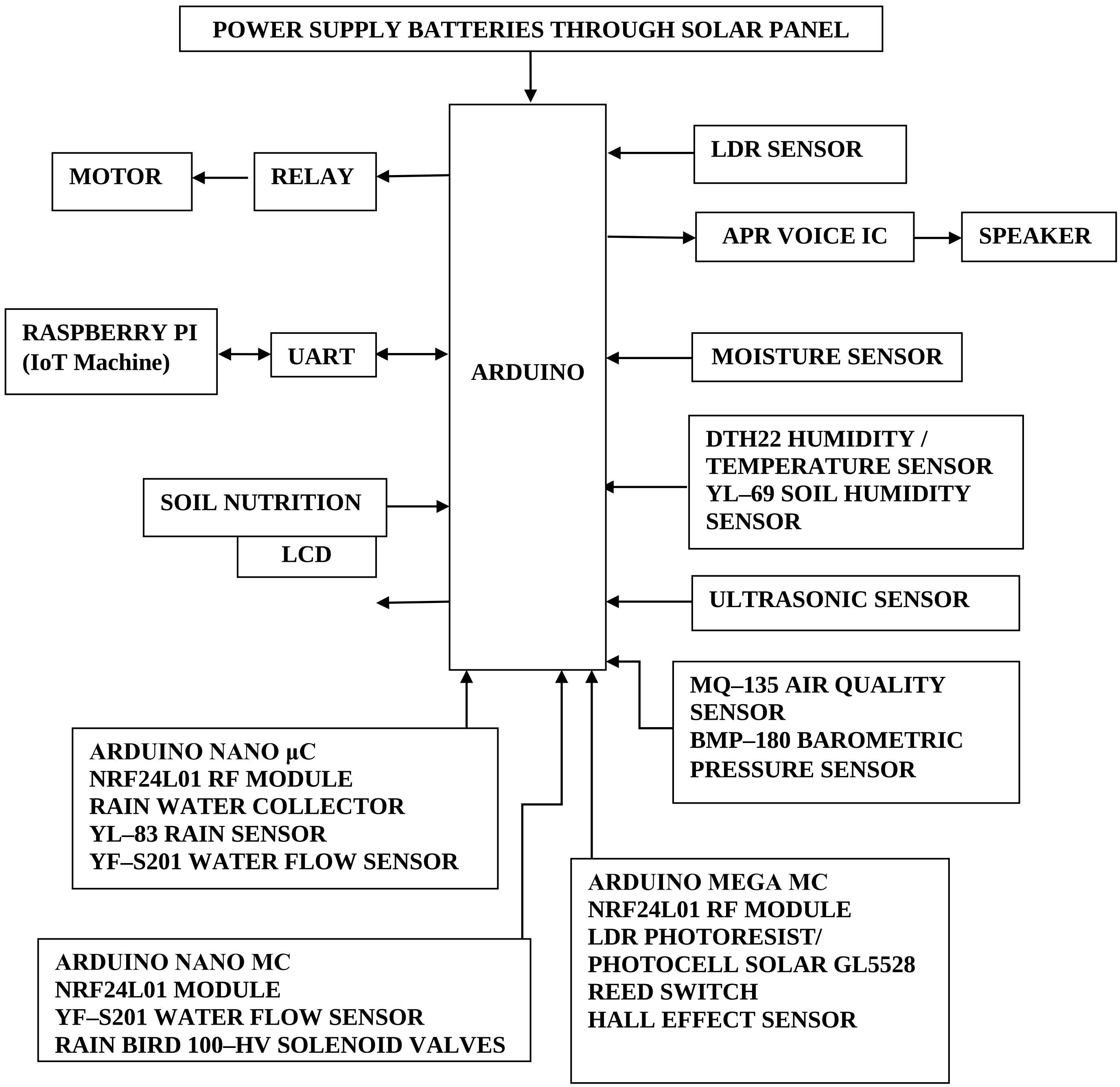


Figure 1 Block diagram of the proposed Machine Learning based Automated Irrigation System

Figure 1 shows the block diagram of the proposed ML based automated irrigation system. The series of electronics devices are interconnected and the data acquisition is obtained based on various sensors allow us to read the evolution of various environments and physical elements like air quality, soil moisture, humidity, soil quality ambient temperature, intensity of rainfall, level of precipitation, direction and speed of wind and pressure of atmosphere. The major constrain of the PA is power supply. The power supply is taken from batteries through solar panel.

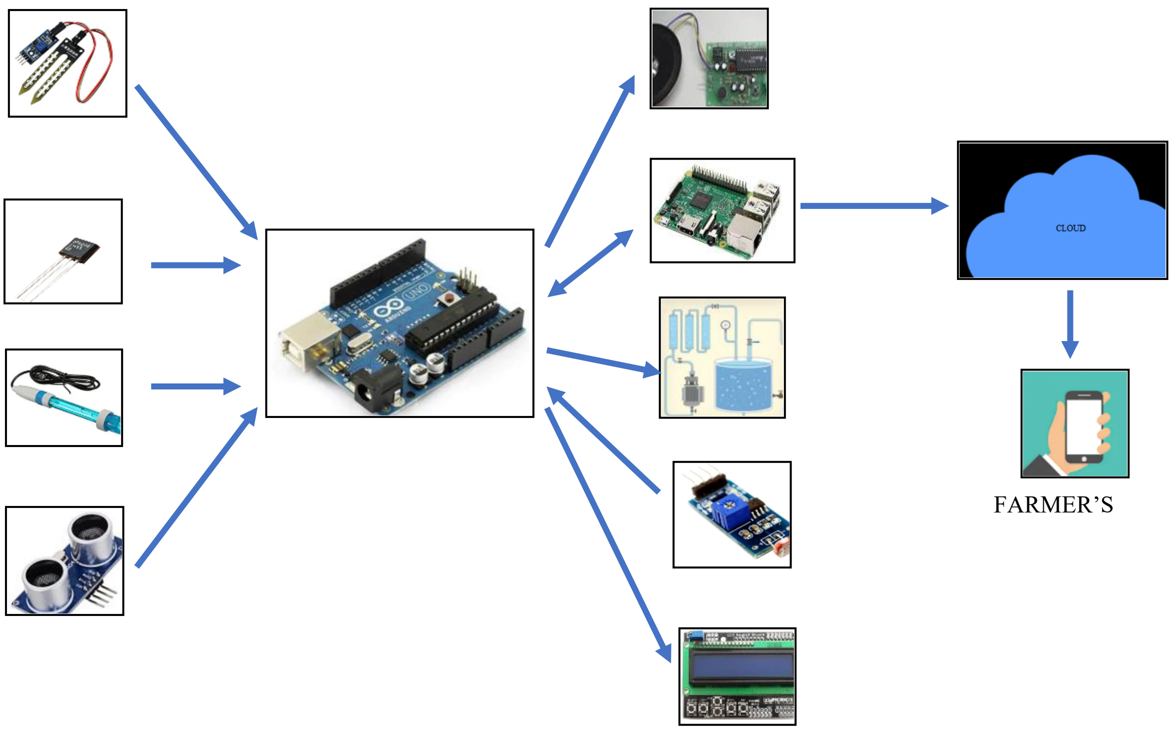


Figure 2 Proposed Architecture of the Machine Learning based Automated Irrigation System

The figure 2 shows the proposed architecture of ML based on Automated Irrigation System. The entire data is connecting to cloud storage through IoT for easy access of farmer from remote through mobile devices.

7.3. Hardware Details and Description

The hardware components used in our work are the soil moisture sensor, temperature sensor, soil pH sensor, light sensor, ultrasonic sensor, LCD, voice sensor, Arduino and the Raspberry Pi.

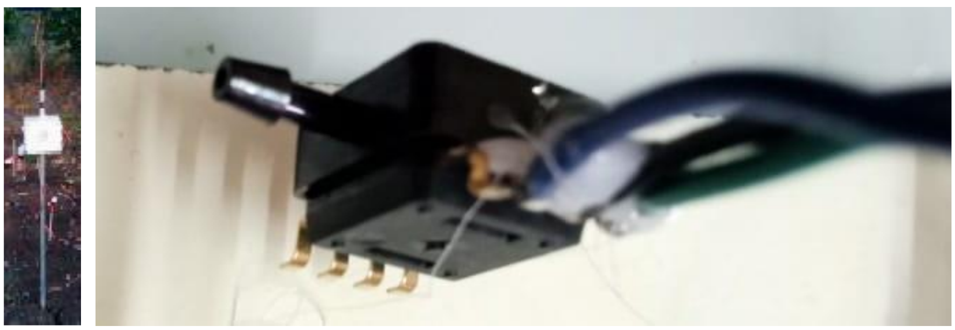
7.4 Wireless Sensors Materials

Wireless sensors permit wireless networking of communication systems to be accumulated within the cloud based IoT, mobile network and various prospective applications. Different materials are used for fabrication of wireless sensors by considering different aspect such as minimizing loss, improving conductivity, avoiding errors, etc., The development model has since adapted to different material groups like eco-friendly materials, materials with less cost, recycled products, materials for coming generations, conductive polymers, Nano tubes, materials for saving energy and specific electronic components. Owing to their efficient manufacturing process and the modification of the structure of their raw resources, these components play a significant role in the construction of electronic devices. The production process of devices begins with the processing of the raw resources, gallium (Ga) and arsenic (As). The essential aspects of the conductive polymer and semi-insulating Gallium Arsenic (GaAs) cubes are some ingredients.

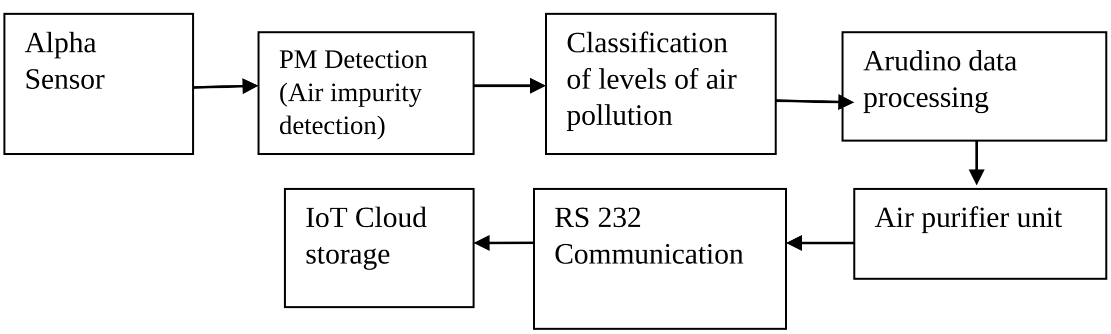
Rainfall Sensor

The rainfall sensor is designed and developed for predict the rainfall and measure the level of rainfall. The rainfall sensing pad with sequence of expose materials of copper traces mutually performs as a variable resistor (for example it shows like potentiometer) whose impedance differs due to the quantity of water on its surface. The impedance is considered as inversely proportional to quantity of water level. The wireless sensor includes a sensing pad with sequences of uncovered materials of copper traces that is positioned out in unwrap possibly over the covering or where it may be highly affected by heavy rainfall.

Air quality sensor



Air quality sensor device and purification of impurity air to give filtered air. The alpha sensor can be used for sensing the PM content in the air. The sensor can be connecting to the Arduino board that has the implementation to detect the impurity present in the air. The impurity variation can be stored and retrieved using USB. The Internet of Things (IoT) is used for remote monitoring in variation of impurity in air. The filter device can be turned on and air can be purified while impurity exceeds limit of particulate matter (PM) emissions. The integrate chamber for air purification has to be provided with incorporation of electronics and mechanical support. The quality sensor has to be used for sensing PM content in the air and the PM content has to be purified by using proposed methodology device.



Soil Moisture and Humidity Sensor

On plant growing surface in the soil, the temperature and humidity sensors were located. It is decided to position the nodes in this position since, at the marginal level between the crops, the mean air temperature and humidity are needed. For each 5 m distance, the soil moisture and temperature sensors were mounted approximately 5 cm from one another. The sensors were then mounted a few millimetersbelow the actual floor level, only in the soil.

The soil moisture sensor employed in our system is FC-28. This sensor has an operating input voltage of 3.3V-5V. Its output voltage ranges from 0-4.2V. This sensor utilizes LM393 comparator for its operation. Its output can be obtained in both analog and digital modes. Arduino Uno microcontroller is employed for obtaining the digital output of this sensor. Its output value is proportionate to the moisture content of the soil.

Temperature Sensor

The temperature sensor used was LM 35. This sensor has a linear scale factor of +10-mV/°C. It has an accuracy of 0.5°C. It is an appropriate sensor that is suitable for remote applications. It covers a range of about -55°C to 150°C.

Soil pH sensor

The nutrient content of a soil can be measured by means of soil pH. In our work, Labman pH meter is employed for measuring the pH of the soil. The total range of pH of soil is from 1 to 14. A range from 1-6 refers to acidic soil, 7 refers to neutral and 8-14 refers to basic nature. The operating range of the Labman pH meter is 0 to 100°C. It has an accuracy of about ±0.01 pH.

Light Sensor

The light detecting sensor used in our work is LM393. This sensor is a light dependent resistor (LDR). It has an operating voltage of 3.3 to 5 V. The threshold value of the light can be adjusted using a potentiometer know. It provides a digital output based on this threshold value.

Ultrasonic Sensor

The ultrasonic sensor used in our work is HC-SR04. It takes an input voltage of 5V. It has an accuracy of about 3mm. The operating frequency of the device is around 40Hz. It can be used for measuring a distance of about 2cm to 450cm.

Liquid Crystal Display (LCD)

Arduino Liquid Crystal Display (ALCD) is used in our research for displaying all the input and output parameters.

Arduino Uno

In this work, Arduino UNO as the microcontroller device is employed. It has four digital input/output pins. The total number of analog inputs is 6. It has an operating voltage of 5V. It has 32KB flash memory and a clock speed of 16 MHz.

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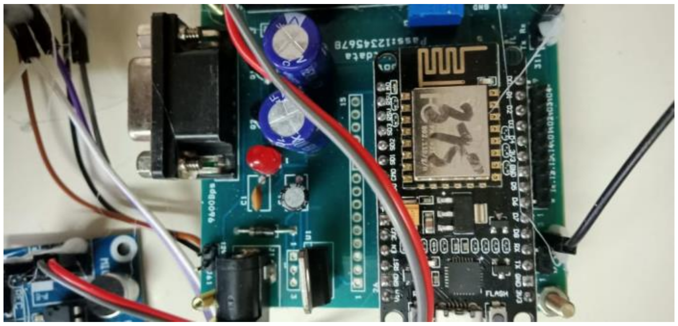
Raspberry Pi

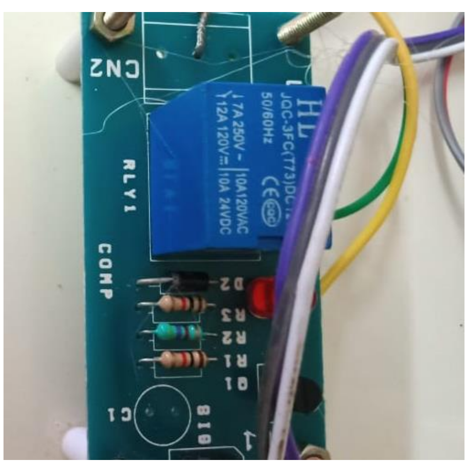
Raspberry Pi 3 model B is employed in our framework. It has a RAM memory of 1GB. It is based on 100 Base Ethernet. It is a cheap, portable device. It has a provision for storing external data using the Micro SD port. It can be programmed and used as per our application.

IoT Module



An IoT device consists of wireless sensor nodes that are lightweight, low-power, and rechargeable batteries. Any standard IoT application system consisted of many such affordable nodes deployed to continuously sense the atmosphere to cover some specific geographic region. For IoT-enabled PA, an energy-efficient model is proposed. The core of the work is focused on designs of solar power. Models of solar power are focused on fixing the challenges of Based on the data, how to predict solar power in the future Data from the environment. Indeed, an existing one was also adopted by Microsoft Solar Model of Electricity. The developed scheme varies with the design proposed. Past research has done in two ways. A new kind of Approach and intention is proposed to respond; how to understand the amount of resource requirements that request resources from the base station. To calculate the energy demands (low power, medium power, and high power specifications) of these interacting entities with the base station, an innovative product density system is proposed. In communication networks, the material density method has been extensively used to identify the complexity of ON and OFF periods. In particular, an Enhanced Duty Cycling methodology is proposed in the research.

Relay network



In order to guarantee and implement WSN Fault Tolerance, the Relay node use is inevitable. The Wireless Sensor Since Low-powered, resource, routing protocols are nodes Account for the fusion of the packet header from the routers of the sensor in their clusters and their transmission to the target/sink Node through Multi-Hop Wireless Routes.

APR Voice IC

The APR voice recording/playback IC used to record the voice and playback the same. The IC 9301 with non - volatile memory chips is a flexible 28 pin IC. It can conduct processing cycles of about 100 K and can preserve memory for about 100 years. It is composed of non memory blocks of the exclusive Inbox analogue / inters flash. More than 256 input voltages can be contained in the memory blocks. The IC model is low-voltage and needs only 5 volts and 25 mA current for normal operating conditions. The voice sensor used in our work is APR 9301. This IC has the capacity to record and play voices for about 20 to 30 seconds. It is based on non-volatile flash memory. It requires an input supply of 5V. The main advantage of this IC is that it does not require any software.

7.4. Proposed Algorithm

The flowchart of the proposed algorithm is shown in figure 3. Initially, the sensors deployed in the agricultural field collect the real-time values using sensors like temperature sensor, moisture sensor, air quality sensor, rainfall sensor, LDR sensor and the nutrition sensor. These values are then transmitted to the Arduino Uno Microcontroller. The microcontroller transfers the input data to the processing unit which is the Raspberry Pi. The Raspberry Pi is loaded with machine learning algorithms. In addition, prior to execution they are trained with a real-time acquired training dataset. Using the trained model, and the acquired data they predict the class to which the input data belongs. The different classes considered while training our system are Close Valve (CV) (L_1=1), Open Valve 50% With Fertilizer (OV50WF) (L_1=2), Open Valve 100% With Fertilizer (OV100WF) (L_1=3), Open Valve 50% With No Fertilizer (OV50WNF) (L_1=4) and Open Valve 100% With No Fertilizer (OV100WF) (L_1=5). If the value of output L_1 from the raspberry Pi is 1, it indicates that irrigation must be stopped. So, the Arduino sends signals to the motor using the relay to stop the irrigation by closing the valve. In case if the value of L_1 is 2 or 3 or 4, then it obtains the input from the ultrasonic sensor. The ultrasonic sensor has two outputs namely L_2=1 or L_2=2. L_2=1 indicates that there is no sufficient water in the water tank. Hence, the Arduino sends control signal to strop irrigation. If the value of L_2=2, it indicates there is sufficient water. Hence based on the value of L_1 the valve of the tank is either opened 100% or opened 50%. Similarly, the fertilizer is added to the water if L_1 is 2 or 3. If L_1 is 4 or 5, it indicates that the soil has sufficient nutrients so no fertilizer is added. Finally, all the data are stored in the cloud using Raspberry Pi module. From the cloud the data can be accessed by the farmers using their mobile phones.

7.4.1. Identification of L_1

To identify the value of L_1, the system is initially trained using various scenarios of real-time values. Around 500 different real-time values were used for training our system. They belonged to five different categories like Close Valve (CV) (L_1=1), Open Valve 50% With Fertilizer (OV50WF) (L_1=2), Open Valve 100% With Fertilizer (OV100WF) (L_1=3), Open Valve 50% With No Fertilizer (OV50WNF) (L_1=4) and Open Valve 100% With No Fertilizer (OV100WF) (L_1=5). Sample of 8 such scenarios are given in Table 1. For each combination of moisture senor, temperature and nutrition senor value, the farmer is made to select one of the five cases. These training data are then loaded in the Raspberry Pi module.

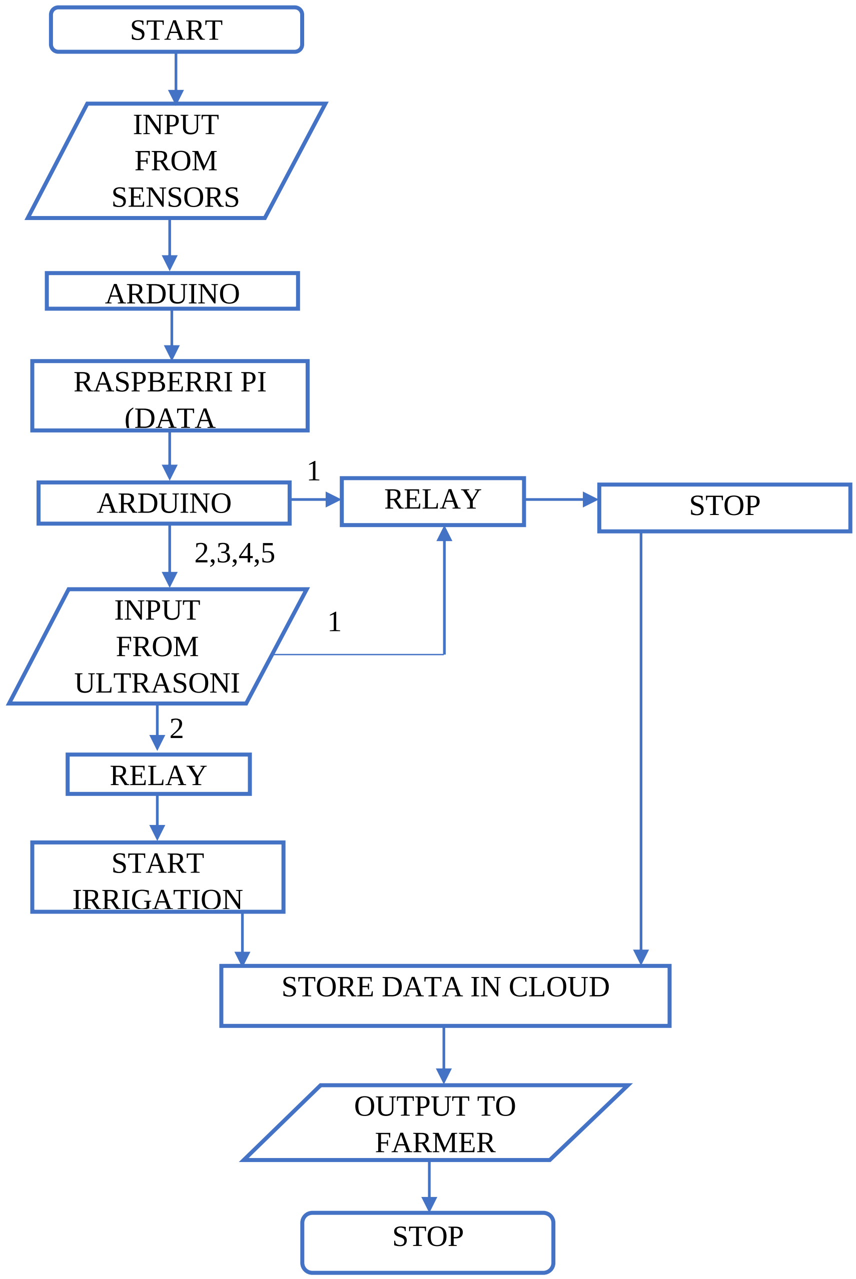


Figure 3 Flowchart of the proposed algorithm

Table 1 Sensor Values with the Farmer Opinion

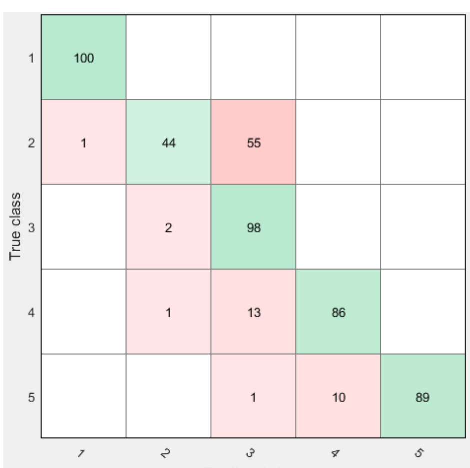
S. No	**SENSOR VALUES**			**FARMER OPINION**				
	Moisture sensor (%)	**Temperature sensor (Celsius)**	**Nutrition sensor (pH)**	**CV**	**OV50WF**	**OV100WF**	**OV50WNF**	**OV100WNF**
1	5.1	33.5	9.1			✓		

2	81	10.6	5.5	✓				
3	7.2	29.7	6.6					✓
4	43.2	21.2	10.8		✓			
5	45.6	23.4	5.9				✓	
6	9.3	36.5	12.4			✓		
7	76	13.1	5.7	✓				
8	6.7	38.9	6.1					✓

From the training dataset, to identify a suitable model, the system is trained using four different Machine Learning algorithms like decision tree, k-NN, SVM and logistic regression. The confusion matrix obtained using all the four algorithms were evaluated using metrics like accuracy, recall, F-score, etc. Based on these metrics, the best model was chosen for classification in our framework. The confusion matrix obtained using decision tree is shown in Figure 4. The decision tree classifier produces moderate results. Its performance is low for classifying Class 2 data.

The confusion matrix obtained using k-NN is shown in figure 5. The performance of classification is better compared to that of decision tree. The confusion matrix obtained using SVM is shown in figure 6.The performance of classification is high for class 5 compared to the k-NN classifier.

The confusion matrix obtained using logistic regression is shown in figure 7.The logistic regression produces best results compared to all other classification algorithms. To further analyze and determine the best algorithm evaluation was performed in terms of classification metrics obtained from the confusion matrices.



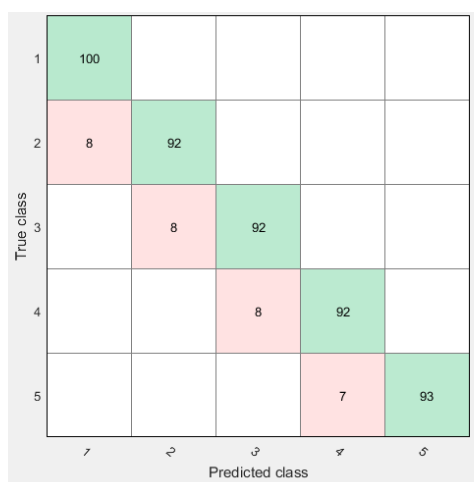
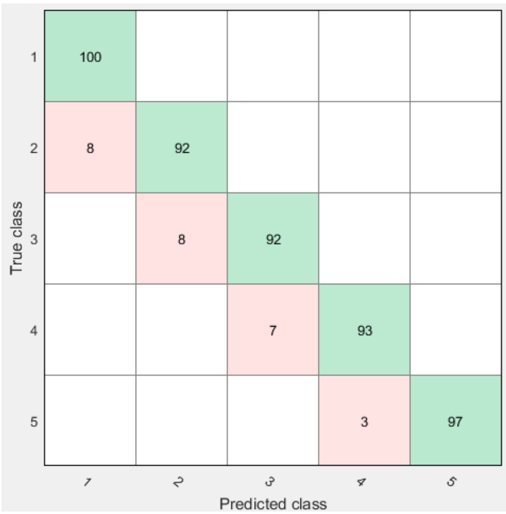


Figure 4 Confusion matrixes for Decision Tree classifier, Figure 5 Confusion matrix for k-NN classifier



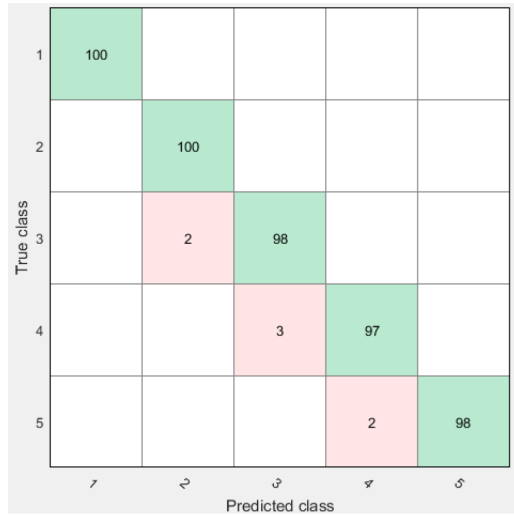


Figure 6 Confusion matrixes for SVM classifier, Figure 7 Confusion matrix for Logistic Regression classifier

Overall accuracy (O_a):

Overall accuracy indicates the overall classification performance of the classifier.

$$O_a = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

Recall (R_e):

The recall refers to the sensitivity of classification and is computed as

$$R_e = \frac{TP}{TP + FN} \tag{2}$$

Precision (P_r):

The precision is the ratio of number of true positives to the sum of true positives and false positives.

$$P_r = \frac{TP}{TP + FP} \tag{3}$$

Specificity (S_p):

The specificity is the ratio of number of true negatives to the sum of true negatives and false positives.

$$S_p = \frac{TN}{TN + FP} \tag{4}$$

F-score (F_s):

The F-score is computes as

$$F_s = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{5}$$

The value of classification accuracy obtained using decision tree is 83.4%. For k-NN, the accuracy is 93.8%. For SVM algorithm, the accuracy is 94.8% and for logistic regression the accuracy obtained is 98.6%. The logistic regression produces maximum accuracy. The comparison of specificity is shown in Table 2. It is clearly evident that, the logistic regression achieves highest specificity for all the five cases.

Table 2 Comparison of specificity for different algorithms

Irrigation Cases	Specificity (%)			
	Decision Tree	k-NN	SVM	Logistic Regression
CV	99.7499	97.9999	97.9999	99.9998
OV50WF	99.2498	97.9998	97.9998	99.4998
OV100WF	82.7498	97.9999	98.2498	99.2498
OV50WNF	97.4999	98.2499	99.2498	99.4998
OV100WNF	99.9999	99.9999	99.9998	99.9998

Similarly, the comparison of precision is shown in Table 3. The average value of precision achieved by decision tree, k-NN, SVM and logistic regression are 88.17%, 93.90%, 94.87% and 98.61%.

Table 3 Comparison of precision for different algorithms

Irrigation Cases	Precision (%)			
	Decision Tree	k-NN	SVM	Logistic Regression
CV	99.0098	92.5925	92.5925	99.9999
OV50WF	93.6168	91.9999	91.9999	98.0391
OV100WF	58.6826	91.9999	92.9292	97.0296
OV50WNF	89.5832	92.9292	96.8749	97.9797
OV100WNF	99.9998	99.9998	99.9999	99.9999

The comparison of recall in the form of bar graph is shown in figure 8. The average value of recall achieved by decision tree, k-NN, SVM and logistic regression are 83.39%, 93.79%, 94.79% and 98.59%.

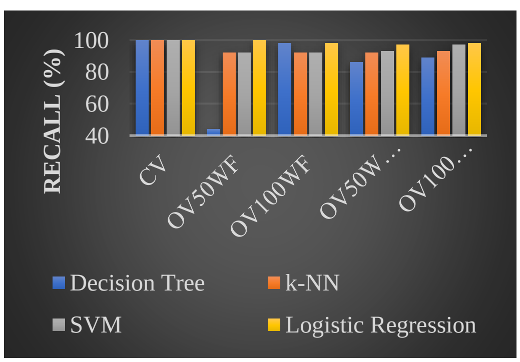


Figure 8 Comparison of recall

The comparison of F-score in the form of bar graph is shown in figure 9. The average value of recall achieved by decision tree, k-NN, SVM and logistic regression are 82.93%, 93.79%, 94.79% and 98.59%. From the simulation results, it is clear that logistic regression produces best results. Hence, the logistic regression model was embedded in the Raspberry Pi module. Hence, in this researchlogistic regression algorithm is used for identification of L_1.

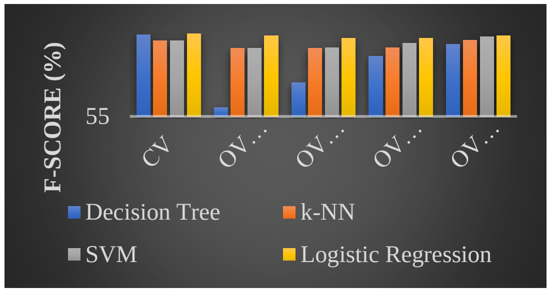


Figure 9 Comparison of F-score

7.4.2. Identification of L_2

The ultrasonic sensor is used for identifying if there is sufficient water in the water reservoir. It works on the basis of piezoelectric effect. It has a trigger pin that transmits ultrasonic radiation. This radiation hits the surface of the water and is reflected back. Based on the time delay (T_d), the level of water is estimated. Here the threshold λ is chosen to be one-fourth of the total length of the water reservoir.

Algorithm 2: Proposed Water Level Label L_2Detection Algorithm.

Input:

Threshold λ

Output:

Label L_2

Steps:

1. Using ultrasonic sensor identify time delay T_d.
2. Compute the distance (cm) of the water from the top level using $D = \frac{(T_d / 2)}{29.1}$.
3. if $D > \lambda$
   L_2=1
4. else
   L_2=0.
5. End

8. Results and Discussion

The proposed system was implemented and the water required for irrigation was monitored for a period of three days. Analysis was done using three schemes namely, scheduled irrigation, automatic irrigation and the proposed irrigation scheme. The moisture level is indicated using Volumetric Water Content (VWC) that gives the amount of water in total amount of soil. Figure 10 shows scheduled irrigation, the land is irrigated for about six times in three days. The system was scheduled to perform irrigation twice each day irrespective of the soil and climatic conditions. Hence, the amount of water required was huge. This leads to wastage of water. It was also cause water clogging issues. Also, there is no mechanism to identify whether fertilizer is required or not, irrigation was performed with the fertilizer during all six instances.

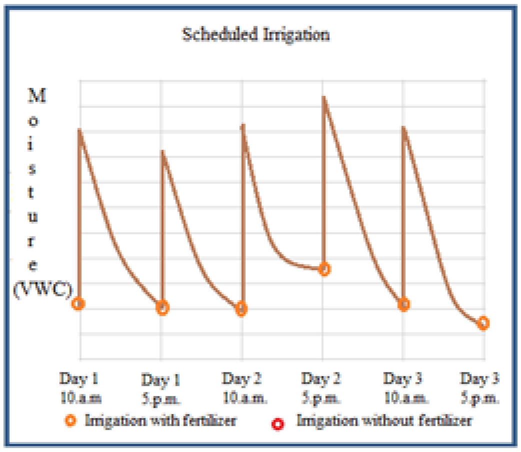


Figure 10 Scheduled Irrigation Scheme

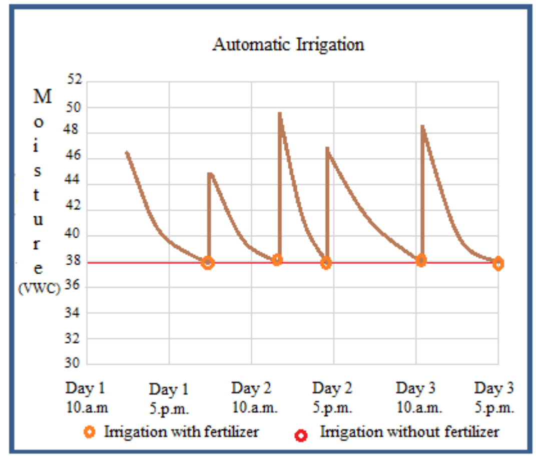


Figure 11 Automatic Irrigation Scheme

The automatic irrigation scheme is shown in Figure 11.In this scheme, the system was programmed to perform irrigation whenever the moisture value goes beyond a particular threshold. Here the threshold was chosen to be 38 VWC. The system performs irrigation five times in the period of three days. Here, similar to previous case, since there is no mechanism to identify whether fertilizer is required or not, irrigation was performed with the fertilizer during all five instances.

The proposed irrigation scheme is shown in Figure 12. In this scheme, irrigation is done based on the results of the machine learning algorithm. Hence this system is more optimal. The irrigation is performed only four times during the span of three days. Also, in the proposed technique, the nutrition requirement of the soil is identified before irrigation. Hence, the first and third irrigation comprised of irrigation with fertilizers. The second and fourth irrigation was performed without fertilizers. Also, it was noticed that during the third irrigation, only 50% of the valve was opened.

The amount of water and fertilizer used by the three schemes are determined and is shown in Table 4. From Table 4, it is obvious that, the proposed system utilizes optimum amount of water and fertilizer. Hence, it is more robust compared to scheduled and automatic irrigation systems. Our system uses only 3500 ml of water with 20 gm of fertilizer for irrigating the land for a period of 3 days.

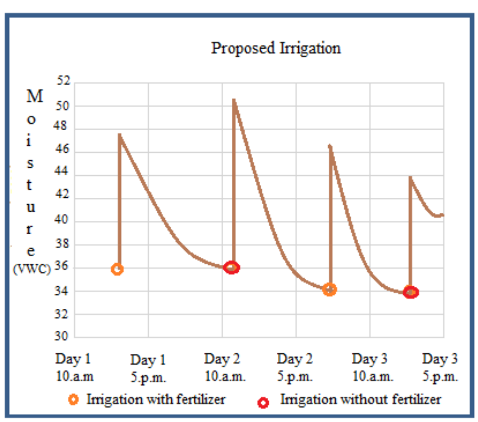


Figure 12 Proposed Irrigation Scheme

Table 4 Comparisons of Water and Fertilizer Used

Type of Irrigation	Total Number of Irrigation in 3 days	Total Water Used (ml)	Total Fertilizer Used (gm)
Scheduled	6	6000	60
Automatic	5	5000	50
Proposed	4	3500	20

9. Conclusion and Future Work

In this research, a novel methodology called Machine Learning based Automated Irrigation System using IoT (MLAIS-IoT) is proposed for precision irrigation. The real-time data is sensed by temperature, moisture and soil nutrition sensors, rainfall sensor, LDR sensor and Air quality sensor. These values are processed in the Raspberry Pi module. The Machine Learning algorithms like decision tree, k-NN, SVM and logistic regression are analyzed. It was inferred that the logistic regression produces best results in terms of various classification metrics like accuracy, recall, precision, F-score, etc. Five different scenarios were considered in our work namely Close Valve (CV), Open Valve 50% With Fertilizer (OV50WF), Open Valve 100% With Fertilizer (OV100WF), Open Valve 50% With No Fertilizer (OV50WNF) and Open Valve 100% With No Fertilizer (OV100WF). Based on the output of the algorithm the irrigation was performed. To validate the proposed methodology, the amount of water and fertilizer required using this MLAIS-IoT method was compared with that of scheduled and automatic irrigation. It was observed that, the proposed technique required lesser amount of water and fertilizer compared to that of scheduled and automatic irrigation. In particular for irrigation of three days, the total amount of water (in ml) required by scheduled, automatic and proposed irrigation schemes were 6000, 5000 and 3500 respectively. Similarly, the total amount of fertilizer (in gm) required by scheduled, automatic and proposed irrigation schemes were 60, 50 and 20 respectively. Thus, proposed system produces robust and efficient irrigation. In addition, the entire data is stored in the cloud and is made available to the farmers through their mobile phones.

Future Work

In future, a novel WSN platform can be applied for Precision Agriculture (PA) based on energy efficient wireless communication and efficient and accurate routing algorithm on 5th Generation wireless communication.

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