

Sustainable Automated CROP Irrigation Design System Based on IOT and Machine Learning

Dr. Shivaprasad K.M

Professor, Department of Electronics and Communication Engineering, R L Jalappa Institute of Technology, Doddaballapur, Karnataka 561203, India

Dr. Madhu Chandra G

Associate Professor, Department of Electronics and Communication Engineering, R L Jalappa Institute of Technology, Doddaballapur, Karnataka 561203, India

Mrs. Vidya J

Assistant Professor, Department of Computer Science and Engg, GITAM School of Technology, Bengaluru, Karnataka 561203, India

Abstract:

Farmers face a difficult challenge of sufficient water management in a period of rising water scarcity, and it is one that must be approached with care. The monsoon rains provide a significant amount of water for agriculture, yet this supply is inadequate. The report advises that farm irrigation systems be automated in order to increase efficiency. Farming's water resources are being managed via the use of a smart irrigation system that includes the Internet of Things (IoT) and Machine Learning technologies (ML). This paper proposes an Internet of Things-enabled, machine-learning-trained recommendation system for effective irrigation water utilisation. In order to keep track of the ground and its surroundings, farmers employ sensors from the Internet of Things (IoT). After being transmitted to a cloud-based server, the data is analysed and converted into irrigation pointers for the farmer with the use of artificial intelligence (AI). Adding a feedback mechanism has improved its durability while also increasing its flexibility. The method appears to be effective on both our own datasets and a dataset from the agricultural department at NIT Raipur, according to our tests. Experiments have revealed By reducing the need for typical irrigation systems, this technology conserves water, labour, and plant nutrients while increasing yields. An innovative technological prototype at an affordable price, as well as a fully operational machine that delivers the best and most accurate results, are included in the package.

Keywords: *IoT, Automated system, Irrigation management, Cloud and Machine Learning.*

I. Introduction

Agriculture is vital to our economic, social, political, and cultural survival. As a result of inefficient and haphazard use of water resources, the agriculture industry is today experiencing a slew of problems. Agriculture is both a sufferer and a perpetrator of water scarcity. Irrigation presently utilises more than 84 percent of the country's available water. The most major contribution to the environment and water scarcity is field water management [1]. Some farmers may also have sufficient of rain, however it frequently falls while it is not wanted and disappears in the course of droughts. The agricultural enterprise likewise has the issue of assembly the developing call for of India's populace even as additionally making sure meals safety while land sources are limited. According to the South China Morning Post (SCMP), the researchers determined that the clever farming approach produced the best output, with 97-ninety nine percentage of the most manufacturing and at a decrease environmental cost [2].

According to, the Internet of Things (IoT) is converting and redefining the entirety from commercial enterprise to person-to-person. IoT is a modern generation that permits statistics to be communicated over a community with out the want for human interaction. As noted in [3,] linked gadgets have permeated each a part of our lifestyles because the IoT has emerge as extra broadly adopted. This consists of agriculture, fitness and fitness, domestic automation, automobile and logistics, clever cities, and commercial IoT. The use of IoT technology in agriculture is progressively increasing. According to BI information, the quantity of agricultural IoT tool installations will attain seventy five million via way of means of 2020, increasing at a charge of 20% year. Agriculture has emerge as greater state-of-the-art and era-pushed in the course of the last few decades. Using diverse clever technologies, farmers have received greater manage over crop boom via way of means of making it greater predictable and effective [5]. Farmers are spending greater time and strength traveling among places to reveal ongoing procedures inclusive of irrigation, cultivation, harvesting, and crop drying, in addition to to test on livestock, manage machinery, and talk with different community nodes. If IoT era is hired in agriculture, a lot of those obligations may be automatic with minimum human involvement. As technology progresses, sensors are growing smaller and smaller, and they are currently used in almost all IoT applications. In WSN [6], sensors collect data on soil quality and water demand from agricultural fields, and actuators manage pumps based on decisions made from the data collected by the sensors.

Subsurface Drip Irrigation (SDI) is one of the numerous smart irrigation methods that have been created to minimise water use in agriculture. SDI, a common irrigation technique, allows farmers to regulate when and how much water is provided to their crops. Drones enable farmers in getting unique data about a subject region, such as crop improvement and soil water requirements, by using a thermal digital to estimate the shadow temperature distribution [7]. Until recently, the majority of irrigation tracking systems did not take precipitation into account when forecasting the quantity of water required for crop growth. Water was wasted as a consequence of crop irrigation as a result of the rain turning into rain now, and agricultural output suffered as a result of the decreased productivity. As a way to aid farmers in dealing with unpredictable rainfall and increasing output, we've created a smart irrigation system that is Internet of Things (IoT)-based and incorporates a machine learning algorithm that accomplishes just that. Within the scope of this research, machine learning (ML) may be utilised to better manage irrigation and increase agricultural output. In order to gather data for these projects, sensor nodes are placed in agricultural fields. These initiatives begin with a data collecting paradigm and progress from there. A machine learning algorithm is then trained on the data, which estimates soil moisture and nutrients in order to maximise yield. Depending on the weather and the amount of water required for production, irrigation is then initiated [8].

1.1. Necessity of Automatic Irrigation

- Installing and constructing it is simple and quick.
- Saving resources and energy so that they can be used in the most efficient and effective way possible.
- The automated distribution of farm or main irrigation allows farmers to distribute the appropriate amount of water at the appropriate time.
- Reduce runoff from overwatering saturated soils to avoid irrigation at inconvenient times of day, which can improve crop yields.
- In an automated irrigation system, a solenoid valve is utilized to control the operation of the motor by turning it on and off. Motors may be readily automated through the use of controllers, removing the need for a manual resource to switch them on and off on a consistent basis.
- It is a specific irrigation technology and a valuable instrument for precise soil moisture control in greenhouse crop production.
- It saves time and eliminates human errors while monitoring soil moisture levels.

A machine learning system powered by the Internet of Things is being used in this study, which seeks to minimise agricultural water waste. It is possible with this prototype for the data to be analysed to be sent from the cloud server to the farmer's mobile phone in advance, allowing him to make use of the knowledge in advance. With the help of this method, farmers may quickly and simply determine whether or not they need to water their fields. A few of the most significant findings from this study are as follows:

1. In agriculture, wireless Internet of Things (IoT) sensors are used to collect real-time floor and environmental data over a wireless network. Agglomerative clustering, as well as machine learning techniques like as the Capsule classifier and regression tree, are used to analyse this data and deliver irrigation suggestions to farmers using cloud-based servers that analyse the data. Temperatures of the air and soil, relative humidity, and soil moisture are all included in this information. By implementing an internal feedback mechanism, recommendation systems may be made more flexible and responsive to their environment.
2. An inner remarks mechanism has been added to this advice gadget to make it extra strong and flexible.
3. Experimentation indicates that the recommended gadget plays nicely on each our very own dataset and the crop dataset from NIT Raipur.

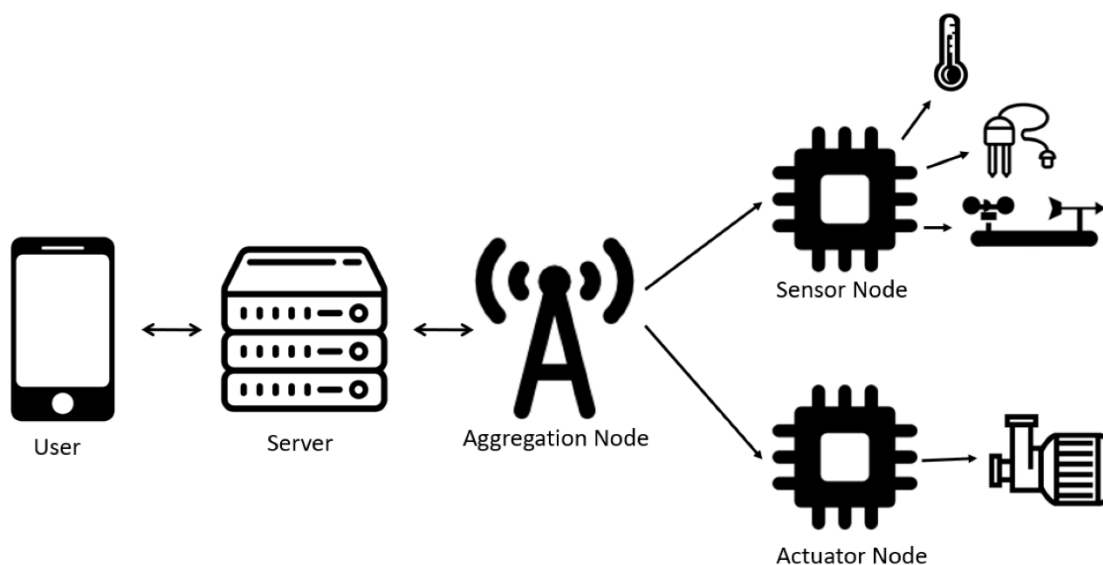


Figure 1: Classical system architecture

The above figure 1 classical agriculture architecture model which is implemented successfully in the field of agriculture.

The paper is further divided into the sections that follow. Section 2 describes in full the relevant work on current irrigation models that has been completed. Section 3 illustrates the paradigm that is being presented in this study. Several of the findings of this study endeavour are described and illustrated in Section 4. Last but not least, Section 5 summarises the suggested model for this work.

II. Related Work

In order to achieve more cost-effective solutions while also protecting natural resources, a number of solutions have previously been created with the purpose of merging the two. Intelligent solutions in the fields of artificial intelligence and machine learning are being produced in parallel with technological advancements and the development of new Internet of Things (IoT) solutions on a daily basis.

When developing a smart and autonomous irrigation system, communication is a critical component of the process. In the last several years, a significant amount of study has been undertaken on the subject of intelligent irrigation systems. Closed-loop watering systems made use of a number of communication techniques to keep the system running smoothly. According to the authors of [9], GPRS can be used to establish a connection between Wi-Fi sensor networks (WSNs) and the Internet. They are deployed in order to save botanical resources by delivering the required volume of water to the intended spot as rapidly as possible. [10] Those in attendance were warned that a Wi-Fi sensor community may be used to construct a soil moisture controller that evaluates soil moisture up to a specific threshold price and estimates the need for irrigation. You may estimate soil moisture and water quantity by executing disciplinary authentication evaluations on a regular basis, allowing you to build a profitable watering machine for your crops. In order to construct a cost-effective irrigation system, it is normal practise to undertake soil moisture and water content tests in the field on a regular basis. If the preserved data does not match the observed soil data, an interruption is sent to the pressure unit, and the irrigation system is switched off as a result.

To guarantee that the agricultural region has sufficient water [11], the government has installed a solar-powered shrewd irrigation system. Sensors that measure moisture and humidity are used to assess whether or not the soil is wet or dry. This information is received by the microcontroller from the sensor node once the sensing process has been completed. As a consequence, the engine starts up and starts working. [12] In the WSN-based system, smart irrigation systems were designed with the use of computerised remote sensing and long-term soil and ambient quality evaluations using machine learning to ensure that the system was effective. The implementation of an automated climate station (13), which collects data in real time and allows for the interpolation of local real-time environmental variables, made it straightforward to interpolate local real-time environmental variables (ASW). This innovative tool also takes advantage of adjacent ASW data to offer historical, present, and future projections while also managing irrigation during times of severe rain or snow. It is necessary to compare interpolated results to soil moisture information in order to identify and resolve irrigation problems. This is accomplished using soil moisture and ASW data. According to the authors of [14], irrigation systems that incorporate WSN and GPRS modules can boost the productivity of any agricultural crop. This approach makes use of a number of sensors, including moisture and temperature sensors, among others. It is necessary to use gateway chemicals in order to communicate sensor data to the base station.

Instantaneously, the sensor unit transmits a command to the actuator, ordering it to change the watering operation and deal with the data acquired. Several algorithms are implemented within the machine, each of which is tailored to the requirements and conditions encountered on the job site. Microcontrollers deliver instructions to actuators through valve units in order for the water to be able to float freely. The complete machine is powered solely by solar panels, which allows for the establishment of a bidirectional link. For irrigation control, Internet programmers rely on regular surveillance and irrigation scheduling [15], both of which are available online. A study of sensor network routing protocols was carried out by the developers of [16] in order to develop both hardware and software. It is now possible to regulate irrigation systems and monitor soil moisture levels in real time using mobile phones and wireless personal digital assistants (PDAs) (PDAs). [17] had developed a WSN-based irrigation system that they were able to market and sell to clients. The emerging system takes use of a neural community and fuzzy common sense to store water in order to maximize efficiency. When combined with neural network self-awareness and fuzzy common-sense reasoning, the fuzzy neural community that was hired creates a potent combo. Sensor nodes are used to assess temperature, humidity, soil moisture, and mild depth, among other things. Information about irrigation management systems is received via gateway nodes that are connected to a local area network (LAN) or a wide area network (WAN).

On the basis of the information that has been obtained, the electromagnetic valve is programmed to provide particular irrigation. Initially, the criteria for estimating soil moisture were constructed by the authors of [18] using simply data from disciplinary sensors and climatic forecasting data, which was a significant improvement over the previous criteria. The approach makes use of the assist vector regression version as well as the k-manner clustering to achieve its goals. Among the suggestions included in this collection of rules are irrigation recommendations that are dependent on how much soil moisture is now present in the soil. All of the tool information that has been collected, together with the results of the set of rules, is saved in a MySQL database on the server's side. An image-capturing machine, which uses a digital camera to capture images, was proposed by the authors in [19]. The amount of water present in the soil's substance is determined by the use of pictures taken at various stages of the procedure. When water is pumped into the crop field, the amount of water pushed in is governed by how much water is contained in the surrounding soil.

An Android application is used to operate the digital camera. The RGB pictures, which allow the camera to identify whether or not an area is damp or dry, are captured through an anti-reflective glass pane, which acts as a moisture sensor. The WiFi connection provided by the smartphone is utilized to transmit the anticipated cost to a gateway through a network, allowing the water pump to be controlled. M2M communication is a low-cost water management solution that is particularly useful in

agricultural irrigation. [20] According to the authors, a distributed network environment based on the Internet of Things (IoT), machine learning, and wireless sensor networks (WSN) is being developed to maximize water utilization while lowering soil erosion [21]. An autonomous irrigation system must be capable of estimating soil moisture levels with high precision.

Water usage can be cut by up to 40% by looking at algorithms that compute the amount of water that must be delivered to the fields, according to prior study. As a result, the use of machine learning technologies, which will be explored in this article, has a good chance of delivering even more savings.

III. Proposed Design

The proposed three-tier architecture as well as the suggested three-tier architecture are described in this section. Our smart irrigation system's solution design is depicted in Figure 2. The specifications of each level are detailed below.

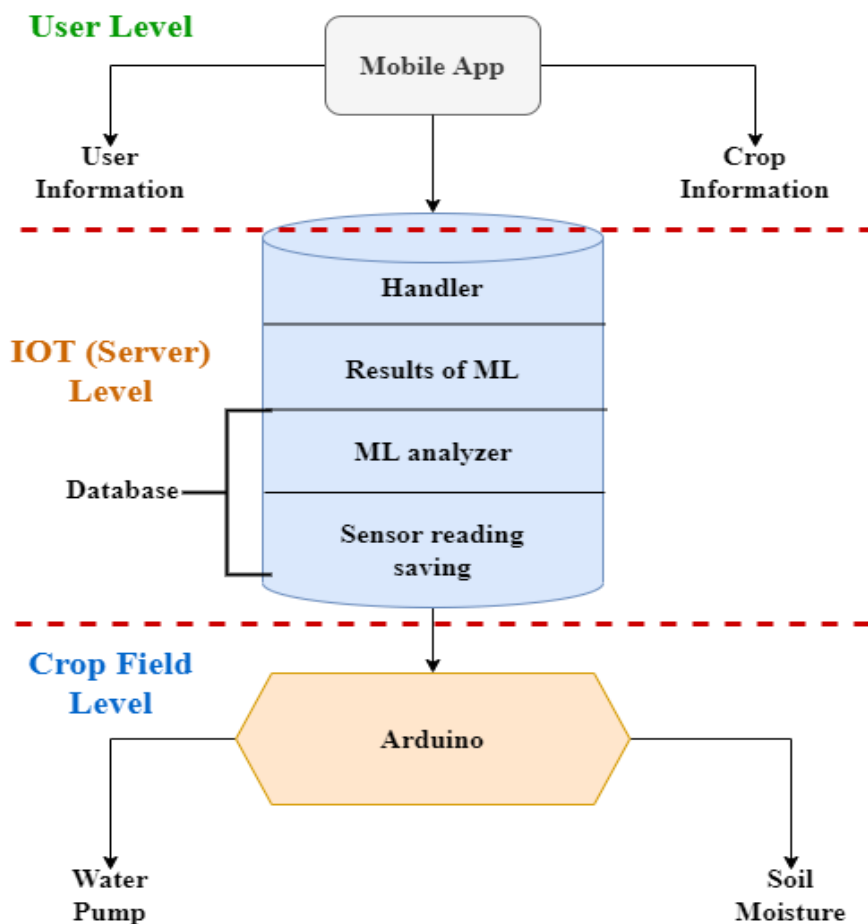


Figure 2. Proposed design of three levels

3.1. User Level

In order to gain a customer's viewpoint on the farmer and the product, the consumer interacts with an Android app. In order to authenticate a user's identity, the farm credentials connected with the user are used. Selecting drop-down options such as "session," "crop name," "generic crop days," "sowing date," and other relevant information might encourage the farmer to enter crop information. Using this technique, farmers may be able to get all of the information they need on their crops and fields. App users may operate the microcontroller by directing it to turn on or off lights, as well as collect sensor data. When the handler is executed, the system responds to user input by including any comments the user has made. The server is alerted if the farmer ignores the advise, and the database is updated as a result. Thus, it is possible to make system modifications depending on user feedback. On or off, the microcontroller activates or deactivates a motor that distributes water to the plants when it receives a command from the user. As a result, irrigation systems have been developed that can increase agricultural productivity by providing the right amount of water at the right time. [22]

3.2. Cloud Level

It is the second level, which is represented by the cloud, which offers services to customers through the use of a cloud server. Sensor data is recorded into a database so that it may be accessed later. Finally, the data is transmitted to the machine learning model, which processes the information.. This machine learning unit serves as the brain of the two-part intelligent system. A regression model can be used to forecast the composition of soil and other environmental components. As a consequence, it may be used to successfully improve the system as a result of the forgoing. The forecasting of weather conditions is dependent on a number of elements. The pressure in the atmosphere, precipitation, sunshine, and wind speed are all examples of environmental variables. In order to decrease the anticipated mistakes in these projected values, clustering techniques are employed. The results

of the clustering model, as well as forecasts for the weather, are fed into the other machine learning model. Water irrigation is required, according to this binary classification model, which splits the anticipated data into two categories: (N). They will be able to be used again and again in the future owing to a database of the results from these models. It is the responsibility of cloud-based server handlers to ensure that real-time communication between user requests and field units takes place. On the basis of the ML model's recommendation [23], the handler will provide irrigation suggestions to the user through the Android app. Equation 1 determines the amount of water required based on information from agricultural literature.

$$EV_o * C_f = W_{need} \quad (1)$$

Where, EV_o =rate of evaporation

C_f = crop factor

W_{need} = amount of water needed

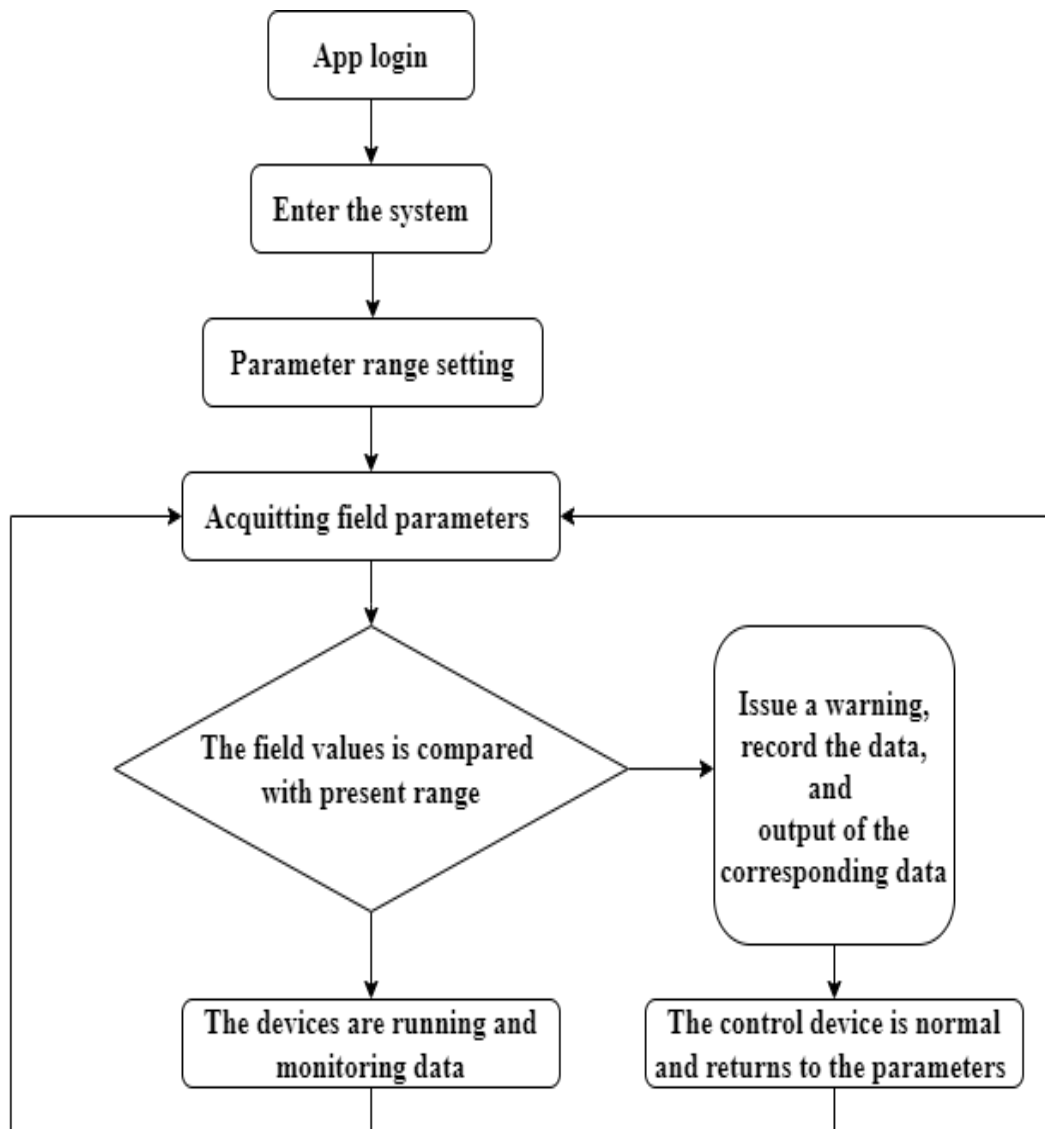


Figure 3. Overall App Flow

3.3. Crop Field Level

Sensors are strategically placed across the field in a variety of locations to serve as the first line of defence at the grass-roots level. In order to monitor all of these soil and ambient parameters, a variety of sensors are used, including soil moisture (EC-1258), soil temperature (DS18B20), air temperature (DHT11), and humidity (DHT11). It is able to monitor soil moisture (DS18B20), soil temperature (DS18B20), as well as the temperature and humidity of the surrounding environment (DS11). The soil is equipped with a moisture sensor (EC-1258). Upon receiving data from each sensor, the data is sent to the Arduino microcontroller, which does additional processing. In the following phase, the sensor data from an Arduino is sent to a cloud-based storage service provider. A sensor data collection device with an integrated microprocessor that gathers data every two days can be used to store and analyse sensor data in the cloud. When calculating an average reading, the last reading for the day is used as a starting point. The Pearson correlation coefficient is determined with the goal of lowering the interdependency between some of the components under investigation for this study. In this particular instance, it has been proved that there is no substantial link [24]. In addition to

an Arduino and a relay switch to link the Arduino to a motor pump, a breadboard and relay switch may also be used to achieve irrigation. Because of the low power consumption of the Arduino microcontroller, authors chose to utilize it for this application.

Algorithm (Working steps for proposed design)

Input: Authentication information for the Android application's login page. From the drop-down menu, choose all of the pertinent crop information.

Output: Turning the motor on and off

1: Using the App, collect all data from the sensors at regular intervals and save it.

The sensor reading is saved in the cloud server database in step 2.

3: Using the soil moisture and weather projected data, the ML analyser model examines the stored sensor data to determine whether or not it should be used.

What if irrigation is necessary, and what if it is not?

4: The suggestion made by the ML model is communicated to the App through the handler function.

5: The user will instruct the App to send an ON/OFF signal to the motor based on the ML suggestion and sensor values.

User may choose to irrigate the land in accordance with the suggestion.

7: If the user does not follow the advice, feedback will be delivered to the system and saved in the database for the sensor readings that were triggered by the recommendation.

3.4. Reasons for sensors in agriculture

In agriculture, sensors and actuators are used to accumulate data on environmental and bodily qualities, in addition to react to remarks on situation control. The sensor received records that characterizes the surroundings and item is utilized to perceive people, their position, and their states [25], and that is referred to as context. This context acquisition is extraordinarily beneficial in area modelling instances related to a huge variety of time and a couple of attributes. Among all of these, agriculture is one of the domain names that has lots of necessities.

- Collecting climate, soil, and crop records
- Supervising allotted land
- A couple of vegetation on a chunk of land
- Numerous fertilizer and water necessities to numerous portions of choppy land
- Numerous crop necessities for numerous soil and climate conditions
- Reactive answers are changed with proactive answers

IV.Result and Discussion

Python was used to analyse the performance of the recommended model, and the results were published. It was necessary to use the Scikit-learn Python package deal in order to implement all of the system learning models. Our own information [26] was combined with the Crops dataset from NIT Raipur to assess the system's overall performance. By utilising the appropriate sensors, it was feasible to collect information on the moisture content of the soil as well as its temperature. It was also possible to obtain information on humidity and temperature as well as UV radiation. The readings that are saved for each day are the same for all of the days. One hundred and fifty samples were gathered from our simulated location for testing purposes. There are 501 samples available in the NIT Raipur dataset for you to use. An interface for climate software programming (CSP) was developed in collaboration with the Indian Meteorological Department (IMD) in order to integrate anticipated climatic data (APIs). In order to increase the accuracy of our irrigation, as part of our efforts to increase the accuracy of our irrigation systems, authors have gathered data on the following day's precipitation, the quantity of precipitation, the amount of precipitation, and so on for a given place. For irrigating purposes, twilight is the most effective time of day, hence the ML version is designed to run at that time every day. In response to the findings of the test that it conducted, it sends irrigation directives to the farmer together with the previously saved and projected parameters. The five-fold cross-validation technique is used in the class project, and it is discussed in detail below. Most often, while assessing the overall performance of a system, the metrics of perfection, recall, F1 measurement, and accuracy are used to assess the system's overall performance (A). Equation (2) to specifies the technical aspects of this measurement (4).

$$Precision (P_r) = \frac{T_p}{T_p + F_p} \quad (2)$$

$$Recall (R_c) = \frac{T_p}{T_p + F_n} \quad (3)$$

$$F_{score} = \frac{2 * P_r * R_c}{P_r + R_c} \quad (4)$$

Table 1: Comparison Performance Evaluation of Irrigation by conventional and proposed design

Dataset	Classifier	Accuracy (%)	Precision (%)	Recall (%)	F-score (%)
Our sensor collected data	Naïve Bayes [27]	84.58	83.77	81.85	82.90
	Decision Tree (C4.5) [28]	86.84	86.22	84.91	84.91
	Capsule classifier (Proposed)	91.39	87.88	86.52	86.52
NIT Raipur Crop Dataset	Naïve Bayes [28]	85.47	84.45	83.73	83.88
	Decision Tree (C4.5) [29]	87.25	86.85	84.99	85.91
	Capsule classifier (Proposed)	93.15	92.55	91.78	91.55

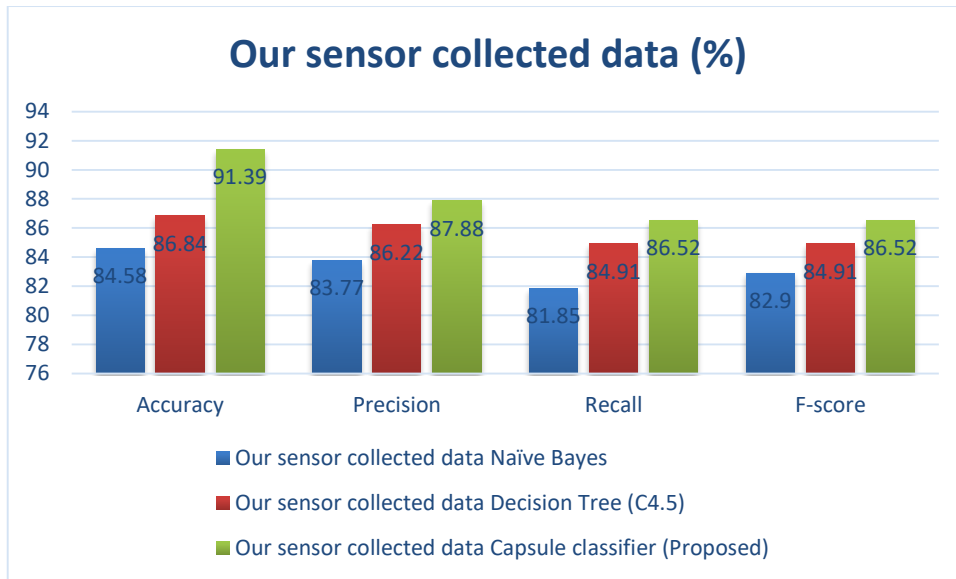


Figure 4. Our sensor collected data of comparison performance

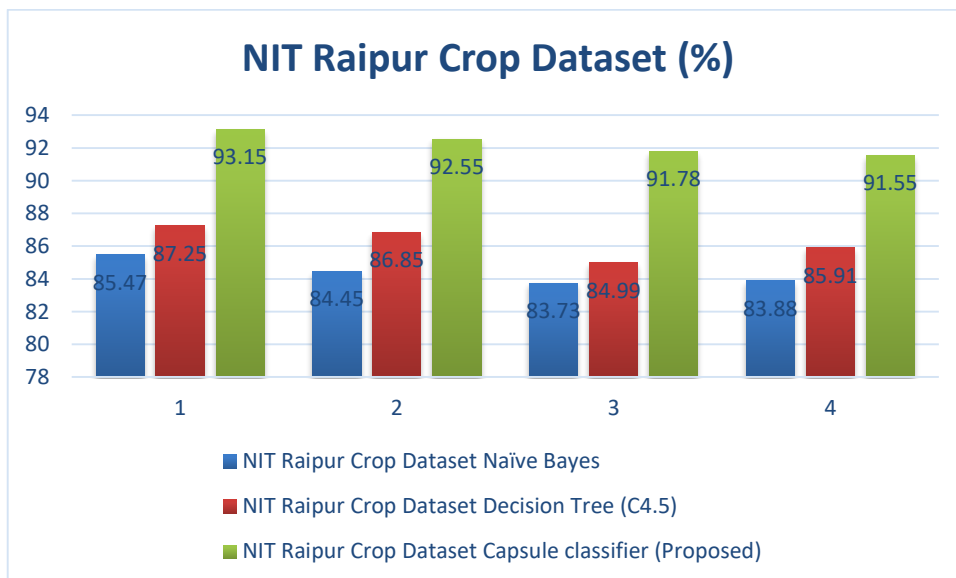


Figure 5. NIT Raipur Crop dataset of comparison performance

Table 2. Valve Irrigation model

Valve Irrigation	Automated Time (ms)	Traditional (ms) [30, 31]
Day 1	6.51	9.95
Day2	5.29	9.76
Day3	6.76	10.98
Day4	6.34	10.74
Day5	7.13	9.98
Day6	6.52	10.55

Table 3. Sprinkler Irrigation model

Sprinkler Irrigation	Automated Time (ms)	Traditional Time (ms) [30, 31]
Day 1	6.51	9.55
Day2	6.12	9.42
Day3	6.06	9.68
Day4	6.72	9.31
Day5	6.10	9.53
Day6	7.05	9.65

Table 4. Drip Irrigation model

Drip Irrigation	Automated Time (ms)	Traditional Time (ms) [30, 31]
Day 1	6.12	8.78
Day2	6.18	8.71
Day3	6.21	8.55
Day4	6.00	8.92
Day5	6.08	8.31
Day6	6.20	8.36

V. Conclusion

Specifically, the scope of this research is to develop a prototype of a smart irrigation system that maximises water efficiency while needing the least amount of physical labour as feasible. The suggested approach of suggestion entails regression of soil and environmental factors, which is subsequently augmented by means of amplification coefficients. Forecasted weather data is used with these expected variables to reduce the likelihood of irrigation errors occurring. Prior to determining whether or not irrigation is required, classification models are used to categorise all of the data into several categories. Following that, the system generates a recommendation for the next watering based on the collected data. If the farmer does not accept the approval, the system provides feedback to him. In order to keep the model up to date, it must be constantly improved and updated. In the testing, the Capsule classifier model outperformed other classification algorithms on both datasets and was shown to be superior to them on both. Because machine learning-based models require a huge quantity of data, the performance of the suggested approach should improve even more with additional samples. Additionally, this technique may be used to decide which pesticides should be sprayed in order to encourage the most optimal crop development possible.

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