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Root Depth Prediction Using Machine Learning for Effective Root Zone Injection Irrigation through IoT Automation

V. Vivekanandhan

Assistant Professor, Department of Computer Science and Engineering, Adhiyamaan College of Engineering, Tamil Nadu, India

acevivek7677@gmail.com

Christopher M, Dilipkumar M, Gopal G

UG Scholar, Department of Computer Science and Engineering, Adhiyamaan College of Engineering, Tamil Nadu, India

ac18ucs019.christopher.m@gmail.com, Dilipkumar1512@Gmail.Com, gopal1052001@gmail.com

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Annotation: Agriculture plays an important role in producing food supply for survival. The agriculture practice is performed by multiple factors such as soil type, fertilisers, plant samplings, irrigation practice, etc. On these factors on which agriculture depends, irrigation is one of the major factors for the better yield of crops, just like any other factor. Therefore, efficient irrigation practice has to be performed to increase cultivation production and preserve available water resources for optimal usage. Traditional methods of irrigation practice are well suited for situations with surplus water resources but not very efficient when it comes to scarce places. So, we propose a new IoT-driven root zone injection method of irrigation which is estimated to perform required irrigation practices in places of high water scarcity. This method is performed with the help of machine learning, IoT devices, wireless neural networking of sensors, and root zone injection equipment for automation. The mechanism starts with collecting real-time data from the agricultural field for specified crop types by using a wireless neural network of sensors and forming the dataset. Once the dataset is formed, it will be processed and cleaned to feed into machine learning algorithms. The machine learning algorithm (here, it is linear regression) will make the required prediction for the water content needed for the irrigation process for that particular day. The dynamic estimation is made as the water content required will vary from the growing phases of plants where it is minimum at the initial phase, peak at middle and reduce or increase depending on the plant species at later phase of growth. This estimated water content is then delivered to the plants through the irrigation process, governed by the IoT devices, which have the procedures encoded for irrigation. ML prediction guides the IoT system on how much water to deliver to the plants. Finally, the injection setup of the root zone passes the water directly to the underground root zones. Thus, completely preventing evaporation wastage and accurate water content estimation and supply, achieving optimal irrigation practice.

Keywords: Agriculture, Irrigation, Machine Learning, Linear Regression, IoT devices, Wireless Neural Network of sensors, Root Zone Injection method.

1. Introduction

Water scarcity is becoming a bigger problem in recent years because, in the past 2 decades, global warming has increased dramatically by greenhouse effects and caused huge calamitic changes. These calamitic changes distorted the rainfall in many places, including rural, semi-arid regions, and urban areas. The distorted rainfall caused the current biggest problem of water scarcity and caused drought in most agricultural areas. Thus, water conservation for agricultural practice has become the need of the hour to save water resources,

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agricultural land and practices. But the conservation alone is not sufficient as it is necessary to meet the expected irrigation practice for better yield of crops. Agriculture is estimated to utilise nearly 85% of the freshwater available [1]. All these signify the importance of efficient agricultural practices. The agricultural practice comprises several factors: fertilisers, irrigation, climate, soil type, plant type, etc. Among these factors, irrigation is the most important factor directly related to water resources [13-15].

Traditional methods fail to use available water resources to their best use and seem inefficient when conserving the water for later use [16-21]. Thus, modern irrigation methods, which include the available technologies of the modern generation, are vital for the survival of agriculture in highly water-scarce areas [22-27]. Technology is a powerful tool that proved its potential in revolutionising many industries, particularly computer engineering, cloud computing, the internet of things, and the most advanced areas such as artificial intelligence and machine learning [28]. Irrigation practice is driven by many factors such as humidity, plant growth phase, nutritional content available in the soil, nature of plant species, root depth, soil type, temperature and climate [29-31]. Among these, temperature and humidity content could be identified through wireless networks of sensors. Still, root depth could not be estimated due to its difficulty residing under the ground level [32]. Thus, another efficient method to estimate the root depth has to be established, and it is crucial as the plants' irrigation practice is wholly taken through their root zone [33-37].

Machine Learning is a recent technology that can solve classification, clustering, and prediction problems by building a prediction model from a historical dataset [38-43]. Since the value of root depth is a continuous value rather than a discrete value, the regression prediction models could be used in machine learning to estimate the root depth of a specified plant type over time. The prediction is performed with the data collected through a wireless network of sensors, which is profound in its utility [2-4]. The prediction model will estimate the root depth value based on time duration from the initial planting day. This root depth value will determine the amount of water content expected to be sufficient for irrigation on that particular day of cultivation [5]. The required water content value is supposed to vary constantly during agriculture until the day of harvesting. Thus, it is necessary to plan the irrigation accordingly. Machine learning allows us to predict the varying value of water content throughout cultivation from the start to till the end of harvest [44-47].

The Root Zone Injection method, also known as RII irrigation, is an emerging irrigation method that uses subsurface infiltration-promoting apparatuses (SIPA) to deliver the irrigation water directly to plant root zones under the soil surface [6]. It is achieved through an RII system injection nozzle drilled into the soil near root zones, and the holes in those nozzles will deliver the water to the underground root system. The depth to which the drill has to be made is determined by the phase of root growth and the root depth estimated using the ML prediction model. And the supply of water is governed by the Arduino Uno board, XBee Module, and Relay Modules which work together with the sensor and ML model to make the whole precision irrigation system model [48-53].

2. Literature Review

This section reviews the automated precision irrigation systems to perform conservative irrigation practices and produce better agriculture yields by using different machine learning methods with intelligent technologies such as IoT and wireless neural networks:

Yan-Ping Wang [6] proposed a new method of irrigation known as root zone injection irrigation (RII) which is proved to be more efficient than the traditional surface drip irrigation (SDI) in water scare areas. In this proposed RII method, a low risk of emitter clogging that uses subsurface infiltration-promoting apparatuses (SIPA) which is drilled into the soil in the 0–0.6 m soil layer (where the apple roots are concentrated) to deliver water directly to the root zone is used and tested in an apple orchard for 3 years. The results show that the RII method restored the water content consistently higher than 60% of field capacity than the traditional SDIirrigation method. Thus, the proposed system yields better irrigation efficiency and water-use efficiency for the same volume of irrigation water compared with all other irrigation modes [54-59].

Chiyurl Yoon [7] proposed a system for the development of agricultural IoT. This smart farm system uses low power Bluetooth and low wide area networks (LPWAN) and existing farm technology of a wired communication network based on Arduino [60-67]. This proposed system implements the monitoring and control functions using MQ. Telemetry Transport (MQTT) communication method, i.e. an IoT dedicated protocol. By merging existing and new technology, the proposed system is estimated to save maintenance costs of existing devices and provide compatibility with new devices [68].

Patil K. A., Kale N. R. [8] proposed an automated data collection and forecasting agriculture system with three modules: Farm side, Server side, Client-side that uses a combined approach with wireless communication, and remote monitoring system (RMS) and internet. The system is designed to collect real-time data of the agriculture production environment utilised to give facilities such as alerts through short message service and advice on weather patterns and crop yield [69-75]. It consists of six modules: sensing local agricultural parameters, location of sensor and data collection, transmitting collected data for decision making, supporting decision making and warnings through data analysis, actuation and control based on decision and crop monitoring by the camera module. This system provides the framework for the initial machine learning approach to data collection and analysis in the agricultural field [76-81].

Rajinder Kumar Math [9] proposed a framework for precision agriculture through IoT. The system uses low-cost environmental sensors, Arduino Uno board, wireless transceivers (XBee ZB S2) and actuating circuits to enable automated irrigation [82-89]. The proposed system employs ZigBee technology built over IEEE 802.15.4 standard. This technology provides real-time data collection by sensing parameters such as humidity, moisture content, temperature for proper growth of plants and automated irrigation system [90]. The advanced IoT system enabled this system to use the resources only when required by the crops and in the precision quantity, therefore achieving reduced water content wastage [91-95].

Harmantoa [10] experimented with four different levels of drip irrigation equivalent to 25, 50,75, 100% evapotranspiration (Etc), based on Penman-Monteith (PM) method, to test the effect on crop growth, yield and water productivity [96-101]. They used two modes of irrigation such as continuous and intermittent. The plants were grown in a greenhouse, and the results were compared for the experiment. The distribution uniformity, emitter flow rate and pressure head were used to compute the performance of drip irrigation with the emitter of 2,4,6 and 8 1/h discharge. The results showed that the optimal water requirement for the tomato is around 75% of the ETc. Based on this result, the actual irrigation for the tomato planting is recommended between 4.1 to 5.6 mm per day or 0.3 to 4.1 per plant per day. These experimental results are used in the implantation chapter to estimate the water content required by the cultivation crops [102-107].

Bright Keswani [11] proposed an automated irrigation system that keeps adapting to weather conditions. It is a precision agriculture model where an independent wireless sensor network consists of soil moisture probes, soil and environmental temperature sensors, humidity sensors, and daylight intensity sensors to collect real-time farm data through multi-point measurement [108]. This acquired farm data generates necessary action for the entire farming period [109-115]. It utilises a structural similarity index (SSIM) based water valve management system to control the water value for precision irrigation. The forecasting of soil moisture content is performed on an hourly basis [116-121]. A moisture content distribution map is created [122]. The moisture content deficiency is calculated all over the farm area. For the areas of deficiency, the exact amount of water needed is irrigated by controlling the water valves, which is performed through control commands

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processed using a fuzzy logic-based weather condition modelling system that considers different weather conditions [123-129].

3. Proposed System

The proposed automated, precise irrigation system model is designed and implemented in three modules [130]. The first module is wireless sensor network data collection. In this module, the farming data is collected in a wide range of formats and scopes in a raw format. In a wireless sensor network, the raw data contains information gathered by all sensors, such as humidity, moisture, temperature, climatic condition, and soil texture. This data is then processed and cleaned to build the dataset for the prediction model [131-136]. The resulting dataset will be in a format that can be fed into the second module. The data collection, data cleaning, dataset formatting, data feeding, and the model building will be discussed in detail in the dataflow section [137].

The second module is the machine learning module. The dataset created in the first module will be used along with the botanical natures of crops and user input on the planted day to predict the root depth of farming crops [138-141]. The prediction model will be generated once the dataset is fed into machine learning algorithms, such as linear regression and random forest. The root depth of the selected crop will be estimated [142-147]. Predicting the root depth is an essential part of the proposed system because water content estimation will be carried out from the field data collection using WSN and with root depth prediction value [149-153]. Therefore, a primary model for root depth prediction is developed first. Based on the output of that primary model and the data collected from the field, a secondary model is created to predict the water content required for precision irrigation [154].

The third module is where the actual irrigation will occur using IoT devices such as Arduino and valve controlling commands processed by fuzzy logic [11]. The IoT devices read the final predicted value of water content required for that particular day and time and initiate the irrigation process by controlling water valves that utilise structural similarity (SSIM)-based water valve management mechanism [155-159]. The flowing water from neutron probes finally reaches the RII system injection nozzle drilled into the soil surface to the level where root depth is heavily concentrated and delivers water directly to the root zones of farming crops [6]. Thus, achieving precision irrigation with zero evaporation, minimum water wastage and maximised resource utilisation with the help of dynamic root depth prediction and irrigation throughout the farming timeline. In Fig.1, all three modules are presented as the complete proposed system architecture [160-167].

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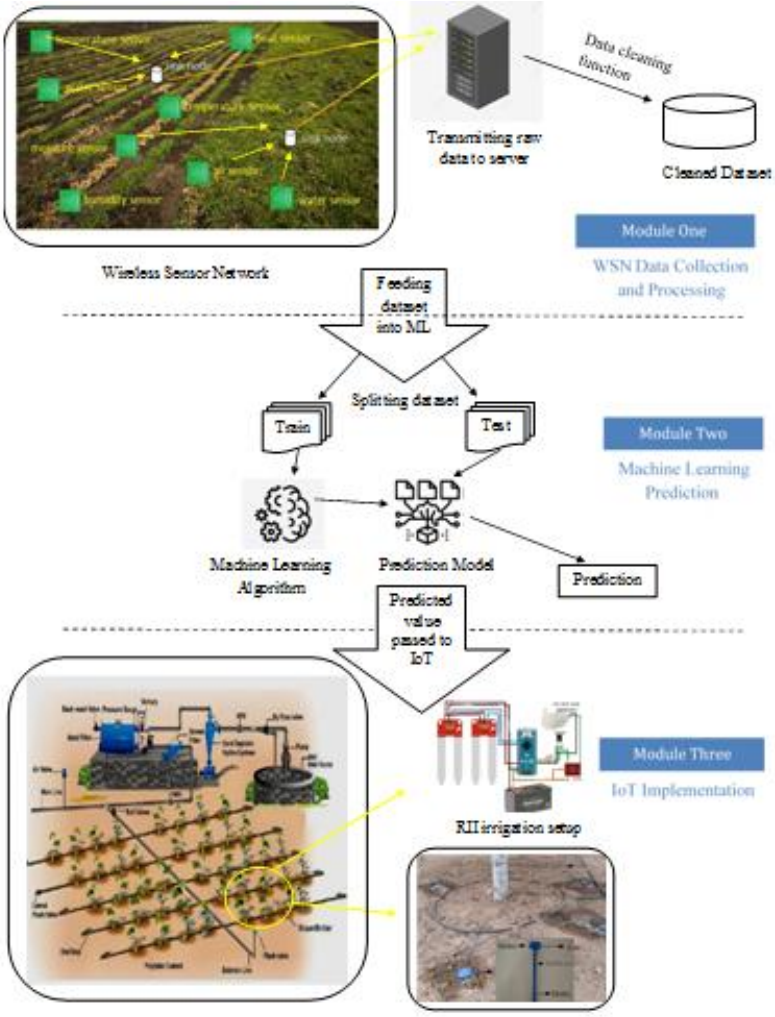

Figure 1: Proposed System Architecture

4. Implementation

The implementation of the proposed system is performed in multiple stages, which involve the three main modules described in architecture Fig.1, along with several sub-modules in each section of implementation. Thus, the overall vivid explanation of the implementation and working portion of the proposed system is presented in this section as follows,

4.1 Wireless Sensor Networks

The WSN is a group of spatially distributed sensors for monitoring and recording the physical changes of the environment and storing the recorded data at a central server. The environmental changes can be any metric value such as temperature, wind, humidity, etc [168-174]. The functionality of WSN is characterised by two different nodes, namely sensing nodes and receiving nodes. The sensing nodes are the task-specific sensors, such as moisture sensor, temperature sensor, which keeps tracking the physical changes in the given environment, whereas the later node, i.e. receiving nodes, also known as sink nodes, are responsible for receiving the data from sensing nodes and transmit the raw data to the processing area. This collection and transmission of data in a wireless sensor network can be performed in two different methods known as single-hop and multi-hop data transmission. It is described in Fig.2 [175].

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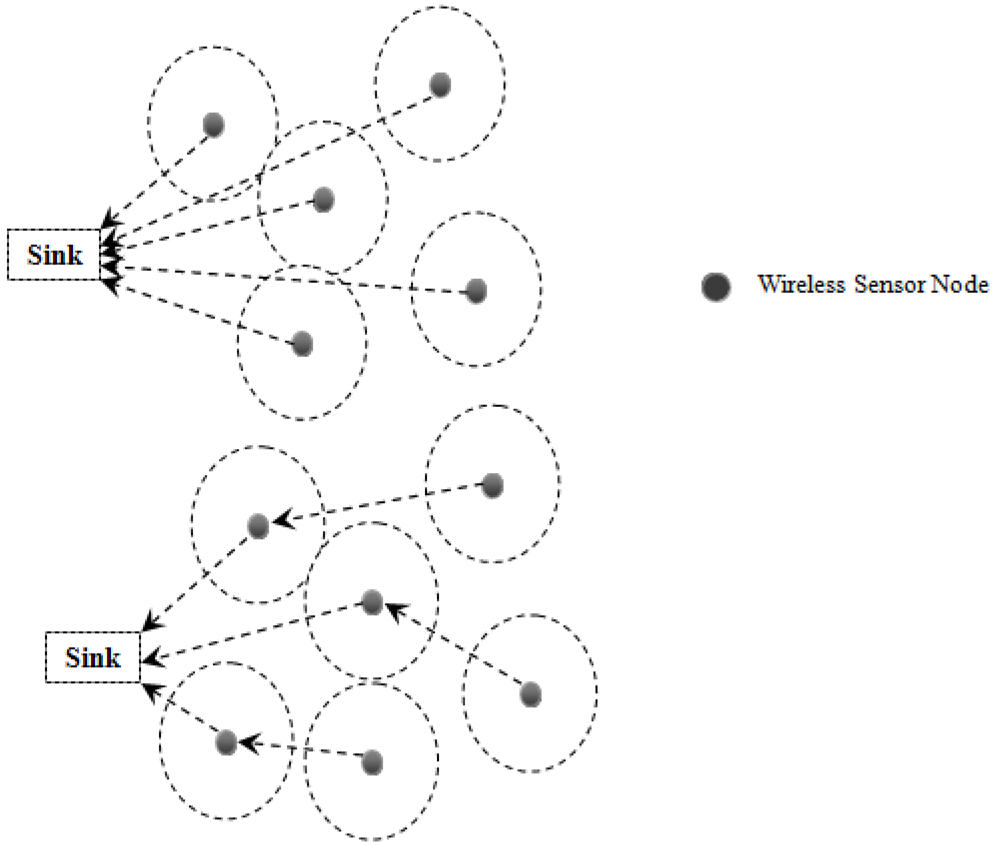

Figure 2: Single hop and Multi-hop data transmission

The dotted circles in Fig.2 represent a group of sensors called a cluster, and the black nodes in the cluster are the cluster head (CH) [176-181]. The collected data is transmitted from cluster head to sink in single-hop data transmission without any intermediate transmission. In contrast, in the case of multi-hop transmission, a CH can transmit the collected data to sink through multiple intermediate transmissions to other cluster heads before reaching the destination, i.e. sink node [182-189]. This process of multi-hop transmission is much useful in the case of large transmission distances. Both single and multi-hop transmission is used in this system according to the ground that needs to be covered [190]. To farmland with a relatively smaller area to cover, single-hop is an efficient protocol to transmit the data since the transmission distance is short and the network model is much simpler to execute [191-193].But, in the case of a huge area to cover, multi-hop transmission is an excellent choice because the network is characterised by its sensor's limited wireless channel bandwidth. Therefore, single-hop will cause a huge energy consumption for transmission, whereas multi-hop by multiple intermediate transmissions will significantly conserve energy resources through complicated interconnected data transmission networks. Depending on the transmission type, the communication between the nodes can be classified into two types direct and cooperative communication. As the name implies, each sensor node has to send its data directly to the sink or the cluster head in direct communication. In the case of long distances, this protocol will shortly drain the CH battery and lifetime. Thus, direct communication becomes a good choice only in nearer situations or with larger battery capacity. But due to its long-distance characteristics, data packets (collected data) loss may occur. Therefore, a better alternative for long-distance transmissions is done with cooperative communication, where the data packets loss is resolved. Cooperative communication is, also known as Energy-Efficient Cooperative Communication

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Scheme (EECC), considers a multi-hop data transmission scenario where the next intermediate transmission node is determined by the "Cooperation Rule" [12]. The packet reception rate (PRR) over the transmission distance of "d" is determined by,

$$p(d) = \{1 - e^{\frac{-(\frac{\gamma(\mathrm{d})B_N}{2R})}{2}}\}^{8\rho f} \qquad (1)$$

Where p = packet reception rate, d = transmitter-receiver distance, γ = signal noise ratio, B_N = noise bandwidth, R = data rate in bits, ρ = encoding ratio, f = frame length in byte.

Based on the packet reception rate for a particular node as mentioned in eq (1), the neighborhood set G(u) of that particular node can be given as,

$$G(u) = \{v \in V | v \neq u \wedge (u, v) \in E\} \qquad (2)$$

Where $G(u)$= neighbourhood set of a node u, V = set of sensor nodes, v = sensor node belongs to V, E = set of wireless communication links.

The eq (2) states that the next neighbourhood node to which the intermediate transmission of data has to be performed should provide a balance between hop count and link quality. The next node should be in the range of the first node and must cover many nodes within its perimeter, and should be in the intended path to the destination when compared to other nodes. Therefore, by following these cooperation rules, the loss of data packets will be resolved by successive intermediate transmission in the intended path, rather than one long-distance transmission that overloads the receiving sink node and consumes more energy in the transmitting node. Hence, cooperative communication of wireless sensor networks achieves better energy efficiency and data loss-free transmission over other modes of transmission.

4.2 Machine Learning Algorithms

Machine learning is a technique that uses past existing data to make future predictions. ML techniques mainly solve prediction problems such as classification and clustering through supervised, unsupervised, and semi-supervised approaches. In this proposed system, prediction of water content needs to be performed for which the value of root depth is required. Thus, we developed a prediction model for determining the root depth-first. The second prediction model will use the predicted value of the first model to estimate the required water content. The root depth is a continuous value. Therefore a machine learning algorithm such as regression models that could solve continuous value problems has to be deployed. Here, the Linear Regression model has been used as this model is best suited for predicting a single dependent variable (root depth) over multiple independent variables (period, crop characteristics, climate conditions). Linear Regression assumes that there is an approximately linear relationship between the independent variables and dependent variables. This linear relation is described as follows,

$$y \approx a_0 + a_1 x \qquad (3)$$

Where a_0 and a_1 are unknown constants representing the slope and intercept of that slope in the linear model, also known as model coefficients, x is an independent variable, and y is a dependent variable that depends on x in approximately a linear format. Here x represents days, and y represents root depth. Then it is said that root depth is regressing onto days. It is given as below,

$$\text{Root depth} \approx a_0 + a_1 * days \qquad (4)$$

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Once the model is trained by using the coefficients a_0 and a_1 to produce the values $\hat{a}_0$ and $\hat{a}_1$ we can predict future root depth values based on a particular value of days passed to the prediction model. This can be computed as,

$$\hat{y} \approx \hat{a}_0 + \hat{a}_1 x \tag{5}$$

Where$\hat{y}$Denotes y (root depth) prediction based on x (days). This describes how the dependent variable linearly depends on the independent variables. The unknown future value can be estimated, i.e. predicted by training the model with past data.

The following section evaluates the proposed framework using a linear regression algorithm in a jupyter notebook environment, as shown in Fig.3. Initially, the required packages such as Pandas, Num Py, Matplotlib, and seaborn are imported. The Pandas library is used for data manipulation, cleaning, and importing and analysing numerical data much more easily. It also offers various files operations while working with CSV files. The numpy library is the primary package for scientific computing in Python, which provides multidimensional array object manipulations. Matplotlib library provides a huge range of data visualisation techniques, i.e. an object-oriented API for employing plots such as graphs using general-purpose GUI toolkits. Seaborn is an extension of matplotlib, which provides extended plotting techniques that operates on dataframes and arrays with whole datasets. Thematplotlib library is made inline to visualise the corresponding outputs within the execution environment.

```
In [1]: import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        import seaborn as sns
        %matplotlib inline

In [2]: plantDepth = pd.read_csv('Tomato_Plant_Root_Depth.csv')

In [3]: plantDepth.head()
Out[3]:
```

	Planted day	Root depth in cm	water required in Lit
0	1	1.512	0.212588
1	2	3.024	0.235588
2	3	4.536	0.246587
3	4	6.048	0.256588
4	5	7.560	0.257659

```
In [4]: plantDepth.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 80 entries, 0 to 79
Data columns (total 3 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   Planted day            80 non-null     int64
 1   Root depth in cm       80 non-null     float64
 2   water required in Lit  80 non-null     float64
dtypes: float64(2), int64(1)
memory usage: 2.0 KB
```

Figure 3: Algorithm Description

The data collected in module one is processed and cleaned with cleaning methods. A compatible dataset is formed, known as Tomato plant root depth in CSV format (here, we only focused on tomato planting for implantation purposes). Th header of this dataset is visualised in the above segment, where it displays the planted day count, the root depth in cm and required water content in litters. The Planted day column is an integer datatype of 64 bits, representing the number of days from planting the crop in the farm field. The root depth column describes the root length that has grown over the days mentioned in the first column. It is of 64 bits float data type, and the last column represents the water content required for one crop with the specified root depth on that particular day, and it is represented by the float data type of 64 bits.The describe () python method is used for calculating statistical data such as the number of rows, mean value of each column, standard deviation, minimum and maximum value available and percentile distribution of values of the numerical values of the DataFrame as shown in Fig.4. It helps us analyse numerically and object series and the Data Frame column sets of mixed data types. Therefore, the describe function will enable us to understand

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the entire dataset at a glance. After we get the overview of the entire dataset and the value distribution among those data, the prediction model can be developed with a linear regression algorithm.

```
In [5]: plantDepth.describe()
Out[5]:
```

	Planted day	Root depth in cm	water required in Lit
count	80.0000	80.000000	80.000000
mean	40.5000	61.236000	1.922599
std	23.2379	35.135705	1.089463
min	1.0000	1.512000	0.212588
25%	20.7500	31.374000	0.981838
50%	40.5000	61.236000	1.916359
75%	60.2500	91.098000	2.850879
max	80.0000	120.960000	3.785400

```
In [6]: plantDepth.columns
Out[6]: Index(['Planted day', 'Root depth in cm', 'water required in Lit'], dtype='object')
```

Figure 4: Dataset Range Description

The prediction model is developed through steps using the machine learning technique, as shown in Fig.5. First, the independent (x) and dependent (y) variables are assigned to an array that will hold the column value of those variables. Once the variables are determined, the splitting of the dataset will happen. Splitting the dataset is a tedious process to perform manually, but the library called scikit-learn has many built-in functions that facilitate this process.

```
In [10]: X = plantDepth[['Planted day','Root depth in cm']]
         y = plantDepth['water required in Lit']

In [11]: from sklearn.model_selection import train_test_split

In [12]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.4, random_state=101)

In [13]: from sklearn.linear_model import LinearRegression

In [14]: lm = LinearRegression()

In [15]: lm.fit(X_train,y_train)
Out[15]: LinearRegression()

In [16]: # print the intercept
         print(lm.intercept_)
         0.016975966560510 26

In [17]: coeff_df = pd.DataFrame(lm.coef_,X.columns,columns=['Coefficient'])
         coeff_df
Out[17]:
```

	Coefficient
Planted day	0.014306
Root depth in cm	0.021631

```
In [18]: predictions = lm.predict(X_test)
```

Figure 5: Fitting data and training the prediction model

One of which built-in functions is train_test_split(). This pre-existing function will split the dataset into two sections, i.e. train and test datasets. The split occurs at the specified size, which is commonly in a proportion of 70% -30% or 60% -40% train-test ratio. This ratio is passed as the parameter of test_size.The train test split is stored in four variables such as x_train, x_test, y_train, y_test. They store the split datasets as training and testing data. Once the splitting operation is performed, the scikit learn library enables us to import required ML algorithms. The Linear Regression algorithm is imported using LinearRegression() in sklearn. This function gets stored in lm variable, and then fiiting function fit() is called through lm.fit(). Fittiting function will get the known value as input for the function, i.e. the training split dataset and trains the prediction model internally. Once training is completed, the coefficient of the trained model is calculated. It is performed using DataFrame() function in pandas library. Coefficient is calculated for individual columns that indicate how well the model was fitted by estimating the squared mean error rate of fitting data. In Fig.5, the coefficient

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value for planted day column is 0.014, which is a 1.4% error rate, and for the root depth column, it is 0.021, i.e. 2.1% error rate. Therefore, it indicates that the model has fitted well with the training dataset and is ready to predict unknown values with the least error with maximum accuracy.

Finally, the prediction model is called by the function predict(), a built-in function in the LinearRegression() module for testing the test dataset. It is passed with a parameter X_test (the known value of an independent variable) and expected to determine the unknown value required for water content. In the last plotting, a scatter plot technique is used to observe the relationship between the variables and dots are used to represent the relationship between those variables. To perform the scatter plot technique, the function called scatter() in the matplotlib library is used to draw a scattered dots diagram along a linear line. The farther the dots are plotted, the more mismatched relationships between the variables are shared. And the closer the dots get plotted along the linear line, the best correlations the variables are considered to have and thus, it proves the model is built correctly. Scatter plots are widely used for representing the relationship among multiple variables and how the change in one variable affects the other. These effects and relationships are well studied by observing the distribution of plots as mentioned above to determine the prediction model's correctness.

```
In [19]: plt.scatter(y_test,predictions)
Out[19]: <matplotlib.collections.PathCollection at 0x223997b7d00>
```

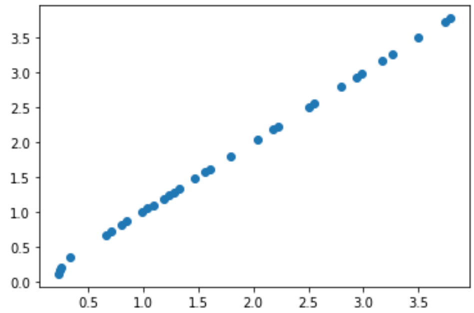

Figure 6:A prediction model

The final prediction is performed for the new incoming dataset in Fig.6, and the output visualisation is made using the scatter plot technique mentioned above. In the final results, the scatter plot seems to be very thin, with all its dots were plotted along the linear line and are inline with each other. This states no significant deviation in the predicted values compared to the trained dataset values. Therefore, the predicted values correspond with the prediction model's values when it gets trained with the training dataset. Thus, the model predicts the new incoming values in the excepted manner. Furthermore, its efficiency will be discussed in the result section.

4.2.1 Water Need Estimation

The water content prediction in the above section is only a single plant sapling that grows over time. Therefore, the water need estimation of the entire farmland with "n" number of saplings has to be calculated. This calculation is only for the crops, which supports the previous drip irrigation method since the root zone injection is only an advanced method of the traditional SDI method. For the plants that require constant flowing water, such as paddy and sugarcane, the water need estimation method will vary depending on the crop we choose. As said above, we are considering the tomato plant for this implementation process since it is an essential crop in Indian agriculture and its preservation period is very short compared to other types of crops.It has been measured that a fully-grown tomato plant requires an area width of around 21 inches. i.e. 1.75 foot. Thus, each sapling requires an area of 3.0625 square feet. This brings us to the next estimation of

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land area calculated in acres. An acre of farming land is estimated at 43560 square feet. Therefore, an acre of farming land will enable the farmers to plant 14,233 tomato plants for each season, lasting for 3 months. The number of saplings that can be planted in an acre of farming land is calculated using the simple division arithmetic in eq (6) as follows,

$$\frac{1\ acre}{area\ \ required\ \ for\ 1\ sapling} = \frac{43560\ sq.foot}{3.0625\ sq.foot} = 14233\ saplings\ per\ acre \qquad (6)$$

Therefore, from eq (6), the number of plants to be planted is estimated. At the point of its fully matured state, each of these plants will require 1 gallon of water at the sun's peak. i.e. at the worst condition. A gallon of water equals 3.7854 litres. This is the amount of water required for one fully-grown plant in well-drained soil with the sun at its peak. And at an average time, the water content required is1.2 inches, that is 2.36 litres of water per day per sapling. Thus, an acre worth of tomato plants, 14,223, will require a water content of 53,839.912 litres, rounded off to 53,840 litres of water each day at the end of harvesting (fully-matured) at the worst climate condition. It amounts to 980 barrels with 55 gallons (208.2 litres) each. This amount may seem big, but at the mass production scale of farming products (here, tomato), it is much lesser than the actual water content used in traditional irrigation methods. At an overall estimation, a maximum of 40 – 60% lesser water resource is required compared to traditional methods due to its increased evaporation prevention. This estimated value will not be the same for the entire course of farming which is one of the reasons for using ML. Still, it illustrates the water need estimation for a given acre of agricultural land during a particular time near harvesting.

4.2.2 Water Estimation and Display Using Streamlit API

The Stream light API is a python library that enables us to create web applications for machine learning and data science and to write the app the same way as writing python code, with all web technologies such as HTML, CSS, and JavaScript being executed internally. Here, the backend used for real-time water estimation is performed through this Streamlit powered web application to display the results' purposes. The integration of machine learning algorithm in Streamlit API based web application is performed. It is the same as discussed in the machine learning implementation section, but here it is executed in Stream light to display the results in the web application for the user. The page is named notebook.py as it holds the jupyter notebook python code, and implementation starts with importing all necessary libraries such as NumPy, pandas, matplotlib, seaborn, sklearn and other metrics and functions. One key significance is, here, the algorithm is written within a function called function_pred(). This function will be triggered by a function call from the web application. Thus it passes user input into the function_pred() function, and the expected prediction output will be returned to the function call area, i.e. to the web page where the user can see it. Here the predict() function computes the output and stores the value in a variable called predictions. This value is returned using the return statement as 'return predictions' in the last line of the function_pred() method. The Stream light based web page is created, and the names predict_page.py. It is intended to display the resulting output of the ML prediction model through function call and overall water estimation for the required amount of farming area. The implementation starts with importing all necessary streamlet libraries such as no_type_check, streamlet, pickle, time, datatime, NumPy and finally, the notebook.py page is imported here to access the function_pred(). Once all necessary libraries are imported, the entire coding snippet is written inside a function called show_pred_page(). Another streamlet page will later call this function for effective code management.

The show_pred_page() function body holds all the coding portion, that inturn makes use of Stream light components such as St.text_input, St.date_input, St.number_input, etc. These components provide user interaction features such as text box, numeric input, and data selector, through which the user can input

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necessary details required for the computation process. Initially, the web page starts with the title of water content prediction for best irrigation practice and instructs the users to enter the following details to calculate water requirements. After that, a drop-down box lets the user pick a crop they have planted for farming, such as tomato, potato, brinjal, or corn. And then, a date picker requests the user to select the date on which the plantation of crops takes place. The next computation uses this selected date input and the current date, which will be automatically selected, and subtract the two dates to determine the number of days in between the current date and plantation date. Then, the users are requested to enter the number of acres utilised for farming. Once all of these inputs are retrieved from farmers, the computation of root depth takes place. The root depth is linearly incrementing from the machine learning prediction model. Therefore, a coefficient value of how much, on average, the root depth grows every single day is calculated to be a constant value. It is 1.5112centimeter per day, thus distributed for three seasons, i.e. 80 days gives the maximum length of 120 centimetres. Therefore, the computed value of the number of days passed is multiplied by the coefficient constant of linear growth rate and root depth denoted by ‘b’ for that current date is calculated.

At the final stage of computation, the total water requirement is estimated. For this, a linear relationship between root depth and water requirement is determined in ML implementation, and the water need estimation section, which is found to be for the minimum value of root depth of 1.512 centimetres, the approximate water required for tomato planting is 0.212588 litres or 212 millilitres per day per plant. And the linear computation of root depth vs water requirement is used for incrementing the value of water need based on incrementing the value of root depth. Therefore, the ‘b’ value of the previous calculation (for one plant) is multiplied by 14223, i.e. the total number of plants that could be planted in an acre (calculation from section 4.2.1). That gives the water requirement for one acre. And then, the last input of the number of acres is multiplied by this intermediate value to give the final value of water required for the total number of farming acres denoted by ‘T’ in the function show_predict_page().When the user enters the button calculate water, and the boolean turns true, a function call will be triggered from a Streamlight page known as app.py for the show_predict_page() function and the estimated water requirement displayed in litters in the web page through that function call. The resultant output is shown in the results and discussion section. This web application displays the water need estimation part of the proposed system, and the actual implementation does not include an API display. In contrast, all of this computation and implementation will occur within IoT devices and decisions on the irrigation process are performed in the IoT automation circuit itself.

4.3 Root Zone Injection Setup

Over usage of water resources for each plant more than required will lead to the decay of plants due to overstressing; just like overstressing, decreased use of water resources less than required will cause a problem of plants getting dried and dead. These overstressing and under-usage of water resources can be eliminated by using the injection method of water conduction, which is directed to deliver at the root of every plant, as illustrated in Fig.7, after performing the water estimation process which is described in ML implementation section.

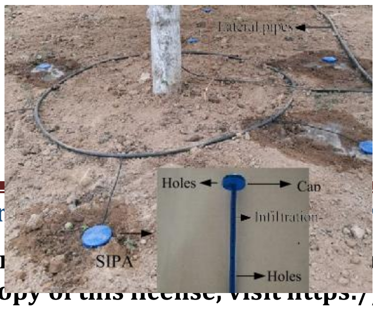

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Figure 7: Injection of water resources directly to root zones illustrating the RII method.

It describes how the pipes are interconnected to deliver irrigating water resources straight to the roots of the plants. This mechanism can be controlled using an automated irrigation system setup that functions through a microcontroller to determine the period of water supply and the time interval gap to shut down the system before the next irrigation process begins. The entire system can be built to deliver the water resources as per farming requirements and based on changing climatic conditions. A regular 2 times week of irrigation in autumn seasons, 3 times a month during rainy seasons and each time a day during high-temperature sunny seasons to avoid the death of plants from overheating, overcooling and overstressing problems that arise each of the different climatic conditions. Based on all of these requirements from user, climate and environment conditions, the appropriate time interval of irrigation through the root zone injection method is designed and implemented using the IoT hardware systems in real-time agriculture fields. This IoT hardware system is discussed in detail in the next section of IoT implementation.

4.4 IoT Implementation

The final module of the proposed system is the IoT implementation of automated precision irrigation that leverages the outputs obtained from machine learning algorithms. In this module, the automated irrigation is performed using IoT devices such as Arduino Uno board, water pump, relay, and fuzzy logic commands to control water pump valves. Arduino is an open-source microcontroller with 14 I/O pins and an in-circuit serial programming header (ICSP). This microcontroller enables us to perform particular tasks (controlling water pump valves) based on the programming encoded within. The Arduino Uno board is described in Fig.8.1.

Figure 8.1: Arduino Uno Board

Figure 8.2: Relay Module

Once the Arduino issues the command to initiate the irrigation process and the estimated water content, it activates the relay module shown in Fig.8.2. This will regulate water valves on and off conditions to perform automated irrigation. The advanced relay module can run on AC and DC and has better performance than traditional transistor driver circuits. Thus, it ensures an uninterrupted and efficient control mechanism for automated water delivery. The water-conducting pump is then installed with the relay module that controls the pump's active time. The water pump shown in Fig.8.3 will deliver water to RII injection nozzles attached to the neutron probes drilled into the soil layer. Thus, when the water finally reaches the probes' holes, water gets delivered directly to the underground root zones where roots are heavily concentrated.

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Figure 8.3: Water Pump

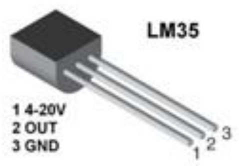

Figure 8.4: Temperature Sensor

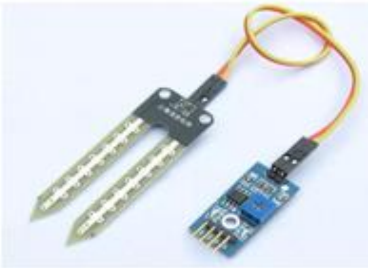

Figure 8.5: Moisture Sensor

The temperature and moisture sensors illustrated in Fig.8.4 and Fig.8.5 are used in the first module, where the field data were collected. But they could also be used in the last module of the proposed system for performing adaptive irrigation based on weather conditions such as rainfall and sunny time zones [11]. After assembling all IoT devices and hardware components mentioned above, the final IoT setup will be ready for deployment that needs to be programmed with fuzzy logic control commands for automated water valve control in precision irrigation. The completed IoT setup is illustrated in Fig.9.

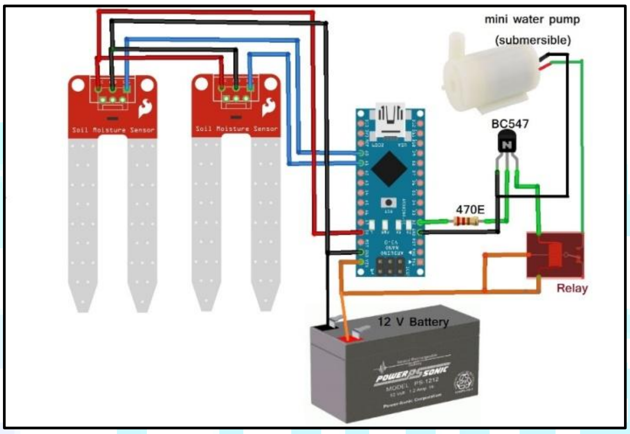

Figure 9: IoT Setup for Automated Irrigation driven by the fuzzy logic control command

The complete IoT model for automated precision irrigation in Fig.9 describes the intricate connections among the IoT components. The sensors were connected to an Arduino board to transmit farming environmental data. The sensors, relay module, battery, LED. Since Uno is the microprocessor, the indicator and water pump were all connected with Arduino for control operations. A power supply in real-time implementation will replace the battery in the setup, and the water pump capacity will also be scaled to meet the requirements. The LED. indicator will tell us whether the pump is turned on or off. The activation commands will be passed by fuzzy logic with absolute precision as the practice evolves for farming time since it is subjective and heuristic. Therefore, this comprises the entire implementation process from module one of wireless sensor networks to module three of IoT implementation of precision farming and achieves the entire proposed system.

5. Results and Discussion

In this section, the results obtained by implementing the proposed system are evaluated and discussed in detail to extract the superior advantages of the proposed system, which is the RII method based on root depth prediction over the existing systems of the traditional SDI method other automation driven approaches of irrigation. The results are evaluated through data analytics tools available in the jupyter notebook, and coefficient metrics such as error ratios, MAE, MSE, and RMSE, which are available in the sci-kit learn

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library, are used to estimate the efficiency and accuracy of the proposed system. Thus, the machine learning approach of data analytics is used to evaluate the overall system.

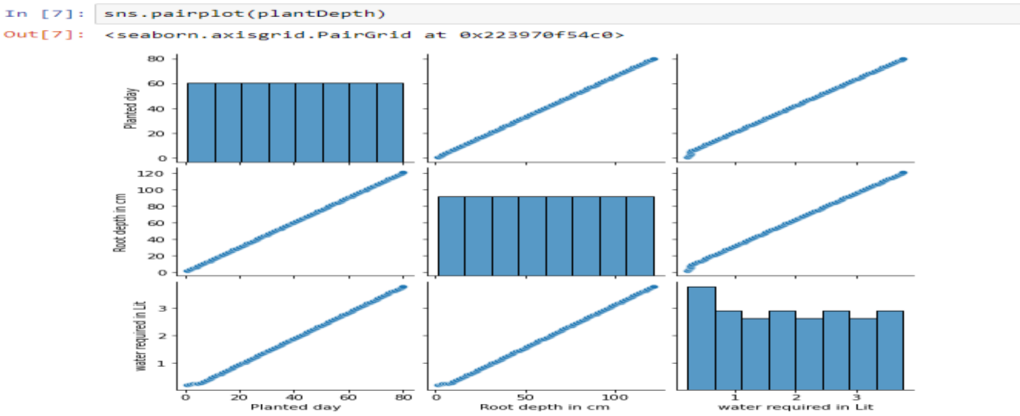

Figure 10: Pair-plot comparisons

The pair plot of each column value vs every other column value is represented using the sea born library, as illustrated in Fig.10. It is seen that the value of root depth increases linearly as compared to the number of planted days increases. And the same pattern of linear increment occurs even for the plotting between water content required vs root depth. Thus, it is clearly shown that the depth of the root increases as the number of days increases, and the water content required also increases as the root depth increases. Thus, the plotting between planted day and water required tends to be linearly incrementing by the association rule. The plotting of the same columns, such as planted days vs planted days, root depth vs root depth, shows a constant slop as the two columns' recorded values were identical. Yet, the similar column of water required vs water required shows a fluctuating value as the amount of water needed will fluctuate daily or weekly, depending upon many factors such as sunlight intensity, rainfall, and retained moisture content.

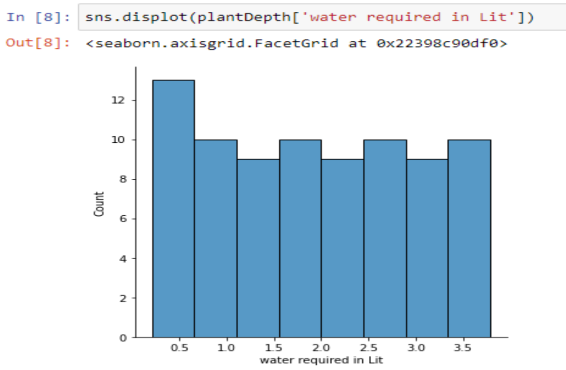

Figure 11: Displot representation of water requirements

The Water requirement in litters is plotted against the range of days to which the estimated quantity lasts described with the displot in Fig.11. Displot or distribution plot helps us illustrate the variation in data distribution. Here, the water required is taken as the x-axis, and the days' count is taken as the y-axis. The graph shows that 0.5 lit of water is required for the first 13 days of the plantation as the plant was budding. And then a litre of water is required for the next 10 days range, i.e. 14-24 days of plantation period. This sequence of water required for a specific time range is illustrated in Fig.11 for the entire period of farming, that is, 80 days (nearly 3 months of the season). This 3-month farming season comprises three different phases based on the plant maturity stage initial and crop development, midseason, and late season. The water

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requirement needed will change according to these maturity seasons, based on their botanical characteristics. Thus, a varying water estimation that keeps fluctuating by weather conditions is obtained as the output from the displot representation. Furthermore, the accuracy of a more detailed illustration of this representation can be viewed by *increasing the number of histogram bins* to specify more separated values. For an even better description, the heat-map technique will help us visualise the intensity of values distributed across all three columns. It ranges from minimum to maximum gradian values depicted using a colour-changing heat-map scale. In Fig.12, this min-max gradian ranges from 0.9 to 1.0 with all minor deviations in-between, representing the value distribution by density.

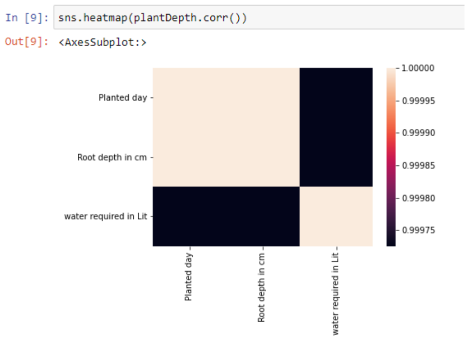

Figure 12: Heat-map illustration

As seen in the pair plot comparison, a similar pattern of constant value exists between similar columns here as well with the maximum gradian of 1 since it is a constant value, and fluctuating linearly incremental values occurring between different columns were distributed in the range of 0.975 to 0.980 in the heat-map scale. This enables us to understand where the data collected from the farm is heavily concentrated and at places where it is partially dispersed. Thus, appropriate water estimation and the areas where the water needs to be rinsed are determined based on the heat-map distribution of data and output values.

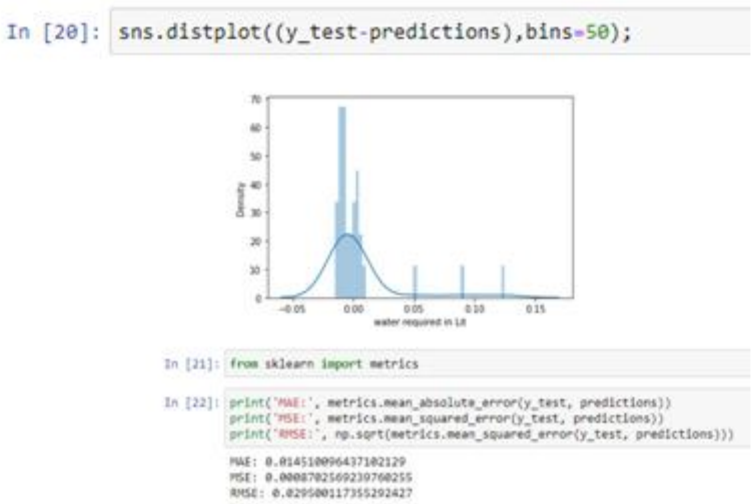

Figure 13: Metrics Evaluation for model accuracy

The final evaluation of the accuracy of the prediction model is performed in Fig.13. Here, the error percentage of the model is calculated using metrics available in scikit learn. The metrics are the tools in the scilit learn library to determine the accuracy of models using different methods, such as mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE) and so on. These metrics take the inputs

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such as several data points, observed values, predicted values, and true values and perform mean calculations to estimate the maximum deviation of predicted values from original values, thus calculating the error percentile of prediction model accuracy. The following eq (7), (8), (9) describes the MAE, MSE, and RMSE metrics formulae.

$$MAE = \frac{\sum_{i=1}^{n} |(y_i - x_i)}{n} \tag{7}$$

Where MAE = mean absolute error, n = number of data points, y_i= prediction value, and x_i= true value in the corresponding input dataset.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \tag{8}$$

Where MSE = mean squared error, n = number of data points, Y_i= observed values, $\hat{Y}_i$= predicted values in the corresponding input dataset.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \hat{x}_i)^2}{N}} \tag{9}$$

Where RMSE = root mean squared error, N = number of non-missing data points, i = variable i, x_i=actual observed values, $\hat{x}_i$= estimated values.The RMSE can also be said as the squared root value of MSE; thus, an advanced method of calculating precision magnifies small errors that go unnoticed in other methods by squaring them and then taking the root value of the squared values. These metrics, as mentioned earlier, are imported in Fig.13 by the scikit learn library and performed error rate estimation. And the results show that the prediction model's error percentile tends to be 2% in RMSE metrics and 1% in MAE metrics. This seems to be an extremely accurate prediction model in this case of the experiment. Still, these results will vary hugely when implemented in real-time agricultural practice. The error rate will also increase due to a wide range of volatile data recorded from real-time farming. As the model is justified to be accurate in terms of error rate, the web application developed in the Streamlight API section can be used to display the results to the users. Fig.14.1 and Fig.14.2 show the "Water Content Prediction for Best Irrigation Practice" web page. This web page provides the UI interface for recording three inputs from the user-end and a submit button called "Calculate Water".

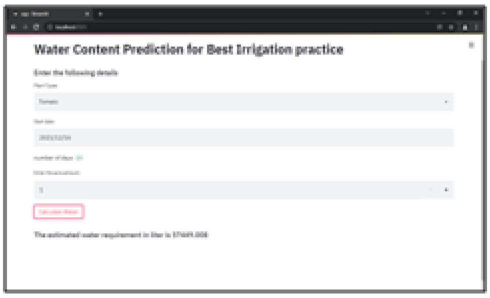

Figure 14.1: Result displayed through a web

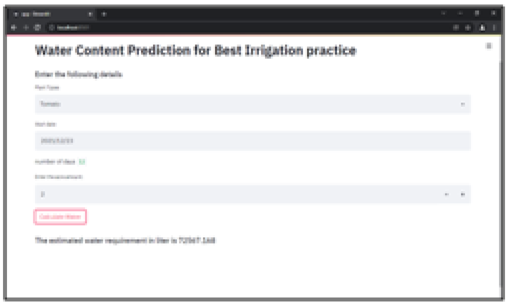

Figure 14.2: Result displayed through a web application for 2 acres

The users are required to enter three inputs such as the plant type which was planted for farming, such as tomato, sugarcane, corn, brinjal, etc., the day on which the plantation was done, i.e. the first day of agriculture (this will act as the initial point of growth phase from which necessary period calculations will be performed), the number of acres for which the user cultivated the specified plant species. From the 1st input, a specific model created for that crop type will be imported into the ML algorithm. Each crop type has a different root system, such as tap root, fibrous root, maturity phases like s-growth types, linear growth types, different water

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requirement cycles, and completely different botanical characteristics for plant metabolism and nutritional intakes. Therefore, a plant-specific prediction model will be imported to determine the root depth and water requirements for the specified plant type. The 2nd input, i.e. the day on which the plantation had been done, will let the system calculate the time range (in terms of the number of days)between the point of planting to till-date by automatically picking the current date and subtracting the difference. It is also used for all forms of period analysis and calculations in the prediction model by considering the date of the plantation as the initial stage of maturity. And finally, the 3rd input, an integer type denoting the number of acres utilised for cultivation, will be used for determining the “n” number of plants that could be planted and the total quantity of water needed for that area of farmland.Fig.14.1 and Fig.14.2 show that two different planted dates have been chosen, and the time interval is estimated to be 19 days and 12 days for matured plants. As it is already discussed in the Stream light API section of implementation, this value, along with the last input, will be fed into water need estimation logic, which will predict the water required for irrigation for the given number of aces on that particular day for the specified plant species, i.e. in this caseas tomato crop. Thus, the final results are displayed in Fig.14.1 and Fig.14.2, as 57449.008 litters and 72567.168 litters for the cultivation land with 19 days maturity crop of one acre and 12 days maturity crop of 2 acres, respectively. These results will vary when weather conditions are considered during the real-time implementation of agricultural land.

6. Conclusion and Future Work

Agriculture needs significant attention from multiple areas to better utilise its limited resources that are getting scarce every year. Water conservation practice and precision irrigation are the need of the hour, especially in drought areas. Thus, in this work, we first developed a module for data collection and energy-efficient transmission via wireless sensor networks and then the transmitted data is cleaned, processed and fed into machine learning algorithms for predicting the root depth of cultivated crops and based on the predicted root depth and processed weather data, an automated precision irrigation practice is performed with the help of IoT based automated irrigation setup. And the overall irrigation is concluded by performing the root zone injection mode of water delivery, which directly delivers the required water content to root zones underground. Thus, reducing extra usage of water and preventing evaporation wastage. As described in the Results section, the efficiency is much greater than all the traditional methods and recently automated irrigation methods in farming. But, the accuracy and efficiency might be reduced when implementing the proposed system in real-time agricultural practice for a huge area with very high volatile collected data. Thus, multiple ML algorithms and more botanical characteristics of planted crops such as bark width, nutritional requirements for plant metabolism, location and soil-based trait modifications have to be added shortly. And supporting multiple crop types individually with specific approaches, incorporating secured implementation to avoid intrusions, and scalability of the system will all be considered and performed in future enhancement work.

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