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Internet of Things and Machine Learning Based Smart and Intelligent Irrigation System

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ABSTRACT

Water is wasted significantly in traditional irrigation systems. Not only is an intelligent irrigation system required to optimize water use, but it is also required to increase crop yield. The Internet of Things (IoT) and Machine Learning (ML) have enabled the development of intelligent systems capable of achieving these goals with minimal human intervention. This paper proposes an IoT-enabled and ML-trained irrigation system to optimize water usage while requiring minimal user intervention. IoT devices are used to collect soil and environmental data. In real time, this data is sent to and stored on a cloud server. From historical field data collected at the agricultural research site over a ten-year period, ML algorithms are used to generate a model. This model uses IoT sensor data to make real-time recommendations about the state of an agricultural field, such as the need for watering. Both simulation and prototype implementations are used to compare the performance of the proposed system to similar previous works. In addition to the features made available to users via a cloud platform called Thing Speak, the proposed system made better use of resources such as water. Our system reduced Garlic's Crop Water Requirement (CWR) by 6.45% and 6.72%, respectively, during the Initial and Development stages. The system can also predict the type of crop that should be planted in the current year based on the data collected. Longer-term agricultural field data would provide more insight into the area if it was analyzed with more performance evaluation parameters.

Keywords: Agricultural Automation, Internet of Things Based Systems, Machine Learning Techniques, Prototype Implementation, Simulation Modeling, Smart and Intelligent Irrigation Systems.

INTRODUCTION

Agriculture, without a doubt, has the potential to contribute to industrialization by providing raw materials for industries, bringing foreign exchange for the country, securing food on the plate for families. That is particularly true for developing countries like Ethiopia where agriculture is the livelihood of the majority (Vanderheiden, 2015). Ethiopia's economy is mostly centered on subsistence agriculture, which contributes for 50% of the country's GDP and employs approximately 85% of the workforce. According to World Bank (Farooq et al., 2019), in 2018 Ethiopia has around 16.187 million hectare of arable land with a wide range of weather possibilities. By 2050, the world's population is predicted to reach about 10 billion. That is 3.4 billion extra mouths to feed. Besides, global food demand is expected to rise as high as by 98%. This necessitates that agriculture must improve production and yields of products (Gebre-Selassie & Bekele, 2012). This demands the use of technological solutions to optimize agricultural resource usage. At places where agricultural production merely depends on seasonal rainfall, like Ethiopia, it has become increasingly erratic and unreliable due to global climate change and man-made causes (Awulachew et al., 2011; Welteji, 2018). Rapid developments in crop production technologies are required to keep up with the steady rise in food consumption. In

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developing countries, food insecurity is a big issue. In Ethiopia, where the economy is mostly built on agriculture, the use of technology to increase yields is a major requirement (FAO, 2021).

Irrigation systems have been under pressure to produce more with lower supplies of water. Various innovative practices can bring economic advantages while reducing environmental burdens such as water abstraction, energy use, pollutants, among others by using technology (Risheh, 2020; Morin & Orsini, 2020).

Therefore, in this work recent advancements in Internet of Things (IoTs) and Machine Learning (M)L algorithms are used to use historical and real-time weather data to predict the need of water and fertilizers and control the same remotely.

Here, relevant works since 2017 are collected on notable research databases, see Table 1, using keywords like "smart irrigation", "intelligent irrigation", "IoT based irrigation system", "ML based irrigation system", and "smart and intelligent irrigation system".

As shown in Table 2, the main research gaps identified include, but are not limited to: While some works attempted to use ML techniques and sensors, they only focused on data collection and prediction. There is no classification or decision-making. Furthermore, none of them used a remotely accessible platform to make decisions like watering. It is also uncommon to come across a simulation study of a smart and intelligent agriculture system that is supported by a prototype implementation.

The majority of irrigation systems in Ethiopia are operated manually (Zerssa, 2021). The following are the most serious agricultural problems during crop production both locally and globally based on (Kassa, 2020): Nutrient imbalance, Water-logging, Acidification, Contamination, Erosion, Salinization; Water wastage related to drainage, outflow, inflow and evaporation; Crop yields are reduced due to non-uniform availability of moisture; The amount of labor used in manual irrigation system is higher.

These points demonstrate the importance of monitoring the levels of nutrients, water, moisture, labor, and contextual knowledge in the administration of a successful agricultural system. However, now is the time for technology to take over such activities by automating with fewer resources to extract knowledge and aid in better decision making. As a result, the primary goal of this research is to use ML algorithms to design a model based on historical data and IoTs to collect real-time data to remotely monitor and control agricultural fields at any time. With less human intervention, this is expected to improve water usage, nutrient imbalance, and other aspects.

MATERIALS AND METHODS

In this research work both simulation study and prototype implementation are used. A simplified version of the methodology used in this work is depicted in Fig. 1.

Description of the Study Area:

The Debre Zeit Agricultural Research Center, located in the Oromia Regional State in the East

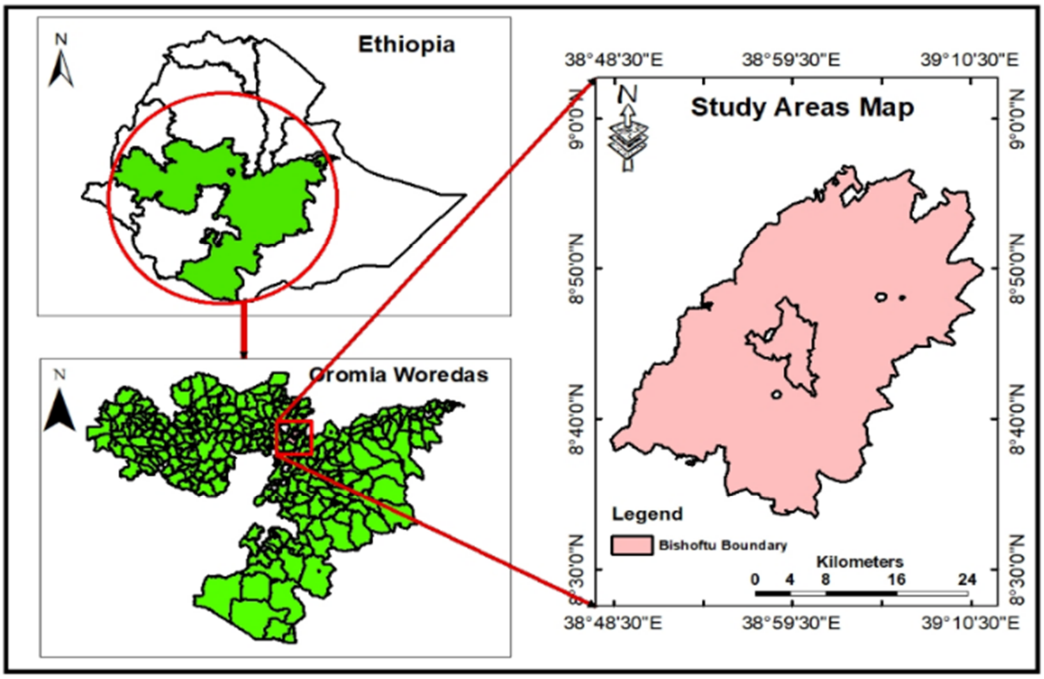


Fig. 1: Map of the Study Area

Shoa Zone, is where historical data is collected and field experiments are carried out. Debre Zeit, as depicted in Fig. 1, is a small town located approximately 42 kilometers east of Addis Ababa. The annual mean rainfall in the area is approximately 810.3 mm, with a bimodal trend and medium yearly variability (Zerssa, 2021).

Seasonal fluctuations and atmospheric pressure systems create four distinct seasons in Ethiopia: Kiremt/Meher or summer (June-August), Tsedey or spring (September-November), Bega or winter (December-February), Belg or autumn (September-October) (March to May) (Kumari & Yadav, 2018; Yimam et al., 2021). Around 76 percent of the area's total rainfall falls during the Kiremt or rainy season, 15% during the Belg season, and the

Table 1: Summary of Research Databases Where Articles are Retrieved

Research Database	Search String Used	Date Accessed	Filter Applied	Result	Remark
IEEE Xplore	Smart irrigation	April-May 2022	Conference Proceedings	90	25 are applicable
Science Direct	Smart, IoT & ML in irrigation system	April-May 2022	Journals	65	18 are applicable
Scopus	Smart, IoT & ML in irrigation system	April-May 2022	Journals and Conference Proceedings	35	10 are applicable
Web of Science	Smart irrigation systems	April-May 2022	Journals	20	3 are applicable

Table 2: Technologies Used in Recent Related Works

Author	Technology Used			Features Implemented	
	Central Controller	**IoTs or Sensors**	**AI or/and ML Algorithm**	**Data Collected**	**Monitoring & Controlling**
(Madushanki et al., 2019)	Raspberry pi and Arduino	Rain and soil Moisture sensor	Neural network	Soil moisture and rain	Predict the future of soil moisture.
(Najeeb & Kamalakkannan, 2022)	Raspberry pi	Soil moisture, Humidity & temperature	No	Humidity, temperature, & Soil moisture	Management of Water
(Chowdary, 2019)	RFID PCA	pH and Temperature sensors	Linear regression & decision tree	Soil nutrient level, temperature of atmosphere	Soil Nutrient Degradation Level.
(Arvind et al., 2017)	NodeMCU	Soil Moisture, pH sensor and PIR sensor	No	Soil moisture and pH of the soil	Watering the field based on the threshold value.
(Bolfe et al., 2020)	ZigBee	Soil moisture, Temperature & Water level	K-means clustering algorithm	System analyses weather reports.	Control pests Weather forecasting
(Fraga-Lamas et al., 2020)	ZigBee Raspberry Pi	Soil moisture & Humidity sensor	Random Forest	Soil moisture Nutrient	Crop management Nutrient Detection
(Pooja et al, 2017)	LoRa technology	Water level sensor	No	Optimal time irrigate and amount of water	Management of Water.
(Campoverde et al., 2021)	Wi-Fi Raspberry Pi	Temperature, soil moisture and light sensor	MQTT protocol	Humidity, temperature, soil moisture & light intensity	Weather monitoring and precision farming.

MQTT - Message Queuing Telemetry Transport; RFID – Radio Frequency Identification; PCA - Principal Component Analysis; LoRa - Long Range Radio; PIR - Passive InfraRed.

remainder during the Bega or dry season, necessitating irrigation. (Kumari & Yadav, 2018; Yimam et al., 2021).

Data Collection:

In this research work, data has been collected using both primary and secondary sources.

Primary Data: The primary data is collected from various field sensors in order to capture the instantaneous environmental data of soil moisture, temperature, pH, and rain. To collect primary data from the 1m2 research areas, the MH Sensor Series for soil moisture, the LM35 sensor series for temperature, the pH meter v.1.1, and the YL-83 for

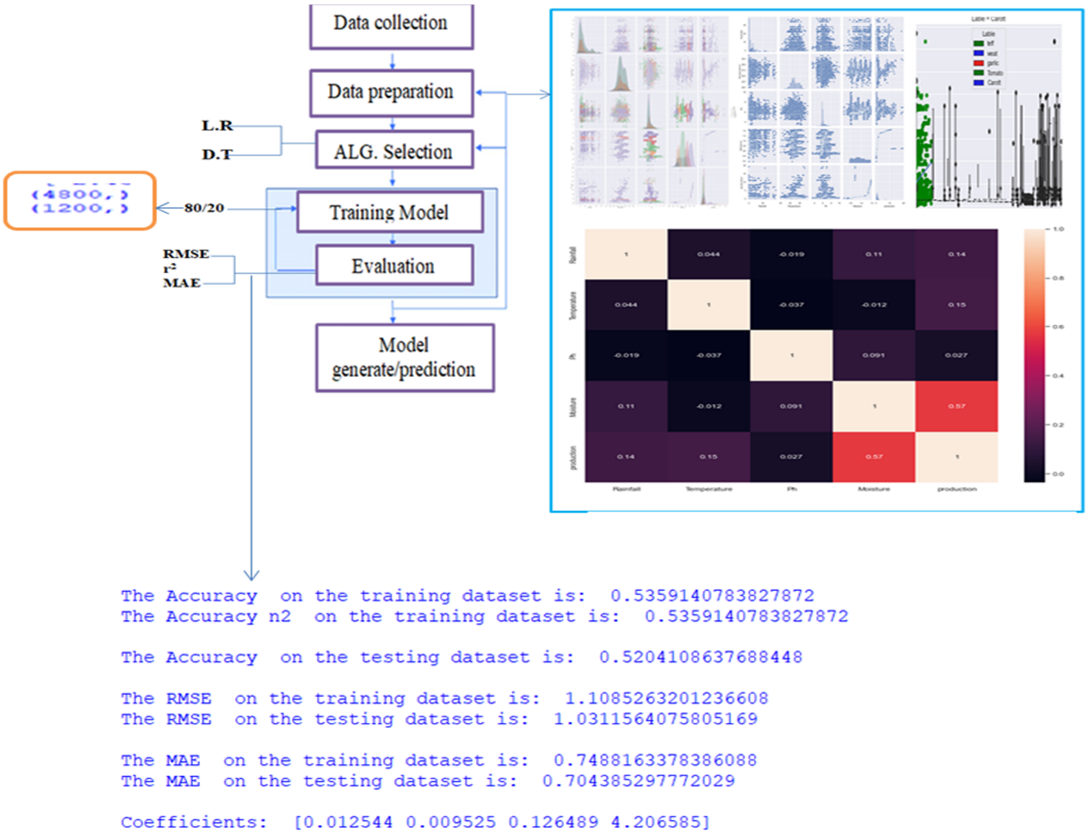


Fig. 2: Data preprocessing steps

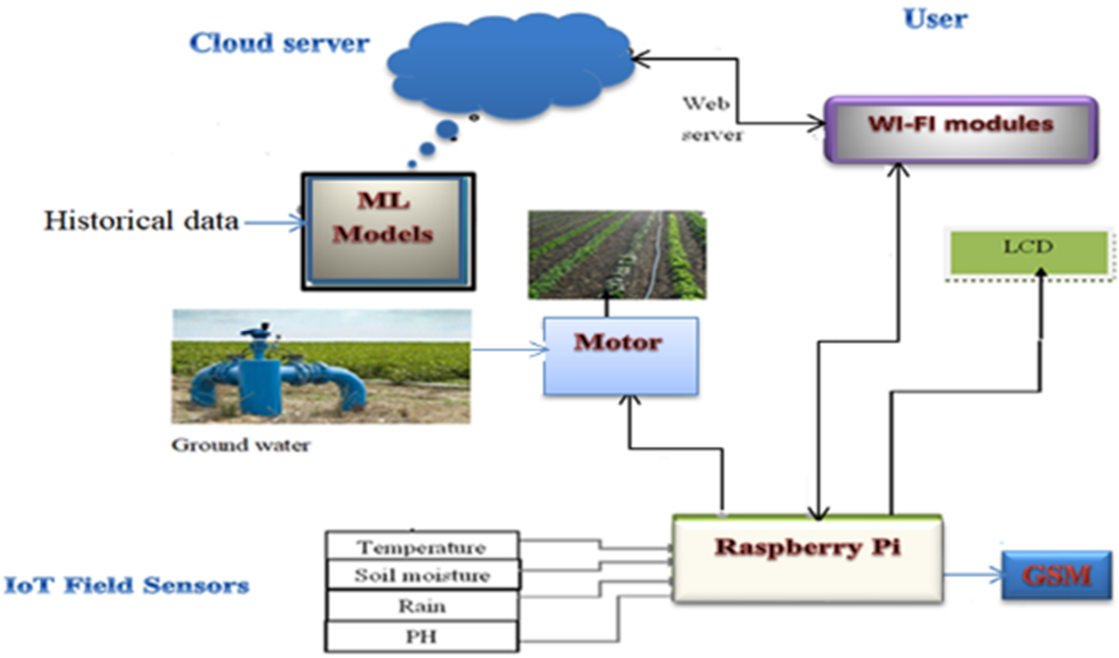


Fig. 3: Proposed System Architecture

rain are used. The data was collected over three months, from November and December 2021 to January 2022. The total data size was 1657 rows by 4 columns, with the columns representing rainfall, temperature, pH, and moisture.

Secondary Data: The secondary data used in this work are obtained from Debre Zeit Agriculture research center (DZARC). Document analysis such as archives and reports, filed visits, and face-to-face interviews with agronomists and researchers are among the data collection techniques used.

Furthermore, desk research was extensively used to gain access to published documents relevant to the research topic and research area. The overall data collected includes ten-year weather data, including rain, humidity, temperature, and moisture.

The data preprocessing steps used in this work are depicted in Fig. 2.

Simulation Modeling and Analysis of Results:

Simulation modeling and analysis has been conducted using Proteus 8.10 Professional, python, ThingSpeak and Matlab. Proteus is used to design and simulate the proposed system. Python is used to write the different features of the simulation, and ThingSpeak is IoT based cloud platform that stores and analyzes the various data collected, and finally, displays the overall result. It uses Matlab for data analysis and presentation.

Prototype Implementation and Analysis:

During the prototype implementation, Raspberry Pi 3 is used as the central controller, four sensors to monitor moisture, temperature, pH, and Rain, and various modules like GSM module to send data to the user/farmer, display module for local visualization, analog to digital converter (ADC1115), motor drive are used.

Comparative Analysis of Results:

Finally, both the results obtained from simulation and prototype implementations are comparatively analyzed against the state-of-the-art to showcase the contributions made and open issues to be workout in the future

RESULTS

The Proposed Smart and Intelligent Irrigation System (SI2S):

This study suggests an IoT-enabled and ML-trained irrigation system for optimal water usage with minimal human intervention. IoT sensors are used in agriculture to collect real-time soil and environmental data. The data is sent to and stored in a cloud server, which analyzes it and makes irrigation/watering and soil nutrient recommendations to the farmer. As a result, a smart and intelligent irrigation system with a lower total cost of ownership that can be used in a variety of application scenarios is being developed.

System Architecture:

Fig. 3 depicts the proposed solution's system block diagram. It depicts the three main elements of the proposed system. The first type of IoT sensor collects environmental data such as soil moisture, temperature, pH, and rain. The second component is the microcontroller module, which integrates and analyzes real-time data collected from various sensors with historical data stored in the cloud to make various decisions. The third component is the cloud system, which stores historical data as well as data collected from various sensors. The ML model is stored on a Google cloud server, allowing for further communication with the user/farmer.

Simulation Modeling and Implementation:

For prediction and classification, we used two different ML algorithms. In smart agriculture research, the most commonly used algorithms for prediction and classification, respectively, are linear regression and decision tree. (Abioye et al., 2022; Jahanavi & Sushma, 2020; Klompenburg et al., 2020; Maulud & Abdulazeez, 2020; Rashid et al., 2021; Rayhana et al., 2020).

Prediction Algorithms Used:

Linear Regression is used in our work for prediction based on the recommendations of the aforementioned researchers. According to the researchers, Linear Regression is the best ML algorithm for agricultural systems. This model is used in our work to predict crop production based on historical data and current field sensor data. It is used to determine whether irrigation and nutrients are required. Following equation that describes the linear regression model (Yimam et al., 2021).

$Y = a + \beta 1\ X1 + \beta 2\ X2 + \ldots + \beta n\ Xn + e$

Where:

Y = either a dependent or a response variable.
X = denotes a predictor or independent variable.
α = an abbreviation for 'constant'.
β = estimated coefficient or slope.
e = is the error.

In this work the above equation is contextualized as shown in equation (1).

$Y = a + \beta 1$ * rainfall + $\beta 2$ * soil moister + $\beta 3$ * pH + $\beta 3$ * temperature + e (1)

Classification Algorithm Used:

Decision trees are intended to mimic human decision-making abilities (Neina, 2019). The fallowing decision tree algorithm is used in this work to classify the research area's historical weather data.

Step 1: Start with the root node, which holds the entire dataset.

Step 2: Using the Attribute Selection Measure (ASM), find the best attribute in the dataset.

Step 3: Subdivide the data into subsets that contain the best value the given attribute.

Step 4: Create the node of the decision tree that has the best attribute value.

Step 5: Create additional decision trees in a recursive manner using the subsets of the dataset obtained in step 3.

Continue this process until the nodes can no longer be classified, at which point the final node is designated as a leaf node.

As selection criteria, the same recommendation as the prediction algorithms was used (Abioye et al., 2022; Jahanavi & Sushma, 2020; Klompenburg et al., 2020; Rashid et al., 2021; Rayhana et al., 2020).

Schematics of the Simulation Implementation:

Fig. 4 depicts the Proteous implementation of the proposed system simulation model. It includes a Raspberry Pi 3 microcontroller, four sensors, and various other components.

This system uses temperature, pH, moisture, and rain sensors to monitor the current weather conditions in the agricultural area. The water pump motors are activated by a relay module, while the GSM module transmits messages to the user's phone, the LCD panel displays field data, and the analog to digital converter (ADC) converts analog signals to digital for the Raspberry Pi. The ADC is required because the Raspberry Pi only has digital GPIO pins, whereas the moisture, pH, and temperature sensors generate analog outputs. The ThingSpeak cloud is linked to the Raspberry Pi via the Wi-Fi module.

The Raspberry Pi sends data from the four sensors to the cloud, where it is analyzed and saved on the ThingSpeak server. Furthermore, the data is displayed in real time on the ThingSpeak Dashboard.

Flowchart of the overall implementation:

When the ML algorithm and field sensor data reach the threshold value, the water pump turns on to efficiently irrigate the plant until it reaches the specified value.

The soil has enough nutrients when the pH is between 5.5 and 7.5 without inclusion. Otherwise, the soil lacks nutrients and minerals.

Fig. 5 depicts the steps that the proposed system takes to monitor the agricultural field using sensors, push the data to the cloud whenever Wi-Fi is available, use ML algorithms to predict whether irrigation and/or nutrients are needed, and notify the user. Furthermore, whenever the user receives notification that the agricultural field requires irrigation, the relay can be activated to start the

Analysis of Simulation Results:

A) Thing-Speak IoT Simulation Results:

The simulation's expected outcome is that all sensors are properly connected and configured to

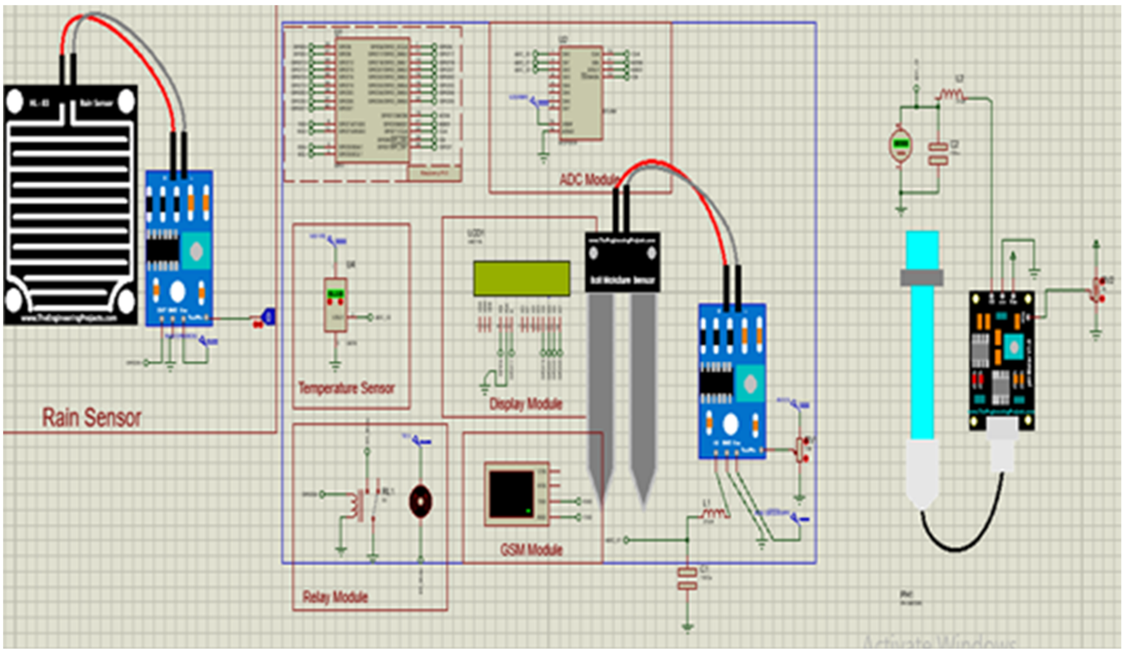


Fig. 4: Proteus Simulation Design Schematic Diagram

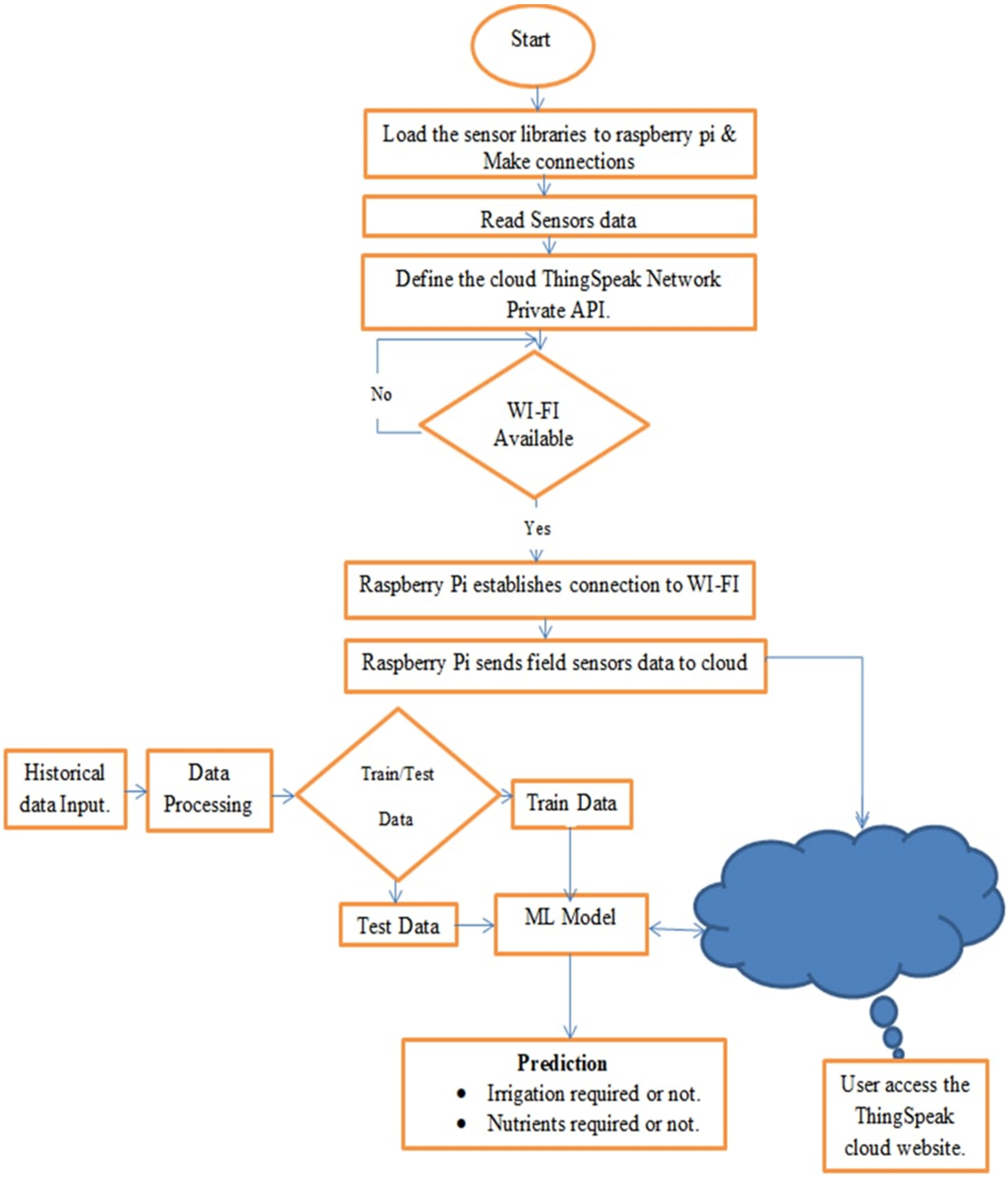


Fig. 5: Flow Chart of the Overall Implementation

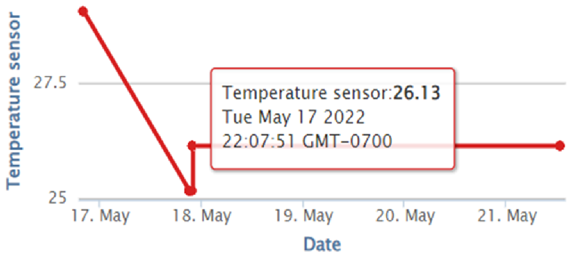
communicate with the Raspberry Pi via Python programs. The data is then transmitted to the cloud server via a Wi-Fi connection. Finally, as shown in Fig. 6, the real-time data is displayed on the Thing Speak cloud server platform.

The data can be remotely monitored from anywhere using the Thing Speak Application's Cloud web server. Fig. 6 shows how to monitor the field sensors for rain, soil moisture, pH, and temperature, as well as the relay status.

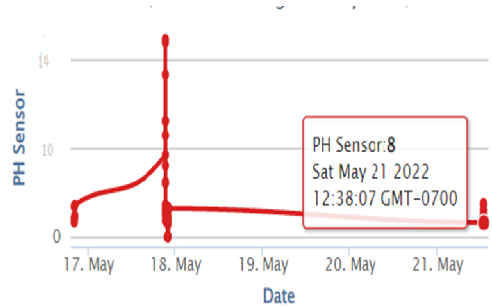
B) Production Model Result:

This model is used to determine the relationship between crop production and field data characteristics. This model aids in estimating the amount of crop production. We use linear regression to determine the relationship between production and each of the four parameters (soil moisture, temperature, pH, and rain). Fig. 7 depicts the output rate with the four parameters.

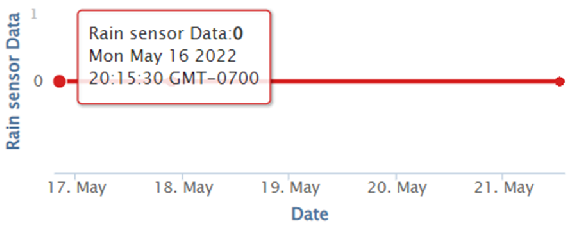
Fig. 8 depicts the real-time agricultural field data gathered by the four sensors. It also suggests irrigating the field based on both historical and real-time weather data. Because the system recommends irrigation, the user activated the relay motor to pump water and irrigate the field, and thus the motor status is on. When the moisture sensor exceeds the threshold value or rain falls



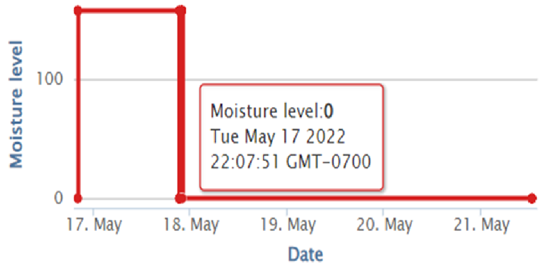
(A)



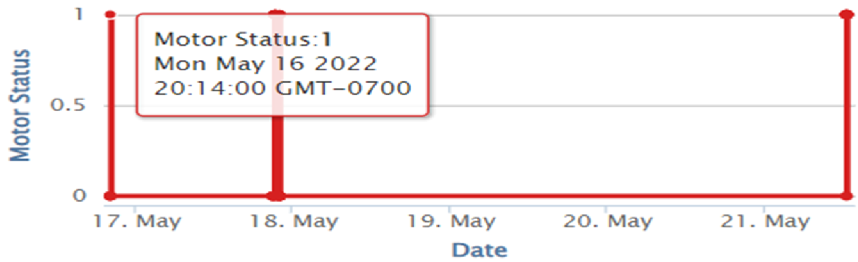
(B)



(C)



(D)



(E)

Fig. 6: Real-Time Data from Field Sensors (A) Temperature, (B) pH, (C) Rain, (D) Moisture, and (E) Motor.

where both are detected by the sensors, the system automatically turns off the motor.

C) pH Value Prediction Result:

Soil pH, also known as soil response, is a measure of soil acidity or alkalinity. The pH scale runs from 0 to 14, with 7 indicating neutrality.

As the amount of hydrogen ions in the soil increases, the pH of the soil decreases, making it more acidic. From pH 7 to 14, the soil becomes more acidic, and from pH 7 to 14, it becomes more alkaline or basic (Najeeb & Kamalakkannan, 2022).

Soil pH indicates whether or not crops require nutrients to maintain the proper pH balance. Fig. 9 shows typical crops and pH values.

The pH of the soil is zero, as shown in Fig. 10. This alerts the user that the soil is becoming increasingly acidic due to a lack of fertilizer and minerals. Depending on the crop, appropriate acid treatment could be achieved by using the appropriate fertilizers.

Based on historical data, the system can also predict and suggest crop types that may provide better production, as shown in Fig.11.

Prototyping of the Smart and Intelligent Irrigation System (SI2S):

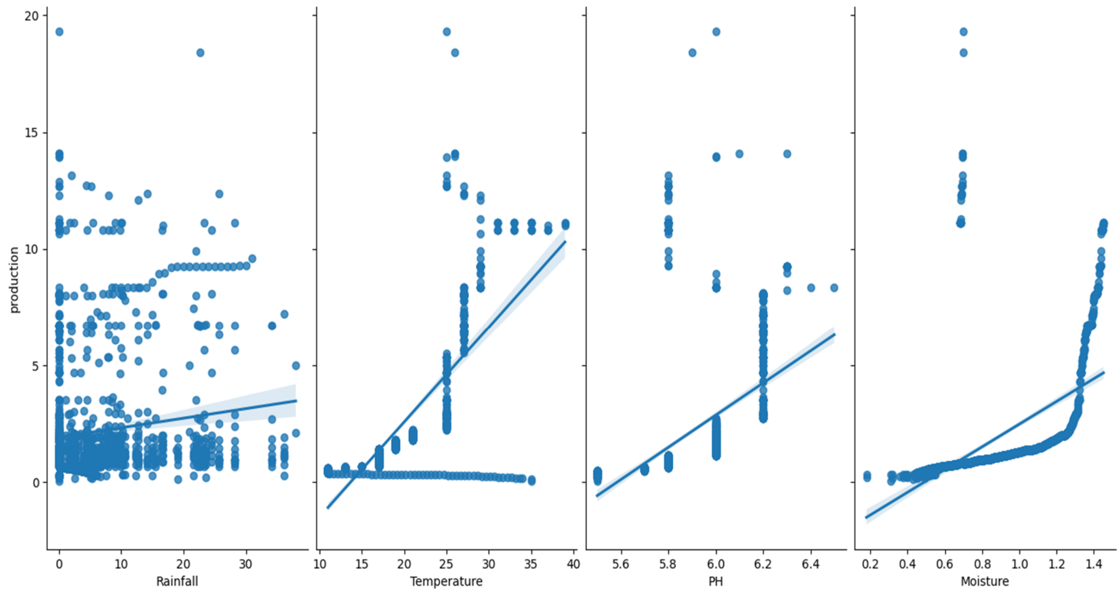


Fig. 7: Production Predicted Model

A smart and intelligent irrigation monitoring and control system has been designed using a prototype implementation of low-cost field sensors interfaced with a Raspberry Pi microcontroller.

```
['28.06', '0', '1']
Temperature:  28.06
Moisture of the soil is:  0
Motor status:  1
rain:  0
Irrigation is required
Root Mean Square error is:  1.7032768222093186
```

Fig. 8: Information Generated based on Historical and Real-time Data

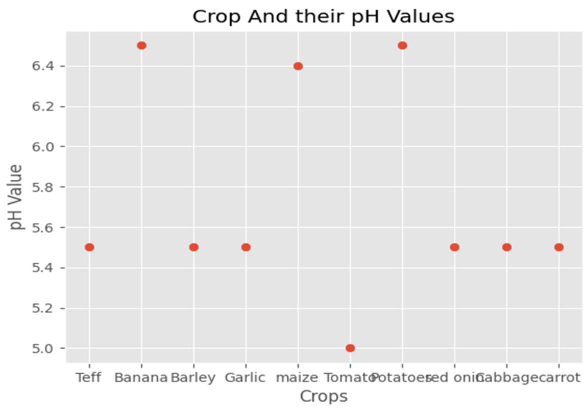


Fig. 9: pH Value Prediction Model Result

Prototype Model and Components:

The proposed prototype is built with a variety of hardware, software, and platforms. Fig. 12 depicts the experimental setup, including the main hardware components, their interconnections, and interfacing with the microcontroller.

Moisture, pH, rain, temperature, and humidity are all factors to consider. Sensors were installed in the field. The sensors send a signal to the Raspberry Pi to control and send field data information to the cloud server once the soil reaches the desired moisture, temperature, and pH level. The cloud-based ML model processes real-time data using the model developed from historical data. The ThingSpeak cloud server web application allows users to view, monitor, and control data from anywhere.

Weather Data Collection using the Prototype System:

The historical weather data used in this study was provided by the Deber Zeit Agricultural Research Center. Garlic was chosen for the prototype implementation because it is already well-cultivated in the center and has sufficient historical data for the proposed system to compare with. According to Table 3 and Fig. 11, the cumulative reference evapotranspiration (ET 0) in the research center for garlic was 77.5 mm for the initial stage and 136.7 mm for the development phase of net crop water demand. The cumulative reference evapotranspiration (ET 0) was 72.5 mm for the starting stage and 127.7 mm for the development stage for the interval between planting at the same month from the research center practice start and the beginning of the irrigation experiment, which is November.

Table 4 and Fig. 14 show the proposed system water usage in comparison to the research center practice. During the development stage of both the proposed system and the research center practice, the highest water demand was reported. However, the proposed system used less CRW (6.45% and

6.72%, respectively) during the initial and development stages.

DISCUSSION

When the proposed smart and intelligent irrigation system (SI2S) compared with traditional irrigation systems, it is more intelligent in that it chooses when to irrigate the plant based on real-time data from IoT-based field sensors. Moreover, it uses ML based prediction and classification models to achieve better resource utilization with minimum physical intervention. The prediction model, which is based on linear regression model, analyzes both historical weather data and real-time sensor data to recommend whether irrigation is required at that specific time. The classification model uses

```
H1.py
Coefficients:
 [ 2.43293158e-17 -2.01227923e-16  1.23859256e-15  1.00000000e+00]
Variance score: 1.00000
Mean squared error: 0.00000
['28.06', '314', '0']
pH of the soil is:  0
The soil is deficient of nutrients and minerals
```

Fig. 10: pH Data Generated to Indicate Current Soil Condition

```
>>>
==== RESTART: C:\Users\samiok\Desktop\MOCK DOC FOR DR,AST
 FOR DEPARTEMENT\ML Codes and datasets\crop predection\cr
.py ===
The accuracy of this model is:  99.35483870967742
['29.03', '157', '0']
pH of the soil is:  7
The soil has enough nutrients
The predicted crop is barley
>>>
= RESTART: C:\Users\samiok\Desktop\MOCK DOC FOR DR,AST\FI
R DEPARTEMENT\ML Codes and datasets\crop predection\crop_
The accuracy of this model is:  99.46236559139786
['29.03', '157', '0']
pH of the soil is:  10
The soil is deficient of nutrients but has minerals
The predicted crop is barley
>>>

= RESTART: C:\Users\samiok\Desktop\MOCK DOC FOR DR,AST\FI
R DEPARTEMENT\ML Codes and datasets\crop predection\crop_
The accuracy of this model is:  99.13978494623656
['29.03', '157', '0']
pH of the soil is:  11
The soil is deficient of nutrients but has minerals
The predicted crop is Garlic
```

Fig. 11: Crop Prediction Result

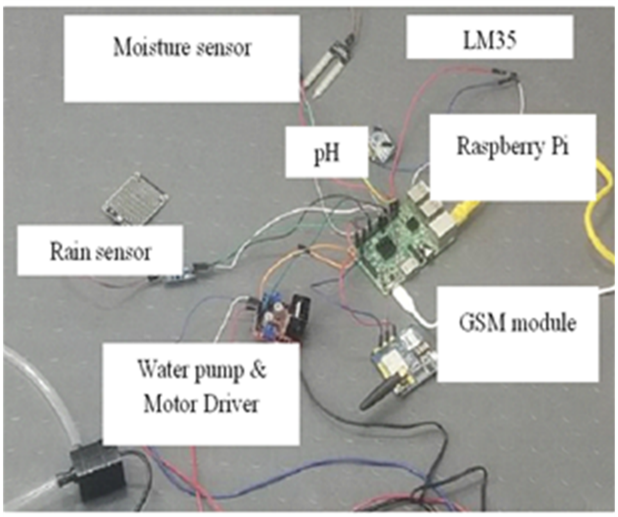


Fig. 12: Prototype Implementation of the Proposed Irrigation System

decision tree to recommend the type crop to plant this season. This is also done using historical weather data and current soil data collected from the IoT sensors. These approaches not only save lots of time it improves resource utilization like water and nutrients. The water demand of the crop can be monitored via the moisture, temperature and rain sensors whereas; the level of soil nutrients is monitored based on pH sensor. In traditional irrigation systems, there is a waste of resources such as water, nutrients, labor, and time (Awulachew & Ayana, 2011; Belay & Bewket, 2013; Lee et al., 2014). To justify this, the proposed smart and intelligent irrigation system (SI2S) is compared with traditional irrigation systems, and with selected and appropriate smart irrigation systems previously proposed with detailed analysis, in Table 5, Table 6, and Table 7, respectively. More specifically, based on the results shown in Table 3 and 4 the proposed system improved the CWR of Initial and Development stages of the selected crop during the prototype study, which is Garlic, by 6.45% and 6.72%, respectively.

As can be seen in Table 5, traditional systems lack much of the means to utilize agricultural resources including labor, time, water, and fertilizers, among others when compared to the proposed system. Primarily, that is why emerging technologies need to be adapted to such application domains (Bolfe et al., 2020; FAO, 2021). Obviously, the proposed

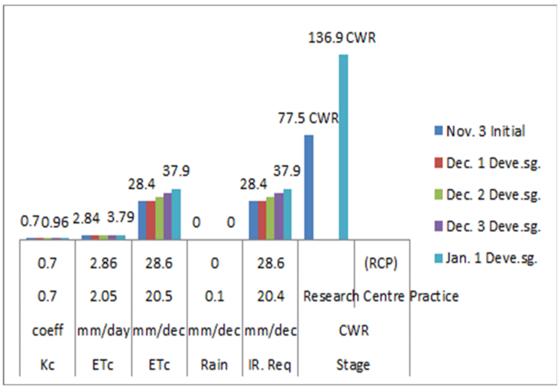


Fig. 13: RCP water demand of Garlic

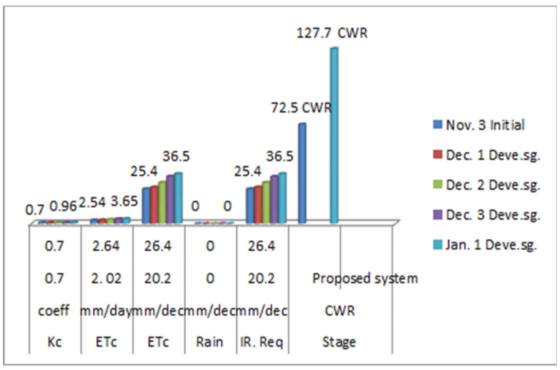


Fig. 14: Water Demand for Garlic in the Proposed System

system performed better in almost all aspects when compared with traditional systems. Apparently, that is something expected. Hence, Tables 6 and 7 compared the proposed system with similar systems to get a more critical and realistic performance comparisons with related works that identified as smart and intelligent (Madushanki, 2019; Patil & Sachapara, 2017; Rao & Sridhar, 2018; Rayhana, 2020).

Table 6, shows selected related works that are similar to the proposed work where many lacks the automatic controlling of the agricultural field using actuators or motors to initiate irrigation, for example. In the proposed system the farmer or user can monitor the agricultural field being anywhere in the world via the online system through her smart phone. While doing so she can initiate irrigating the plants based on the sensors data that indicated the need for water. Moreover, none attempted to use ML algorithms to create an AI Model that can predict the type of crop that better be planted in the area.

When it comes to Table 7, detailed performance comparison is made between the proposed SI2S system and the selected related works that are claimed smart and intelligent. The proposed model is better in some critical aspects like the use of both simulation analysis and prototype implementation. The prototype implementation is made using low cost hardware where it is possible to replicate the work for real world implementations by low income farmers both in rural and urban settings. As long as electric power is made available through commercial lines or batteries backed by, for example, renewable energy sources, then it is possible to deploy it in any setting to monitor and control a farming area of crops, vegetables, horticulture and fruits.

In conclusion, this work discusses a smart and intelligent irrigation system (SI2S). It is smart because the proposed model has four sensors that monitor moisture, pH, rain, and temperature of the soil. And, it is intelligent because it has ML models built using a ten-year historical data of Debre Zeit Agricultural Research Center where the prototype was deployed for three months. The classification model, which is based on decision tree algorithm, categorizes the type of crop that could better be planted. This model, though trained and tested using the historical data uses the real-time sensors data to further fine tune its classification. The prediction model, which is based on the linear regression algorithm, suggests the need for water/irrigation and nutrients of the soil based on both historical and instantaneous weather data.

Though there are many possible extensions, this system has improved the CWR of garlic at its initial and development stages when compared with previous works. Moreover, it can be used to get suggestions about which crop could be better planted in the current season to get better production based on the historical and real-time data of soil pH and other parameters. Farmers and agriculturalists can remotely monitor their fields using a computer or mobile device via the cloud based web application. The data collected through the sensors which is saved in the cloud could be used for further research and analysis in numerous ways to improve production.

By doing so, this system avoids physical presence, saves time, and improves water usage, among other things. Installation is simple, and the amount of labor and time required to control the irrigation process is minimal. Better performances and features are observed from the system when compared with similar recent works.

The following are the study's main contributions: First, the proposed system reduced Garlic's Crop Water Requirement (CWR) by 6.45% and 6.72%, respectively, during the Initial and Development stages. Second, it can be used to forecast the type of crop that should be planted in the current year based on the primary (sensor) and secondary (historical) data collected. Third, using mobile devices, users/farmers can remotely initiate irrigation or watering of crops via the ThingSpeak cloud platform. Furthermore, real-time data from the sensors can be downloaded and used for further analysis and insights.

This effort can be improved in the future by using valves to remotely apply nutrients based on pH sensor results. Furthermore, a camera system can be used to improve monitoring of the entire agricultural field. This research attempted to develop agricultural field monitoring and control mechanisms that were both generic and specific (to garlic). It can also be extended to other crops that can be planted in various geographical areas throughout the country. Furthermore, crop production or yield monitoring and analysis of the suggested crop type by the classification model would provide us with a better understanding of the commonly used technique known as "crop rotation." It goes without saying that using longer-term agricultural field data with more performance evaluation parameters could yield better results.

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