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Soil Fertility and Plant Nutrient Management using IoT and Machine Learning

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***Abstract*—Smart devices are revolutionizing daily life by making them more intelligent and efficient. In agriculture, sensors are being used to detect soil pH, moisture and nutrients in order to grow high-quality crops. The health of crops is heavily influenced by the quantity and quality of the soil, which can be affected by physical factors such as soil composition and density, as well as chemical factors such as nutrient accessibility. By using the DS18B20 Waterproof Temperature Sensor to measure soil temperature and rain sensors to monitor moisture levels, farmers can gain valuable insights into the health of their soil. Advancement of big data technologies and powerful computers, machine learning is providing new opportunities for research in the field of Agri-technology. By applying machine learning techniques to sensor data, farm management systems are becoming real-time intelligent systems that can provide precise recommendations and insights for farmers to use in their decision-making. In this study, a Recurrent Neural Network (RNN) approach was used to determine the suitability of a soil sample for plant nutrition and soil fertility. Proposed system results and evaluated them with numerous conventional classification algorithms. the RNN higher accuracy of 94% on the real-time dataset. This research has the potential to be highly beneficial for the Agri-tech industry in the near future by providing farmers with valuable recommendations for plant nutrition and soil fertility management.**

Keywords— Internet of Things, Soil Fertility, Raspberry Pi, DS18B20, Machine Learning.

I. INTRODUCTION

India is a rapidly developing country with abundant natural resources and a wealth of knowledge. One of the major challenges facing society is ensuring food security [1]. Therefore, managing agricultural activities, such as precisely forecasting crop developments, is crucial in the agricultural field. IoT technology is currently being used to monitor and evaluate basic soil properties using sensor data [2]. Soil is composed of minerals, organic matter, and fragments of worn rock [3]. In order to boost efficiency, maximize production and minimize waste, Smart objects are increasingly being employed in smart agriculture to collect real-time field measurements, analyze data, and apply control methods [4],[5] . In this research, we aim to examine the potential of connected sensor networks to enhance agricultural productivity and profitability by implementing Machine Learning (ML) techniques and IoT technology.

ML is a technique that enables machines to imitate the human learning process, acquire new knowledge, improve efficiency, and mature to a certain degree [6], [7]. It can be applied to various areas of agriculture such as detection and diagnosis, crop recognition, hydrological management, poor soil, weed classification, grain prices, and weather prediction. It can also be used to evaluate product quality, conduct market research, determine the freshness of fruits and vegetables, and predict storage time [8], [9].

IoT, which integrates various intelligent sensors, is another powerful technology [10]. Various fields, such as solar power plants, agricultural lands, and industrial facilities, can be monitored with these sophisticated sensors. In this research, we will be using Recurrent Neural Networks (RNN) to analyze the data collected from IoT sensors and provide insights to farmers. We will also be examining the improvements to connected sensor networks to enhance the number of farmland operational developments.

Using IoT-based technology, this research aims to develop a smart agriculture system that helps farmers with the most recent information on soil nutrients, pH value, temperature, moisture, and humidity. This information will allow farmers to practice smart farming and increase crop output. The research will describe the most important farming and growing technologies and evaluate whether connected connected the sensor networks are suitable for boosting productivity and profitability. India is a rapidly developing country with abundant natural resources and a wealth of knowledge. One of the major challenges facing society is ensuring food security. Therefore, managing agricultural activities, such as precisely forecasting crop developments, is crucial in the agricultural field. IoT technology is currently being used to monitor and evaluate basic soil properties using sensor data. Soil is composed of minerals, organic matter, and fragments of worn rock. In order to boost efficiency, maximize production and minimize waste, Smart objects are increasingly being employed in smart agriculture to collect real-time field measurements, analyze data, and apply control methods. In this research, we aim to examine the potential of connected sensor networks to enhance agricultural productivity and profitability by implementing ML techniques and IoT technology.

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IoT, which integrates various intelligent sensors, is another powerful technology. These sophisticated sensors can be used to gather data from a variety of fields, including solar power plants, agricultural lands, and other industrial plants. In this research, we will be using Recurrent Neural Networks (RNN) to analyse the data collected from IoT sensors and provide insights to farmers. We will also be examining the improvements to connected sensor networks to enhance the number of farmland operational developments.

The study will also explore the potential of ML techniques and IoT technology in addressing agricultural issues and enhancing agricultural production in terms of quantity and quality. The research will also propose solutions to address the challenges associated with the implementation of smart agriculture systems such as device security issues and cost. Following are the remaining sections of the paper: the second section will discuss related works. In section 3, the materials and methods used in the research will be explained, followed by results and discussion in section 4. Finally, conclusion and future scope of the research will be discussed in section 5.

II. Related works

In a previous study, Bhuyar et al. [11] developed a system that used soil as one of the factors to improve crop yield and predict soil fertility. They employed various classification methods to train the data set. Their classification of soil fertility rates using the J48, Naive Bias (NB), and Random Forest (RF) approaches was their significant contribution to the field. They found that the J48 algorithm was the most effective. J48 is a Java-based open-source implementation of the C4.5 decision tree induction algorithm. The ID3 (Iterative Dichotomiser 3) algorithm is expanded in C4.5. and it is used for solving both classification and regression problems. The farmers and leaders can identify the soil fertility rate using the decision tree structure created by the J48 computation. Several organic fertilisers can be suggested depending on the justifications for supplementation revealed in the soil sample. Hemageeta et al. [12]. utilized data mining classification techniques to determine the suitability of soil in the Salem district for agricultural production. The results indicate that the J48 algorithm outperforms other algorithms such as Naive Bayes, JRip, and BayesNet in terms of accuracy. The study also shows that the majority of the soil in the Salem region is suitable for growing various crops. Additionally, it highlights that the cost of using J48 algorithm is relatively low compared to other methods. Devi et al. [13] showed Precision agriculture can monitor and manage greenhouse parameters because of the advancements in wireless sensor systems technology. After doing research on the matter, scientists discovered that agriculture's yield is steadily declining. Nayyar and his team [14] presented the use of intelligent sticks to record and analyse real-time events in the fields. This variable analysis includes measurements of soil moisture levels and surface temperatures. This approach is commonly used to gather real-time data collected from mobile applications, which can then be analyzed by any farming specialist located anywhere in the world using cloud computing. However, there are significant challenges in terms of device security that need to be addressed for this method to be fully effective. Mittal et al. [15] proposed the development of a monitoring and control system for terrace gardeners by integrating IoT-based technology with image processing methods. The system would alert users if any of the instrument data obtained falls below a specified threshold value. The proposed system includes the use of motion sensors as a protective measure against damage to crops caused by birds or humans. Additionally, a webcam is employed to monitor the terrace garden and provide real-time updates on the web service.

III. Material And Methods

We have collected the sensor data using Raspberry Pi. Over- all there are 5 sensors were connected to R-Pi 3 model. The sensors were the Ph sensor, DHT11 temperature and moisture sensor, Ds18b20 waterproof temperature measurement Probe, soil moisture sensor and rain sensor.

Figure 1 shows the different components used in the project. Fig. 1 (a) shows Raspberry Pi used to collect the sensor data, and Fig. 1 (b) shows Ph Sensor used to measure Ph Value. Fig1 (c) shows a DHT11 sensor that collects data about ambient temperature and moisture levels in the air. For accurate temperature measurement, DS18b20 probe is used with 12-bit resolution and it is shown in Fig. 1 (d). Fig. 1 (e) shows a soil moisture sensor, that measures water available for plant roots. Fig 1 (f) shows a rain sensor to measure any precipitation near the farm.

Figure 2 shows a picture of a hardware setup during the testing phase. It can be seen that current measurements during testing were done in the small pots. All the sensors are placed near the measurement zone and I2C interface sensors were directly connected to Raspberry Pi. The analog sensors were connected via a small ADC (8-bit) module with an I2C interface to the Raspberry Pi. The Power was given through a 5 Volt 3 Amp power adaptor.

Figure 4 shows the flowchart of the proposed method. The first step is to set up the hardware near the region of interest. The data from all five sensors were gathered from the Raspberry Pi periodically. For analysis purposes, the values were stored. The scanning frequency was set to 500 msec. The data was stored on a 32Gb class 10 SD card. [16] with our own fuzzification logic and RNN.

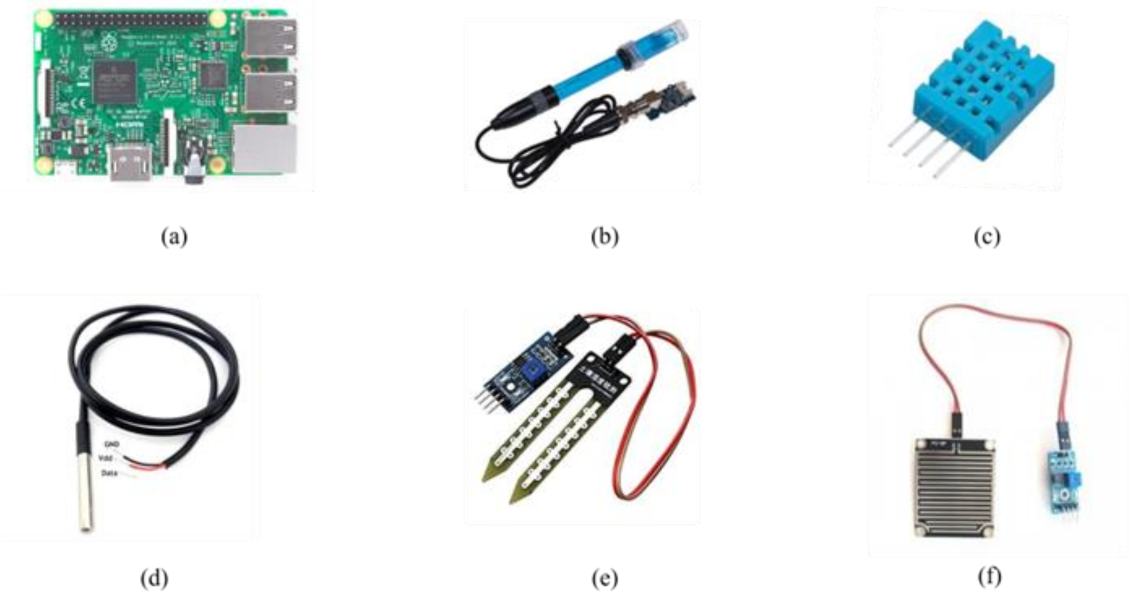


Fig. 1. (a) Raspberry Pi used to collect the sensor data (b) Ph Sensor (c) DHT11 sensor (d) DS18b20 probe (e) Soil moisture sensor (f) Rain sensor

Fig. 2. Picture of a hardware setup during the testing phase.

Q-learning algorithm is a model-free reinforcement learning algorithm. The learning algorithm determines the optical action to be taken in a given state by all five sensors. A dynamical model of the environment is not required for this algorithm We designed a Q-table, which is a table that stores the value of taking each action (prediction in our case) in each state (based on inputs), and updates the table according to a set of rules.

The algorithm iteratively improves the estimates in the Q-table by using the Bellman equation. The goal of Q-learning in our proposed method was to find the best crop that maximizes the yield. Recurrent Neural Networks (RNNs) process sequential sensor data time series using neural networks. In our proposed method Q-learning was combined with Recurrent Neural Networks (RNNs) to create a hybrid algorithm (QRNNs). QRNNs use the Q-learning algorithm to learn the optimal crop prediction policy for a given state, but instead of using a user-defined Q-table. Instead, we use an RNN to learn the Q-function.

The RNN was trained to predict the Q-values for given sensor values, based on the current state, the previous state, and the prediction action taken to transition between the two states. The RNN was also trained to take into account any other relevant information, such as the higher accuracy in prediction received for taking the action or the current time step. Fuzzy logic was then added to the QRNN algorithm. It was used to represent the uncertainty or imprecision in the Q-values, thus allowing the algorithm to handle incomplete or noisy data. Wealso used fuzzy logic to define the rules for updating the Q- values, allowing the algorithm to adapt to changing conditions.

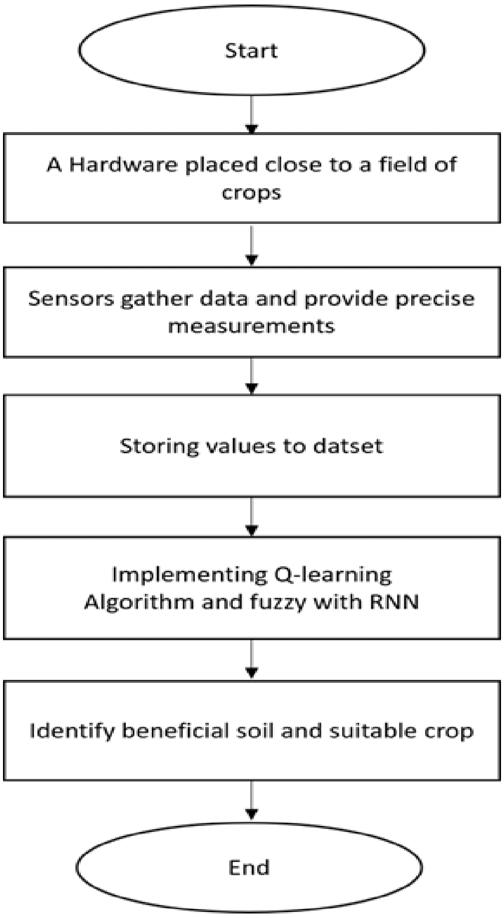


Fig. 3. Flow chart of proposed method

IV. RESULTS

Figure 4 shows obtained data from the sensor's databases. The readings displayed contain soil moisture sensors, a rain sensor, a soil pH sensor, a DHT11 temperature sensor, and waterproof Ds18b20 probes reading respectively after every 500 mSec.

This project used a handheld device to automate the process of testing soil and predicting best crop using QRNNs and fuzzy logic. The sensor-based soil monitoring system evaluates values and recommends which crops are best for a given soil which is shown in fig 5. Figure 6 presents several plots and screenshots related to the monitoring and analysis of soil conditions. Panel (a) shows the variation of humidity levels over time for 14 different hourly time points. As demonstrated by the plot, the humidity variation is found to be within 1% range. Panel (b) presents a temperature plot for the same 14 hourly time points, displaying the temperature values inside the soil. In panel (c), a screenshot of Q-learning is depicted, which was used to make predictions about soil conditions based on data inputs. Panel (d) displays the results of a Recurrent Neural Network (RNN) that were used to analyze the soil conditions, revealing that the soil is fertile. Finally, in panel (e), the error between the actual temperature measured by a thermometer and the temperature calculated through a DHT11 sensor is shown.The majority of prediction agriculture solutions currently in use involve the use of fertilizers to improve soil richness and increase yields. However, long-term environmental harm is often caused by overusing fertilizers. Therefore, there is a need for a system that allows farmers to perform accurate farming using a sustainable strategy for soil management. This will enable high yields to be achieved while also protecting the environment.

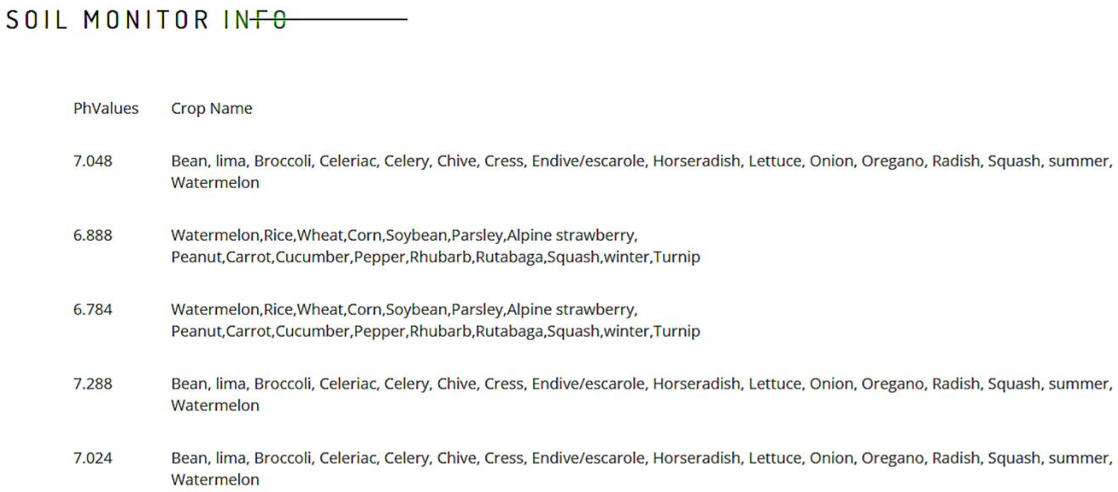
This research focuses on using sensor data to provide precise measurements of soil conditions. A Q-learning algorithm, along with fuzzy logic and a recurrent neural network (RNN) are implemented to evaluate the sensor data and provide recommendations for which crops are best suited for a given soil. This proposed QRNN algorithm is beneficial not only for the soil and agriculture but also for farmers. By evaluating all the crops that are best suited for specific soils, a fuzzy rule base is created. The results of the study demonstrate that the proposed method is able to correctly predict the beneficial soil for agriculture. Thus, this algorithm can be used by farmers to make informed decisions about crop selection and soil management for

SOIL MONITOR INFO

ID	Humidity	Temperature	Soil Temperature	Ph Values	Moisture	Rain Values
289	53.0	32.0	32.687	7.024	0	0
288	53.0	32.0	32.687	7.288	0	0
287	53.0	32.0	32.687	6.784	0	0
286	53.0	32.0	32.687	6.888	0	0
285	53.0	32.0	32.625	7.048	0	0
284	53.0	32.0	32.625	6.936	0	0
283	53.0	32.0	32.687	6.992	0	0
282	53.0	32.0	32.687	7.28	0	0
281	53.0	32.0	32.687	7.032	0	0

Fig. 4. Screen shot of results obtained on the designed web interface

optimal growth and yield, while also taking into consideration the long-term environmental impact.


SOIL MONITOR INFO

PhValues	Crop Name
7.048	Bean, lima, Broccoli, Celeriac, Celery, Chive, Cress, Endive/escarole, Horseradish, Lettuce, Onion, Oregano, Radish, Squash, summer, Watermelon
6.888	Watermelon,Rice,Wheat,Corn,Soybean,Parsley,Alpine strawberry, Peanut,Carrot,Cucumber,Pepper,Rhubarb,Rutabaga,Squash,winter,Turnip
6.784	Watermelon,Rice,Wheat,Corn,Soybean,Parsley,Alpine strawberry, Peanut,Carrot,Cucumber,Pepper,Rhubarb,Rutabaga,Squash,winter,Turnip
7.288	Bean, lima, Broccoli, Celeriac, Celery, Chive, Cress, Endive/escarole, Horseradish, Lettuce, Onion, Oregano, Radish, Squash, summer, Watermelon
7.024	Bean, lima, Broccoli, Celeriac, Celery, Chive, Cress, Endive/escarole, Horseradish, Lettuce, Onion, Oregano, Radish, Squash, summer, Watermelon

Fig. 5. Screen shot of plant recommendation system using QRNNs algorithm with fuzzy logic.

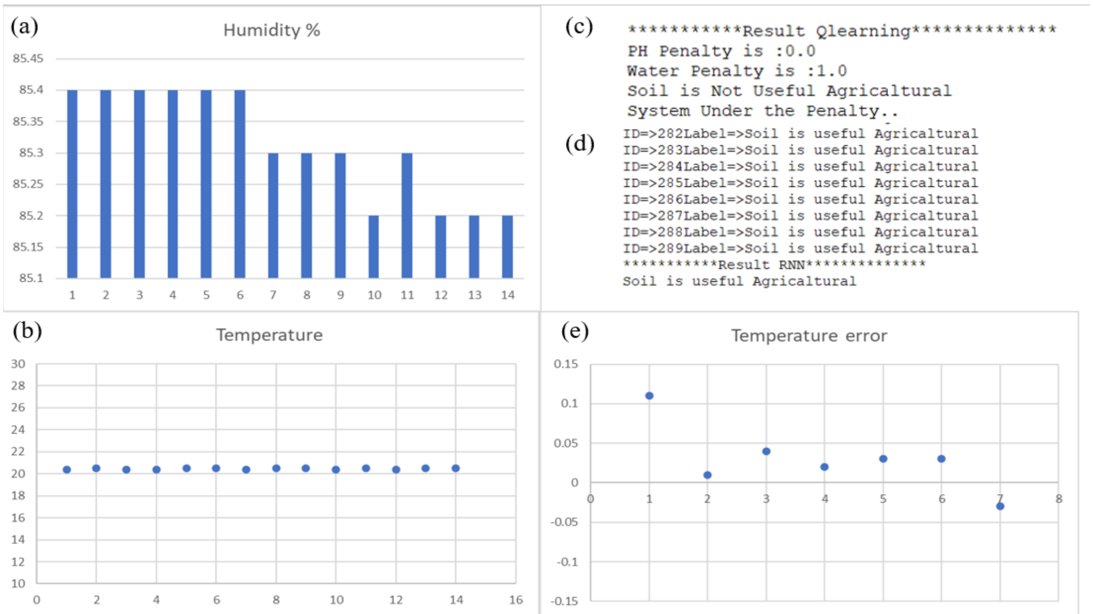


Fig. 6. (a) Plot of humidity for different 14 hourly time points showing variation is within 1%.. (b) Temperature plot for 14 hourly time points inside the soil. (c) Screenshot of Q-learning (d) RNN results showing soil is fertile (e) Error between actual temperature measured on the thermometer and calculated through DHT 11 sensor.

Method/ Author	**Accuracy (%)**	**Soil Temperature Resolution (degree)**	**pH sensor (mV/Ph)**	**ADC Resolution (Bit)**	**Atmospheric Temperature (Degree)**	**Humidity Error (%)**
Jang et al. [18]	92	1	-	8	-	-
Park et al. [19]	95.6	1	-	-	-	6
Adamchuk et al. [20]	83	0.5	59	12	-	-
Liu et al. [21]	-	1	-	8	-	-

Lata et al. [22]	97	-	-	8	3	10
Proposed System	94	0.5	240	12	2	5

Table. 1. comparison of the performance of various soil monitoring systems, including the proposed system.

V. Discussions

Table 1 provides a comparison of the performance of various soil monitoring systems, including the proposed system. The table presents the accuracy percentage achieved by each system, as well as the soil temperature resolution, pH sensor resolution, atmospheric temperature, and humidity error. According to the table, the proposed system achieves an accuracy of 94%, with a soil temperature resolution of 0.5 degrees and a pH sensor resolution of 240 mV/pH. The system also has an atmospheric temperature that can be 1 degree off and a humidity error can be a maximum of 5%. Comparatively, other systems in the table have varying levels of accuracy, temperature resolution, pH sensor resolution, atmospheric temperature, and humidity error.

Overall, the proposed system performs well in terms of accuracy and resolution, while also offering relatively low humidity errors.

VI. Conclusions

In conclusion, this research paper presents a study on using the Internet of Things (IoT) and machine learning techniques to improve crop health and soil fertility management in agriculture. The study used a combination of various sensors, including the DS18B20 Waterproof Temperature Sensor, to collect data on soil temperature and moisture levels. This data was then analyzed using a Q-learning algorithm with a recurrent neural network (RNN) approach, and with fuzzy logic. Other supervised learning algorithms are not as powerful as the RNN module that was proposed because it has an average accuracy of over 94% in different soil samples. The study has the potential to greatly benefit the agricultural sector in the near future by offering farmers helpful suggestions for managing soil fertility and plant nutrition.

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