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IOAT in Agricultural Research: Continuous Monitoring and Analysis of Demographic Data to Assess Cotton Crop Potential in Paddy Fields

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Abstract: The escalating global demand for agricultural and horticultural products, driven by rapid population growth and exacerbated greenhouse effects, underscores the urgent need for technological advancements in these sectors. Notably, the horticulture and agriculture fields grapple with many diseases, particularly pronounced in vital crops like cotton, often called "white gold." Despite its widespread utility, cotton is susceptible to significant losses once afflicted by diseases. This research paper addresses this challenge by predicting conditions based on soil mineral deficiencies. We introduce an innovative system under the Internet of Agriculture Things (IoAT). This system continuously monitors essential soil parameters, including pH, humidity, Temperature, Nitrogen, phosphorus, and potassium levels in cotton paddy fields. The acquired data is processed and stored in a cloud database. Advanced data prediction techniques are then employed to forecast potential cotton diseases. Furthermore, data visualization techniques provide a comprehensive assessment, equipping farmers with insights to optimize soil conditions and enhance cotton yield. Through this integrated approach, the research offers a proactive solution to mitigate disease-related losses in cotton crops, emphasizing the pivotal role of technology in modern agriculture.

Keywords: *Internet of Agriculture Things, Prediction, Cotton Diseases, Data Visualization, Predictive algorithms*

1. Introduction

The fifth-largest fiber plant in the universe is cotton. Cotton is a profitable cash crop that supplies fiber, oil, and animal feed worldwide. Food and fiber are in greater demand, but agricultural production is struggling to meet the population's needs because of climate change. Although water supplies are constrained, intensified crops are necessary to provide more food, fiber, and feed. Although considered a drought-resistant crop, cotton suffers from drought stress and nutrient scarcity, resulting in reduced growth and functional, enzymatic, and molecular developments [1]. In a developing nation, agriculture is the primary source of income for about two-thirds of the populace. Agriculture's quality affects the economy. A nation's economy is dependent on the caliber of its agricultural output, and the caliber is impacted by disease recognition. A complex subject for agriculture professionals that necessitates scientific procedures and extensive observation is the identification of plant diseases [2]. One of the most significant fiber crops in the world, cotton provides the fundamental raw materials for the cotton textile industry. The illness that significantly damages the cotton crop and makes it impossible to detect with the naked eye causes the crop numerous issues. The plant's leaf is the component most severely impacted by the illness.

The plant's leaves contain 80–90% of the disease. Examples of damaged and healthy cotton leaves are, Therefore, rather than studying the entire cotton crop, our study focuses on the crop's leaves [3].

- Red Spot Disease is one of the illnesses affecting the crop (Lalya)
- White Spot Disease (Pandhari Mashi)
- Crumpled-leaf disease (Kokoda)

By utilizing technology to collect data on soil moisture, plant illnesses, insect assaults, meteorological conditions, and agricultural production growth, an AI may anticipate crop yield. With the use of artificial intelligence (AI), the employment of robots, drones, and sensors in agriculture has allowed agronomists to generate and increase high-quality output in exchange for necessary input. The main lessons of AI in agriculture are its adaptability, extreme performance, accuracy, and cost-effectiveness. By combining data from numerous sources into datasets that can be reliably examined, smart farming employing artificial intelligence will be developed to decrease crop losses, enhance output, and use less water, fertilizer, and pesticides. The agriculture datasets are broken up into

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smaller pieces, and their patterns and behaviours were understood for processing a vast amount of data [4].

2. Contribution of the Work

New possibilities have opened up for the automation of agricultural irrigation networks with the recent implementation of LPWAN wireless communication networks (SIGFOX, LoraWan, and NBIoT), as well as the growing market for electronic controllers based on open-source hardware and software (such as Arduino, Raspberry Pi, ESP, etc.) that consume little energy. The autonomous cloud-based irrigation method described in this study is inexpensive. In this study, a node network design based on the ESP32-Lora microcontroller.

And a SIGFOX network-based Internet connection is suggested. The outcomes demonstrate the design's resilience and stability [5].

Several sorts of soil exist, and each type has a unique set of properties. Testing soil properties is, therefore, essential. Several instruments are available for soil analysis, but these tools do not always provide precise and desirable results, and farmers must also endure the inconvenience of traveling to laboratories for soil analysis. However, testing all soil types quickly from a lab is exceedingly challenging. Additionally, the instruments available for soil analysis are not in the regional tongue. As a result, a tool for doing soil analysis that the farmer can use is needed. Our primary goal is to create a system for regional soil analysis that uses suggestions for soil-based fertilizers to assist farmers in planting and harvesting the right crop. This tool will be written in a local tongue so that farmers may readily grasp it[6].

When crops produce poorly, fertilizer use—whether excessive or insufficient—is likely to blame. To guarantee efficient crop development, the number of nutrients in the soil must be assessed. The foundation of IOT-enabled soil testing is the measurement and observation of soil characteristics. This technique helps to preserve crop health and lessen the chance of soil degradation. A wifi module attached to an Arduino board shows test results data and a list of specific crops suitable for the tested soil. Additionally, a website that gives information on the fertilizer(s) required for their produce has been developed online.[7].

The study also covers the strengths and possibilities of computer tools used in agriculture, such as wireless sensor networks, the Internet of Things, data analytics, and machine learning, as well as the difficulties encountered when integrating these technologies. In an Internet of Things system, data analytics and machine learning were used to develop a prediction model for apple disease in Kashmir Valley apple orchards. A local survey of farmers was also conducted to understand more about the most recent technologies and how they affect precision agriculture. The study's last portion discusses the challenges of incorporating modern technologies into traditional farming practices. conventional agricultural techniques [9].

3. Proposed Object

In a Cotton crop paddy field, one of the essential things is identifying cotton diseases. In this regard, the research paper conducts the last five years' literature survey on cotton leaf diseases through the image process for identification through computer vision techniques.

Only. And few researchers are researching paddy field soil testing using Humidity and Temperature sensors only, But in conducting the cotton, diseases occur not only depending upon the factors of soil temperature, humidity, and pH values in soil. The most critical factors are Nitrogen, Phosphorus, and Potassium also. But few of the authors are getting the data from the ground. They are not predicting the type of diseases is occur by depending upon these factors' combination. So, in this regard, by relying upon the gap analysis, In this research paper's main objective is to design the IoT with the help of the NPK(Nitrogen, Phosphorus, and Potassium) Sensor to get the data and predict the kind of diseases that will be occurred by depends on upon above parameters.

4. System Design and Working Model

In this section, the first step will be implemented using the IoT and Machine Learning Techniques to achieve the above object of this research paper. In this regard, the system's mechanism is defined below as a flow diagram of attaining the object of this research work.

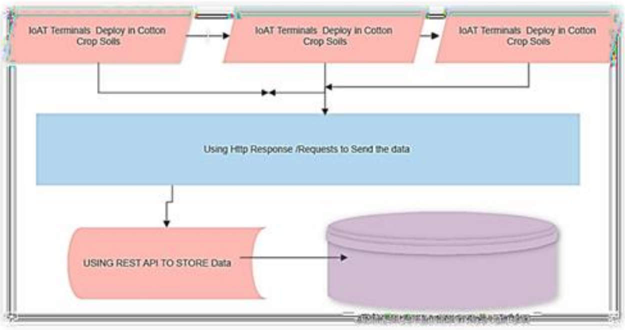

Fig 1: Flow diagram for the continuous monitoring system

The above fig 1 describes the constant monitoring system for developing the to identify the different situations in the cotton paddy field soil. Farmers in real-life situations need to identify the various soil tests for crop growth. The system was developed for the

Farmers get the soil strength in the parameters of the soil temperature, humidity, Nitrogen, Phosphorus, pH value, and potassium type of minerals needed for the growth of the cotton field. These are the growth factors different combinations of soil minerals are the primary impact factor for the growth rate of cotton in black soil.

The above fig 1 describes the process of the system; first of all, to get the minerals like Nitrogen, Phosphorus, potassium, and pH values need to continue monitoring, designing, and developing the board of the IOAT (Internet of Agriculture Things).

There are three stages in the above Figure 1 flow diagram.

First Stage: To Design shown in Figure 2 IOAT terminals to get the data from the cotton paddy fields to get the data like getting from sensors Probe Temperature sensor, Soil Humidity sensor, pH Value from the soil, another sensor NPK Sensor getting the soil minerals Nitrogen, Phosphorus, and Potassium getting the data these all sensors interface with the Arduino UNO.

Second Stage: By using the theses sensor and interfacing the microprocessor with the Arduino UNO board and writing the embedded C code to put the HTTP request to get the data from the Sensor ESP8266 Wifi Sensor to push the data to the cloud server database using REST API URL.

Third Stage: The data is transported from the external terminals through the REST API HTTP request and Responses to store the terminals' sensor data in the field for Cloud Data storage.

5. Design and Working Model

This is the first stage of the object in research to design the IOAT board to interface with the Soil Moisture, pH Sensor, humidity, and NPK Sensor and for transporting the data by using ESP8266 Wifi Sensor to Arduino UNO Board. Figure 1 shows the design and build of the continuous monitoring system and the connectivity between the Sensor and to Arduino UNO Board. Figure 1 in 1 shows that the temperature probe sensor has three pins that indicate colors yellow and connect to the data, the black color indicates the ground connects to Arduino, and the final red color is displayed and connected to 3.3v power connections. At the same time, the remaining sensor connections, numbers are, 2,3,4, and 5 relationships are related to the Arduino board with power and data connections; after connecting these connections, finally ESP8266 wifi sensor to connect the Arduino board to connect and transport data to the Cloud server.

Table 1 shows all the Sensor's delay, error, and precision rates.

Sensor	Power	Measuring Range	Operating Temperature	Resolution	Baud Rate	Precision
NPK	9V-24V	0-1999 mg/kg	5-45 degrees	1mg/kg	9600	+ or – 2 FS
Temperature	3v-5.5v	-55 to 125°C	Plus or minus 5	9-12 bit	9600	±0.5
Soil Moisture	3v-5.5v	–40°Cto 60°C	+/- 3	12 bit	9600	+/- 0.9

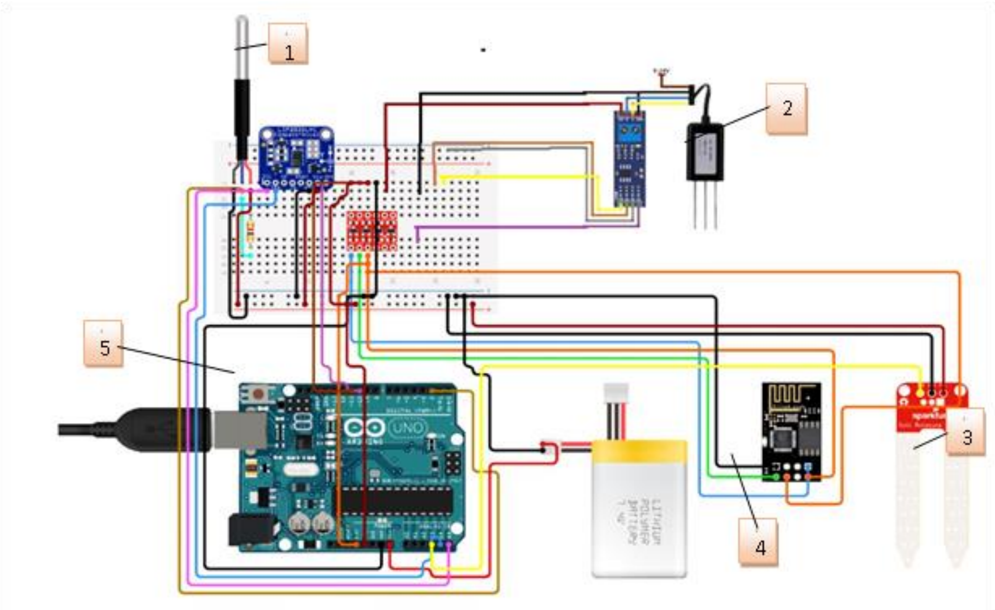

Fig 1 Designing of the Continuous Monitoring System for getting Data from the cotton field sensor.

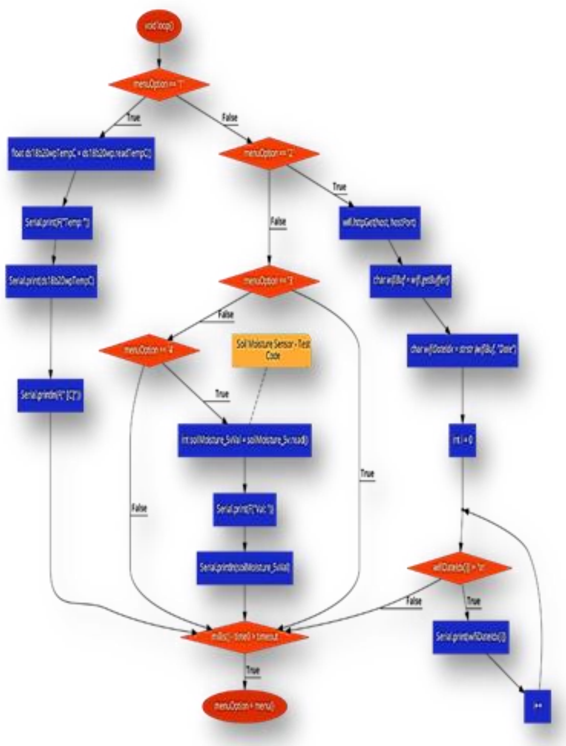

Fig 2: Flow chart for Sending the data from Terminals for the cotton crop filed to a cloud database

The above section shows the after establishing the connections of the sensors and wifi sensor connections. To dump the above embedded C code into Arduino Board. The first steps wifi sensor pins Rx and Tx connection 11 and 12 of the Arduino UNO board and also connect the A3 pin means the analog pin to the Soil moisture sens to the board pin and Arduino Board Connects to the 20v Battery to connect the Arduino UNO. At the same time, this circuit deploys on Black soi in the Cotton paddy field to get the sensor data to and upload through the HTTP connection establishment to the cloud send through the parameters pass through REST API URI. The above figure 2 shows the flow chart of the embedded Code; this Code consists of two sections. One is initialization, and the second one is loop methods in Embaded C. In the setup code to initialize the variables and sensors' baud rate, the second stage is in the loop function implements the Code to read the sensor data sent to the cloud database using the ESP8266 sensor through HTTP protocol.

6. Proposed Methodology

In the above section, discuss the design of an IoT module for the cotton paddy field and get the data from the soil. This soil data consists of the Nitrogen, phosphorus, potassium, pH values, Temperature, and Humidity sensor data directly sent to the cloud and made into a cloud database. Using the cloud data, consider raw data; this raw data can be required converted as a classify data as which kind of data.

Consider that the suggested fertilizer rates for cotton grown under irrigation are 100:50:50 NPK kg/ha, 80:40:40 NPK kg/ha for cotton hybrids fed by rain, and 50:25:25 NPK kg/ha for desi varieties. Cotton seeds will only begin to sprout slowly in soil that is below 15 °C. For active growth, temperatures between 21 and 37 °C are ideal. A temperature lower than 37 °C is preferred. However, the average cotton plant can withstand temperatures as high as 43 °C for a limited period without experiencing any significant damage [W1].

Based on these research values, train the classification algorithm to and test on real-time data set on these features to decide whether soil quality related to cotton fields and improve the production of the cotton crop outcomes will be predicted. In this regard the following section propose the algorithm for classification with the help of a neural network called the Multilayer Perception Algorithm.

One perceptron with several layers is not what is meant by the phrase "multilayer perceptron." It is made up of many layers of perceptrons instead. There is a possibility to use the term "Multilayer Perceptron Network." Furthermore, MLP "perceptrons" don't perform the same functions as real perceptrons. The Heaviside step function is a component of the threshold activation function used by real perceptrons, officially a subset of artificial neurons. In MLP perceptrons, many activation techniques are available. While an MLP neuron may do either classification or regression depending on its activation function, a genuine perceptron only performs binary classification. Later, rather than referring specifically to perceptrons, the word "multilayer perceptron" was used to describe nodes and

Layers that might contain artificial neurons with arbitrary definitions. According to this view, "perceptron" does not refer to all artificial neurons.

6.1 Multilayer Perception Algorithm

Below is a description of the fundamental MLP learning algorithm. It would help if you tried to put this into action.

1. Set all weights in the network to random values between -1 and +1 to initialize it.

2. Get the output after presenting the first training pattern.

3. The goal output and the network output should be compared.

4. Backward-propagate the error.

(a) Use the formula below to adjust the output layer of weights.

$$qho = qho + (\eta\delta owh) \qquad (1)$$

where wh is the output at hidden unit h, qho is the weight used to connect secret unit h with output unit o, and is the learning rate. The following equation yields δo.

$$\delta o = xo(1 - xo)(so - xo) \qquad (2)$$

Where Xo is the output from output layer node δo, and so is the desired output for that node.

(b) The following formula should be used to adjust the input weights.

$$qih = qih + (\eta\delta hwi) \qquad (3)$$

The input at node i of the input layer is represented by δh, the weight which is the weight linking node i of the input layer with node h of the hidden layer and is the learning rate. The formula for calculating h is

$$\delta h = qh(1 - xh) \sum 0(\delta 0q) \qquad (4)$$

5. You can determine the error by averaging the differences between the output vector and the goal. For instance, you may use the following function.

Equation missing – unable to copy

q, the number of units in the output layer. q, the number of units in the output layer.

6. Repeat from 2 for each pattern in the training set to complete one epoch.

7. Randomly mix up the practice set. This is crucial to avoid impacting the network by the data's chronological sequence.

8. Return to step 2 until the error stops changing or for a certain amount of epochs.

7. Results and Inferences

This section mainly discusses how to prepare the data set from the field terminals and after preprocessing the data accordingly. And also, the proceed data apply to the multilayer perception algorithm with different optimization techniques. And the simulations and the data analysis were also done by the R programming and ggplot2 graphs.

TABLE 2: Describe the sample data set for the training data set on algorithms.

ID	Temperature	Humidity	Nitrogen	Phosphorus	Potassium	pHValue	diseases
1	22	89	582	775	302	6.83	1
2	23	77	674	478	505	5.78	2
3	24	88	534	520	837	6.22	2
4	26	83	867	371	718	6	1
5	22	54	708	358	310	6.94	0
6	24	49	505	360	510	6.52	1
7	26	98	886	728	883	5.86	0
8	22	73	379	518	558	5.92	2
9	26	48	261	293	346	6.3	0
10	25	87	684	579	470	6.24	2

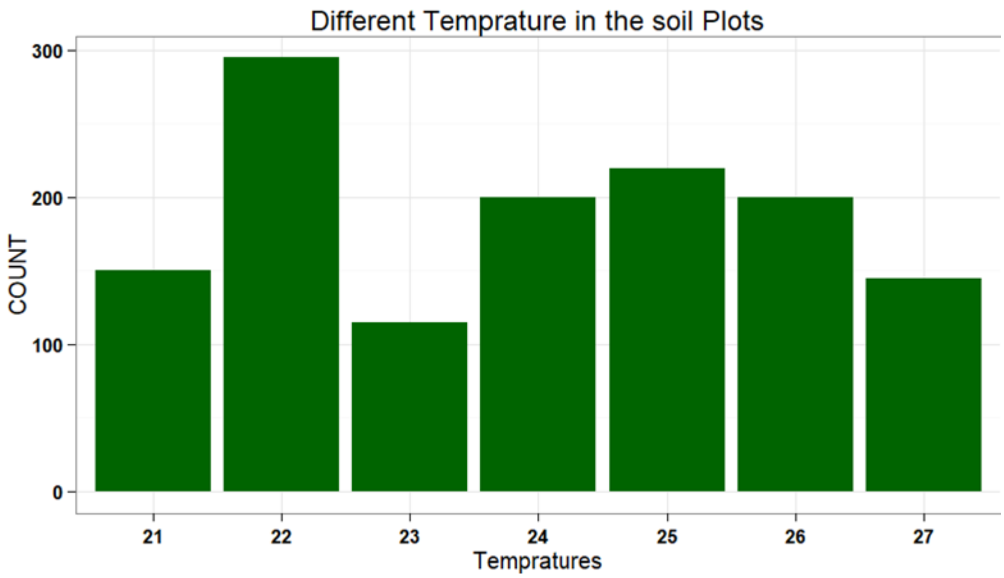

Fig 3 Describe the Count of the Temperature of the field soil and humidity for the growthof the cotton.

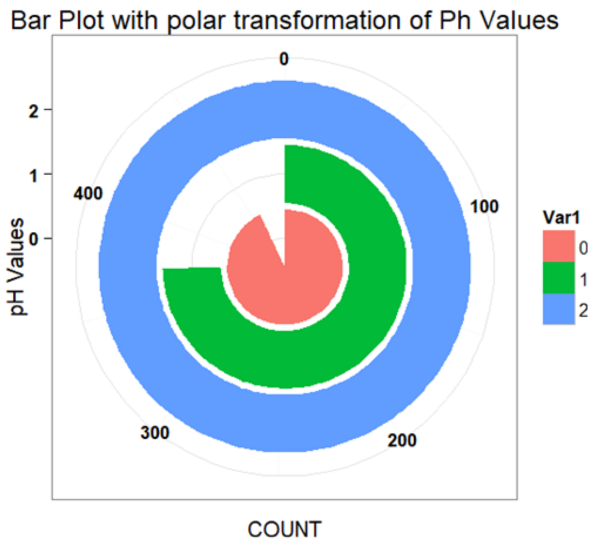

Fig 4 Describe the Count of the pH value of the field soil using a polar bar chart representation.

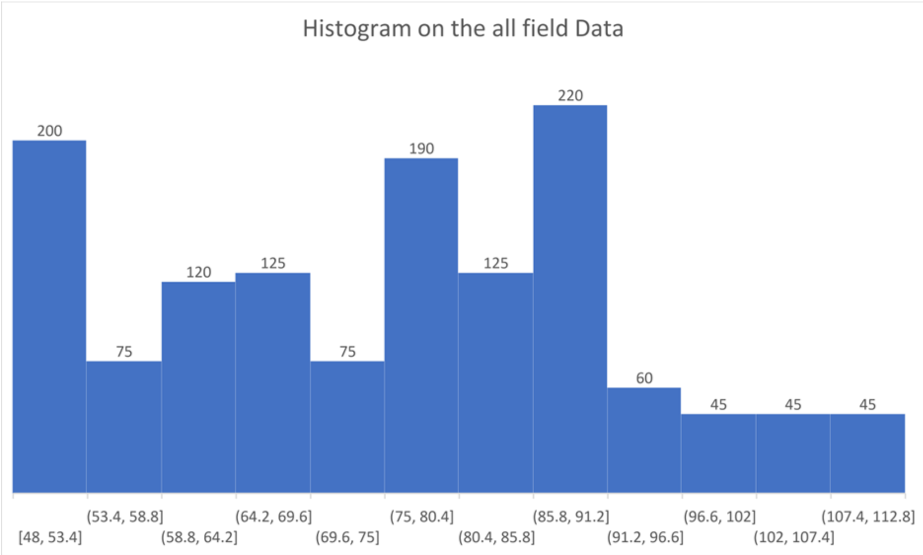

Fig 5 Describe the Histogram chart of all the data set on a cotton field

Table 3: Following shows the algorithm performances metrics and tests on different datasets

Alg orithm	**Data Set**	**Accuracy**	**e rror rate**	**Precision**	**Recall**	**Sensitivity**	**Specificity**
Mu ltilayer Perception	Diabetes	0.85	5.8	0.75	0.84	0.77	0.7
	Breast	0.75	6.2	0.65	0.74	0.68	0.67
	Liver	0.84	5.6	0.77	0.68	0.82	0.81
	vegetable	0.88	5.1	0.76	0.87	0.83	0.81
	Cotton	0.95	2.3	0.92	0.91	0.94	0.95

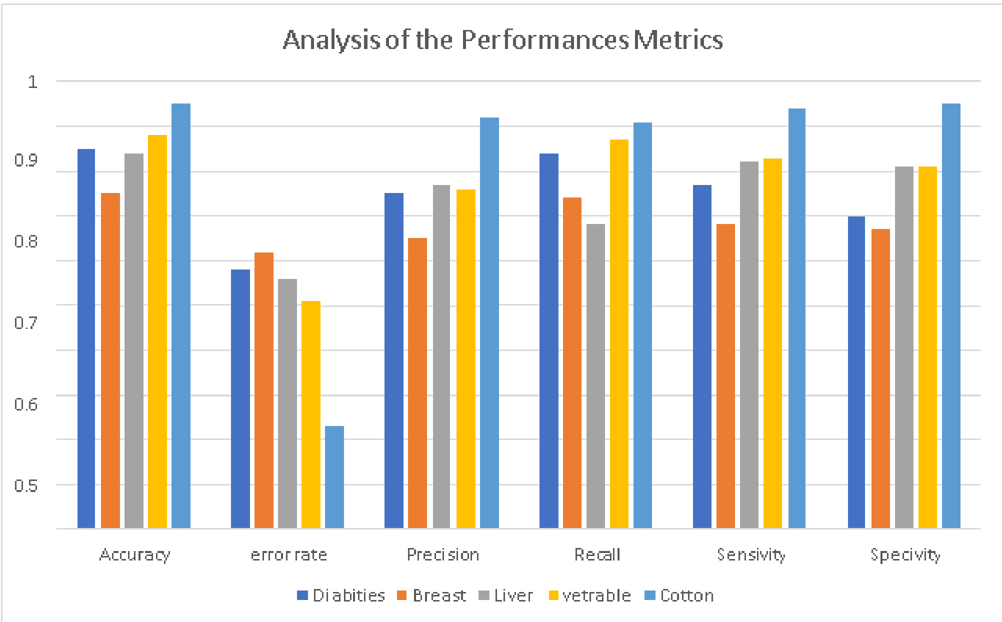

Fig 6: Comparisons of the different data sets on the performance metrics of the Multilayer perception of the algorithm

Table 4: The following table describes the analysis performances of the different algorithmson cotton data sets

lgorithm	Accuracy	error rate	Precision	Recall	Sensitivity	Specificity
Multilayer Perception	0.95	0.23	0.92	0.91	0.94	0.95
Linear Neural Network	0.84	0.32	0.8	0.78	0.79	0.82
Multiple Regression	0.92	0.2	0.87	0.84	0.88	0.89
Logistic Regression	0.91	0.21	0.87	0.82	0.86	0.87
Multilabel Regression	0.9	0.31	0.84	0.79	0.82	0.83

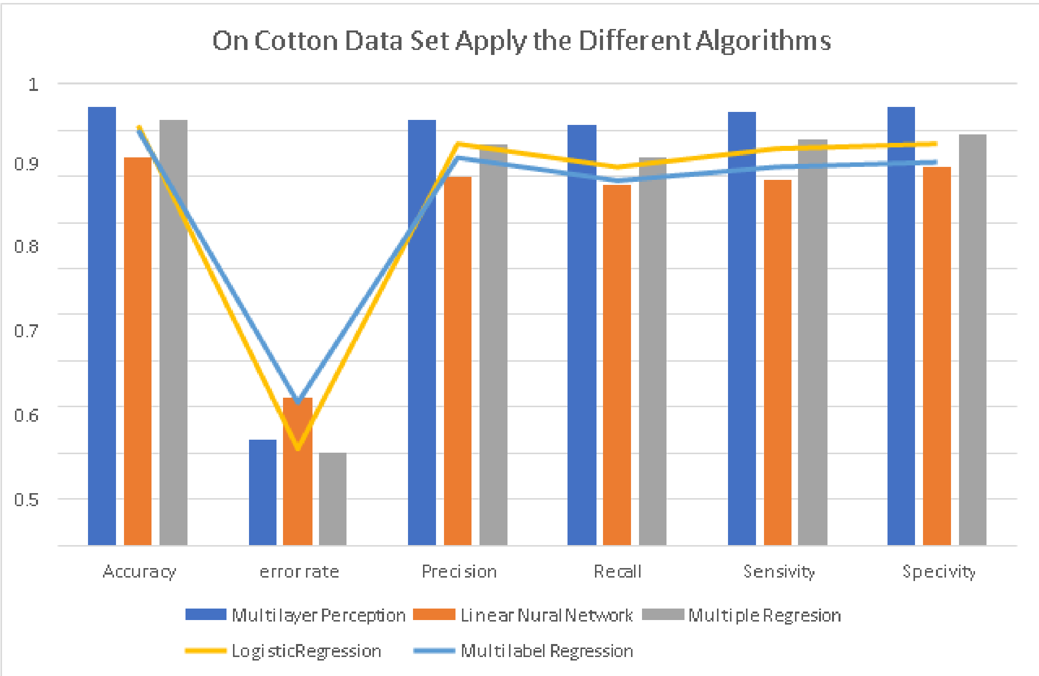

Fig 7: Above chart describes the analysis performances of the different algorithms on cotton data sets

8. Conclusion

In this paper primary outcome is to design and develop the Internet of Health Things to build the board BY using this board to get the data through the HTTP Request to through Internet store in the clouds database. In this regard, design the panel and the API(Application Program Interface) Through the transport of the data through HTTP request and response. These data got from the database, and pre-processed the data after applying the preprocessing of data to use different data sets and applying the cotton field data set to predict whether the soil is suitable for the cotton crop yielding. The other algorithms to compare the performances of the different algorithms are Multilayer Perception Nural Network, Linear Nural Network, Multiple Regression, Logistic Regression, and Multilabel Regression algorithms, and Accuracy 0.95,0.84,0.92,0.91,0.9. Finally, the prediction accuracy of the Multiperception neural network algorithm is the best algorithm for the prediction suitable for the Cotton crops Yielding.

Reference

[1] Akhter, R., & Sofi, S. A. (2022). Precision agriculture using IoT data analytics and machine learning. In Journal of King Saud University - Computer and Information Sciences (Vol. 34, Issue 8, pp. 5602–5618). King Saud bin Abdulaziz University. https://doi.org/10.1016/j.jksuci.2021.05.013

[2] Bhende, N., Kumar, D., & Purohit, J. (2022). MULTILAYER FERTILIZATION TECHNIQUE SCRUTINIZATION IN COTTON CROP. https://doi.org/10.17605/OSF.IO/78K23

[3] Bodake, K., Ghate, R., Doshi, H., Jadhav, P., & Tarle, B. (n.d.). Soil based Fertilizer Recommendation System using Internet of Things. https://doi.org/10.18311/mvpjes/2018/v1i1/18273

[4] Chehri, A., Chaibi, H., Saadane, R., Hakem, N., & Wahbi, M. (2020). A framework of optimizing the deployment of IoT for precision agriculture industry. Procedia Computer Science, 176, 2414–2422. https://doi.org/10.1016/j.procs.2020.09.312

[5] Dilip Charaan, R. M., & Therasa, P. R. (2022). SMART Agriculture using IoT in Tropical States of India. International Journal of Advanced Research in Computer and Communication Engineering Impact Factor 7.39 Vol, 11(1). https://doi.org/10.17148/IJARCCE.2022.11151

[6] Durai, S. K. S., & Shamili, M. D. (2022). Smart farming using Machine Learning and Deep Learning techniques. Decision Analytics Journal, 3, 100041. https://doi.org/10.1016/j.dajour.2022.100041

[7] Fernández-Ahumada, L. M., Ramírez-Faz, J., Torres-Romero, M., & López-Luque, R. (2019). Proposal for the design of monitoring and operating irrigation networks based on IoT, cloud computing and free hardware technologies. Sensors (Switzerland), 19(10). https://doi.org/10.3390/s19102318

[8] Fernández-Ahumada, L. M., Ramírez-Faz, J., Torres-Romero, M., & López-Luque, R. (2019). Proposal for the design of monitoring and operating irrigation networks based on IoT, cloud computing and free hardware technologies. Sensors (Switzerland), 19(10). https://doi.org/10.3390/s19102318

[9] Kapse, S., Kale, S., Bhongade, S., Sangamnerkar, S., & Gotmare, Y. (n.d.). IOT Enable Soil Testing & NPK Nutrient Detection.

[10] Patki, S. S., & Sable, G. S. (n.d.). A Review: Cotton Leaf Disease Detection. IOSR Journal of VLSI and Signal Processing (IOSR-JVSP, 6(3), 2319–4197. https://doi.org/10.9790/4200-0603017881

[11] Cybenko, G. 1989. Approximation by superpositions of a sigmoidal function Mathematics of Control, Signals, and Systems, 2(4), 303–314.

[12] Hastie, Trevor. Tibshirani, Robert. Friedman, Jerome. The Elements of Statistical Learning: Data Mining, Inference, and Prediction. Springer, New York, NY, 2009.

[13] https://www.cicr.org.in/

[14] C. Soumya, Praveen Raj, B. Deepanraj, N. Senthilkumar, Islanding power quality detection using lighting search optimization with deep learning model on distributed generation systems, Renewable Energy Focus, Vol. 43, 2022, 74–83