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Integration of IoT and DNN Model to Support the Precision Crop

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Abstract: Agriculture filed is the major source of living for humans in many countries. As the population is increasing there was no proportionate growth in in agriculture productions which may leads to the harm to the societies. Most of the cases we depended on natural resources for cultivation, due to geological disasters many times there may be damage of the fields. Our main focus is to suggest precision crop based on climatical situations. We integrated IoT with ML algorithms for this purpose for enabling precision crop. Combining IoT with DNN (Deep Neural Networks) for making various aspects of test such as soil, temperature, humidity, pH values generating from various sources can be decided which crop is suitable the conditions. This paper gives the usage of IoT sensors for decision making for crop fields, optimizing the usage of resources and directs various farming methods. The comparative study proved our results are better than the many existed works.

Keywords: *IoT, DNN, crop precision, sensor data, precision agriculture, soil test, pH data collection.*

1. Introduction

In order to ensure both economic stability and food security worldwide, agriculture is essential. The need for food production is gradually increasing as the world's population remains to rise. Traditional agricultural methods, on the other hand, frequently result in the inefficient use of resources, such as water, fertilizers, and pesticides, which causes environmental damage and financial losses. An answer to these problems is precision agriculture, which seeks to maximize crop management and resource allocation. Precision crop management is now possible because to the combination of IoT and DNN models.

Using IoT and DNN models together offers a revolutionary way to control precision crops in agriculture. Farmers can optimize resource use, boost crop yields, and support sustainable agriculture by utilizing live data from IoT sensors and the analytical strength of DNNs. Although there are difficulties, the advantages might make this integration a promising path for agriculture's future. It is crucial for politicians, academics, and farmers to work together in order to fully use this integrated strategy as technology develops.

The biggest issues in the agriculture industry are related to a lack of understanding of how the climate is changing. Precision farming techniques may be used to overcome the difficulties in agriculture since every crop has unique climatic characteristics that make it suited for that crop. Precision farming aids in supplying the world's growing population with food while also preserving agricultural productivity and raising crop yield rates. India's population and expanding requirements favor supportable agriculture.

Although several measures have been taken to reduce crop loss, the conventional approach has certain drawbacks. Crop selection alternatives, such as precision farming, can be utilized to get around the drawbacks of conventional agricultural techniques. IoT and prediction systems are used in precision farming, which is a key component of decision-making.

To decrease crop loss, the agricultural industry has recently been working to implement smart agriculture applies using the Internet of Things. Sensors enable the IoT structure to get data from the field. The prediction framework may then be provided with the sensor data to receive suggestions [1]. Crop selection and shifting climatic conditions are the two main issues in agriculture that farmers encounter. There is no ideal crop recommendation, but these issues may be handled with the use of current forecast and monitoring techniques. Lack of sufficient fertilizer delivery, inaccurate analysis, choosing efficient algorithms, and efficient selection of characteristics are some of the flaws detected in the

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current system. All of these factors may have an impact on the crop production.

In general, weather-based frangible agriculture systems produce greater crops. A survey has disputed the idea that, with a population increase to 10 billion, we would undoubtedly reach food catastrophe by 2050. It means that if we don't develop and enhance smart agricultural technology, our capacity to produce enough food would go bankrupt.

As a result, it's essential to create a cost-effective solution for Indian farmers in order to manage the country's scarce resources properly. The method ought to assist farmers in increasing food production and quality while promptly preventing crop illnesses.

2. Related Work

Inputs for the CNN-RNN model developed by Khaki, Wang, and Archontoulis (Citation2020) included meteorological variables, soil characteristics, and management techniques. Additionally, a guided backpropagation approach was utilised to choose features, which improved the model's explicability.

One of the most crucial components of any nation's economic and social growth has been the agricultural sector. With a population of over 7 billion people, the globe is barely meeting its food demands. Moreover, our existing food supply could not be adequate given the exponential expansion in population expected over the next 25 to 30 years. In order for the world to survive, it is anticipated that we will need to raise our food supply by at least 70% [1]. Contrary to other industries, the agriculture sector has not yet seen a "boom" in the present millennium.

Thomas Malthus asserted in his well-known "theory of population growth" [2] that population growth follows a geometric trend as opposed to an arithmetic progression for agricultural output. The Stanford University researchers Ehrlich & Ehrlich [3] and Jared Diamond [4] agree that growing consumption and the limited supply of resources increase the chances of famine and hardship.

In light of the fact that land, labour, material, and capital are all finite resources that are becoming more and more scarce, agricultural output must increase significantly and productively.

With the UN estimating that the world's population will likely reach 8.9 billion by 2050, highest soil eroding, arable land-dwelling, oceans partially turning into deceased zones, and marine classes dwindling, Philip Kotler [5] explains that it appears to be incredible to feedstuff the hungry entrances at the present manufacture rate. Another revolution is about to occur as a result of human creativity to avoid this potential situation.

Smart agricultural scheme based on detection technology was proposed by R. Ramya, C. Sandhya, and R. Shwetha. In essence, their system measures light intensity using sensors, including pH, temperature, moisture, and sensors. The sensors are positioned such that they are able to perceive the ambient conditions well. Without any processing, this device only gathers data from the surroundings. It is thus advised to include the gathered data into the procedure for improved crop output [2]. Using artificial neural networks and cellphones, Giritharan Ravichandran and Koteeshwari R S suggested a forecaster for the crop that provides farmers with information. In this, a strategy to prevent crop loss is suggested. The suggested approach aids farmers by selecting crops that may enable them to increase agricultural yield. An ANN-using android application is used to create a system. The method considers variables including rainfall, temperature, depth, pH, nitrogen, phosphate, and potassium. The advisor will recommend a crop and predict its productivity. The fact that farmers may simply utilise this system is a benefit.

If the advisor settings could be controlled in real-time, this system would perform better [3].

As a consequence, the system advises using various cutting-edge strategies to improve the outcomes.

In their study, Rekha P, Maneesha V. Ramesh, Venkata Prasanna Rangan, and Nibi K V suggested a farming prediction framework that comprises sensors that detect the agricultural features with the use of IoT framework in order to provide advise to the farmers. These sensors, which are used in agricultural fields to measure things like soil moisture, temperature, and pH, communicate using radio frequency technology.

Methods	Algorithm	Parameter for Input Data	Parameters for Output Data	Resource
Regression	Linear regression	Real-time data collected	Apple scab prediction	[10]
Regression	Edge and cloud computing using IoT sensors	Sensors used for analyzing water cycle and irrigation	Soil and water data collection	[12]
Regression	Exploration and exploitation method and improved genetic Algorithm	Soil nutrient data	Optimal nutrition recommendation	[13]
Classification	Map-Reduce functionality and NB classifier model for crop prediction	Satellite images, sensor data, irrigation report, and crop and weather data	Recommending crops	[14]
Classification	Artificial neural network and principal component analysis	Soil analysis	Classification of crops, fruits, taste, and odor detection	[15]
Classification	Random forest, linear SVM, and naive Bayes	Soil, rainfall, and surface temperature parameters	Crop selection	[16]
Linear regression and RMSE	Random forest, Gaussian naive	Bayes and support vector machine Soil sample	Soil grade, predicted crops	[17]
Clustering	k means clustering algorithm	Crop images	NPK values and deficiency identification	[18]
Unsupervised neural network	CNN and MLP	Satellite images	Predict crop type (wheat, maize, sunflower, soybeans, and sugar beet)	[19]

Table 1. Various works on precision crop.

3. Proposed Work

Everything is now feasible thanks to current technical progress that uses the Internet of Things and deep learning. The IoT system is very beneficial for employing the sensors to get real-time data. Utilizing the useful data will allow it to be put into a trained deep learning system, such an artificial neural network, for prediction. The results are very helpful in determining the best crop to plant in the particular field location. The dataset, characteristics, preprocessing stage, Internet of Things design, and Deep Neural Network are all described in this part.

PRECISION CROP APPROACH

Environmental monitoring systems assist in acquiring the quick, precise, and consistent measurements needed for precision agriculture, hence promoting the growth of automation in the agricultural sector [6]. GPS, soil scanning, and IoT technologies are all used in precision agriculture to precisely quantify field fluctuations. The field is divided into a grid of tiny, equal cells as the initial step in grid soil sampling [7]. A satellite scans the field grid, sending signals to a tractor-mounted dish antenna that aids in physically collecting soil samples from each cell. These samples are then tested for physical and chemical characteristics in a modern soil testing facility. A variable-rate fertiliser application technique [8] is used to produce colour grammes for the entire field in order to autonomously administer fertilisers at different rates only where they are needed. This optimizes crop production by bringing consistency and balance to soil fertility. These methods of selective application can significantly improve the efficacy of insecticides and herbicides.

Soil health cards, which are tangible records of historical data, are kept both electronically and physically. Within arable fields, it's critical to recognise, assess, and swiftly avoid or correct site-specific variations. For instance, the quantity and flow of water for irrigation may be precisely controlled specific to a domain or cell, taking into consideration the moisture content of the soil and surroundings, by integrating humidity sensors and weather predictions using geospatial systems. This makes it possible to utilise and save water in the best possible way.

As a result, precision agriculture makes use of technology to provide precise information and data in real-time and dynamically across the whole crop cycle. In order to maximise yields, farmers are able to control every aspect of crop cultivation, including soil properties, humidity levels, insect penetration losses, and environmental factors.

In order to ensure both economic stability and food security worldwide, agriculture is essential. The need for food production is gradually rising as the world's population continues to rise. Traditional agricultural methods, on the other hand, frequently result in the inefficient use of resources, such as water, fertilizers, and pesticides, which causes environmental damage and financial losses. An answer to these problems is precision agriculture, which seeks to maximise crop management and resource allocation. Precision crop management is now possible because to the combination of IoT and DNN models.

4. Agricultural Aspects of Iot

IoT uses networked sensors, gadgets, and systems to gather, transmit, and process information from the real world. IoT technology is used in agriculture to track a number of characteristics that are important for crop development and health, such as soil moisture, temperature, humidity, and insect activity. Important IoT elements in agriculture include:

Sensor networks are used in fields to deploy sensors that wirelessly send data to a central database or cloud platform.

Data analytics is the processing and analysis of IoT data to produce actionable insights, such as the timing of fertilizer applications, irrigation, or the detection of disease outbreaks.

Remote monitoring: Farmers may use computers or cellphones to get real-time data on crop conditions, allowing them to make decisions quickly.

DEEP NEURAL NETS IN AGRICULTURE

A subclass of artificial neural networks known as DNNs has proven to have exceptional skills in image and data processing. DNNs are used in agriculture to do tasks including weed identification, crop disease diagnosis, and yield prediction. DNNs have several important agricultural uses.

Image Recognition: By examining photos taken by drones or cameras, DNNs can categories and identify pests or illnesses in crops.

Predictive modelling: DNNs can anticipate agricultural yields, assisting farmers in determining the best times to sow and harvest their crops.

Precision pest management: By locating locations with the most insect activity, DNNs make it possible to apply pesticides in a targeted manner.

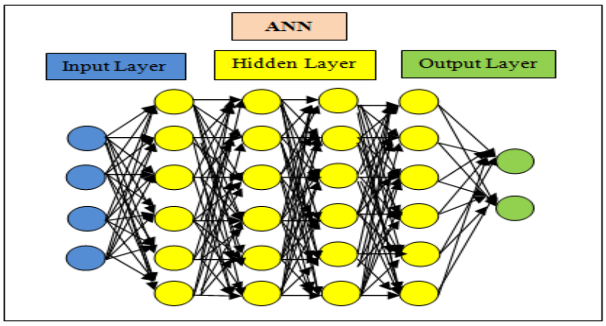

Fig 1. Model for DNN

Due to the fact that noisy, inconsistent, and missing data cannot be handled by deep learning, the dataset for the crop recommendation model must be preprocessed. The data is noisy, which causes outliers and errors to exist. The data is contradictory or inconsistent in that it demonstrates a discrepancy in attributes. The phrase "incomplete data" describes information that is missing from a dataset's properties or attribute values. The core steps in every data preparation phase are data integration, data transformation, data reduction, and data cleaning.

Open source that provide lists of many elements of crop growth were used to create the dataset for the crop suggestion algorithm. The dataset includes thirteen distinct variables in total, including soil type, land type, soil moisture, temperature, humidity, pH, the area planted, soil N, soil P, soil K, rainfall, production, and class label. Factors that affect crop suggestion include soil type, land type, temperature, humidity, the area seeded, soil moisture, and pH. Rice and maize are among the crops that are taken into account.

$$Z = z - \min(z) / \max(z) - \min(z) \text{-------Eq (1).}$$

Z is the value of the normalised data, where Z is the original value that has to be normalised, max(z) is the feature's highest possible normalised value, and min(x) is the feature's lowest possible normalised value. Through the process of binarization, the numerical feature value of the feature scaled value may be changed into a Boolean value.

Implementing the model architecture, creating the DNN model, collecting IoT data, training the model on the preprocessed data, and testing the learned model are all crucial. The best activation functions must also be chosen, learning rates must be increased to reduce error rates, and accuracy must be increased via gradient descent and backpropagation.

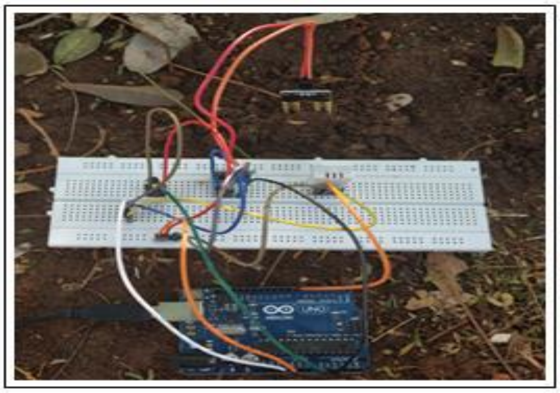

Fig 2. Sensor data collection with IoT devices.

Since water is the foundation for supplying nutrients to the soil, the purpose of the Arduino soil moisture sensor is to measure the water content. The surrounding field area's temperature is measured using an LM35 temperature sensor. Similar to this, the pH of the soil needs to be continuously regulated since it affects both the crops' pace of growth and the availability of soil nutrients. The pH metre may be used to determine the pH level. The data that is detected through Wi-Fi will be saved in an excel document. The Arduino software and the Parallax PLX-DAQ data acquisition tool are used to save data in an excel file. Table I displays the data that was gathered from IoT sensors using PLX-DAQ.

S. No	Time	Temperature (C)	Humidity (%)	Moisture (%)
1	5:44:25	32.55	43.5	78.55
2	6:44:28	32.55	43.5	82.10
3	6:44:26	32.55	43.6	83.44
4	6:44:32	32.55	43.8	83.12
5	6:44:35	32.55	44.5	82.32
6	6:44:38	32.55	44.7	83.45
7	6:44:39	32.55	44.8	81.55
8	6:44:42	32.55	42.3	80.12
9	6:44:45	32.55	41.5	80.05
10	6:44:48	32.55	41.8	81.34
11	6:44:52	32.55	42.2	82.35
12	6:44:58	32.55	43.8	82.09

Table 2. Data collection with PLX-DAQ

An artificial neural network prediction model, real-time data collection, and forecasting are all used in the development of the crop recommendation system. The flow of the architecture starts with preprocessing. Following preprocessing, an ANN approach is used to train the dataset and provide a prediction model for crop suggestions. To put the established model to the test, data is given. When testing, which compares the trained model to random input data, gradient descent backpropagation is used to alter the weights based on the prediction model's accuracy rate and error value. Until the accuracy rate rises and the error value falls, this process is repeated.

After receiving data from the user and IoT sensors through the GUI, the crop suggestion model provides precise crop recommendations. The precision crop recommendation system's architecture, which includes training, testing, and prediction, is depicted in Fig. 4 below.

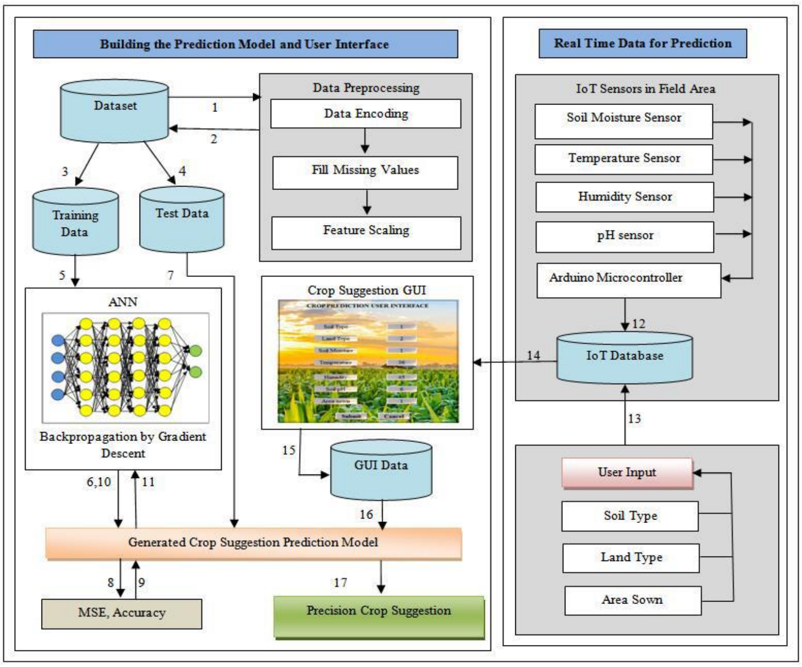

Fig 3. Architecture precision crop flow chart.

5. Rate of Learning

The algorithm's learning rate must be provided in order to train the model. A neuron cannot be educated if the learning rate is too high. The model will have been improperly trained if the learning rate has increased. The weights of a neural network are modified based on learning rate using the gradient descent error computation approach. When the number of epochs is increased, the loss drops for learning rates that are good, grows for learning rates that are very high, is slightly low for low learning rates, and is high for high learning rates. Mean Squared Error (MSE), a measure of loss, is used. Therefore, if the learning rate is low, the training will be trustworthy; nevertheless, it will take some time for the optimizer to reduce the loss function. The training will get poorer and the loss will be significant if the learning rate is large; these effects cannot be minimized. The most prudent method for selecting the learning rate is to start by providing random numbers and then check for the lowest loss possible to avoid delaying training pace. A big number, such as 0.3 or 0.2, can be chosen at first and lowered over the course of 100 iterations or epochs to smaller values, such as 0.01 or 0.001.

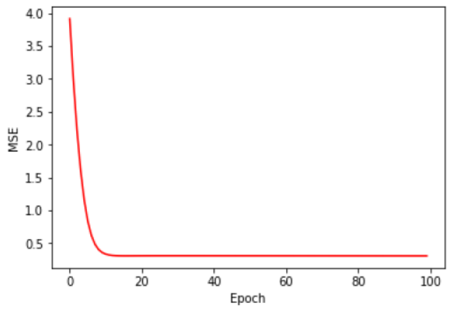

Fig 4. MSE learning rate.

The initialization of the weights occurs during the creation of a neural network using a method called random value weight assignment. To do this, the gradient of the loss function is calculated. The prediction model's cost is decreased with the aid of the gradient descent optimization. The gradient is a metric that reveals how the error changes in response to a change in weight. As a result, the weight may be modified depending on the error generated; this step is required to ensure that the number chosen will match our model. The actual output and anticipated output are observed to vary throughout training, which indicates an rise in fault rate. In these situations, backpropagation using gradient descent determines the least error by propagating both frontward and rearward. The masses are changed in order to minimises the loss in error value and the cost function. As a result, the accuracy is raised to almost 97% in the final analysis.

In addition to its core usage, the spyder may be used with other apps like Qt Designer. The application in question is a graphic user interface (GUI) development tool. For building interactive GUIs, Anaconda provides the PyQt5 package. By converting the.ui user interface file to the.py Python file using the pyuic5 (python user interface) function on the anaconda command line, this package may be used to execute the GUI created by the Qt Designer. The Qt designer is used to develop the crop proposal Graphical User Interface (GUI), which pulls information from the user view such as soil type, land type, and area seeded. The extra data, which includes pH, temperature, humidity, and soil moisture, is gathered via an IoT database. Information obtained from the relevant field area is included in the IoT database.

6. Activation Function

The artificial neuron uses one of its functions, which is activation. The output of a typical neuron is shown in (2), where

y = sum (weights * inputs) + bias---Eq (2).

If x1 and x2 are the inputs and w1 and w2 are the weights of the neuron, then these values represent the output of the neuron.

In this equation, y stands for the weighted input value's output, input stands for the number of inputs sent to the network, weights stands for the amount of weight assigned to a neuron during processing, and bias stands for the parameter used to alter the output. The range of the neuron's output, from - infinity to +infinity, is infinite.

HL	AF	HN	TA
2	Sigmoid	4	92.23%
3	Sigmoid	6	94.12%
4	Sigmoid	9	93.45%
5	Sigmoid	12	92.25%
2	ReLU	4	82.12%
3	ReLU	6	85.32%
4	ReLU	9	84.23%
4	ReLU	12	79.12%
5	Tanh	4	79.54%.
2	Tanh	6	80.56%
3	Tanh	9	82.47%
4	Tanh	12	83.23%

(HL: Hidden Layer, AF: Activation Function, HN: Hidden Neurons, TA: Test Accuracy)

Table 3. Summary of Activation functions comparison.

S. No	Crop Filed	Longitude	Latitude
1	Rice	18.12430	82.0912
2	Barile	18.32156	82.8651
3	Ground Nut	18.12480	82.4561
4	Cotton	18.21430	82.2457
5	Mango	18.12611	82.3245
6	Maize	18.08965	82.5542
7	Tomato	18.06542	82.9847
8	Potato	18.06523	82.8956
9	Beans	18.01247	82.8754
10	Rice	18.13255	82.9865
12	Cotton	18.22134	82.5478
13	Ground Nut	18.09875	82.3654
14	Rice	18.12360	82.8723

Table 4. Various locations data collection with GPS.

Each layer uses an activation function to translate the input value into the binary range of (0, 1) and generate the desired output. Whether a certain neuron is active or inactive is determined by the activation function. Tanh, ReLU, and Sigmoid are the three most often utilised activation functions. Table 2, below illustrates a comparison of several activation functions depending on the hidden layer and their test accuracy.

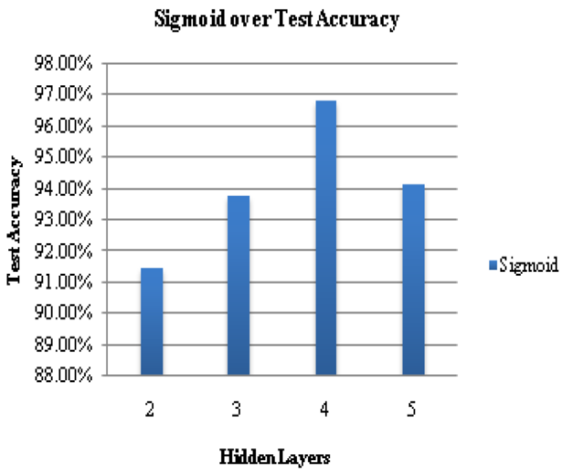

Fig 5. Accuracy rate of Sigmoid function.

When the amount of data in a DNN increases, so does the accuracy of the neural network. The Deep Neural Network's architecture includes additional hidden layers to increase accuracy. It is well known that a feature is taken from each buried layer. To avoid overfitting and underfitting, it is also important to choose the number of neurons for each hidden layer. When fewer neurons are employed, underfitting develops in the buried layer. In a similar manner, a large number of neurons causes overfitting in the hidden layer.

The hidden layer set S1 to S11 identifies the number of neurons needed for processing in each of the hidden layers H1, H2, H3, and H4. With nine neurons in each layer, the S7 set is found to have the highest accuracy, measuring at about 95.65%. An input layer, one or more hidden layers, and an output layer are the standard three levels of the multilayer perceptron model. The number of neurons and hidden layers should be carefully considered since they have a significant influence on the outcome. Thirteen neurons make up the model's input layer. In the hidden layer's output layer, which is thought to include four neurons, two neurons decide whether to plant rice or maize. It is assumed that nine neurons can be utilised for processing in each buried layer.

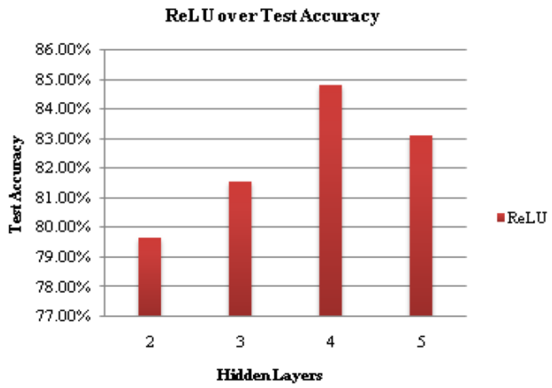

Fig 6. Accuracy rate of ReLU function.

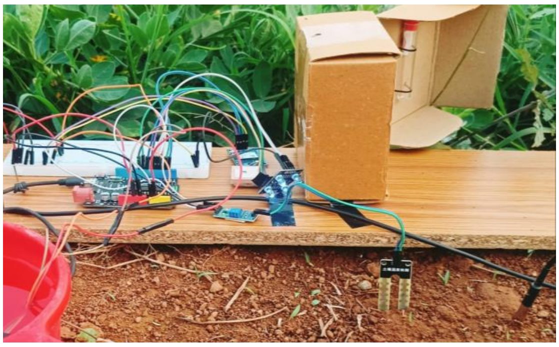

Fig 7. Device used to connect IoT sensor with Arduino.

It is shown that the sigmoid obtains the maximum accuracy among the three activation functions, scoring around 96.81%, when compared to Tanh and ReLU. A prediction may be made using a probability measurement and the sigmoid function. The sigmoid curve's value ranges from 0 to 1. The sigmoid activation function predicts that the output will be one when the value is greater than 0.5 and zero when the value is lower than 0.5.

7. Conclusion

Future generations will need to priorities the agriculture industry. Even though DNN has been used in several works, its performance is continually improving. In general, the Deep Neural Network has a great processing capacity, and the little dataset has no effect on how well it performs. As a result, when Deep Learning is used to train an ANN, its performance is enhanced by taking into account more datasets. The present agricultural methods employ an effective forecast approach to try to resolve the problems. The precision crop recommendation model is created in a way that it can deal with the difficulties that farmers encounter. Thus, the crop prediction algorithm effectively recommends the proper crop for production regardless of seasonal fluctuations. The GUI's recommendations for crops tremendously assist farmers in choosing the right one for their particular land. The method may be improved in the future by utilizing hybrid ways to recommend fertilizers that should be supplied in a timely manner in order to achieve high profit and yield. Finally, the study discussed the challenges involved in creating and deploying such real-time systems. To this end, a local poll was carried out to see what local residents thought about precision agriculture. However, there are still a lot of obstacles to overcome before the suggested framework may be widely used. These include the upfront cost of implementation, deployment, training, environmental factors, and other aspects. But the gains will take on a visible and usable shape after the aforementioned constraints are surmounted. In the future, the study will be expanded to cover other factors affecting the crop. According to the article, precision Aggie is based on four pillars: the right source, the right place, the right quantity, and the right time.

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