DESIGN AND IMPLEMENTATION OF SMART AGRICULTURE SYSTEM AND PLANT DISEASE RECOGNITION

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This Report Presented in Partial Fulfillment of the Requirements for

The Degree of Bachelor of Science in Computer Science and Engineering

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DHAKA, BANGLADESH
DECEMBER 2019

APPROVAL

This Project/internship titled **"Design and Implementation of Smart Agriculture System and Plant Disease Recognition"**, submitted by Md Rahmat Ullah, Abir Hasnat, Nagifa Anjum Dola, ID No: 161-15-6970, 161-15-6789, 161-15-6822 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 6th December, 2019.

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We hereby declare that, this thesis has been done by us under the supervision of **Abdus Sattar, Assistant Professor, Department of CSE** Daffodil International University. We also declare that neither this thesis nor any part of this thesis has been submitted elsewhere for award of any degree or diploma.

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ACKNOWLEDGEMENT

First we express our heartiest thanks and gratefulness to almighty God for His divine blessing makes us possible to complete the final thesis successfully.

We really grateful and wish our profound our indebtedness to **Abdus Sattar**, Assistant Professor, Department of CSE Daffodil International University, Dhaka. Deep Knowledge & keen interest of our supervisor in the field of “**IoT and Machine Learning based agriculture**” to carry out this thesis. His endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticisms, valuable advice, reading many inferior draft and correcting them at all stage have made it possible to complete this thesis.

We would like to express our heartiest gratitude to **Pro. Dr. Akhter Hossain, Professor, and Head,** Department of CSE, for his kind help to finish our thesis and also to other faculty members and the staff of CSE department of Daffodil International University.

We would like to thank our entire course mate in Daffodil International University, who took part in this discuss while completing the course work.

Finally, we must acknowledge with due respect the constant support and passion of our parents.

ABSTRACT

Human existence cannot be envisioned without agriculture. Soil is one of the major components of agriculture. Depending on the PH scale, soil temperature and moisture of soil, various types of soil are suitable for a variety of crops and food grains. But due to the farmer's lack of absolute knowledge about soil utility makes them face many more difficulties in the way of growing crops. For these inconveniences, every year a huge number of crops are being wasted. Furthermore, crops are also being damaged by various types of diseases and lack of quick remedy adopted by the farmers. The fastest stratagem of predicting plant diseases is to analyze leaf's physiognomy changes and compare them with their actual color, shape, structure, etc. We have used Convolutional Neural Network as a training method. CNN works via 3 dimensions of layers where neurons of every layer aren't fully connected to the next layer rather only a small portion is connected and the output will be decreased to a single dimension. For this, even with big datasets CNN works faster than any other networks. The program will exert plant images as input and detaching them to predict plant diseases. Plant disease recognition on the basis of leaf's physiognomy changes and embedded based agriculture system are the fundamental purpose of our project. This paper represents a system where it is possible to predict and suggest which crops are compatible with any specific lands based on soil moisture and PH scale and all the information related to the weather in a particular area and detect the actual diseases of different types of crops.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

The way a human body can't be imagined without the spine, similarly country without agriculture is like a fish without water. Agriculture not only secures the health of a nation but also the economic system of a nation depends directly or indirectly on agriculture. Agriculture is the largest source of food, clothing, and employment. Foods like fruits, crops, vegetables, etc. food grains are produced by agriculture. Through agriculture, clothing materials like cotton, jute, silk, and other fibers are yielded. Agriculture offers poorer farmers to work through that they can earn their living by doing farming. In the present world, Plant diseases are a leading threat to food production and food diversity caused by different environmental conditions and pathogens. Worldwide, plant diseases have become an incubus because of the reduction in yield grain and fruits. Plant disease is not only reducing the quantity of production of fruits and grains but also causes of decreasing the quality level. Plant diseases influences our ecosystem negatively by damaging crops, soil, etc.

Bangladesh is a land of agriculture. Agricultural sectors play an exigent role in the economy of Bangladesh. Here in Bangladesh, most of our poor village people are farmers where their livelihood fully depends on agriculture. Every year Bangladesh is suffering from unrecoverable loss in order to meet the food needs due to plant diseases and insufficiency of smart agriculture technology.

To reduce the losses of crops it's very necessary to find out the reason behind these losses. Usually, it is seen that farmers literally have no actual idea of the properties and predispositions of agricultural land's soil and crops. They do not even take this matter into consideration. Due to their lack of knowledge about soil, weather and plant diseases, they can't take initiatives at the right time while growing crops. As a result, soil fertility declines, as well as more crops, are lost. If a system can be developed which allows farmers to be aware of soil and weather conditions as well as give a suggestion on which crops are suitable to grow on a given land and plants are defected in which particular diseases, then it will be possible to save most of the food grains from being wasted. In order to ensure the quality of food products and monitor environmental circumstances and plants growth, an embedded sensor system and machine learning algorithm are used for analysis in less time period.

In our proposed embedded system, we have used four sensors including DHT22 sensor, Soil moisture sensor, Soil temperature sensor, and pH sensor. By using a soil moisture sensor, it easily gets to know if the given land soil is having a shortage of water or not. In addition to using the weather sensor, farmers can get all weather-related data, and air temperature and also soil temperature is also being calculated by using soil temperature sensor. Soil can be acidic or alkaline. pH sensor works to investigate the pH level of soil whether the soil is acidic or alkaline. We amalgamate these four types of sensors for querying properties of soil and atmospheric weather conditions. After getting all the valid information from these sensors, our embedded system model suggests a bunch of crops and food grains through that farmers can be able to know about the properties of soil as well as which soil is particularly capable for fulfilling the nutrients that any precise plants need in what temperature or weather conditions.

Detection of plant diseases can be easily done through image processing. Digital images are being analyzed and processed through image processing using computer algorithms to detect specific objects differently. As in our machine learning based model, plant diseases can be recognized through the images of plant leaves and detect the diseases by an automated system. Artificial Neural Network (ANN) is inspired by human's nervous system so it can process an image using its numerous layers of neuron & can detect the problem like the brain do with its large number of interconnected neurons. Among the various algorithms of ANN, we have used the Convolutional Neural Network (CNN). CNN works based on some layers, few of them are convolutional, pooling and activation layer. By using the first few layers, CNN identifies the lines and corners of an image. As far as image processing goes deeper, CNN analyses image patterns and also finds more complex patterns and features of an image. After finishing all the process, proper image recognition can be possible. The major convenience of CNN is if we feed the CNN algorithm with raw images then CNN can learn apposite features for a specific task. CNN algorithm works faster while image processing.

Our embedded based system approach is about 30 different types of food grains and our machine learning proposed approach is about 26 diseases and 12 healthy classes of 14 vegetables and fruits. By training model with image dataset our model can be able to detect plant diseases to get the best success rate.

1.2 Motivation

Our country faces many agricultural destructions due to climate change in recent years. Last time, after visiting a village, we noticed that most of the village's farmers were planting various crops without absolute knowledge about environmental parameters such as soil, weather and temperature which is why they are not getting good yield even after the end of the season. Also they don’t even concern about their lack of knowledge pertaining to crops growth and its different kinds of diseases. To know more deeply about our agricultural circumstances, we went through a few villages and realized that most of the farmers are doing the same thing. After seeing their problems, we have that feeling that we could do something or create a system where we can support them virtually and through which it is possible to measure which crops are suitable for their land to produce and to find out the actual disease of crops have and all the information related to the weather in a particular area so that they can understand which crops they should produce for getting good yield and profit and how to detect plant diseases. If we can adopt such a method, the farmers of our country will be able to produce good yields of food grains with less investments in a short time. Therefore, they can overwhelm their frustrations, overcome the poverty & can live happily. It will be possible to unveil a good way in the field of our agriculture.

1.3 Problem Definition

As an agricultural country, Bangladesh faces a lots of difficulties in the agriculture fields. It is necessary to build a smart agricultural system which should be introduced to the farmers for the development of our country. To reduce the damages, occur in agricultural sector and to optimize country's poverty problem among farmers, they should be practiced with smart agricultural technology while growing harvest in their green fields.

1.4 Research Questions

1. How user friendly the system will be?
2. Is the system online based or offline based?
3. What action should be done for increasing the amount of plant disease dataset?
4. How much will the system cost?
5. This type of work has been done before, so how is this system better than previous work?
6. What benefits farmers will get from this system?
7. How long will the sensor last and is there any extra cost to maintain them?

1.5 Research Objectives

There are some effective objectives of our research work and these are given below:

1. Remediating the confusion about planting crops
   based on the geographical location, sensor based module
2. Knowing the chances of production of grains
   checking the previous data and reports
3. Monitoring environmental parameters
   checking weather and temperature and moisture level of soil
4. Providing necessary smart technology
   avoiding excessive cost
5. Recognizing plant diseases
   using machine learning algorithm

1.6 Research Layout

Chapter 1: We will discuss about introduction, motivation, problem definition, research questions, and researched objectives of our project.

Chapter 2: We will discuss about research background and the related work, research summary and challenges.

Chapter 3: We will describe introduction, research subject and instrumentation, data collection procedure, statistical analysis and methodologies.

Chapter 4: We will discuss about experimental results and discussion.

Chapter 5: It describes the conclusion and future work of this research.

Chapter 6: It describes the all the references used in our research.

CHAPTER 2

BACKGROUND

2.1 Introduction

In the recent years, there are hardly found research works on smart agriculture system along with plant diseases detection in Bangladesh. But currently, many works regarding to agriculture based system are being attempted to made for bringing a revolutionary change in our country's agriculture.

2.2 Related Works

Here several research works are published based on the recognition of various plants having different types of diseases and also based on agriculture-based system for bringing a positive change in agricultural fields.
S. Ramesh et al. (2019) [1] mainly focused on the four most usual paddy plant diseases such as Bacterial blight, Leaf blast, Sheath rot, and Brown spot. To recognize and classify these diseases, optimized DNN with Jaya algorithm was used. For the dataset, images of paddy leaves were directly captured and for preprocessing, they converted RGB images into HSV images and binary images were turned out for partition of non-diseased and diseased portion of plants and also a clustering method was used for these portions. As the experimental results, they achieved 92% accuracy for the sheath rot, 95.78% for the bacterial blight, 98.9% accuracy for the blast affected, 94% for the brown spot and 90.57% for the healthy leaf image.

Konstantinos P. Ferentinos et al. (2018) [2] proposed a CNN model for modeling intricate processes and for executing image pattern recognition. They used an open database of 87,848 images, with a set of 58 separate classes containing 25 different plants which are both the combination of diseased and healthy plants. By using deep learning methodologies, their proposed model achieved 99.53% accuracy in detecting various plant diseases which were able to be diagnosed.

Juncheng Ma et al. (2018) [3] used DCNN for recognizing four kinds of diseases of cucumber such as target leaf spots, downy mildew, powdery mildew, and anthracnose. Data augmentation methods were also being used to expand their dataset, having 14,208 symptom images and they were able to achieve a 93.4% success rate in the identification of cucumber diseases.

Shanwen Zhang et al. (2018) [4] declared a model by using a TCCNN method for the identification of vegetable leaf disease where this method is the combination of three colors materials of RGB infected leaf images. Through different layers of TCCNN, features were turned out for detecting diseases of a vegetable leaf with around 91.15% accuracy or more.

Zahid Iqbal et al. (2018) [5] represents a survey based on image processing techniques to detect citrus plant leaf disease. In their paper, they described the alignment of citrus leaf diseases and also abridgment and challenges of each step of classification and detection of diseases of citrus plants. They also focused on feature extraction and classification, image preprocessing, segmentation, different classifier and several deep learning methods for implementing further identification of citrus plant diseases.

Pooja V et al. (2017) [6] had showcased algorithms of machine learning and performed image processing for identifying transited portion of the plants where they found SVM exhibited better results than previous plant disease detection techniques and their plant disease recognition rate reached 92.4% in terms of accuracy.

Shanwen Zhang et al. (2017) [7] described a model based on K-mean and super-pixel clustering and PHOG algorithms. In their paper, at first super-pixel clustering algorithm parted the infected leaf images into super-pixels. After that, wounded images from super-pixels were segmented through the K-mean clustering algorithm and the POG landmarks were derived from three color material of segmented injured leaf images and its grayscale where combined four PHOG expositor as images and vectors. Their model was only legalized for two plant diseased leaf databases where they gained 90.43% accuracy or less for apple disease recognition and 92.15% accuracy or less for cucumber disease recognition.

Hemantkumar Wani et al. (2017) [8] used data from the web source. Data are divided into two different sets Pest and Crop Dataset. These data sets are also used as training their model. They used some sensors for getting real time data. Raw data is collected from fields and then these were categorized into different dataset. They used the Naïve Bayes Kernel algorithm to classify if the problem is consistent or inconsistent.

Godliver Owomugisha et al. (2016) [9] worked on cassava plants containing 7,386 images as dataset. These images were parted into five categories such as healthy class and four diseased class. For identifying diseases, color and ORB method were used. By using this method, they got 99% accuracy.

Jagdesh D. Pujari et al. (2014) [10] used images from different fields as dataset. They detected fungal diseases from four different kinds of crops such as cereal, fruit, commercial and vegetable crops. For fruit crops, they used GLCM and GLRLM methods and got 91.37% and 86.71% accuracy respectively. After using block-wise features accuracy raised to 94.09%. They used ANN and KNN and got 84.11% accuracy and 91.54% accuracy respectively in the case of vegetable crops. To detect the diseases of commercial crops they used Mahalanobis distance classifier and got 83.17% accuracy which increased to 86.48% by using the PNN classifier. For cereal crops, they used the SVM classifier and got 80.83% accuracy for a color feature and 85% for shape features and 85.33% using color texture features.

Dr.N.Ananthi et al. (2017) [17] proposed an IoT based system for observing soil and irrigation of the agricultural fields. In their proposed system, they had toused embedded based sensors such as pH sensor, humidity sensor, and temperature sensor for soil testing where the values from these sensors were deputized to the field manager via a Wi-Fi router. They also used a mobile app for getting soil information and crop suggestion after analyzing sensor values. Based on the high temperature of the soil, their proposed automatic irrigation system was performed and the crop images were delivered to the manager to suggest pesticides for compatible crops.

Chandan kumar sahu et al. (2015) [18] declared an irrigation controlling system where they used several soil moisture sensors. Through these sensors, they found the required level of water or the water shortage of soil. As required, their proposed system controlled water motor and directed the water flow through the pipe to that land's soil where the moisture level is lower than required and messaged the whole information to the registered number or g-mail account of the user.

K K Namala et al. (2016) [19] represented a web-based automated irrigation system to reduce the waste of water while irrigating plants and to control irrigation without human intervention. In their system, they had used Arduino UNO board, relay, Soil moisture sensor, flow meter, Raspberry pi, and XBee where soil moisture sensor was used for measuring whether the soil is dry or partially wet or fully wet and then XBee transferred information of soil moisture to raspberry pi wirelessly. After that raspberry pi switched on and off a relay to control the irrigation process automatically.

Shweta B. Saraf et al. (2017) [20] proposed an IoT and cloud-based wireless system for irrigation where it had both manual and automatic modes. Their system worked on real-time input data for observing and controlling irrigation. For measuring moisture level of soil, humidity and water level of agriculture lands, the temperature of the environment, they had used the wireless sensor network and they also used zigbee for creating a connection between the base station and sensor nodes. Cloud server accumulated sensed data to make decision and further control irrigation process. Via the mobile application, all the actions taken for irrigation and the overall irrigation procedure could be monitored and controlled anytime by the user.

K.Sathish kannan et al. (2013) [21] introduced a farming based embedded system where zigbee based wireless sensor networks used for observing atmospheric parameters such as soil temperature, humidity, soil moisture, fertility, crop growth, irrigation facility, weed, and weather detection, etc. One of the major facilities of their proposed agriculture based system is that the whole system could be carried on and observed from any part of the world by using their farming webpage via the internet. Microcontrollers are used for controlling farming system and the wireless camera was for displaying the current status of their farm through these farmers could easily get to know about the need of their farm and perform required actions without being present there.

Adnan Shaout et al. (2015) [22] mainly focused on the agriculture of distant places where there isn’t any access to Wi-Fi network for which they had made an embedded based agriculture system. Their paper has approached a robust system where the sensor module was worked for gathering real time data about weather, soil moisture, temperature, humidity, and crops, etc. In their system, there also used a bluetooth tech by which line following robot uploaded the sensed data of the faraway area’s atmospheric parameters and agriculture process for further resolution.

Wenju Zhao et al (2017) [23] approached an irrigation system in their paper which was based on LoRa technology. Their proposed system comprised by using two instruments such as irrigation node and gateway where irrigation node was structured by solenoid valve, LoRa communication module, and hydroelectric generator. On the other hand, gateway was used by the irrigation node while delivering data via Ethernet or LTE to the cloud server. Their system aptness verified by different experimental results and via a mobile application, the entire irrigation system was in the hands of the user to control and monitor the condition of system with ease.

2.3 Research Summary

Bangladesh is agriculture based developing country but in recent researches we have come to know that Bangladesh is not developing in agriculture compared to modern countries. In researchers works we have seen many countries already using AI system and IoT or Embedded system for developing the agriculture for their farmers effectively so that they can get fruitful yield of grains in less effort.

Therefore, we tried to build a system which can detect plant diseases and by researching we came to know many other countries also using the system and many of them used many different ANN algorithms. We used CNN of ANN cause by using CNN we can detect the diseases with highest success rate.

Furthermore, we came to know that in modern countries they already using automated monitoring, controlling and suggesting system for their agriculture. So, we tried to build a system with some sensor modules such as pH sensor, moisture sensor, humidity, etc. Which can suggest the corps which will be good to grow in a particular land.

2.4 Challenges

Though building a new system is already very challenging but to make it usable to other people is more challenging. As our systems are modern technologies it needs little bit training or knowledge for others to use. So, the first and main challenge is farmers are not familiar with embedded technology nor with smart phones very much. Next is it’s hard to make training session for all farmers which can be solved by time to time. Other than that, our model is not with very high-quality sensors which needs funding from government. Moreover, our country has no free wifi everywhere specially in villages nor even Wi-Fi available much. So it’s hard not possible to make the system IoT based due to lack of online environment. Furthermore, Government is not taking special measures for automated systems in agriculture sector.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

To ensure a smart agriculture system and detection of plant diseases system are structured for upgrading the agriculture system in our country. In our system, by processing data with machine learning technologies and by sensing the real time data with embedded based sensor, we have successfully found out plant diseases and also build up an agriculture based system which can give crop suggestions based on the particular atmospheric condition.

3.2 Research subject and Instrumentation

Our research work is based on agriculture where our embedded based system works for forming a smart system of crop suggestion by monitoring various parameters and on the other hand, machine learning based system works for predicting plant diseases.

3.2.1 Instrumental specification of Plant Disease Detection System

The specifications of the computer we have used for machine learning based plant disease detection system are-
Motherboard - MSI Z390-A PRO
Ram - Corsair Vengeance LPX 16GB
Power Supply – Tough power DPS G RGB 750W Gold
Processor - Core i7-8700k
GPU - AMD Radeon RX 590
SSD - Western Digital Green 240GB M.2

We have also used Anaconda software for coding purpose.

3.2.2 Instrumental specification of Smart Agriculture System

Components specification of embedded based agriculture systems are –

i. Arduino Mega

Arduino Mega is used to setting up and connect the sensors. Atmega2560 is the microcontroller of Arduino Mega. The pins it has are 54 digital input/output pins of which 15 can be used as PWM outputs and it also has 16 analog pins, 4 hardware serial ports. It also consists of a 16 MHz crystal oscillator, a USB connection, a power jack, an ICSP header, and a reset button. It has a flash memory of 256kb of which 8kb is used by bootloader. It operates on

5v, 20mA per I/O pin and 50mA for 3.3V in. The power supply can be given by computer USB cable or with an AC - to - DC adapter or battery.

Figure 3.2.2.1. Arduino Mega

ii. Humidity and Temperature Sensor

We used a DHT22 sensor which is widely used as a temperature and humidity sensor. It consists of dedicated NTC to measure temperature and has an 8bit microcontroller to output the values of temperature and humidity. The output values are as serial data. It is factory calibrated that's why can be used easily with other microcontrollers. It has 3 pins which are Vcc. Data, and Ground. It operates in 3.5v to 5.5v, 0.3mA. Its temperature range is -40°C to 80°C and the humidity range is 0% to 100%. It has an accuracy of ±0.5°C and ±1%.

Table 3.2.2.1. Pin Details of Humidity and Temperature Sensor

No	Pin Name	Description
1	Vcc	Power supply 3.5V to 5.5V
2	Data	Outputs both Temperature and Humidity through serial Data
3	Ground	Connected to the ground of the circuit

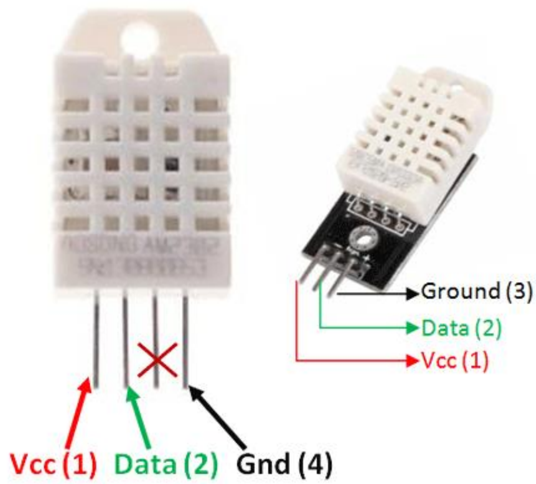


Figure 3.2.2.2. Humidity and Temperature Sensor

iii. Soil Moisture Sensor

We used the soil moisture sensor to check the moisture of the soil. The module's output is at high when soil is in a shortage in water else its output is at low. Moreover, with this sensor, the automatic watering system is also possible. This module has three output modes where digital output is very simple and analog output is more accurate and serial output gives an exact reading. It operates in 5v dc regulated. It has four pins Vcc, A0, D0, and Ground. We can use either A0 for analog or D0 for digital data. It also consists of two Probes which are put on the ground. Its range is 0 to 1023.

Table 3.2.2.2. Pin details of Soil Moisture Sensor

No	Pin Name	Description
1	Vcc	Power supply 3.5V to 5.5V
2	A0	Connected to any analog pin
3	D0	Connected to any digital pin
4	Ground	Connected to the ground of the circuit

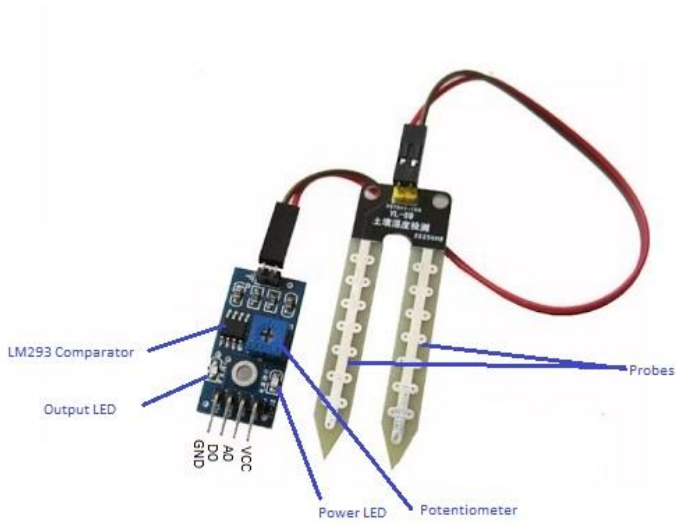


Figure 3.2.2.3 Soil Moisture Sensor

iv. Soil Temperature Sensor

A soil temperature sensor that only created to measure the soil temperature in extreme environments. Proper installation needs a lot of effort because it needed to be calibrated with soil before any output. So the sensor need to be left alone in the soil for a long time. Its measurement range is -60 °C to +150 °C which is a really wide range with the accuracy of +/- 0.25°C +/- 0.15°C. Its pressure resistance is about 6 bar. It has three pins Vcc, D0, and Ground.

Table 3.2.2.3. Pin details of Soil Temperature Sensor

No	**Pin Name**	**Description**
1	Vcc	Power supply 3.5V to 5.5V
2	D0	Connected to any digital pin
3	Ground	Connected to the ground of the circuit

Figure 3.2.2.4. Soil Temperature Sensor

v. pH Sensor

When it comes to the terms of pH we think about liquid acids or alkalines. But soil is also can be acidic or alkaline. The soil pH is an exigent aspect in determining which plants will grow because the nutrients that plants uses are controlled by it. The standard and common method to measure the pH of the soil is by mixing distilled water with equal parts of soil and then using a general pH sensor with electrodes. But the sensor we used has flat glass sensing which makes it easier to measure the pH of semisolids as well. It’s a double junction, sealed, and gel-filled sensor. It’s response time is very fast almost 90% of the final reading within 1.5sec to 2 sec. Its pH range is pH 01-14 with the accuracy of ± 0.2 pH units. It operates in 3.3v to 5.5v. It has three pins Vcc, D0, and Ground.

Table 3.2.2.4. Pin details of pH Sensor

No	**Pin Name**	**Description**
1	Vcc	Power supply 3.5V to 5.5V
2	A0	Connected to any analog pin
3	Ground	Connected to the ground of the circuit

Figure 3.2.2.5. pH Sensor

3.3 Data Collection Procedure

3.3.1 Datasets of Plant Diseases Detection

Our dataset has been generated by collecting images from different websites and captured images with a smartphone in various fields. Some of the images have been downloaded through the Google search engine as well. We collected a total of 14 different plants leaves images which we classified in a total of 38 classes where 26 classes are diseases of those plants and 12 classes are healthy class. The class of plants is classified as apple has 3 diseases and 1 healthy classes, blueberry 1 healthy class , Cherry 1 disease and 1 healthy class, Corn 3 diseases and 1 healthy class, Grape 3 disease and 1 healthy class, Orange 1 disease class, Peach 1 disease and 1 healthy class, Bell pepper 1 disease and 1 healthy class, Potato 2 disease and 1 healthy class, Raspberry 1 healthy class, Soyabean 1 healthy class, Squash 1 disease class, Strawberry 1 disease and 1 healthy class, Tomato 9 diseases and 1 healthy class. Most of the classes have more than 2000 images and some of them even have more than 5000 images.

A total of 217204 images have been collected among them 152044 images are for training the model, 43440 images are for manually testing the model and 21720 images for checking the validity of the model.

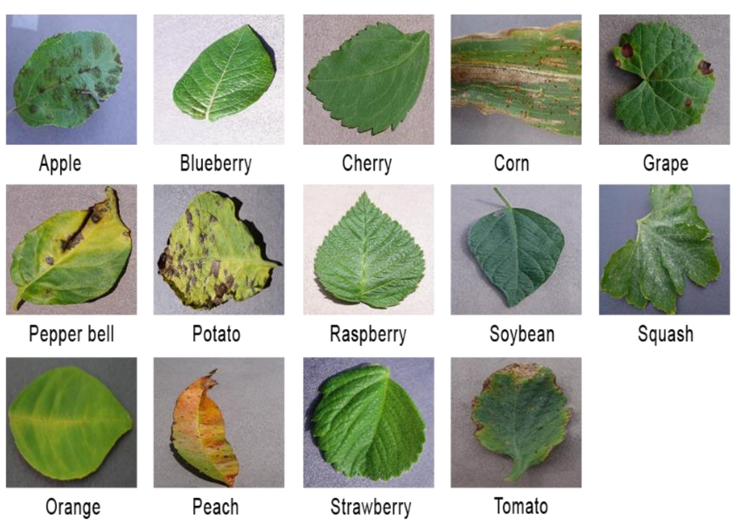


Figure 3.2.2.6. Example of dataset

3.3.2 Preprocessing of Plant Diseases Detection

The images have collected from different sources and also captured with a smartphone. So the images are not the same size and not compatible with training the convolutional neural network on unrefined images, which may lead to a dreadful result and horrifying classification. Therefore, we have resized the images into a square shape (256 x 256 pixels) and cropped the inessential objects from the images.

3.3.3 Datasheet of Smart Agriculture System

This system had worked with 30 different vegetables and fruits. Such as Rice, Wheat, Tomato, Potato, Watermelon, etc. For which the system checks the real-time soi pH and temperature values. To compare with the real-time values with existing proper values in which these vegetables or fruits grow well, we needed the data. So from different sources, we collected the existing data of ph and temperature values for each vegetable and fruit. In the collected data it shows the minimum, maximum, optimum and optimum range for temperature in Fahrenheit.

Table 3.3.3.1. Datasheet of temperature and pH

Vegetable	Min (°F)	Optimum Range (°F)	Optimum (°F)	Max (°F)	Ideal pH
Asparagus	50	60-85	75	95	6.0 - 8.0
Bean	60	60-85	80	95	6.1 - 7.5
Bean, Lima	60	65-85	85	85	5.5 – 6.8
Beet	40	50-85	85	85	6.0 - 7.5
Cabbage	40	45-95	85	100	6.0 - 7.5
Carrot	40	45-85	80	95	5.5 – 7.0
Cauliflower	40	45-85	80	100	5.5 – 7.5
Celery	40	60-70	70	85	6.0 - 7.0
Chard, Swiss	40	50-85	85	95	6.0 - 6.8
Corn	50	60-95	95	105	5.5 – 7.0
Cucumber	60	60-95	95	105	5.5 – 7.5

Eggplant	60	75-90	85	95	5.0 - 5.8
Lettuce	35	40-80	75	85	6.1- 7.0
Muskmelon	60	75-95	90	100	6.0 – 6.8
Onion	35	50-95	75	95	6.0 - 7.0
Parsley	40	50-85	75	90	5.5-6.8
Parsnip	35	50-70	65	85	5.5 – 7.5
Pea	40	40-75	75	85	6.0 - 7.5
Pepper	60	65-95	85	95	5.5 – 7.0
Potato	53.5	60-85	75	93	4.5 – 6.0
Pumpkin	60	70-90	90	100	5.5 – 7.5
Radish	40	45-90	85	95	6.0 - 7.0
Rice	65	75-95	90	105	6.0 – 6.8
Soybean	50	70--85	80	105	5.5 – 6.5
Spinach	35	45-75	70	85	6.0 – 7.5
Squash	60	70-95	95	100	5.5 – 6.8
Tomato	50	70-95	85	95	5.5 – 7.5
Turnip	40	60-105	85	105	5.5 – 7.0
Watermelon	60	70-95	95	105	5.5 – 6.5
Wheat	40	65-85	75	100	5.5 – 6.5

3.4 Analysis
3.4.1 Analysis of Plant Diseases Detection

Table 3.4.1.1. Algorithm analysis

Work	Technology used	Accuracy
Recognition and classification of paddy leaf diseases [1]	Optimized DNN swith Jaya Algorithm	95.78% (bacterial blight) 98.9% (last affected) 92% (sheath rot) 94% (brown spot) 90.57% (normal leaf image)
Plant disease identification and diagnosis [2]	CNN	99.53%
Cucumber diseases recognition [3]	DCNN	93.4%
Vegetable leaf disease recognition [4]	TCCNN	91.15% ± 2.17
Plant leaf diseases identification [6]	SVM	92.4%
Plant diseased leaf segmentation and [7]	PHOG	90.43% (Apple disease) 92.15% (Cucumber disease)
Plant disease incidence and severity measurements [9]	ORB	99%
Plant diseases recognition (proposed model)	CNN	97.33%.

3.4.2 Cost analysis of Smart Agriculture System

Sensors vary in price according to their quality and performance. A smart agriculture system may need very high performance sensors and materials. But here have been used some low budget sensors and materials which can Bangladeshi farmers afford easily. For cost effectiveness and as it is a prototype number of items have been decreased to a minimum as well.

Table 3.4.2.1. Components Cost

No	Name	Price(BDT) (USD)
1	Soil Moisture Sensor	200Tk (2.38$)
2	Soil Temperature Sensor	150Tk (1.78$)
3	pH Sensor	2800Tk (33.33$)
4	DHT22 (Humidity) Sensor	300Tk (3.57$)
5	Arduino Mega 2560	750Tk (8.93$)
6	Breadboard Mini	40Tk (0.48$)
7	Jumper wire	80Tk (0.95$)
8	Battery (3.7V 2x)	180Tk (2.14$)
	Total	4500Tk (53.57$)

This is the approximation cost of the components which have been used in a smart agriculture system and the cost is approximately 4500tk to 4800tk. It is very low cost and can be easily implemented in a field.

3.5 Methodologies

3.5.1 Research Methodologies for Plant Disease Detection System

Throughout the proposed model, Convolutional Neural Network (CNN) is used to recognize the image pattern of various diseased plants, containing 38 different classes and achieved an accuracy of 97.33%.

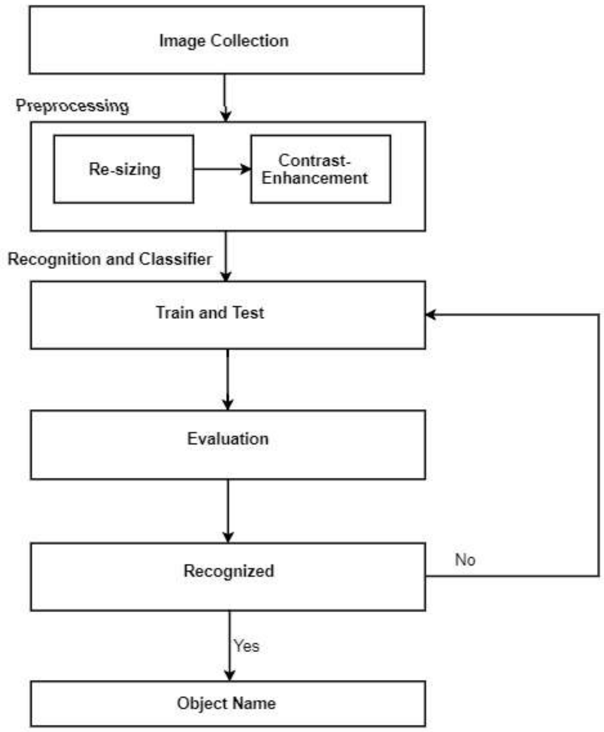


Figure 3.5.1.1. Block diagram for the proposed methodology

Model Architect

Our proposed model aim is to detect plant diseases through leaves that are occurring very often and due to farmer's lack of knowledge can't identify quickly. CNN has been used which works with the Convolutional layer [11] resulted with the pooling layer [11]. Convolution layer contains various primary landmark. Local perception is one of them which minimizes weights amount and also doesn't take any iterative convolution on the same window. There is also a dense layer and a few assigned actions such as batch normalization [12] along with dropout [13] applied to architect the model. In the model, the layer is the Convolutional layer where the size of filter is 32 and 3 in kernel size. After that, size 256x256 of the RGB channel having a depth of 3 have been taking as an input layer. We used padding as same and stride is 1. After that, we used Relu (1) activation in 2^{nd} layer where the layer has the same padding and stride. Higher learning rate enables and learns speedily through 3^{rd} layer which is batch normalization. The max pooling layer which is being used to diminish the number of parameters and abstains overflowing, and that also helps to eliminate unwanted noise is connected with the output of layer 3. It has pool size 3 and stride 3. It also has dropout 25%. This max pool layer is layer 4 which is connected with the next convolutional layer 5. This convolutional layer is similar to layer 1 without the filter size. It has a filter size of 64. The next layer is again activation layer which is 6th. After that, the 7th layer is another batch normalization layer.

$$\boldsymbol{ReLU(X) = MAX(0, X)} \qquad (1)$$

Next, the 8th layer is again the convolutional layer having the same properties as layer 5. It is connected to the activation layer 9. Layer 10 is again batch normalization that connects to the 11th layer which is max pool layer having the pool size 3. This max pool layer again reduces the unnecessary noises. It also has a dropout of 25%. The 12th layer which is convolutional layer is like layer 5 but only their filter size is different. This convolutional layer has a filter size of 128. Next, it's connected with activation layer 13 and that connects with batch normalization layer 14. Next is again convolutional layer 15 which is the same as layer 12. It also connected to activation layer 16 that connects with batch normalization layer 17. Next layer is max pooling layer which has the same pool and stride size that is 2. This outcome mellifluously becomes like an array and undergoes layer 18 which a dense layer having 1024 covert units and normalized with normalization layer 19th that associated with a 50% dropout. Here, all the past flow is connected with a dense later 20 with 15 units which are fully connected with SoftMax (2) activation. Thus the model has been built.

$$\boldsymbol{\sigma(Z)_j = \frac{e^z\, j}{\sum_{k=1}^{k} e^z\, k}} \quad \text{for j = 1 ,…..k} \qquad (2)$$

Our proposed model algorithm

1.Adam(Rate of learning = 1e-3, decay=1e-3 / epochs)

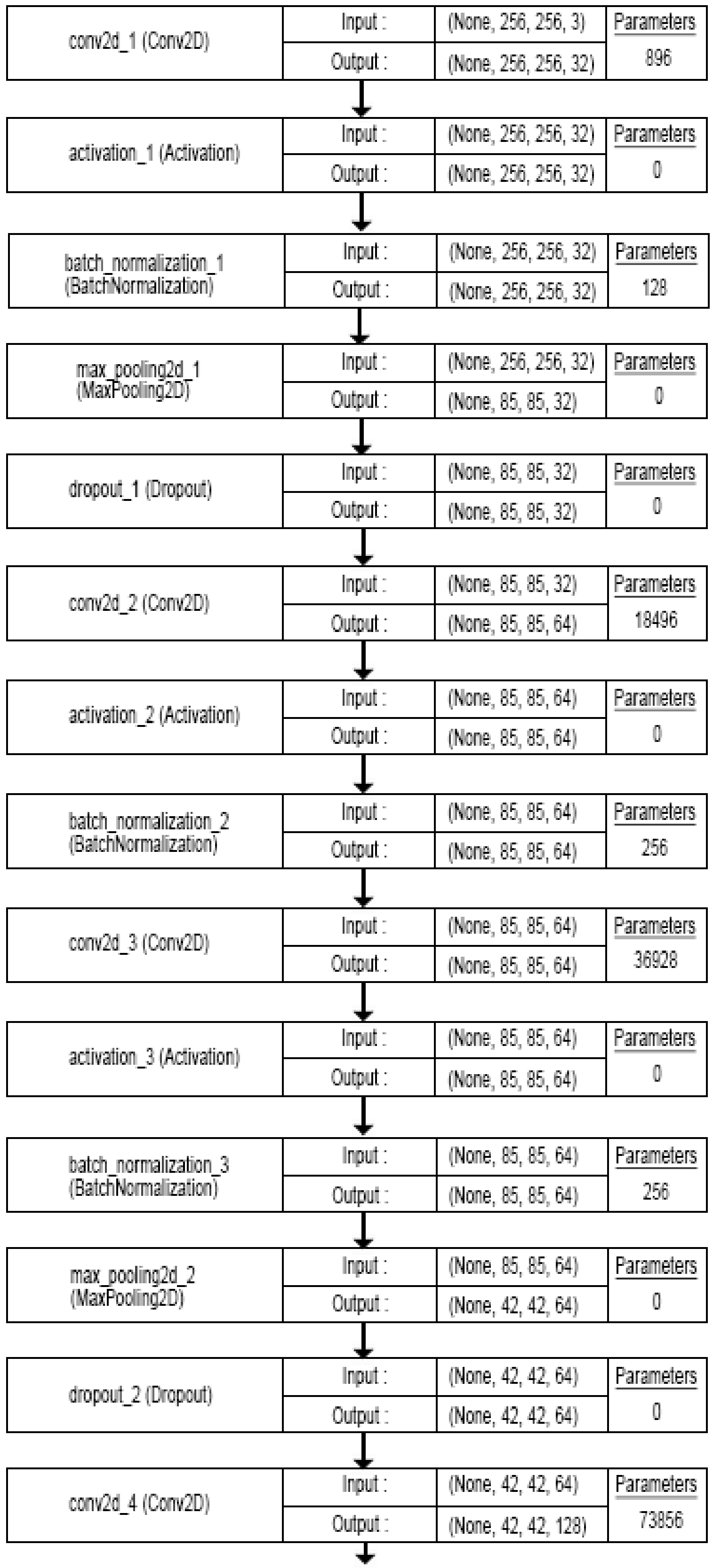
Input Shape = (height = 256, width = 256, depth = 3)

2. Start loop for 150 iterations in all batch:
3. Convolution_1 (Filter size is 32 and Kernel Size is 3, Stride is 3, padding="same" and height, width and depth are 256, 256 and 3)
4. Activation = "relu"
5. Batch Normalization (axis=-1)
6. MaxPooling2D (Pool Size and Stride are 3)
7. Dropout (Rate=25%)
8. Convolution_2 (Filter size is 64, Kernel Size, stride and padding are same as convolution 1)
9. Activation = "relu"
10. Batch Normalization axis=-1
11. Convolution_3 (Filter, Kernel Size, Stride and padding are same as convolution 2)
12. Activation = "relu"
13. Batch Normalization axis = -1
14. MaxPooling2D (Pool Size and Stride are 2)
15. Dropout Rate is 25%

16. Convolution_4 (Filter size is 128, Kernel Size, Stride and padding are same as convolution 3)
17. Activation = “relu”
18. Batch Normalization axis=-1
19. Convolution_5 (Filter size, Kernel Size, Stride and padding are same as convolution 4)
20. Activation = “relu”
21. Batch Normalization axis=-1
22. MaxPooling2D (Pool Size and Stride are 2)
23. Dropout rate is 25%
24. Flatten ()
25. Dense units is 1024
26. Activation = “relu”
27. Batch Normalization ()
28. Dropout rate is 50%
29. Dense units is 15
30. Activation = “softmax”

31. End loop

The architecture for the proposed model is shown in figure 8.


conv2d_1 (Conv2D)
Input :
(None, 256, 256, 3)
Output :
(None, 256, 256, 32)
Parameters
896
activation_1 (Activation)
Input :
(None, 256, 256, 32)
Output :
(None, 256, 256, 32)
Parameters
0
batch_normalization_1 (BatchNormalization)
Input :
(None, 256, 256, 32)
Output :
(None, 256, 256, 32)
Parameters
128
max_pooling2d_1 (MaxPooling2D)
Input :
(None, 256, 256, 32)
Output :
(None, 85, 85, 32)
Parameters
0
dropout_1 (Dropout)
Input :
(None, 85, 85, 32)
Output :
(None, 85, 85, 32)
Parameters
0
conv2d_2 (Conv2D)
Input :
(None, 85, 85, 32)
Output :
(None, 85, 85, 64)
Parameters
18496
activation_2 (Activation)
Input :
(None, 85, 85, 64)
Output :
(None, 85, 85, 64)
Parameters
0
batch_normalization_2 (BatchNormalization)
Input :
(None, 85, 85, 64)
Output :
(None, 85, 85, 64)
Parameters
256
conv2d_3 (Conv2D)
Input :
(None, 85, 85, 64)
Output :
(None, 85, 85, 64)
Parameters
36928
activation_3 (Activation)
Input :
(None, 85, 85, 64)
Output :
(None, 85, 85, 64)
Parameters
0
batch_normalization_3 (BatchNormalization)
Input :
(None, 85, 85, 64)
Output :
(None, 85, 85, 64)
Parameters
256
max_pooling2d_2 (MaxPooling2D)
Input :
(None, 85, 85, 64)
Output :
(None, 42, 42, 64)
Parameters
0
dropout_2 (Dropout)
Input :
(None, 42, 42, 64)
Output :
(None, 42, 42, 64)
Parameters
0
conv2d_4 (Conv2D)
Input :
(None, 42, 42, 64)
Output :
(None, 42, 42, 128)
Parameters
73856

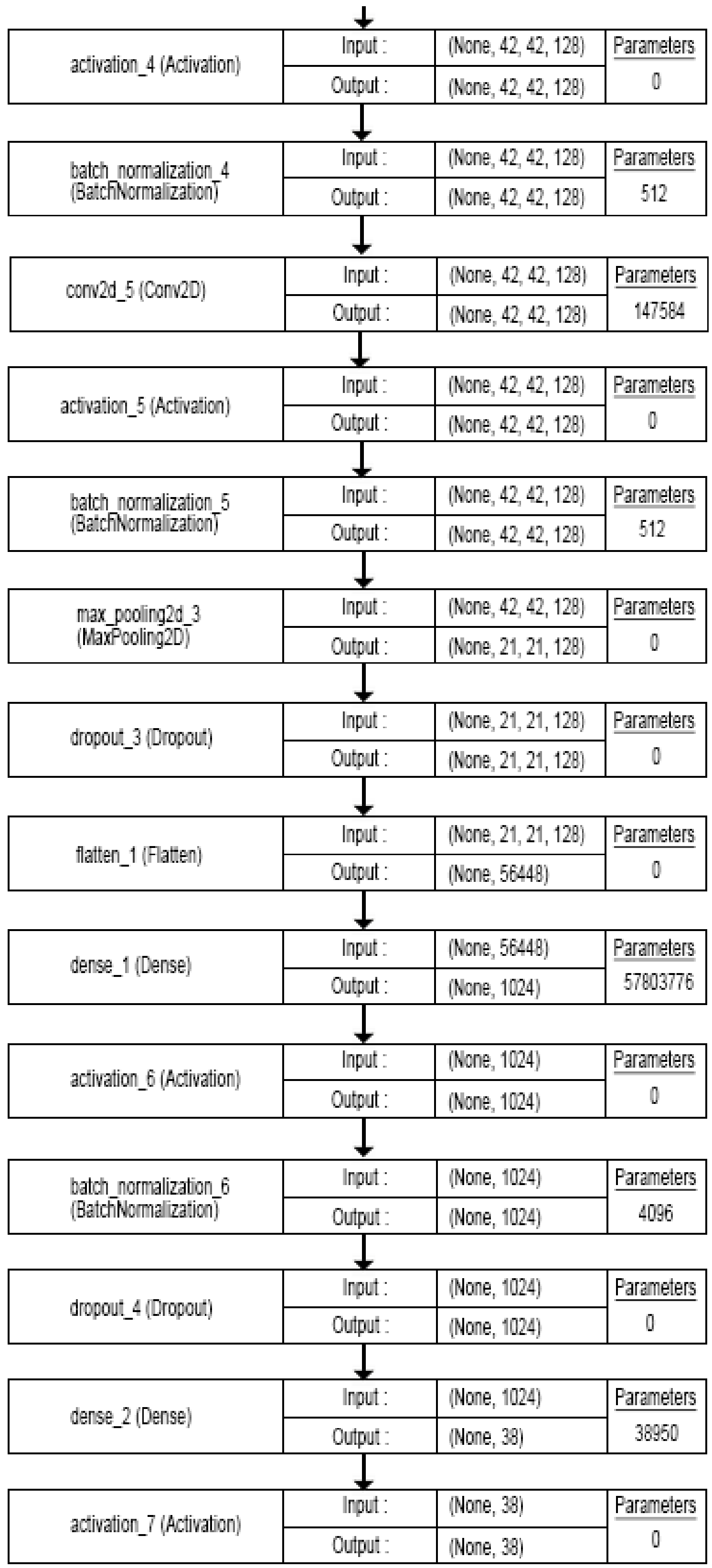


Figure 3.5.1.2. The architecture of Plant Disease recognition

Learning rate and Optimizer

Optimizer performs a vital role to lessen the error of a model. In our model, we have used Adam optimizer [14]. Network weights iteratively updated through classical problematic gradient descent method in training data is altered by it. PC vision analyst utilized it for its better execution. With the rate of 0.001 Adam (3) optimizer is being used in our model.

$$\boldsymbol{\theta_{t+1}} = \boldsymbol{\theta_t} - \frac{\boldsymbol{\eta}}{\sqrt[1]{\hat{\boldsymbol{v}}_t} + \varepsilon}\, \hat{\boldsymbol{m}}_t \qquad (3)$$

Categorical cross entropy (4) function has been used for counting errors. Continuous inquiries exhibits that cross entropy displays some traits compared to other functionalities, such as mean squared and classification mistake [15]. It is preferred for our model.

$$\boldsymbol{L_i} = -\sum_j \boldsymbol{t_{i,j}} \log(\boldsymbol{P_{i,j}}) \qquad (4)$$

To train CNN, learning rate plays a vital role. When learning rate is low, it works perfectly. Moreover, a higher learning rate is not good for accuracy. So the desired goal becomes harder to achieve. We used an automatic learning rate reduction method to overcome this test [16]. At the beginning, learning rate was 0.001 that automatically decreases during analyzing validation accuracy.

Augmentation of Data

A exoteric concept among every analysts is that the better the result the more data you have. By handling some operations augmentation can produce more data artificially. We can multiply the data by three to four fold by using augmentation techniques. For augmentation of data, we have used Zoom in out 20%, randomly, Rescaled 40%, Rotate 30 degree, Shift width and height by 20% Flip horizontally and Shear with the range of 20%.

3.5.2 Research Methodologies for Smart Agriculture System

System Implementation

In an embedded system, it is really necessary to connect the sensors according to their pins to get proper data. Cause using different pins can vary the result and even may not work properly.

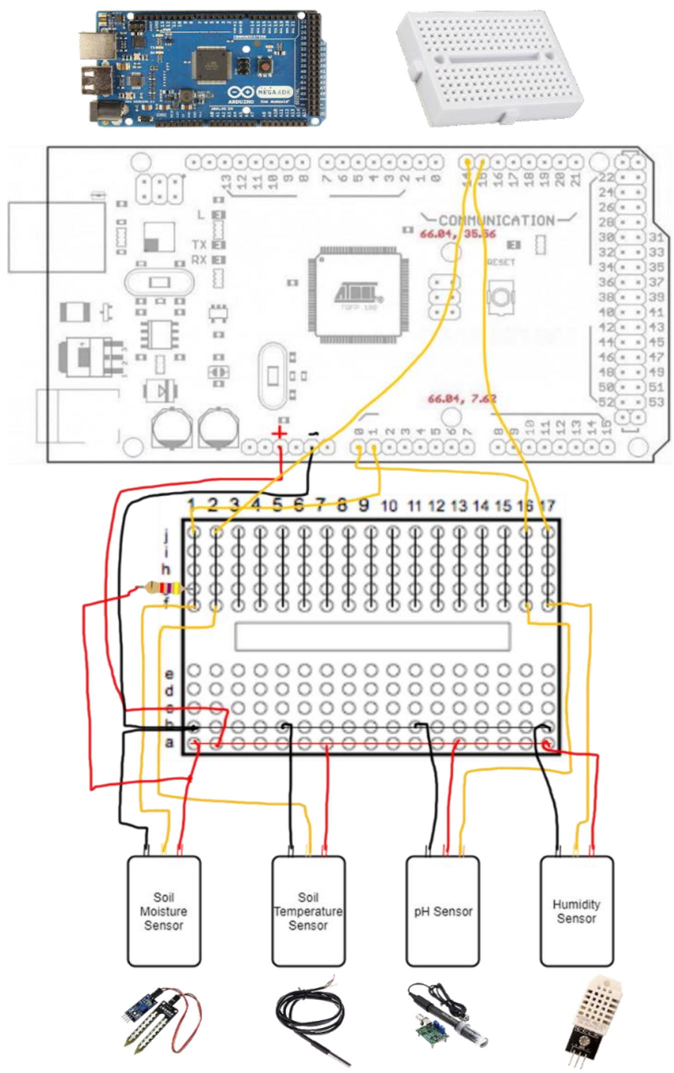


Figure 3.5.2.1. System Diagram

In the system, using a mini breadboard to connect the sensors with Arduino. Vcc and ground connection has been set up in a breadboard for all sensors to use. A0 has been taken to connect the pH sensor and A1 for soil moisture sensors. Soil temperature sensor and humidity sensor has been connected with digital pins 14 and 15. Some resistors have also been used for sensor safety purposes. The power source is used as 2 batteries, each having 3.7v. But with a pc USB cable or external AC - to - DC adapter can also use as a power source.

Software Implementation

No machine is self-programmed. The way a programmer programs the machine it acts according to the way. So the programming of the machine is a very important task.

As in the system have been used Arduino Mega so needed to implement the program from an external source and then import in it. Used the Arduino IDE for programming purposes. An Arduino always consists of setup() and loop() functions. In setup() we have set the appropriate pins pin mode for the module. Such as A0 and A1 has been taken as analog in Pin for input. And in loop() function sensors custom functions have been called for executing accordingly. For each sensor 10 read values have been taken and then the mean value is processed if needed and then processed value is returned.

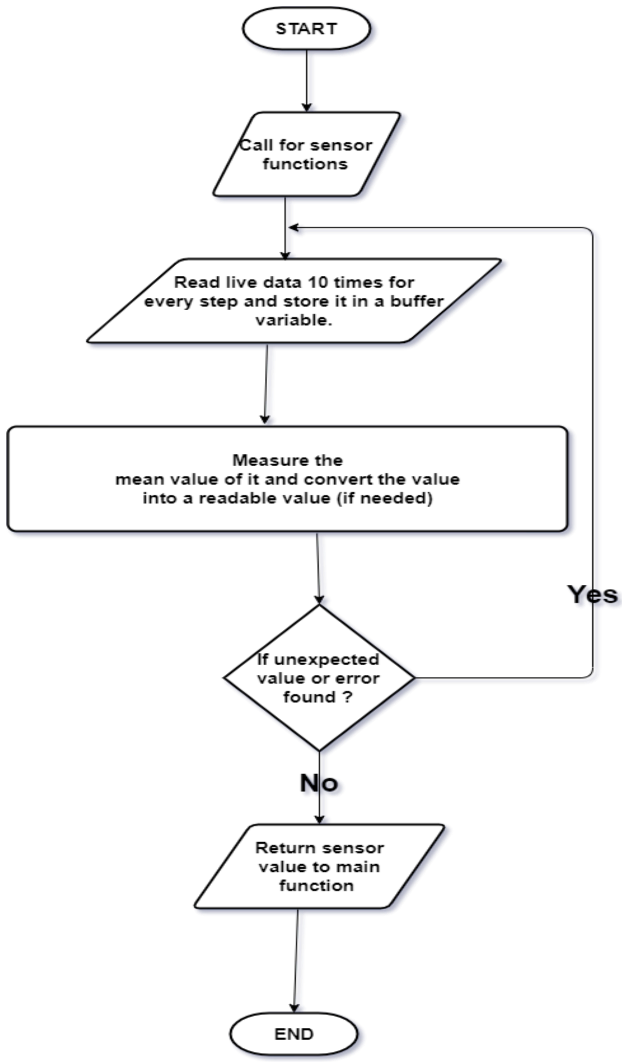


Figure 3.5.2.2. Functional Diagram for each Sensor

Global variables and defines

#define ONE_WIRE_BUS 14

OneWire oneWire(ONE_WIRE_BUS);

DallasTemperature sensors(&oneWire);

```
#define DHTPIN 15
#define DHTTYPE DHT22
DHT dht(DHTPIN, DHTTYPE);
float temperature;
int analogInPin = A0;
int sensorValue = 0;
int soilSensorPin = A1;
int soilSensorValue;
```

Sensors Custom Function

```
function soilMoisture(){
	readValue = 0;
	for i = 1 to 10
		readValue += analogRead(soilSensorPin);
		delay(10);

	readValue = readValue/10;
	return readValue;
}

function soilTemperature(){

	readValue = 0;
	for i = 1 to 10
		sensors.requestTemperatures();
		readValue += sensors.getTempFByIndex(0);
		delay(10);
```

```
    readValue = readValue/10;
    return readValue;
}

function humidityAndTemperature(){
    humidity = 0;
    Temperature = 0;
    for i = 1 to 10
        humidity += dht.readHumidity();
        temperature += dht.readTemperature();
        delay(10);

    temperature = temperature/10;
humidity = humidity/10;
    return  humidity;
}

function pH() {
    int readValue = 0;
    for i = 1 to 10
        readValue += analogRead(analogInPin);
        delay(10);

    readValue = readValue/10;
    float pHVoltage = (float)readValue*5.0/1024;
    float pHValue = -5.70 * pHVoltage + 21.34;
    return pHValue;
}
```

After getting the real time data from these functions the system compares with the existing data and according to this it displays the suggesting vegetables or fruits and if it finds no in suggestion then it collects the closest range data of vegetables or fruits and shows that and suggests how much value needs to be changed for proper values of those vegetables and fruits.

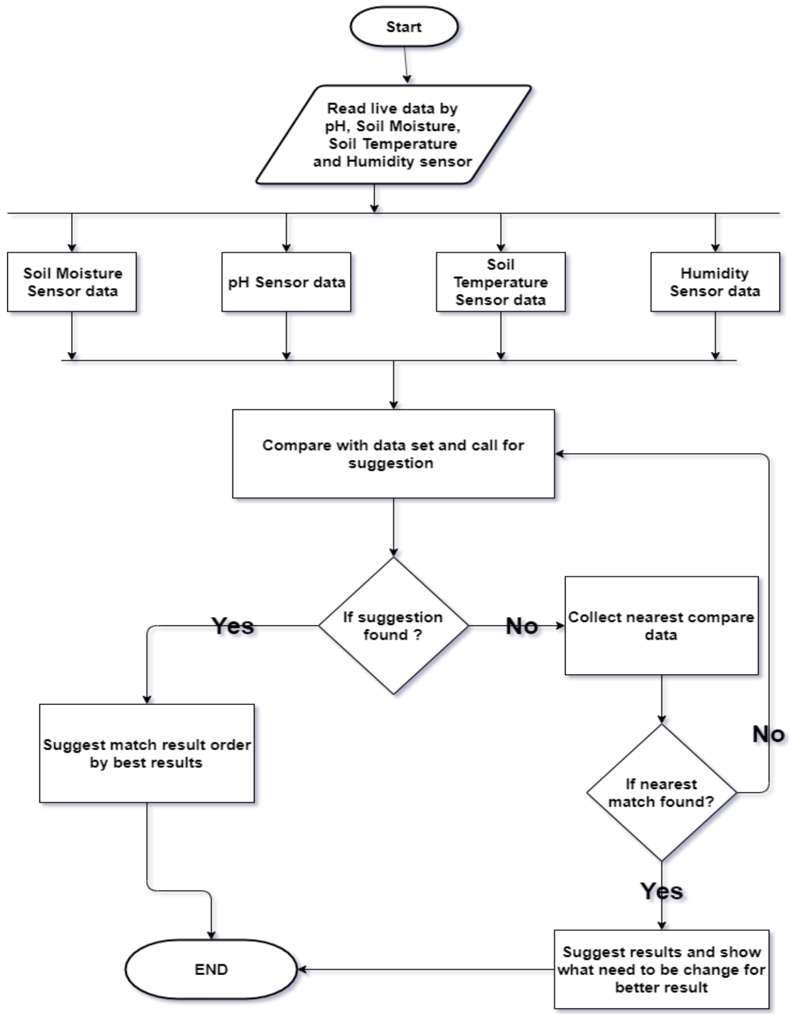


Figure 3.5.2.3. Functional Diagram of the System

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Plant Diseases Detection result discussion

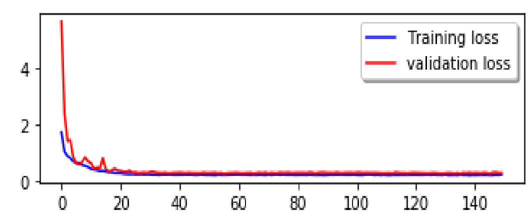
. Training, Testing and the Validation

Our data has been separated into training, testing and validation data for checking performance of our proposed model. To train our model, we have used training data. During the training time validation data is being used to help for tuning the hyper-parameters of the model. The test data has also been used for finding out the performance of the final model.

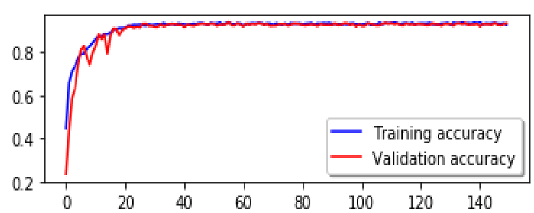
Our dataset s consists of a total of 217204 images. Where 70% of images (152044) are used to train the model and about 20% of images (43440) used to test the model and near 10% images (21720) are used to validate the model. We used around 5000 random images of plant leaves after the training was complete. There are different types of leaves images in our validation data.

Model performance

After 150 continuous epochs, this model achieved success rate of 97.33% to train dataset and 97.78% on the validation set that we created. The test with random images went smoothly after completing the training session. It was a quite astonishing accuracy outcome. After analyzing the outcome and confusion matrix, it is noticeable that the performance of our model is acceptable. The overall performance of our model is given below.



(1)



(2)

Figure 4.1.1. (1) Training and validation loss (2) Training and validation accuracy

Confusion matrix (5) is extensively used to classify model performance justification. The confusion matrix operates on set of the testing dataset. The true values are familiar here. Our proposed model confusion matrix drawing is in figure 9. For each type of dataset, the entries in the matrix are True Positive (TP) rate, False Positive (FP) rate, True Negative (TN) rate, False Negative (FN). The accuracy is the division of the absolute number of predictions and the predictions that were correct. The following rule is the rule by which we found our confusion matrix

$$\textbf{Accuracy} = \frac{(\boldsymbol{TP+TN})}{(\boldsymbol{TP+TN+FP+FN})} \qquad (5)$$

4.2 Smart Agriculture System result discussion

To test the system, it is most important to check the outcome. Though it’s not yet have been practiced in real fields but we used some samples of soils to check the system. We collected 8 different types of soils from different lands. And at first, only checked the pH of each soil.

Soil Samples
1. Calcareous Grey
2. Calcareous Alluvium
3. Calcareous Dark Grey
4. Calcareous Brown
5. Noncalcareous Brown
6. Noncalcareous Alluvium
7. Acid Sulphate Soil
8. Brown Piedmont Soil

Table 4.2.1. Soil pH

Sample	pH
1.1	7.47
1.2	7.67
2.1	8.35
2.2	8.42
3.1	8.27
s3.2	8.22
4.1	7.25
4.2	7.42
5.1	5.45
5.2	5.67

6.1	7.53
6.2	7.77
7.1	3.89
7.2	3.96
8.1	5.23
8.2	5.36

After checking the soil pH and implemented the system we checked the soil for which fruits or vegetables it is suitable and displayed the result in PC, Arduino IDE's serial monitor.

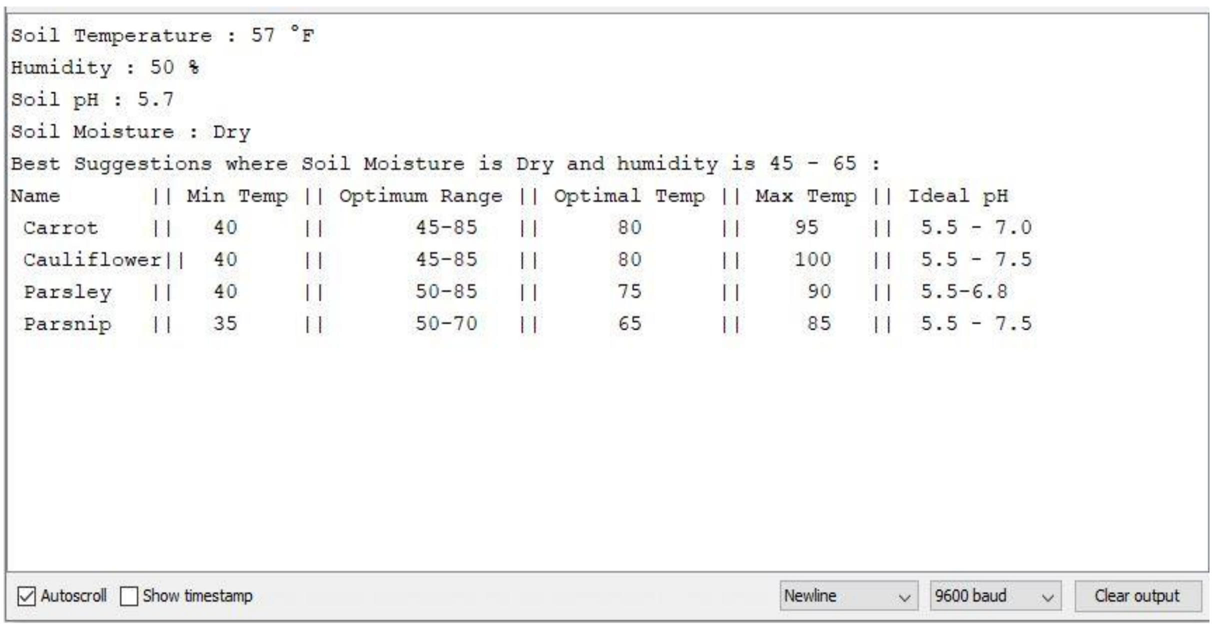


Figure 4.2.1.1. Suggestion 1

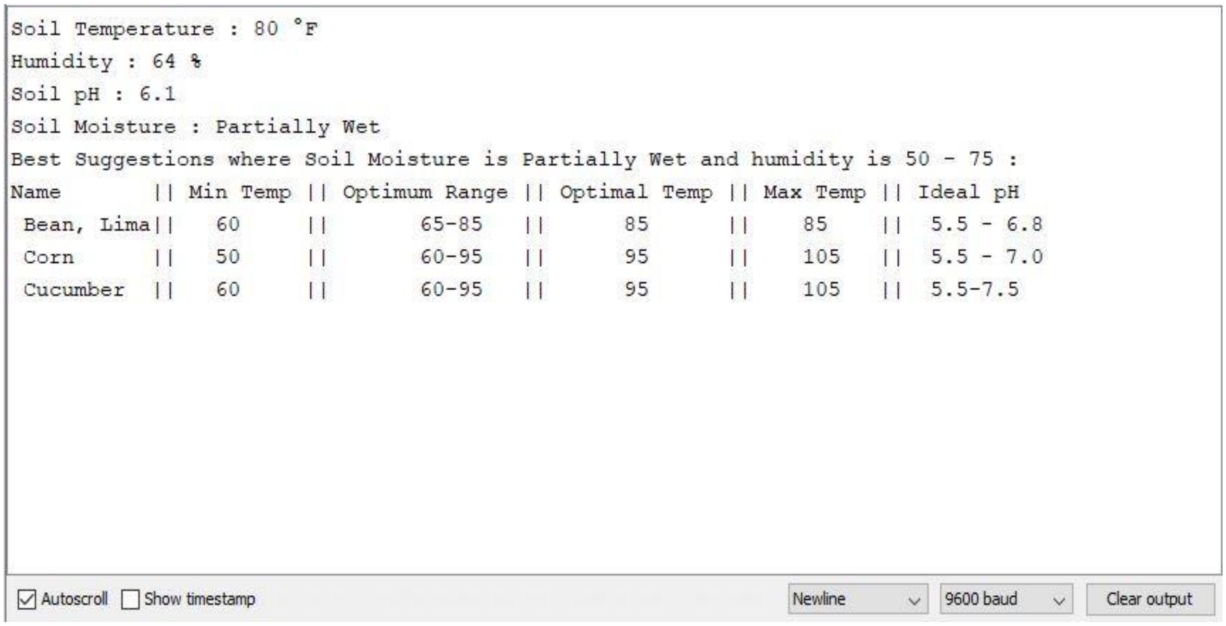


Figure 4.2.1.2. Suggestion 2

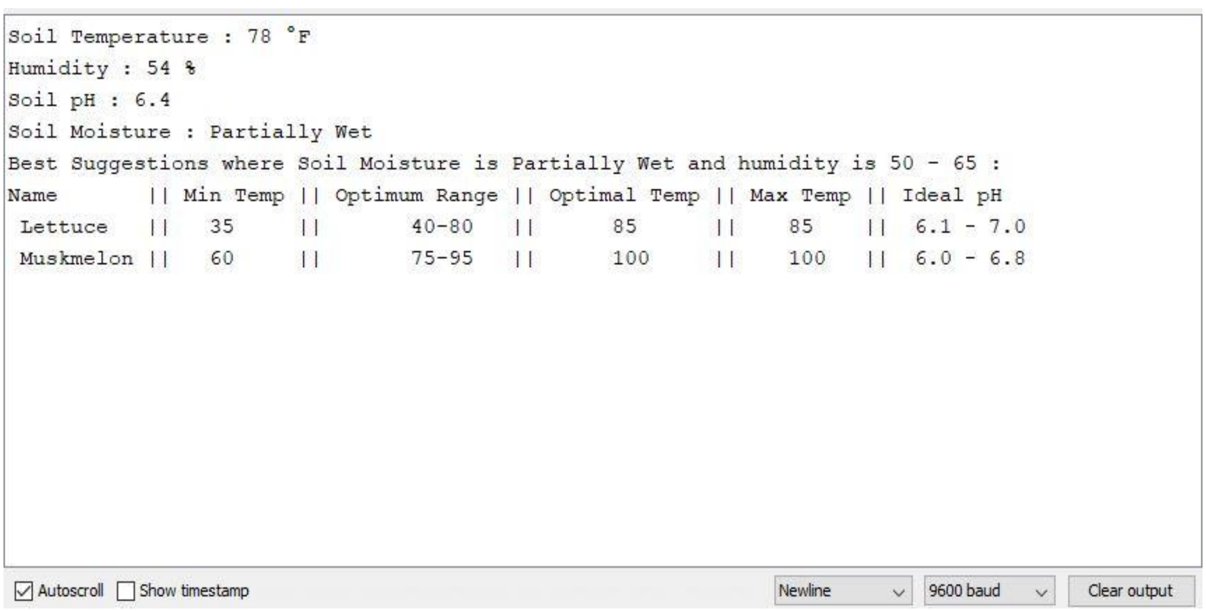


Figure 4.2.1.3. Suggestion 3

Figure 4.2.1. Soil result with Suggestion

The given suggestions are based on mainly soil pH and soil temperature. Soil water level and Humidity is also have been in consideration.

CHAPTER 5

CONCLUSION AND FUTURE WORK

In our work, we have built a model based on Convolutional Neural Network (CNN) to detect several plant diseases from 38 different classes containing 14 different plants and a smart agriculture system based on embedded sensor module to suggest crops suitability over 30 different food grains on a particular land. Plant disease detection technique helps to automatically revelation of plant leaf diseases and categorizing them centered on their morphological features where this model is able to achieve 97.33% recognition rate which is proof of the flourished performance of our model and CNN which is very efficient technique in the way of detecting different types of plant diseases. Besides, our embedded based system is focused on observing soil pH, temperature and moisture along with weather for suggesting appropriate crops to produce efficiently.

In the future, our goal is to develop an android application having easy user interface for finding out the specific diseases of plants in an effective way and controlling and monitoring wirelessly our agriculture system where we also have the plan to add automated irrigation system to make the agriculture system able to solve many problems occurred in the agriculture field. By using our proposed system, poor farmers of our country can be able to grow healthy harvest in a fruitful way.

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