PRECISION AGRICULTURE METHODS FOR TEA AND OIL PALM PLANTATIONS

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23 January 2020

DECLARATION

Declaration by Project Group

We declare that the dissertation entitled Precision Agriculture Methods for Tea and Oil Palm Plantations and work presented in it are our own. We confirm that:

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- Where we have consulted the published work of others, is always clearly attributed,
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ABSTRACT

The agriculture sector plays a major role in a country's economy. According to the records, in Sri Lanka, it contributes about seven percent to the national Gross Domestic Product. In the local agriculture sector, it can be observed that traditional agricultural methods are commonly used in plantations. But to improve the efficiency in the current agriculture process, the methods used in traditional agriculture process need to be evaluated with respect to the modern agricultural methods. Precision agriculture is one of the rapidly developing areas of utilizing modern agricultural technologies which is also known as satellite farming or site-specific crop management. In the Sri Lankan context, high probability and capability in implementing precision agriculture methods can be found especially in export agriculture industries. Tea can be identified as such an agricultural industry, which is a major source of foreign exchange and is continuing to figure prominently in the economy of Sri Lanka. Also, the oil palm industry has recently recognized as a unique and high economically valuable tree. So, it is mainly focused to give precision agricultural solutions in these farming processes.

With further expansions in the farming process of tea and oil palm, serious problems have been encountered. The problems could be identified especially related to watering, nutrient deficiencies detection, disease prediction, and ripeness detection. Therefore, the objectives of this project were to design an automated drip irrigation system for new tea plants, an early prediction system for Blister Blight disease, a nutrient deficiency detecting system, and a ripeness detection system for oil palm fruit. By going through works of literature on areas of watering, disease prediction, nutrition deficiency detection, and ripeness detection generally for the agriculture sector as well as especially for tea and oil palm, the existing solutions and methods were analyzed.

Then methodologies were proposed, to achieve the objectives of the project referring to the data gathered through field visits and literature review. The project implementation was done according to the methodology’s details mentioned in the materials and methodology section. And in the final chapter, we have presented the results which we have obtained and the discussion of the final output of the project.

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1. INTRODUCTION

1.1 BACKGROUND

Agriculture plays a major role in Sri Lankan content. When considering the contribution to the country's economy, export agriculture crops play a major role. The tea plant is such an export agricultural crop, which earns a high profit. Sri Lanka has registered in its name in the world market for its high-quality tea production over the past decades. And when consider other highly profitable export crops, Oil Palm can be identified. According to recent researches, the Oil Palm industry has recognized as an agricultural crop that has a high potential for making a profit in the future.

When analyzing the importance of giving precision agricultural methods especially for these industries there are some key features. Tea uses a larger area of wet zone arable land available for agriculture. The total cultivation area of tea is about 200 hectares. Sri Lanka has produced 280 kg millions of black tea in 1998. It is about 10 percent of total world black tea production. And Sri Lanka exports more than 90 percent of its production annually. According to the Central Bank of Sri Lanka reports, foreign export earnings amount Rs 42.5 billion or about 15 percent of total export earnings that comprised 58 percent of agricultural [1].

Table 1: Tea Production, Export, and Contribution to the National Economy

Year	Production Kg mn	Export Kg mn	Export Earnings Rs million	SDR million	Value added as % of DGP
1983	179.3	167.3	8296.0	330	6.0
1984	208.6	204.0	16764.0	605	7.4
1985	214.1	198.0	12002.8	434	6.6
1986	211.3	207.8	9262.8	261	4.6
1987	213.3	201.1	10663.6	280	6.6
1988	226.9	219.8	12298.7	288	6.1
1889	233.2	204.2	13666.9	296	4.6
1990	233.2	216.0	19823.3	364	4.4
1992	179.0	182.0	14893.0	241	2.0
1993	232.0	218.0	19911.0	296	2.4
1994	242.0	230.0	20464.0	296	2.3
1995	246.0	241.0	24638.0	316	2.1
1998	280.0	272.0	50280.0		1.5

When considering on cultivation area of oil palm plantations, it is spanned into 8,500 hectares. Also, for oil palm, Sri Lankan Government's ambitious goal of planting 20,000 hectares of is declared, to expand the industry further. Therefore, it can be noticed that according to the continuously growing national and international demand, these industries will be expanding even more.

Over the past few years, the quality of tea is well maintained. But when intensively observed, there can be seen a small decline in quality of it due to several reasons. Insufficient watering, lack of required nutrients, disease infection consequences and inefficient utilization of pesticides can be mainly identified as those reasons. However, with the further expansions in the farming process in tea and oil palm industries, serious problems have been encountered. The problems can be identified especially related to watering, nutrient deficiencies, disease, and harvesting.

In giving solutions for the above problems, Precision agriculture can be identified as a very appropriate solution. This rapidly developing method is also known as satellite farming or site-specific crop management. And this farming management concept is based on observing, measuring and responding to inter and intra field variability in crops. A set of technologies is comprised of Precision Agriculture concepts such as sensor networks, information systems, and enhanced machinery. For instance, drone image is used for the identification of precise locations where water resources are scarce and require urgent attention of the farmer, especially in large scale plantations where it is difficult to access to every location. When considering the Sri Lankan content Precision Agriculture methods are hardly utilized even in large scale local farming industries. But there is a growing interest in this concept especially in some of the large-scale farming industries such as tea and oil palm industries, to elevate productivity and maximize profit.

1.1.1 Problems Identified in Watering

When the tea industry is considered, water is an extremely scarce resource. In the current system, a specific method of watering is not being applied and it is mainly dependent on rain and natural springs. For well-grown matured plants, continuous watering is not necessarily required and relies basically on rainfall. Even distribution of annual rainfall is very important in determining the geographical distribution of the tea plant, especially in hot climates [2].

But for new plants the first 12 months are critical. So, irrigation must be reliable and efficient for the newly grown tea plants. Available projections indicate that gradual warming will be experienced through Sri Lanka within this century [3]. In Sri Lanka, rainfall is usually governed by monsoon rains. However, with the changing of global weather patterns, due to many reasons like global warming, increasing environmental pollution, etc. rainfall also becoming unreliable for rain-fed crop growing in Sri Lanka and changing rainfall patterns may result in destroying plants that are in their growing stage. So, for new tea plants, relying on rainfall is not a good practice. As it would disturb the growing process and alternatively lead to an unexpected production loss.

1.1.2 Problems Identified in Nutrient Deficiency Detection

Inadequacy or imbalance of any of the chemical elements which plants need leads to functional disorders or it can be observed as abnormal appearances of the plant organs. Such abnormalities are referred to as deficiency symptoms. The most important elements which are required for a plant can be considered as carbon, hydrogen, oxygen, nitrogen, phosphorus, potassium, calcium, magnesium, sulfur and iron. But when detecting the deficiencies, the lack of nitrogen, phosphorus, potassium, calcium, magnesium, and sulfur, shows exceptional symptoms which can be identified by the color of the leaves. The effectiveness in the detection of color by simply observing the leaves is not quality enough. Because of that, the exact deficiency may not be detected. Also, on the spot detecting and decision making is not possible at the current human-based system.

1.1.2 Problems Identified in Disease Prediction

Tea is an extremely established plant in Sri Lanka that earns a high profit. But due to dynamical atmospheric conditions like variations in temperature, precipitation additionally as relative humidity tea plants are infected by numerous diseases that end in the reduction of the assembly. Blister Blight is such most evident illness damaging the tea plant. It affects the crops in small to larger proportion, thereby causes major losses in production.

Blister Blight is a disease, which affects tea because of weather conditions. At high elevations when the mist is spread, because of the moisture in the surface of the tea leaves, the tendency for infection of Blister Blight disease is increased. Before this scenario happens, the fungicides need to be applied. In the current system, there is no proper method of early prediction. So, it is not possible to predict whether the disease would happen or not, according to the change in weather. When applying fungicides as the common practice, the application is done in regular frequencies, regardless of evaluating the occurrence of the disease. So alternatively, it leads to a waste of money and time.

1.1.3 Problems Identified in Harvesting

And when considering the problems that the oil palm industry goes through, it is mainly of defining the quality of harvesting. In the oil palm industry, quality is defined by its texture, shape, and color. These features of the Oil Palm fruits are always monitored and observed by the human's vision which leads to inaccuracy in harvesting. Early plucked fruits can be reduced the quality of the product and alternatively leads to a huge loss in profit.

1.2 OBJECTIVES

The objectives of this project are to identify the problems related to the farming process of Tea and Oil Palm industries in Sri Lanka, which have the potential to be solved based on Precision Agriculture methods. And thereby propose appropriate and implementable solutions, to address the problems which have been identified.

i. Identification of the problems in the current farming process.

ii. Design an automatic drip irrigation system.

iii. Design an early prediction system for Blister Blight disease.

iv. Design a nutrient deficiency detecting system.

v. Design a ripeness detection system for Oil Palm.

1.3 SCOPE

- Developing an automated drip irrigation system for new tea plants
- Design TensorFlow object detection model to detect nutrient deficiencies and oil palm ripeness detection.
- Design a machine learning model, to predict whether tea plants would get affected by Blister Blight disease.
- Developing a web application to classify tomato leaf diseases.

2. LITERATURE REVIEW

2.1 PRECISION AGRICULTURE METHODS

Different types of implementations have been carried out in precision agriculture. [4] Research paper has proposed a system that takes data from the environment and saves them to calculate the amount of water needed for irrigation. The information is obtained using sensors connected to Arduino Uno. This information is sent to a cloud database. The system in the cloud calculates water needs and gives commands. However, in this system, they have not concerned the power consumption in the sensor node (Arduino Uno).

The agricultural sector is highly affected by wireless sensor network technologies and is equally expected to be benefited by the internet of things. Through a wireless sensor network, it measures physical and environmental parameters like soil moisture, soil temperature, soil pH, leaf temperature, relative humidity, air temperature, rainfall, vapor pressure and sunshine hours. Then the parameters are processed and wirelessly transmitted to a centralized data storage system through a gateway from where they can remotely access and analyzed. For irrigation, they suggested the drip irrigation system. However, they have not considered the power supply to the wireless sensor network [5].

Paper [6] has surveyed IoT in agriculture, recent advances, and future challenges. There they have included IoT related work within the scope of the topic. And they have included promising concepts like precision agriculture, wireless sensor networks, Internet of things enabling technologies, big data phenomenon, wireless communication protocols in agriculture, controlled environment agriculture, agricultural monitoring and control, and livestock applications. When it comes to IoT in agriculture, several challenges arise. Therefore, they have finally done their work to explain those challenges. Some of the main challenges of IoT hardware & software challenges in agriculture are networking challenges and security challenges. Therefore, it can be seen that this research work as a kind of database, from which anyone who expected to optimize agriculture production by many means can move their farmlands or greenhouses from precision to a micro precision level.

Paper [7] has done a review of the need for wireless sensors in different aspects of agriculture. There they have included sensors in the agriculture domain and their vendors. The remainder of the paper discusses topics like communication technologies, wireless sensor networks, issues in wireless sensor networks, energy consumption and design aspects of sensor nodes like fault tolerance, sensor node size, and housing, sensor placement. The final part of their work is dedicated to the wireless sensor network applications in agriculture. In this section, they have included key processes in agriculture industry like irrigation, fertilization, pest control, animal and pasture monitoring and horticulture (Horticulture deals with the cultivation, production, distribution, and use of flowers, fruits, greenhouse, ornamentals, etc. It is also known as small scale or low-intensity farming). Related work on each of these topics has included in respective topics.

2.1.1 Watering

Many factors govern the productivity of tea plants. Among them, photosynthesis of tea leaves and crop water usage plays an important role. Photosynthesis is a key factor that will eventually determine the productivity of a plant. Some factors affect the photosynthesis process of tea leaves are water deficit [8], pests and diseases [9], radiation intensities [10] and temperature [11].

Irrigation is capable of controlling many factors affecting the photosynthesis of tealeaves. Tea crop water emission is related to its transpiration and soil evaporation because the newly growing stage of the plant is small and cannot cover its ground area by its bush. Because of the low availability of water resources, drip irrigation shows itself as a suitable candidate for irrigation purposes of tea plantations [12]. Dripping is preferred because in hill areas wind can disturb sprinkler applications. [13] In their study, results indicated that drip irrigation gave water-saving benefits of up to 50% from the application of 50% less water to remove the cumulative soil water deficit, and with labor-saving of 85% for irrigation. Using drip irrigation for tea plants following things can be achieved: water to the correct place, water in the correct amount at the right time, water all plants uniformly.

2.1.2 Nutrient Deficiency Detection

The diagnosis of nutrient deficiency symptoms is an important feature in precision agriculture. This requires accurate and reliable techniques that permit the identification of exceptional symptoms caused by nutrient deficiencies.

To grow and function properly, every plant requires certain chemical elements in suitable quantities and forms. Imbalance or inadequacy of any of these elements leads to functional disorders or abnormal appearances of the plant organs. Such abnormalities are called deficiency symptoms. The major elements required by a plant for healthy and normal growth can be identified as, carbon, hydrogen, oxygen, nitrogen, phosphorus, potassium, calcium, magnesium, sulfur and iron. Other than the first three, the rest of the chemical elements are absorbed in the form of mineral salts in solution by the roots. The most easily recognizable symptoms are manifested in the overall growth of the plants and especially in their leaves. In the diagnosis of nutrient deficiencies, such symptoms can be used effectively [14].

Conditions of deficiency of several elements have been identified in the research paper [14], in the case of tea. There also cited several records regarding deficiency detection. The earliest record of a deficiency disease of tea was that of Storey and Leach who diagnosed an obscure disease described as "Tea Yellows" in Nyasaland, to be caused by a deficiency of sulfur. Illustrated accounts of individual nutrient deficiency symptoms on Ceylon tea have appeared from time to time. Potassium deficiency was analyzed by Portsmouth, magnesium deficiency identified by Mulder and de Silva, nitrogen by Mulder and Visser, zinc by Tolhurst and manganese by Tolhurst.

According to [15], Most of these physiological disorders affect the composition and proportion of pigments on leaf tissue throughout this research, Tomato seedling was considered. And as Nitrogen has a major influence on the productivity level of it, mainly deficiency of Nitrogen was analyzed. There utilized two indirect methods as Digital color image analysis based in Red, Green, and Blue (RGB) color space and the chlorophyll content in leaves, to detect Nitrogen deficiency. There also cited some relevant researches as, determine the chlorophyll content on plants using a video camera and a computer [16], detecting the level of Nitrogen fertilization using digital photography by employing aerial photographs to estimate the level of Nitrogen fertilization in a wheat field and carrying out digital color image analysis using the Hue, Saturation, Intensity (HSI) model for color image processing to analyze changes in the color of three different species of plants that were subjected to Nitrogen, phosphorous, potassium and magnesium deficiencies.

Changes in leaf spectral characteristics have the potential to serve as indicators of nutrient deficiencies in plants. The advantage of being rapid, nondestructive, relatively inexpensive, can be identified form this method. An example of the successful use of spectral detection is provided by the detection of Manganese deficiency in wheat. Because of the specific role of Mn in electron transport from water to Photosystem II, this approach succeeded. Photosystem II (PSII) is a specialized protein complex that uses light energy to drive the transfer of electrons from water to plastoquinone, resulting in the production of oxygen and the release of reduced plastoquinone into the photosynthetic membrane. When hypothesizing that deficiencies of micronutrient metals that are required in the biosynthetic pathway of chlorophyll or required for electron transport would be most easily detectable by spectral changes in fluorescence or visible and near-infrared reflectance [17].

The use of remote sensing techniques to estimate nutrient status could decrease the amount of labor needed for sampling and could reduce the cost associated with sampling and analysis [18]. The paper [18] also cited the research of Blackmer and Schepers, who found that the chlorophyll meter was a useful method of monitoring corn N status, compared with measuring leaf N concentration, which requires destructive sampling. While the chlorophyll meter is a good indicator of in-season N status, the technique requires time and labor for data collection. The use of remote sensing could help eliminate the need for extensive field sampling while still providing a good detection of deficiencies [19].

2.1.3 Disease Prediction

In searching for the background research on the blister blight disease it can be noticed that there is no exact way of predicting using a software. But there are methods mentioned in some research papers about preventing the disease from using chemicals. And by referring them it can be noticed that there is still a traditional method of applying the fungicides regularly but not in a precise way. So that the application of fungicides may be a waste of money and time. And also, a cause of severe damage made to health and the environment. But by considering the weather conditions the precautions can be taken on time. As mentioned in paper [20] Heavy crop losses, which can be as high as 43% (Ordish, 1952) occur when the tea is unprotected during the period of disease occurrence and to keep the disease under the critical threshold level, it becomes necessary to spray at frequent intervals (7-9 days) with about 20-30 sprays annually, depending on the weather conditions. A weather-based forecasting system reduces the cost of production by optimizing the timing and frequency of application. And alternatively ensures operator, consumer, and environmental safety by reducing chemical usage. A major aim of the proposed forecasting system was to reduce fungicide use and accurate prediction as it is important to synchronize the use of disease control measures to avoid crop losses [21]. For the prediction purpose, developing software can be identified as an effective method. Diverse modeling approaches viz. neural networks and multiple regressions have been followed to date for disease prediction in plant populations. However, because of their inability to predict the value of unknown data points and longer training times, there mentions a need for exploiting new prediction software for a better understanding of plant-pathogen-environment relationships. And this paper introduces a new prediction approach which is based on support vector machines for developing weather-based prediction models of plant diseases [22].

In the paper [23], a comprehensive review of the application of Machine Learning in agriculture, have been presented. The conclusion is given by going through a survey as by applying machine learning to sensor data farm management systems can be evolving into real artificial intelligence systems. And it would be providing valuable recommendations and insights for the subsequent decisions so that the actions can be taken to improve the production.

Disease severity and weather data were analyzed using artificial neural network (ANN) models can be developed. Using data from some or all field sites in Australia and/or South America to predict severity at other sites this has been done. They have developed three series of models using different weather summaries. In the paper it mentions that, Of those ANN models with weather for the day of assessment of disease and the previous 24 hour period had the highest prediction success, and models trained on data from all sites within one continent correctly predicted disease severity in the other continent on more than 75% of days and the overall prediction error was 21.9%. In developing the ANN models, there also mentioned that, moisture-related variables such as rain, leaf surface wetness and variables that influence moisture availability such as radiation and wind on the day of disease severity assessment or the day before assessment were the most important weather variables [24].

2.1.4 Harvesting of Oil Palm Fruit

On extensive literature review which has undertaken on palm oil industries and Background knowledge in the relevant fields from research papers, the following details were found.

As the details mentioned in the research paper [25] it clearly says that color is the most important characteristic to identify fresh fruit bunch ripeness [26, 27, 28]. The important color features are color histogram, color moment, and color correlogram. These are extracted from the Red, Green, and Blue (RGB) images of fresh fruit bunch. But there is some inaccuracy in predicting the ripeness because color histogram has less computational complexity compared to color moment and color correlogram [29], and also, it’s less sensitive to a small color variation in the image. The color correlogram is mainly using in image retrieval and it consumes massive amounts of computation and storage [30]. The color moment is very simple and robust since it’s insensitive to color variations [31].

Various methods of ripeness detection techniques have been investigated by researchers [26, 28, 32]. A rule-based way to detect fresh fruit bunch was discussed it selects three types of Region of Interest for computing. However, this method also particularly suits only for certain cases and not for all situations. A laser-based imaging system was proposed to substitute the traditional method. The research leads to get to know more details. Such as, it is necessary to be known the relation between laser-induced reflectance (measured by red green blue) intensities and ripeness levels of oil palm FFBs. Secondly, it is needed to study the effect of laser wavelength on the relation. Finally, the effect of height varieties on the intensity profile is to be known.

Computer vision techniques are mostly relying on image processing method to extract information such as color and outlook. Hyperspectral imaging technique has been used to predict firmness and soluble solids content of blueberries. This method was more powerful than the computer vision techniques. But it uses lamplight or sunlight as a light source [33].

Using four-band sensors the ripeness detection of oil palm fresh fruit bunch was proposed [34]. The vision system employs a computer and a 4-band sensor device, which are utilized to measure a vegetation index with images that require human analysis and interpretation. The 4-Band Sensor equipment consists of the following bands: 660 nm, 780 nm, 870 nm, and 970 nm. Data analysis using the T-test method was performed to inspect three classes of oil palm fresh fruit bunches ripeness; under-ripe, ripe and over-ripe categories. This paper focuses on reflectance acquisition, which can reveal the essential information of interest using the visible and near-infrared bands of radiation. But its highest classification accuracy was 83% using the Support Vector Machine method.

To find out which algorithm has more accuracy on brain tumor recognition to identify two classes of brain tumor research was done and it results Naïve Bayes surpass Support Vector Machine [35]. Convolutional Neural Network for oil palm grading recognition [36] this research compares CNN, pre-trained CNN model and hand-crafted feature and classifier approach. The result shows that the pre-trained CNN model outperforms other methods. Mostly the red represents ripe, reddish-orange indicates overripe, reddish-black is under-ripe while purplish-black corresponds to unripe. Various color models such as Red, Green, and Blue (RGB) [37] and Hue, Saturation and Intensity (HSI) [38] have been utilized by researchers to classify these various ripeness classifications. And along with that texture feature such as Basic Gray Level Aura Matrix (BGLAM) has also been applied but none of them has 100 % accuracy in predicting [39].

Furthermore, these types of hand-crafted methods and feature extraction needs extensive time in classification and identifying suitable feature.

Nowadays most of the researches have been investigated using Convolutional Neural Network in many computer vision tasks related to fruits and plant recognition such as leaves identification [40], classification of fruits [41]. A comparative study of Alex Net and handcrafted feature and classifier approach for leaves identification shows Alex Net produces better results [42].

2.1.5 Tomato Leaf Disease Detection

Here we have taken some of the paper related to the plant leaf disease detection using deep learning techniques. On a few selected diseases and crops various machine learning algorithms have shown better results on plant leaf disease identification [43]. The introduction of the convolutional neural network for image classification further enhanced accuracy and identification [44]. For classifying 8 different tomato diseases AlexNet and GoogleNet were used [45]. The transfer learning method using pre-trained AlexNet for image classification was used [46] it was able to classify 26 different diseases on 14 selected crops using 54,306 images with an accuracy of 99.35%. Using the Plant Village dataset of 14 plant species research was evaluated the performance of different deep learning models such as Visual Geometry Group (VGG) net, Inception V4, ResNet and DenseNet results shows that DenseNet provided the best performance with the validation accuracy of 99.75% [47]. The performance of the AlexNet and SqueezeNet was evaluated with the Plant Village dataset consists of 9 different diseases and healthy one of tomato crops the outcome is AlexNet resulted in an accuracy of 99.65% whereas SqueezeNet results 94.3% at lower computational load [48]. A novel approach to classify fruits using a convolutional neural network was proposed [49] they used transfer learning using the Faster R-CNN model and they got the score 0.83 in a field farm dataset. Training the machine learning model from scratch takes a lot of time and needs more computational power because that a method transfer learning was introduced, it can improve the performance of deep neural networks by avoiding complex data mining and data-labeling efforts [50].

There are mainly two ways of disease occurrence one is because of bacteria, insects, fungi and different viruses in the category of living agents whereas the other way is excess moisture, temperature changes, fewer nutrients, insufficient lights, and different environment parameters [51]. Different classification algorithms are used in the past work such as neural networks [52], support vector machine [53] and rule-based classification [54,55]. K-mean clustering, texture and color analysis method were presented on disease detection in Malus Domestica this uses the texture and color features that commonly appear in normal and affected areas [56]. In paper [57] the author proposed a methodology for early and accurately detecting plant diseases using artificial neural networks and diverse image processing techniques. It gives better results with a recognition rate of up to 91% this method uses the combination of textures. It uses color and features to recognize those diseases. In the past decade for the image classification, problem researchers have often been conducted based on the classification process by using features such as color, shape, and texture [58,59,60]. The major disadvantages of using those methods are they have low performance and require the use of segmented methods. Using the transfer learning method [61] the pre-trained model LeNet architecture was used to classify image datasets, including being able to contrast healthy and diseased banana leaves. They [62] developed a classification system based on convolutional neural networks it shows an average of 82.3% under a fourfold cross-validation strategy. Their system was able to classify seven disease types. [62] Proposed a new method to classify 13 different varieties of plant diseases by using deep convolutional neural networks. In [63] developed a robust deep learning-based classifier for real-time usage to recognize nine different tomato diseases and pests. In the ILSVRC-2014 competition, the Oxford Visual Geometry Group proposed a homogeneous architecture which results in better accuracy [64]. Smartphone-based applications for shape and disease identification in plant leaves have been developed [65, 66]. A powerful framework was developed in the recent past using a convolutional neural network a specific type of deep neural network for feature representation and recognition for a variety of image domains [67]. In [68] deep learning was used to identify the type of plants based on their leaf vein patterns. They were able to classify three legume species, including white bean, red bean, and soybean using convolutional neural networks having up to 6 layers.

3. MATERIALS AND METHODOLOGY

3.1 DESIGN OF AN AUTOMATIC DRIP IRRIGATION SYSTEM

In the process of achieving the main objective of applying precision agriculture methods for tea plantations, we have designed a system for a new growing tea plant nursery. After observing a real environment tea plant nursery setup which shows in Figure 1, we have gathered the information on its requirements and arrangement.

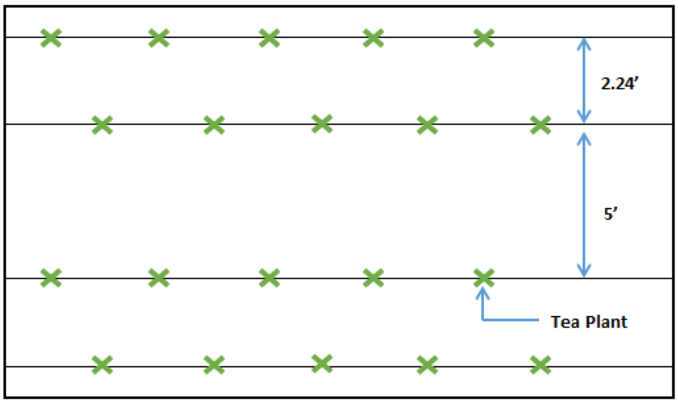


Figure 1:The arrangement of new plant area

The new tea plantation area in which the precision agriculture methods to be applied for watering was designed to facilitate the machine tea leaves plucking system. Therefore, there can be seen the spaces in between individual plants and rows of plants, to satisfy that requirement.

The drip irrigation system which consists of precision agricultural methods was designed considering arrangement. In the prototype, four-sensor nodes were implemented considering four rows of tea plant nursery. According to that in the prototype, there is the main pipeline. And form that main pipeline four sub pipelines (laterals) were added to facilitate water for four rows of tea plant nursery. There are drip emitters in the laterals to emit water drips. The distance between the drip emitters is 2 feet according to the real plantation setup. The type and size of pipelines, the kind of drip emitters that need to be used were decided according to the watering requirements of new tea plants.

The main pipe which has used for the irrigation prototype was $1\frac{1}{2}$ inch PVC pipe. That main pipeline was divided to 4 sub lines of $\frac{3}{4}$ inch PVC pipe lines. Each sub-line then connected to a solenoid valve. After connecting to the solenoid valves the pipeline is connected to the lateral lines. The lateral lines are the special purpose pipes used in drip irrigation systems. The lateral pipes which we have used in the prototype are of 16mm diameter.

Figure 2:The lateral pipes

The drippers which have selected for this new tea plantation irrigation system were 4 liter per hour liquid emitting 16mm online drippers. There are several types of drippers with different drip emitting techniques. Therefor according to the agriculture instructors' recommendations, the following type of drip emitters was used.

Figure 3: Water drip emitters

The automatic drip irrigation system consists of two main circuit designs. Those are the relay circuit and sensor node circuit. The block diagram of both circuits and their interconnections are shown in Figure 4. The relay circuit is equipped with a power regulator, relay module and an ESP8266 Wi-Fi module to communicate with the central hub, relay module as well as with microcontroller modules of sensor nodes. The relay module is connected to solenoid valves to control the irrigation. The sensor node circuit is consisting of an ESP8266 microcontroller, soil moisture sensor, temperature and humidity sensor.

Soil moisture, temperature, and humidity are the parameters that can be measured by each sensor node. For that purpose, we have used a capacitive soil moisture sensor and a temperature and humidity sensor. These sensors have then connected to the ESP8266 microcontroller. To run safely ESP8266 module requires 2.5V to 3.6V power supply. Therefore, in each sensor node, there are Li-ion rechargeable batteries that are charged form solar panels through charging modules.

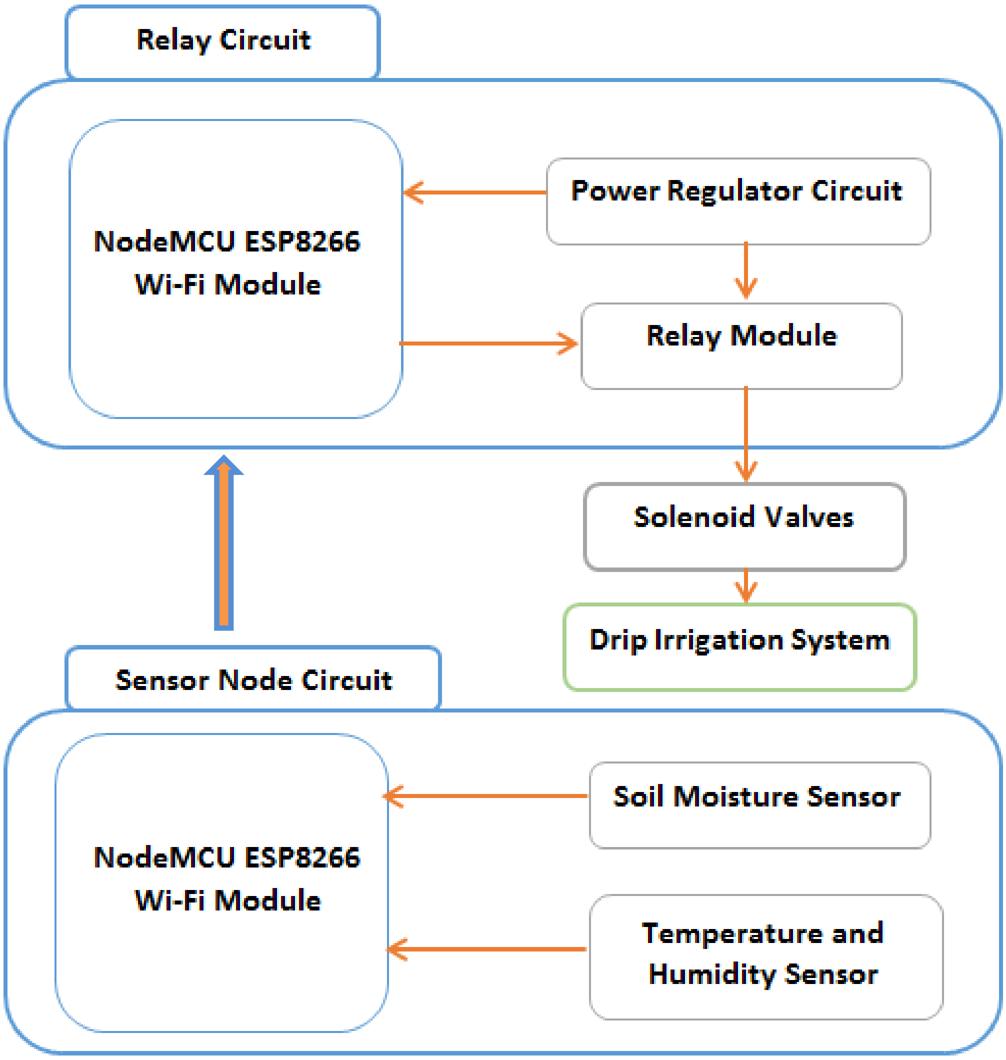


Figure 4: The block diagram of the proposed drip irrigation system

3.1.1 Details of Components

Wireless Sensor Node is the key object in each plant row that senses environmental parameter values. In the sensor node, there is a microcontroller, a capacitive soil moisture sensor, and a humidity and temperature sensor.

There are several components with special features that we have used in developing the above-mentioned block diagram. Figure 5 shows the microcontroller module used in both the relay controller circuit and sensor node circuit.

Figure 5: NodeMCU ESP8266 Wi-Fi module

The ESP8266 can be identified as high performance as well as a low-cost Wi-Fi module which is mostly used for the development of IoT embedded applications. NodeMCU ESP8266 includes various features such as embedded Wi-Fi capabilities, GPIO (General Purpose Input/Output) pins, presence of shield, antenna, memory, and external analog signal handling. This packed feature in one module is an advantage as it requires minimal external circuitry. The ESP8266 requires a 3.3V and up to 250mA power supply. To optimize power, the ESP8266 module can operate in various modes. This power-saving architecture is so useful in making power efficient system.

During deep sleep mode, only the real-time clock will be powered on and the rest of the chip will be powered off. Basic 'Wi-Fi Connecting' information can be kept by the recovery memory of the real-time clock. In our proposed sensor node, the ESP8266 module was set to wake up in regular intervals to measure soil condition and go back to deep sleep mode after measuring.

Figure 6: Capacitive soil moisture sensor V 1.2

Figure 6 shows the capacitive soil moisture sensor which measures soil moisture level by capacitive sensing while most of the other sensors measure the soil moisture by resistive sensing.

The DHT22 sensor which shows in Figure 7, is made of two parts. A capacitive humidity sensor and a thermistor are those two parts. And it gives the temperature and humidity values at the same time.

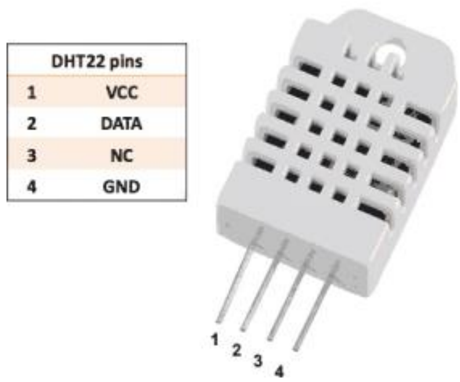


Figure 7: Temperature and humidity sensor DHT22

Soil moisture, temperature, and humidity are the parameters that can be measured by each sensor node. For that purpose, we have used a capacitive soil moisture sensor and a temperature and humidity sensor. These sensors have then connected to the ESP8266 microcontroller. Values obtained by the sensors are goes directly into the microcontroller and the microcontroller will send this data to the central hub via Wi-Fi. For this Wi-Fi, repeaters are used to keep the sensor nodes connected to the same network without loss of connection.

After the data is received to the central hub, it will then send this data to the relay microcontroller, which is also connected to the wireless sensor network. Depending on the predefined values of soil moisture levels, the relays will operate accordingly. Each relay is connected with a solenoid valve, which will supply water to an entire row. A solenoid valve is an electromechanically controlled valve. The valve features a solenoid, which is an electric coil with a movable ferromagnetic core in its center. This core is called the plunger. In the rest position, the plunger closes off a small orifice. An electric current through the coil creates a magnetic field. The magnetic field exerts a force on the plunger. As a result, the plunger is pulled toward the center of the coil so that the orifice opens. This is the basic principle that is used to open and close solenoid valves.

Figure 8: The solenoid valve

To power the sensor node, we have used 3.7 V, 5000 mAh Li-ion rechargeable batteries which will be energized by 6V, 2W solar panels.

Figure 9: Li-ion rechargeable batteries (18650 left) & solar panel (right)

3.1.2 Sensor Node Enclosure Design

When we implement these circuit setups in the real environment there can be several issues that will cause damage, especially for the electronic equipment. The circuit boards should be covered by a well-designed enclosure to protect the inner equipment from water and dust. Therefore, an enclosure was designed for both sensor nodes is shown in Figure 9. The enclosure design was designed by using Solid works tool.

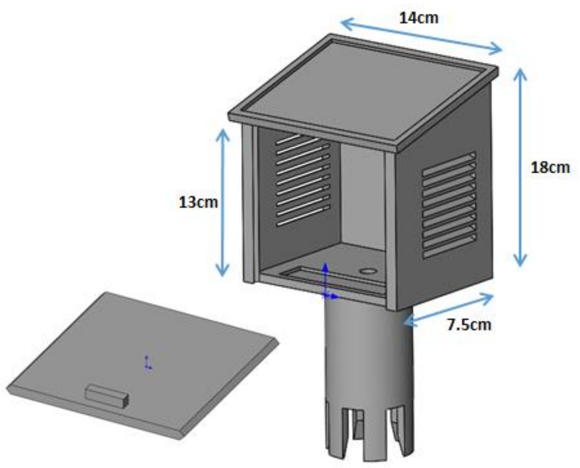


Figure 10: The enclosure design of a sensor node

3.1.3 Details and Prices of Materials

Table 2: The details and Prices of Materials

Item	Description	Quantity	Per Unit Price/Rs	Total Price/Rs
NodeMCU 12E	Microcontroller	3	1100	3300
ESP32	Microcontroller	2	1200	2400
DHT22	Temperature & Humidity Sensor	4	775	3100
Capacitive Soil Moisture Sensor	Soil Moisture Sensor	5	241	1205
TP4056	Li-ion Battery Charging Board	8	100	800
Solar Panel	5.5V 220mA Solar Panel	4	280	1120
Switch Mode Power Supply	230VAC-12VDC Power Supply	1	1450	1450
Breadboard Power Supply	Power Supply	2	200	400
PCB Terminal Blocks		15	10	150
Pin Headers	1*40 Pin headers Socket Female	16	15	240
PCB (Sensor Node)	Ordering PCB from JLPCB	5		377
PCB (Relay Circuit)	Ordering PCB from JLPCB	5		377
Solenoid Valves	Valves	4	700	2800
4 Channel Relay Module	Relay	1	400	400
18650 Li-ion Batteries	Batteries	8	380	3040
Li-ion Battery Holder	Battery Holder	4	100	400
PVC Pipes & Related things				800
Irrigation Pipes & Its equipments	Irrigation Pipes, Drippers, Connecters etc			1725
Wires				300
Jumper Wires (Male/Male)	Wires	2	150	300
Jumper Wires (Male/Female)	Wires	2	150	300
PC 817 IC	IC	10	20	200
BC 337	Transistors	10	6	60
Cladding (material)	Sensor node enclosure box material			2000
	Total			**27244**

3.1.4 Powering the Sensor Node

For the continuous function of the sensor node, we have to maintain continuous power supply. Otherwise, the system may not work efficiently. The best way to supply continuous power to the circuit is by using a battery. But after some days the battery power will run out and it can be found difficult to replace it every time. With the use of solar panels and solar charging circuit, energy from the sun can be harvested to charge the batteries in the designed system which is shown in Figure 10, the battery is charging from a 6V solar panels that can deliver 2W of power through a TP4056 charging module.

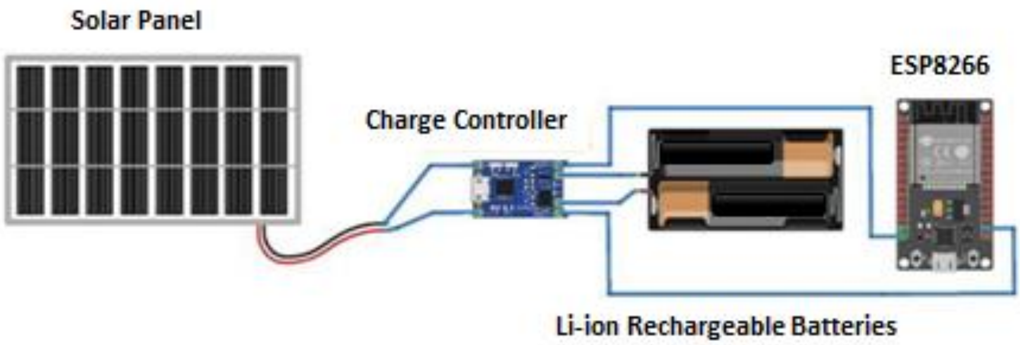


Figure 11: Powering sensor node with solar panel

The figure bellow shows the calculation [69] we used to choose a suitable battery and solar panel. Here, the load current is used as the maximum current that the ESP8266 can draw according to the datasheet. By using that value, we can make sure the battery will not drain because of more load current. The graph is slowly ascending because of the solar charging then it comes to its maximum limit. After some time when the sun sets solar charging is not available and the microcontroller uses battery power. That is why the graph is slowly descending with time. But it can be seen that it will not drain full battery capacity. This estimation gives approximate calculation to choose a feasible battery and solar panel and these values can be changed because of many reasons like environmental factors, conditions of the battery, etc.

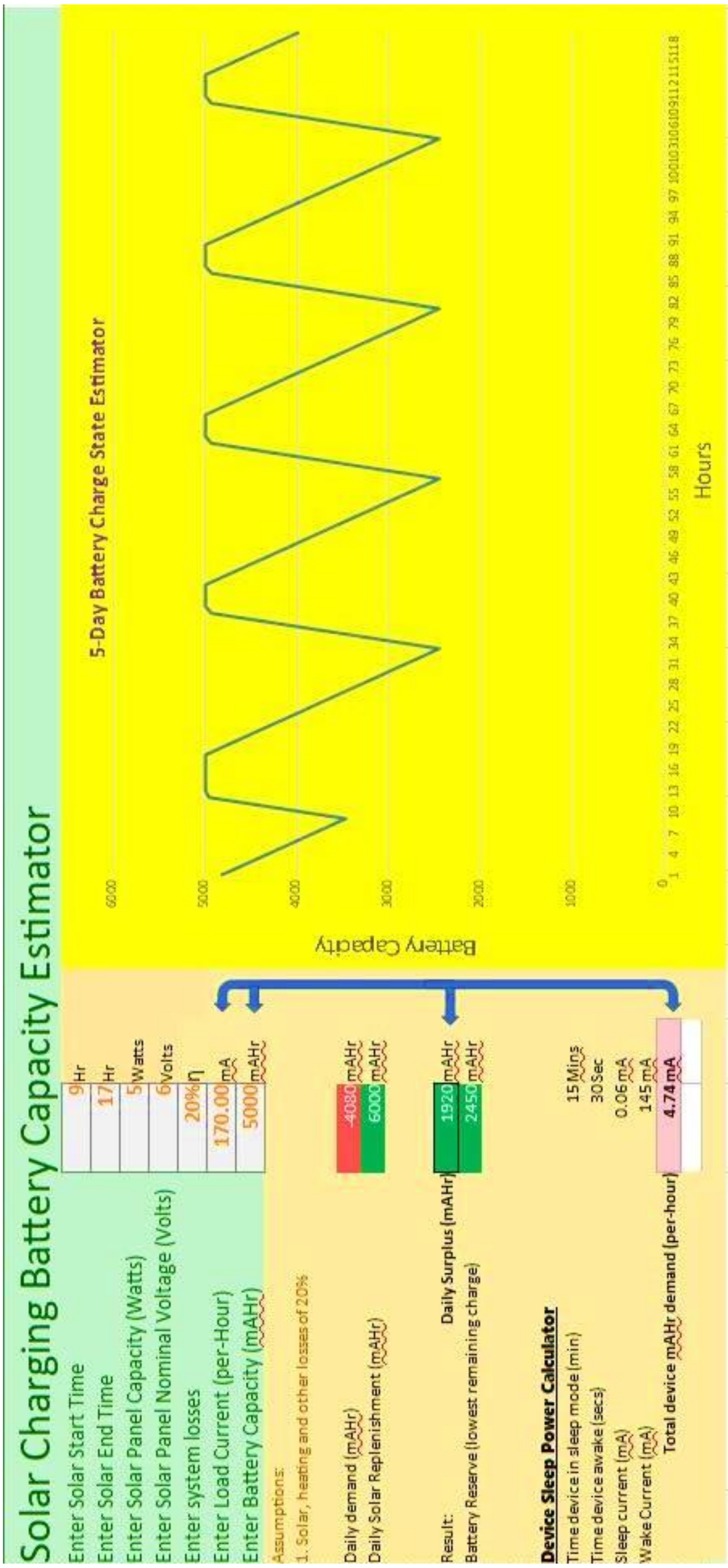


Figure 12: Battery charging & discharging during the hours of the day according to the specification of the solar cell & batterie

3.1.5 PCB Design

According to the sensors and microcontroller arrangement the PCB was designed for sensor nodes. The designed drip irrigation system consists of a NodeMCU ESP8266 Wi-Fi module, 4-way relay module and solenoid valves for controlling mechanism. Including these components, the relay controller circuit PCB was designed. To reduce the size of the sensor node and during the practical time we encountered the connection errors so we designed the printed circuit board using Eagle Cad and we ordered the design to pcb manufacturing company through online.

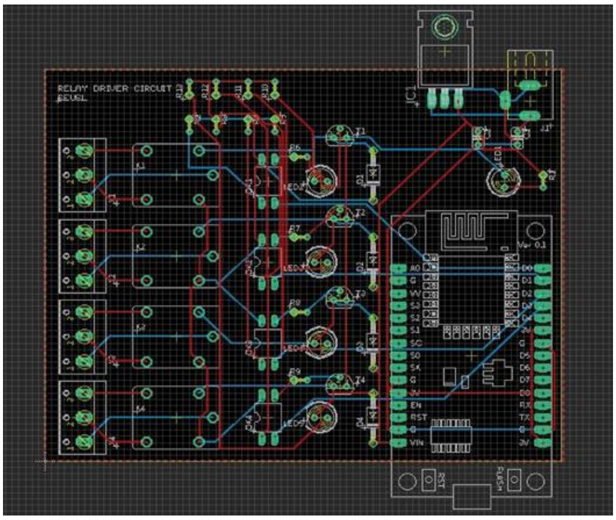
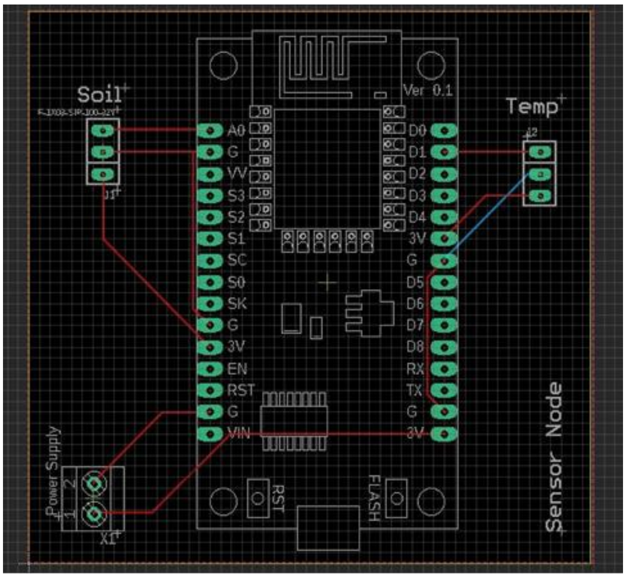


Figure 13: The PCB design of the relay circuit



. **Figure 14: The PCB design of the sensor node**

3.2 DATA COMMUNICATION MANAGEMENT

All sensor nodes send environmental parameter values to one central hub in this design. The communication is done with the help of Wi-Fi using the MQTT (Massage Queuing Telemetry Transport) protocol. For the communication purpose, it requires an MQTT broker that dispatches all massages between senders and their relevant receivers. In this project Mosquitto, MQTT broker is used. First sensor nodes are subscribed to topics. Then they publish sensed data to relevant topics. In the central hub, using the NodeRED programming environment, each sensor data published on particular topics is grabbed. NodeRED is a virtual programming environment where the user can configure a different kind of nodes according to the task needed. As shown in the block diagram in Figure 11, the sensor values are sent to the central hub and then they are stored in a local database for further data processing purposes.

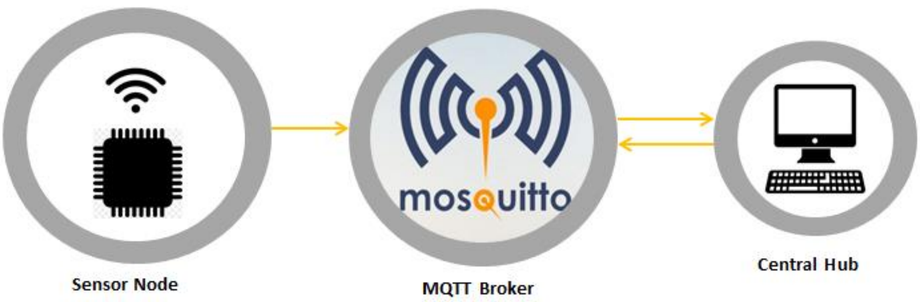


Figure 15: Data communication flow chart

3.2.1 WEB Application Development

In the process of gathering data through sensor nodes, there should be a structured system to store. The structured data is useful in the decision-making process. According to our sensor node structure, four data can be collected. Those are timestamp, soil moisture, temperature, and humidity. These continuously updating data should be put in a well-organized and structured database. And also, there should be a method of accessing that database anytime we need it. Therefore, designing a web application can be identified as the best option. The following requirements can be identified as objectives of designing the web application.

- Insert each sensor node data in an organized database.
- Display the present values of each sensor node separately.
- Graphical representation of sensor node readings.

- Calculate the average values of sensor readings and representation.
- Maintain a database of average values per day and representation.

The structure of the databases is represented in the Figure 16.

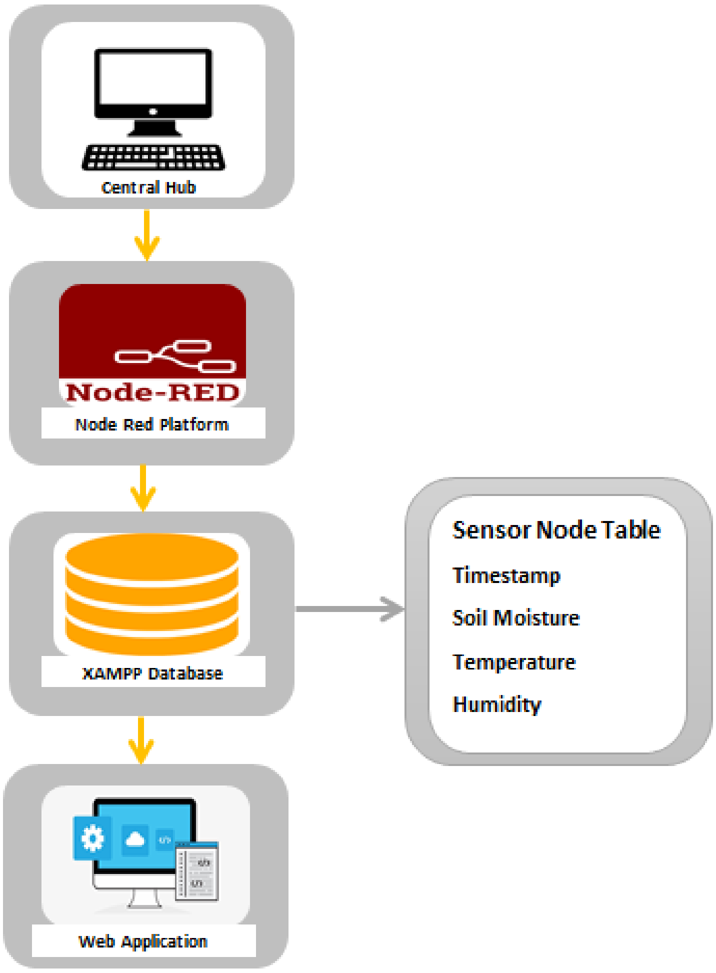


Figure 16: The block diagram of the proposed drip irrigation system

In the developing process of the web application, we have used XAMPP, which is an open-source cross-platform web server solution stack. MySQL, PHP and HTML languages were mainly used in the development of this web application.

3.3 DESIGN OF SYSTEM TO PREDICT BLISTER BLIGHT DISEASE OCCURRENCE

The proposed solution is a more convenient way of preventing the damages caused by blister blight by predicting the tendency to get infected. There are several weather conditions which have been identified that give forecasting details of the disease such as, temperature, relative humidity and soil moisture level. Using these details, a web application can be developed which will predict the vulnerability to the infection. This proposed weather-based prediction web app will reduce the cost of production by optimizing the timing and frequency of application of chemicals. That ultimately ensures healthy and environmentally friendly system. So, an accurate prediction is required to control the disease and to avoid crop losses. So, we have created two different machine learning algorithms they are support vector machine and k-nearest neighbor and choose the model which give more accuracy and we deployed it into flask web application and also stored it in cloud so it can be access by anyone.

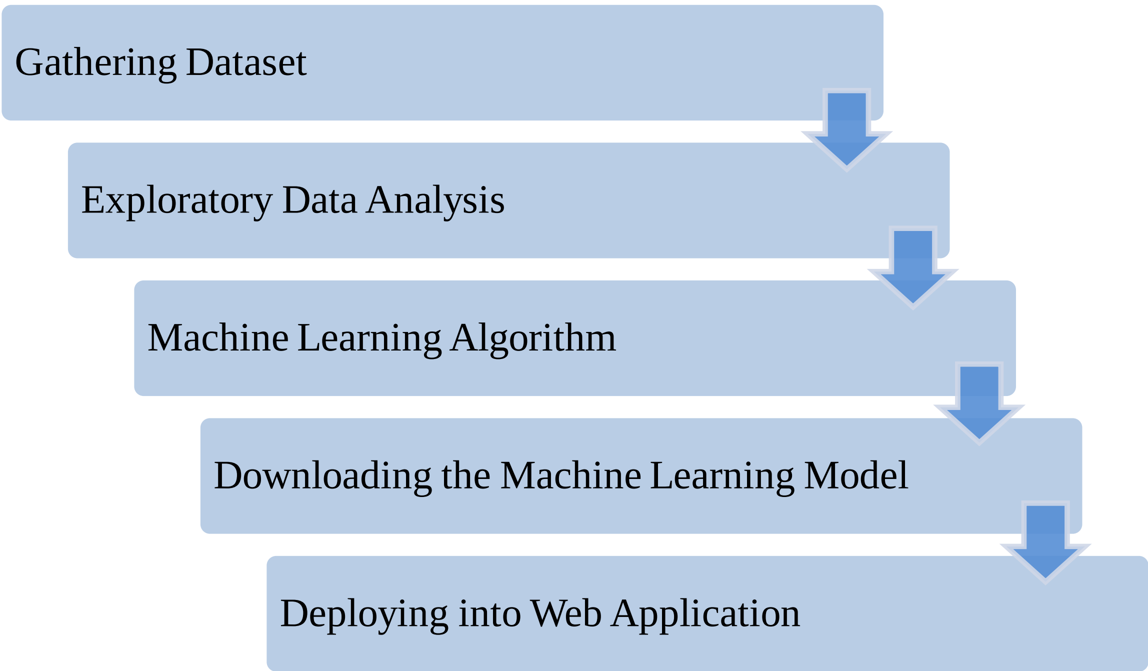


Figure 17: Workflow of the proposed method

3.3.1 Methodology for Disease Prediction

Step 01: Gathering dataset.

Gathering dataset is the main work in the machine learning concepts. We went to Nayapana tea estate to gather relevant data and also, we search in the internet to collect data for our problem.

Step 02: Exploratory data analysis.

Before feeding the collected data into machine learning algorithm we need to do exploratory data analysis. Exploratory data analysis means we need to remove the unwanted data columns and also, we need to make sure there is no missing values in the relevant columns. After that we need to separate columns into input and predicted output here in our case the readings of soil moisture sensor, humidity and temperature are the input and the labels whether the blister blight disease occurred or not is the predicted output. Finally, we need to separate the dataset into two parts training and testing with that we can test our model.

To do data analysis we used Python libraries such as NumPy, Pandas and to visualize the plots we used Matplotlib, Seaborn and to create the model we used Sklearn package.

Step 03: Machine learning algorithm.

1. Support Vector Machine

Support vector machines (SVMs) are supervised learning models with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis. Given a set of training examples each marked for belonging to one of two categories, SVM training algorithm builds a model that assigns new examples into one category or the other, making it a non-probabilistic binary linear classifier.

2. K – Nearest Neighbor

K – Nearest Neighbor is a classification algorithm that operates on a very simple principle. First, the model has been trained using data set later in the prediction algorithm for new test points, which works like calculate the distance from new data to all the points in the data set then sort the points near data by increasing distance from new data. Then the majority label of K is predicted, and being a number of closest points choosing K value will affect which class a new point is assigned to. This prediction is on binary classification, the expected output is True or False.

Step 04: Downloading the machine learning model.

After calculating the accuracy and classification report we need to download the model to deploy into web application. Otherwise if we not downloaded the model, we need to train it again to predict the new results. Because of that reason we downloaded the model in .pkl format.

Step 05: Deploying into web application.

Deployment of machine learning models or putting models into production means making your models available to the end users or systems. Machine Learning models are powerful tools to make predictions based on available data. To make these models useful, they need to be deployed so that others can easily access them through an API (application programming interface) to make predictions. This can be done using Flask and Heroku - Flask is a micro web framework that does not require particular tools or special configurations.

These are the reasons we choose Flask for our model deployment they are its easy to use, built in development server and debugger, integrated unit testing support, RESTful request dispatching and extensively documented.

The complete contents in the folder as follows; -

1. model.py – This contains the code to develop the machine learning model.
2. app.py - This contains Flask APIs that receives input details through GUI, computes the predicted value based on our model and returns it.
3. request.py - This uses requests module to call APIs defined in app.py and displays the returned value.
4. HTML/CSS - This contains the HTML template and CSS styling to allow user to enter input detail and displays the predicted output whether the blister blight is occurred or not.

3.3.2 Serializing/De-Serializing

In simple words serializing is a way to write a python object on the disk that can be transferred anywhere and later de-serialized (read) back by a python script.

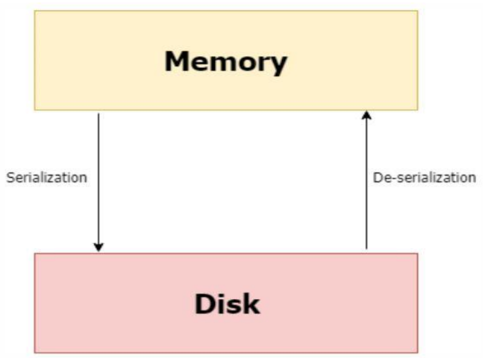


Figure 18: Serializing / De-Serializing

We converted the model which is in the form of a python object into a character stream using pickling. The idea behind here is the character stream contains all the information necessary to reconstruct the object in another python script. The next part was to make an API which receives input details through GUI and computes the predicted output value based on our model. For this We de- serialized the pickled model in the form of python object. We set the main page using index.html. On submitting the form values using POST request to /predict, we get the predicted sales value. The results can be shown by making another POST request to /results. It receives JSON inputs, uses the trained model to make a prediction and returns that prediction in JSON format which can be accessed through the API endpoint.

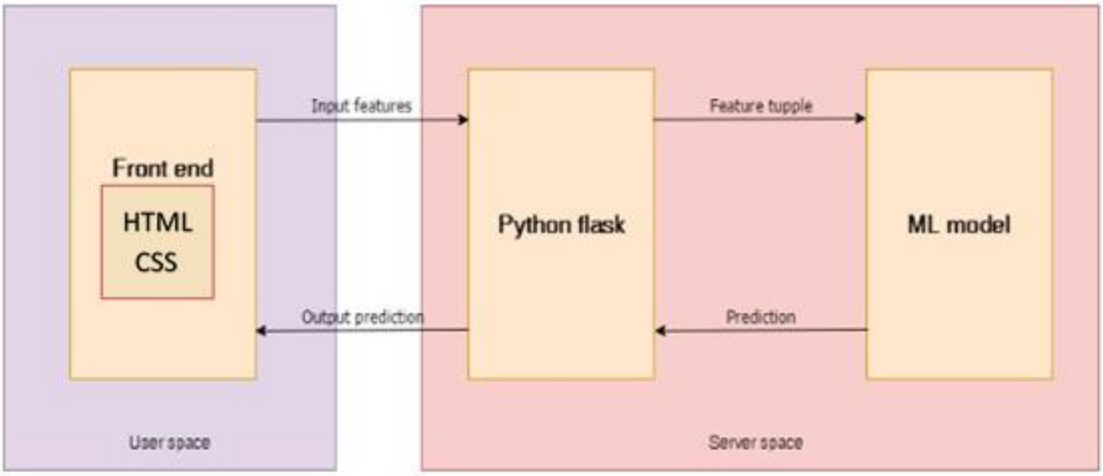


Figure 19: Dataflow

3.3.3 Heroku

Heroku is a platform as a service (PaaS) that enables developers to build, run and operate applications entirely on cloud rather than doing locally on your machine. In this project we deployed using Heroku git. There are other methods as well to deploy. We uploaded our code project into the GitHub and then we clone the project with the Heroku platform.

Link to the Web application - https://diseaseprediction-api.herokuapp.com.

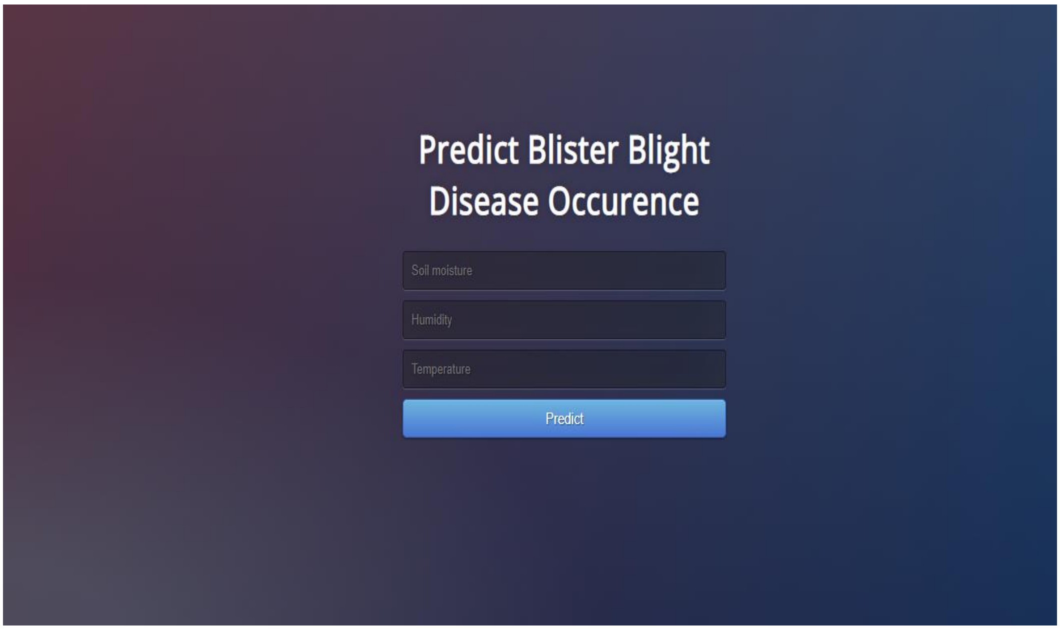


Figure 20: Input GUI

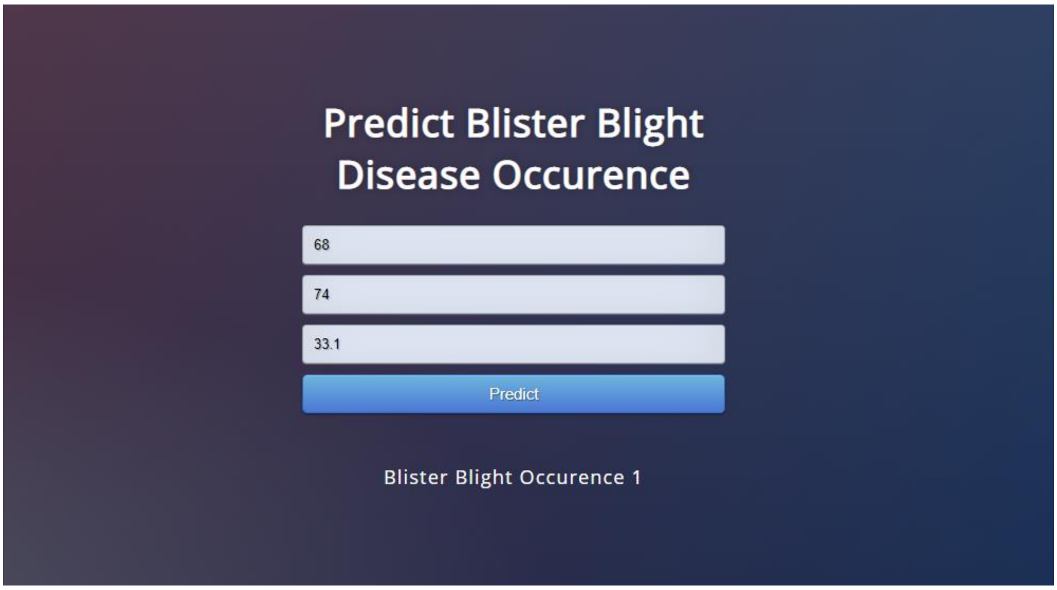


Figure 21: Results

3.4 DESIGN OF SYSTEM TO DETECT TOMATO LEAF DISEASES

The methodology that we have used here was for tomato plant leaf which is a similar applicable methodology for tea plant leaves. Tomato plants are susceptible and can die if do detect and react to blight and leaf spot infections. The main objective of this proposed method is to create a machine learning model that could able to classify tomato leaf diseases and also created a web application so anyone can easily excess to it. In this study, we used the transfer learning approach which is the application of using pre-trained deep learning models for classifying new class of objects. In practice, training a neural network from scratch is very difficult because it is rare to get lots of datasets. So, using the pre-trained network as initializations or a fixed feature extractor helps in solving most of the problems in hand. The other problem is very deep neural networks are expensive to train and also it needs more computational power. The following steps show the methodology of how we built the system.

Step 01 – Gathering Datasets

Image dataset that contains tomato leaf diseases were collected from crowdAI. The crowdAI platform is an open source infrastructure that hosts open data science challenges. We found the dataset from “Plant Village Disease Classification Challenge” competition. Required Packages: - Keras, NumPy, TensorFlow, Pillow and Flask.

Step 02 – Split the dataset

Table 3: Image Dataset

Label	Class name	Number of Images	Training Set	Validation Set	Testing Set
1	Tomato Bacterial Spot	2127	1694	422	11
2	Tomato Early Blight	1000	792	198	10
3	Tomato Healthy	1591	1272	309	10
4	Tomato Late Blight	1909	1518	380	11
5	Tomato Leaf Mold	952	748	184	20
6	Tomato Mosaic Virus	373	290	73	10
7	Tomato Septoria Leaf Spot	1771	1400	350	21

The above table shows how we separated the dataset into training, testing, and validation. The dataset consists of six different tomato leaf diseases and healthy leaves. We have separated the total number of images into 80 percentages for training and 20 percentage for testing.

Figure 22: Tomato leaf diseases

Data augmentation is a strategy used to increase the amount of data by using techniques like cropping, padding, flipping, etc. To combat the high expense of collecting thousands of training images, image augmentation has been developed to generate training data from an existing dataset. Image Augmentation is the process of taking images that are already in a training dataset and manipulating them to create many altered versions of the same image. This both provides more images to train on, but can also help expose our classifier to a wider variety of lighting and coloring situations to make our classifier more robust.

Data augmentation makes the model more robust to slight variations, and hence prevents the model.

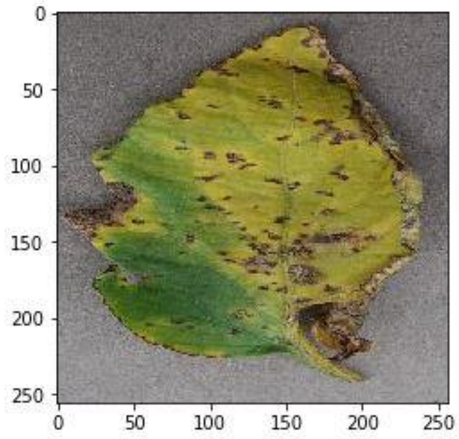


Figure 23: Original image

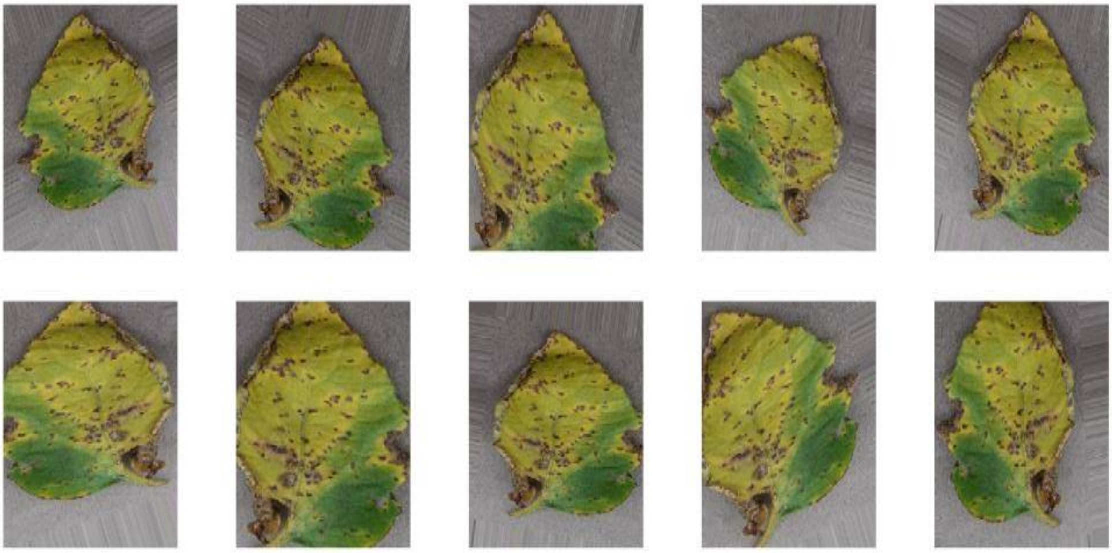


Figure 24: Augmented images

Step 03 – Download VGG-16 pre-trained model

In computer vision, transfer learning is usually expressed through the use of pre-trained models. A pre-trained model is a model that was trained on a large benchmark dataset to solve a problem similar to the one that we want to solve. Accordingly, due to the computational cost of training such models, it is common practice to import and use models. Advantages of Transfer Learning

1. Super simple to incorporate.
2. Achieve same or even better (depending on the dataset) model performance quickly.
3. There's not as much labeled data required.
4. Versatile uses cases from transfer learning, prediction, and feature extraction.

The convolutional neural network mainly consists of two blocks they are convolutional blocks and fully connected blocks. Using the transfer learning method, we freeze the convolutional blocks of the pre-trained model VGG – 16 and change the parameters in the fully connected layers.

A Convolutional Neural Network (CNN, or ConvNet) is a special kind of multi-layer neural networks, designed to recognize visual patterns directly from pixel images with minimal preprocessing. VGG Net is invented by the Visual Geometry Group (by Oxford University). VGG-16 network is trained on the ImageNet dataset which has over 14 million images and 1000 classes and achieves 92.7% top-5 accuracy. It surpasses Alex Net network by replacing large filters of size 11 and 5 in the first and second convolution layers with small size 3x3 filters.

VGG16 consists of convolution layers, max pooling layers, activation layers and fully connected layers. It has 16 layers.

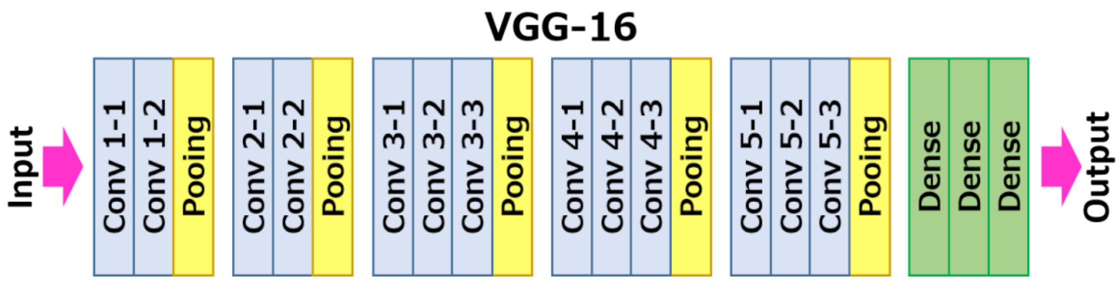


Figure 25: VGG-16 layers

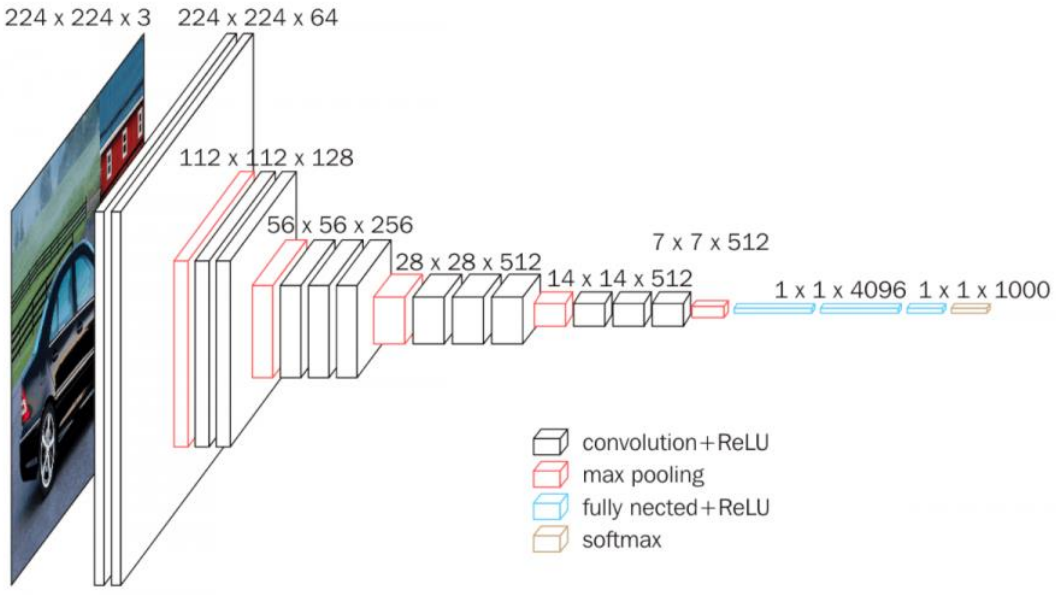


Figure 26: VGG-16 architecture

VGG 16 has 13 convolutional layers, 5 max-pooling layers, and 3 dense layers which sum up to 21 layers total 138 million parameters. Conv 1 has several filters as 64 while Conv 2 has 128 filters, Conv 3 has 256 filters while Conv 4 and Conv 5 has 512 filters.

VGG – 16 Network Architecture

- Input image size = 224 x 224
- Kernel size = 3 x 3
- Convolutional stride = 1 pixel
- Activation function = Relu
- The last layer is a SoftMax classification layer with 1000 units (Representing the 1000 ImageNet classes)

We import the VGG-16 model and dropped its last layer. The dense layers must have the Relu activation function and the last layer, which contains as many neurons as the number of classes in our case it has 7 classes also it must have the SoftMax activation.

Steps 04 – Training the model

Training the model using our personal computers won't possible. Therefore, we need Graphical Processing Unit (GPU). For that we used Google Colab. Google Colab is Google's free cloud service which provides free GPU for Artificial Intelligence developers. To access our dataset first we want to store our data in Google Drive then we want to give permission to access it.

We set some hyperparameters as flows in the convolutional neural network.

- Batch size = 32
- Epochs = 1500
- Activation function = Relu

For complete training it takes 3 hours and gives the accuracy.

Steps 05 – Evaluating the accuracy and loss

After finishing 1500 epochs we plot the graph against epochs vs accuracy and loss. It shows that model is not over fitting.

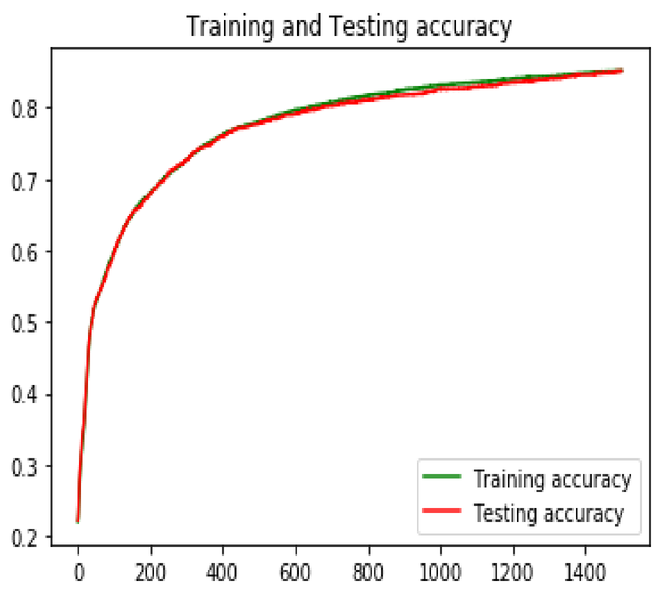


Figure 27: Epochs versus accuracy

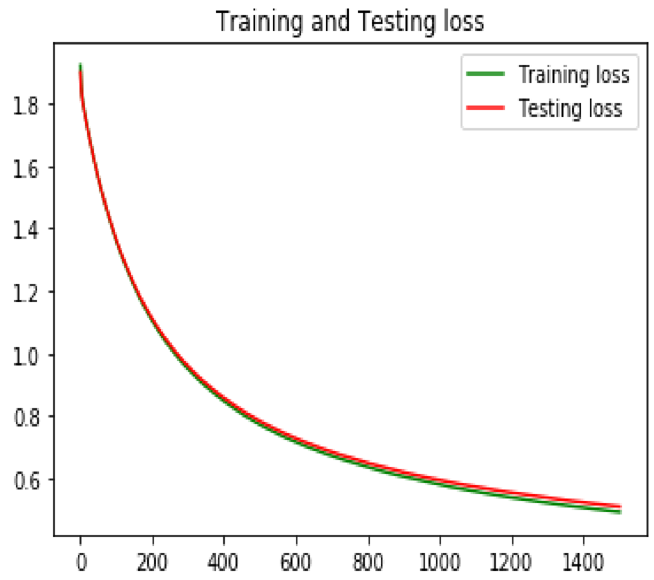


Figure 28: Epochs versus loss

Running the code in the Jupyter notebook and getting the output can be done by only experts, so we need to create a system that can be access by anyone. We developed a web application so user can input the image and get the result. To develop the web application the front-end part was developed using HTML, CSS and Java Script and the back-end was developed using Python Flask framework. Flask is a lightweight framework for building web applications in python.

3.5 DESIGNING A SYSTEM TO CLASSIFY RIPENESS OF OIL PALM & NUTRIENT DEFIECIENCY OF TEA LEAVES

We have used the TensorFlow platform to deploy a CNN object detection model designed to classify ripeness of oil palm and nutrient deficiency of tea leaves. We utilize the Single Shot Multibox (SSD) model and deploy it in the raspberry pi model 3B+ and classifier pre-trained on the COCO dataset (Common Objects in Context) of 1.5 million images (80 object categories). We employ transfer learning to fine-tune the model parameters to the image dataset.

3.5.1 Capturing Images from Multi spectral camera

Traditionally Crop monitoring for nutrients, water-stress, disease, insect attack and overall plant health has been carried out by visual examination of crops on the ground or sometimes from the air. However, these methods are limited by the ability of the human eye to discriminate between healthy foliage and foliage suffering various kinds of stress. Often a specific condition must be well advanced before visual symptoms become noticeable even to experienced observers. Multispectral imaging camera sensors on agricultural drones allow the farmer to manage crops, soil, fertilizing and irrigation more effectively. Multispectral camera remote sensing imaging technology use Green, Red, Red-Edge and Near Infrared wavebands to capture both visible and invisible images of crops and vegetation.

A multispectral image sensor captures image data at specific frequencies across the electromagnetic spectrum. The wavelengths may be separated by filters or by the use of instruments that are sensitive to particular wavelengths, including light from frequencies beyond our visible sight, such as infrared. Spectral imaging also allows for extraction of additional information that the human eye fails to capture. Even though human cannot see them, these invisible wavebands are very indicative of the agronomic characteristics of soil, plants and crops.

Hyperspectral imaging involves dividing light into thousands of small bands to gain detailed information. This compares with multi-spectral, which deals with far fewer bands. Precision agriculture requires more than just basic RGB information. Looking at the spectral content in the pixels, hyperspectral solutions can detect chlorophyll or very small color-changes on foliage. Color information can be useful to distinguish brown from green, but more bands are required for finer details. The following are examples of multispectral camera: -

- DJI Mavic Pro 2 / Zoom
- DJI Mavic 2 Enterprise

- DJI Phantom 4 Pro
- DJI Phantom 3
- DJI Mavic Pro
- DJI Inspire 1
- 3DR SOLO
- SenseFly eBee
- DJI MG-1S

3.5.1 Data Preprocessing

The palm oil fresh fruit bunch dataset of JPEG images was taken with a camera. It contains these number of pictures for the variety of grading in ripeness. LabelImg, an open source graphical annotation tool for manually drawing and labeling object bounding boxes in images, was employed to draw ground truth bounding boxes and create corresponding xml files with stored xmin, xmax, ymin, ymax data for each ground truth box. Here we will go through all the steps needed to make our own object detection using TensorFlow.

The steps needed are:

1. Gathering data – Get the photos of ripped and unripe palm oil fresh fruit bunches.
2. Labeling data – Labelling using software divide two classes
3. Generating TF Records for training
4. Configuring training
5. Training model
6. Exporting inference graph
7. Testing object detector

To train a robust classifier model, we need a large amount of data sets which should vary a lot from each other. So, they should have different backgrounds, random object, and varying lighting conditions and different angles.

Steps 01: - The images we took are high resolution so we want to transform them to a lower scale so the training process is faster. Below script helps easy to transform the resolution of images.

Steps 02: - Now we got our images we want to split the data set into 80 percent of the images to train and 20 percent of the images to test. In order to label our data, there is a software LabelImg it's a great tool for ding labelling

Steps 03: - Generating TF Records for training. After finishing the labeling the images, we need to create TF Records that can be served as input data for training of our object detector. (*xml_to_csv.py and generate_tfrecord.py)*. Before going to transform the newly created files to TF Records we need to change the lines that how many different types of labels which we have in our data set. The TensorFlow Object Detection API allows you to create your own object detector using transfer learning.

4. RESULTS AND DISCUSSION

4.1 PROBLEM IDENTIFICATION AND GATHERING DATA

4.1.1 Field Visit to Nayapana Tea Estate

In the progressing stage of the project, some relevant initial details have been gathered by doing a literature review on these industries. That review contained the problems which, tea and palm oil industries are going through, what are the existing technological solutions for them and what are the other possible solutions that can be developed in the future. But to get a better picture of the scenario, more information from the field was needed. As it is more effective to get the experience on the field rather than referring documents, this field visit was organized.

In the process of gathering information we were able to get help from the Nayapana Tea estate which was so dynamic and so open minded to welcome new technology into their system.

Figure 29: Elpitiya tea plantation

As noticed during the field visit, in the current system there is no specific method of watering. According to the information gathered, well-grown plants do not require continuous watering. But when considering new plants, the first 12 months are critical. So, irrigation must be reliable and efficient for them. The water resources of tea plantations are depending on rainfall and natural springs. So, water is an extremely scarce resource in there. And according to the current unreliable rainfall conditions, unexpected droughts can occur which can bring huge damage to new plants.

Therefore, it is a fact that new tea plants need an irrigation system which is well controlled and maintained. There an automated irrigation system can be proposed to the system, where decisions are taken according to the field capacity of the soil. The critical point of field capacity is 40%. Plants can be wilted if the value gone down below it.

In a new establishment of tea crops, it could be observed an already installed sprinkler irrigation system. There was a problem of wasting a lot amount of water and there was no continuous monitoring of field capacity and any automated system.

Figure 30: Existing sprinkler irrigation system

4.1.2 Field Visit to Talgaswella Estate

Figure 31: Talgaswella oil palm plantation

In order to find out the problems in the oil palm industry we visit to Talgaswella estate and the following data was gathered.

- The harvesting process is done by lay men who don’t have the knowledge of detecting the ripeness of the fruit.
- Without considering whether the harvested fruits are ripped or not they are transported to the industries where the palm oil making process is done.
- It takes 3 years to fruitful an oil palm fruit bunch and if it didn’t get enough water and nutrition it will not give a quality output. And also, if it is harvested before getting ripped it will be a waste of three years of investment.

Figure 32: Fully ripped oil palm fruit

4.2 THE DRIP IRRIGATION SYSTEM PROTOTYPE

To simulate the action of sensor nodes first, two sensor nodes were deployed and depending on their success and errors encountered, the final prototype was built. Water was supplied by the nearest tap to the prototype location. Water supplied by this tap is first to go into ¾ inches PVC pipe. Then the pipe is connected to the main horizontal pipe that is on the ground level. Then it is continued until very near to the plant bed (prototype). Then the pipe divided into two ½ inches pipes that are connected with solenoid valves that are operated by the relay module. Outputs of solenoid valves are again connected with ½ inches pipes. These two pipes are now connected with drip irrigation pipes (laterals). Based on our observation during the field visit to the tea estate, it was noted that the distance between the two nearest plants is two feet. Therefore, in this prototype, we decided to keep that distance between two nearest nozzles that supply water from laterals to the plant. Usually, in drip irrigation, the lateral end is closed. When considering the power, solenoid valves are powered by a 12V DC power supply.

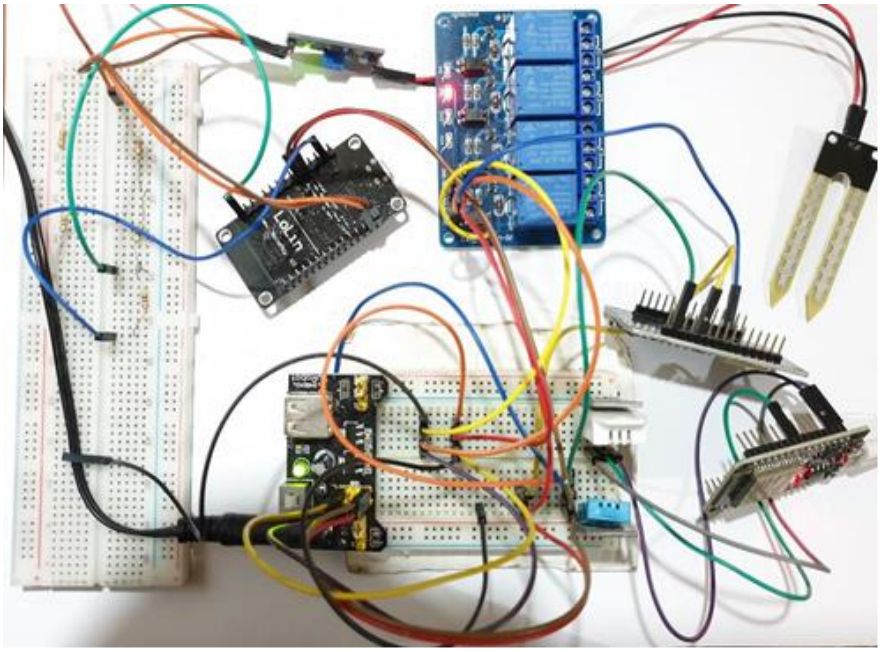


Figure 33: Equipment used for prototype sensor node (testing in the lab)

Figure 34: Main Pipe Line and Solenoid Valve Setup (Initial two solenoid valves)

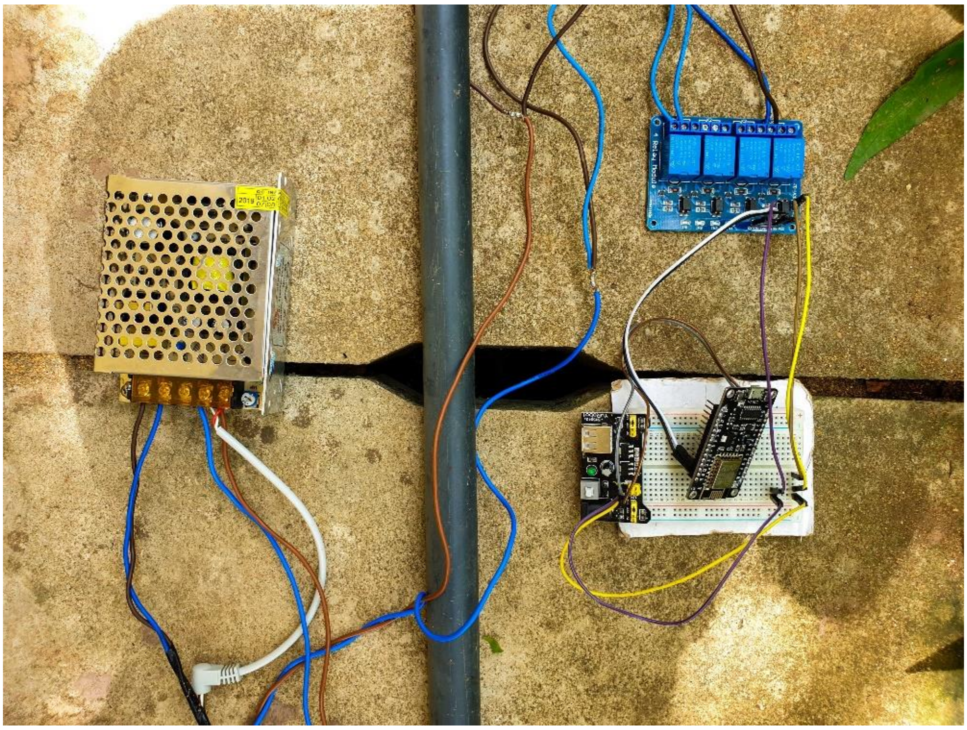


Figure 35: Main sensor node controlling solenoid valves

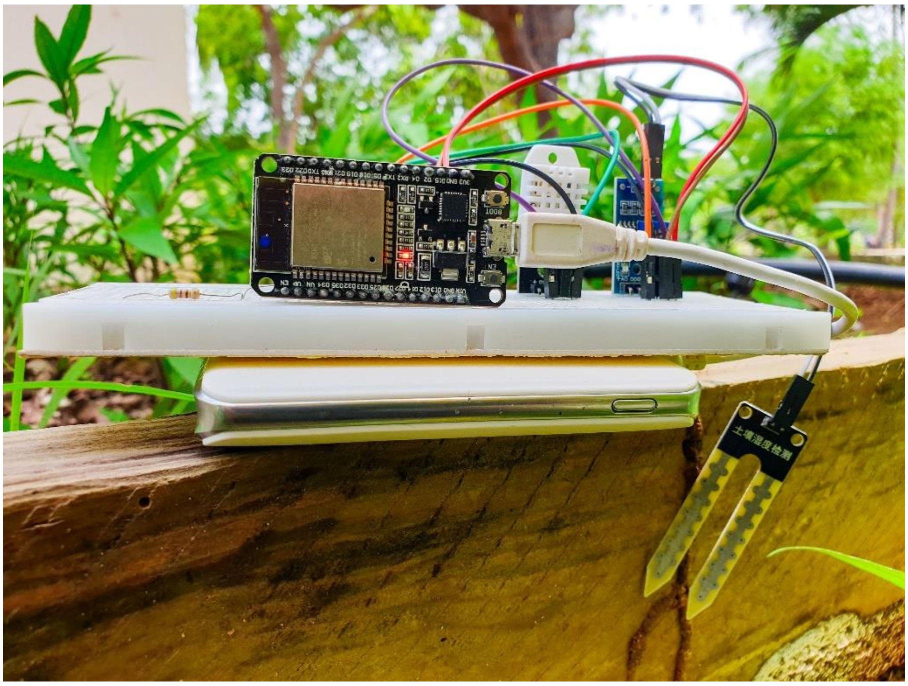


Figure 36: Sensor node testing in the field using battery power (testing stage)

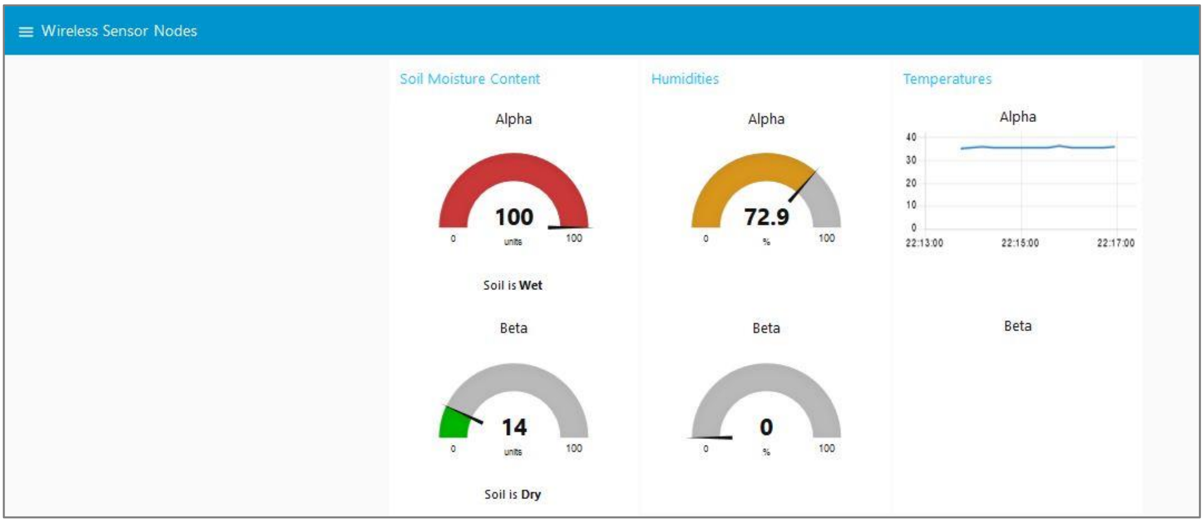


Figure 37: NodeRED dashboard for two sensor nodes (testing stage)

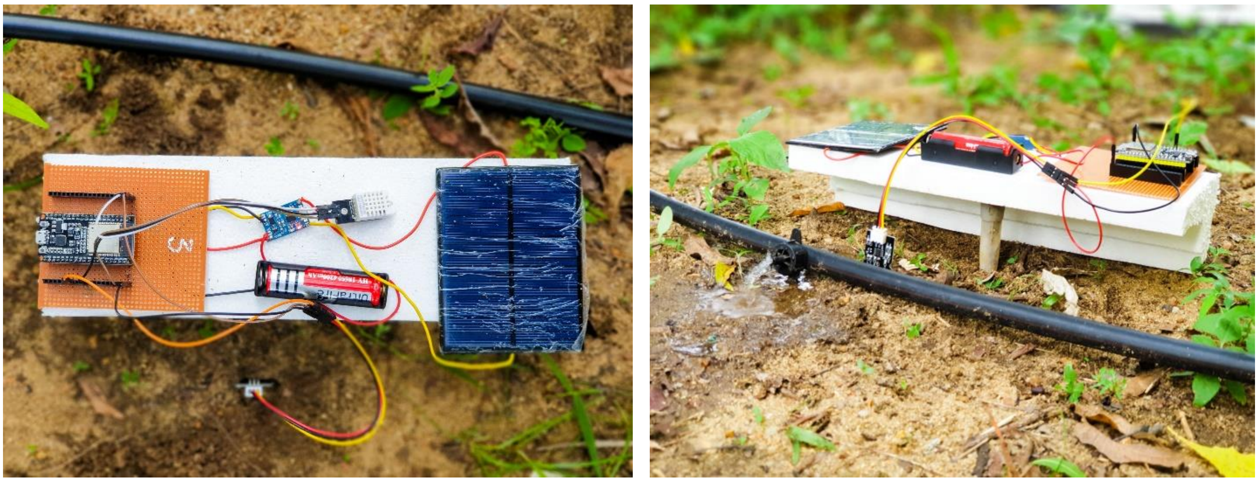


Figure 38: Sensor nodes testing with solar cells & battery power

Figure 39: Deploying four sensor nodes

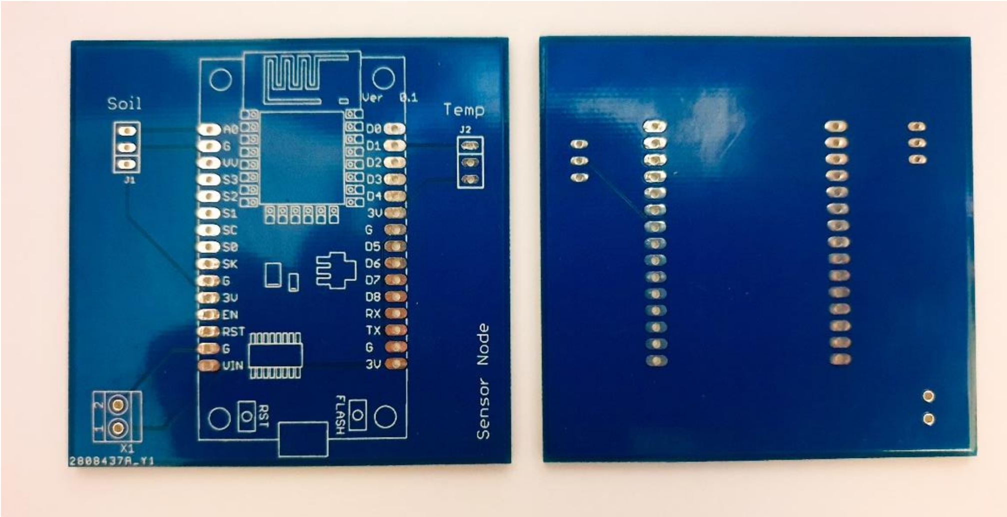


Figure 40: Sensor node PCB after manufacturing

Figure 41: Testing PCB inside temporary enclosure

Figure 42: Deploying four solenoid valves

Figure 43: Node RED dashboard when all nodes are working simultaneously (only three nodes are shown)

Figure 44: PCB mounted inside the designed enclosure box

Figure 45: Final appearance of the sensor node in the field

4.3 POWERING THE SENSOR NODE

Power is a major concern in sensor nodes in the field because it is difficult to use power wire lines in the field. As a solution for that issue sensor nodes are powered using batteries that are charged by solar cells. Solar power is a viable candidate for power supply because sensor nodes can be thought of as a low power electronic device. Power consumption of the sensor node can be minimized by putting the microcontroller into the sleep mode.

Sleep mode is a power-saving state that microcontrollers can enter when not in use. The microcontroller's state is maintained in RAM. When microcontroller enters sleep mode, power is cut to any unneeded digital peripherals, while RAM receives just enough power to enable it to retain its data.

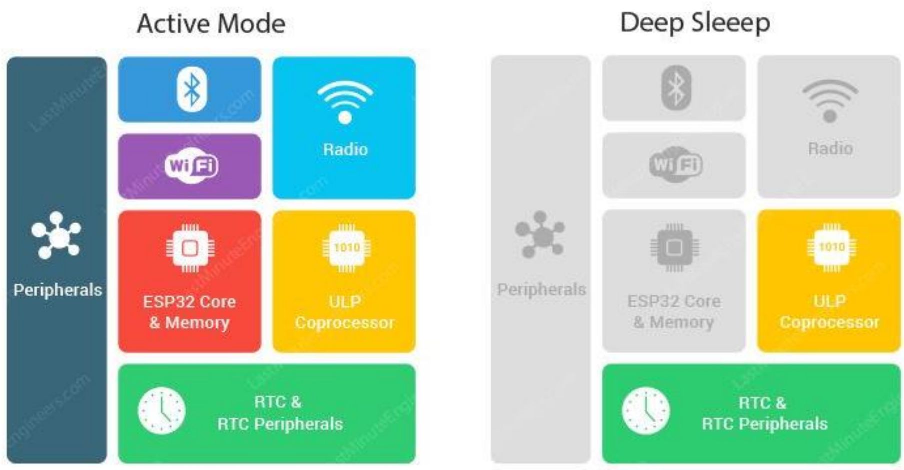


Image from https://lastminuteengineers.com/esp32-sleep-modes-power-consumption/

Figure 46: Power consumption of microcontroller (only colored ones are powered)

In deep sleep mode, the CPU, most of the RAM and all the digital peripherals are powered off. The only parts of the chip that remains powered on are RTC controller, RTC peripherals (including ULP co-processor), and RTC memories (slow and fast). During deep sleep mode, the main CPU is powered down, while the ULP co-processor does sensor measurements and wakes up the main system, based on the measured data from sensors. This sleep pattern is known as ULP sensor-monitored pattern. However, the RTC memory is kept powered on. So, its contents are preserved during deep sleep and can be retrieved after waking the chip up. Wake up from deep sleep mode can be done using several sources. RTC controller has a built-in timer that can be used to wake up the chip after a predefined amount of time [70].

In our proposed sensor node design, two Li-ion rechargeable batteries were used to supply power. Three testing were conducted to study the power consumption of the sensor node. In the first test, the microcontroller was not set to sleep and solar charging was not given. In other words, the sensor node operated only on batteries and the battery voltage level was measured. The second test conducted with five minutes of deep sleep and then the battery voltage level was measured. Finally, the same as the second test but this time solar charging was allowed. Test results are visualized graphically in Figure 46.

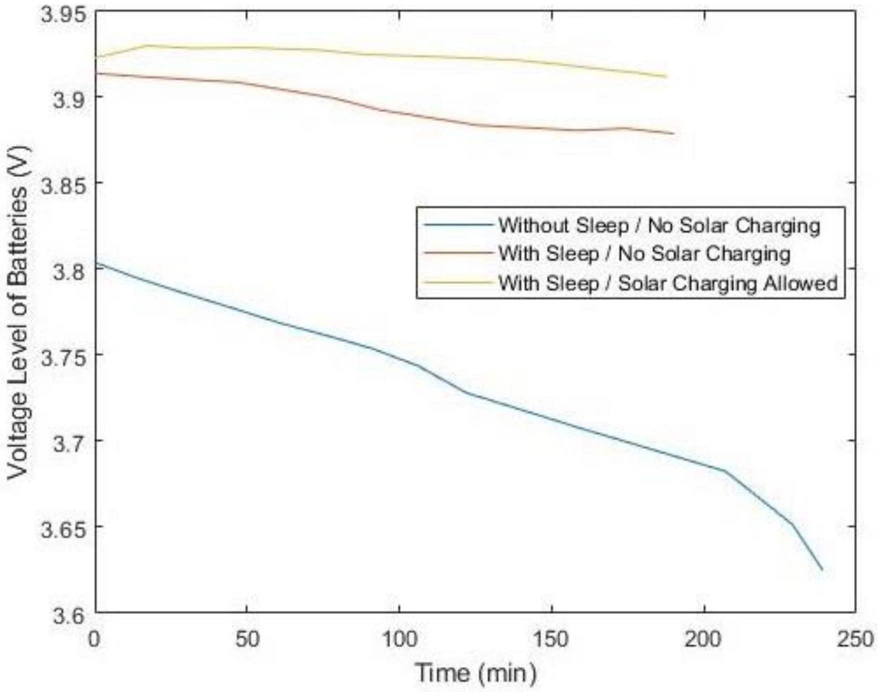


Figure 47: Variation of voltage level of batteries with time

4.4 MQTT VISUALIZATION

With the help of MQTT broker and Node-Red virtual programming environment central hub is able to get the sensor values of each node. Therefore, user can view environment parameter values through the dashboard of Nod-Red. Figure 47 shows the Node-Red dashboard which displays the readings of different sensor nodes.

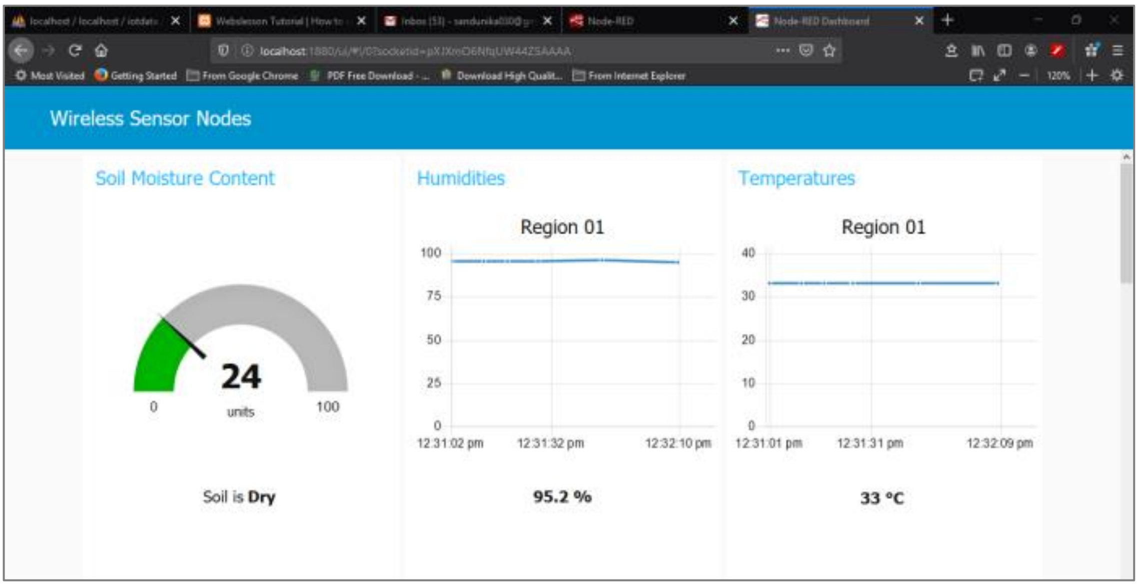


Figure 48: The MQTT dashboard

4.5 WEB APPLICATION OUTPUT

The desired output of creating a web application was to have a well-structured database and an advanced data representation interface. Using the XAMPP platform we were able to achieve that output. The front page of the web application includes links to four sensor nodes. When we select a particular sensor node there will appear the graphical representation of real-time sensor node readings of soil moisture, temperature and humidity values according to date and time. That web page also included with the access link to the relevant sensor node database.

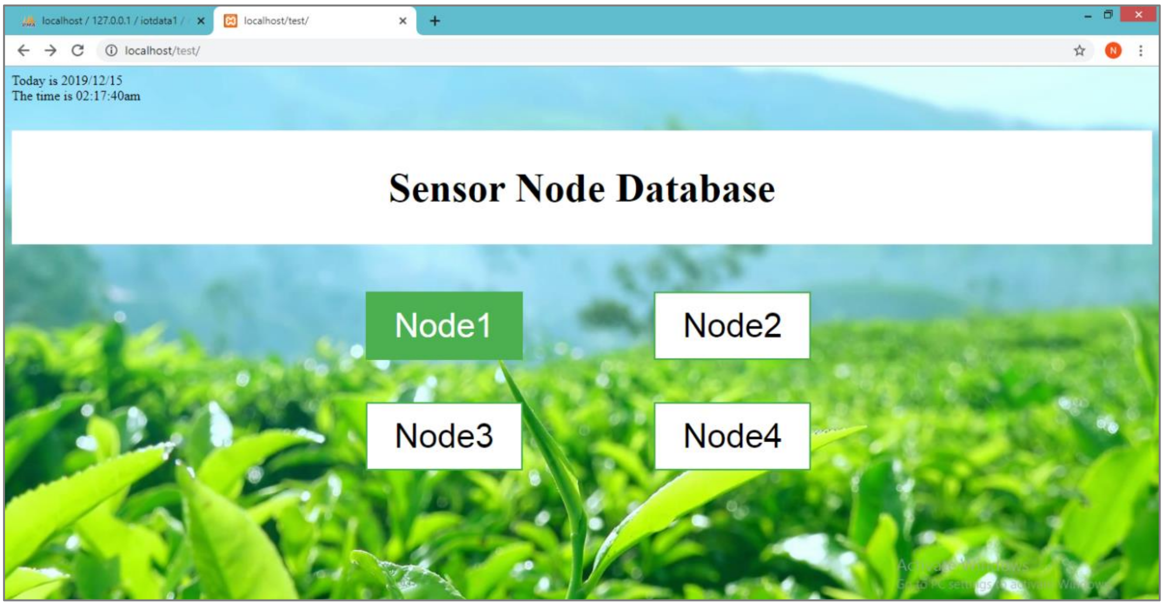


Figure 49: Front page of the web application

The sensor node web page displays the graphs of soil moisture readings, temperature readings and humidity readings that come from the relevant sensor node. And it includes access to the database and today's data representing web page.

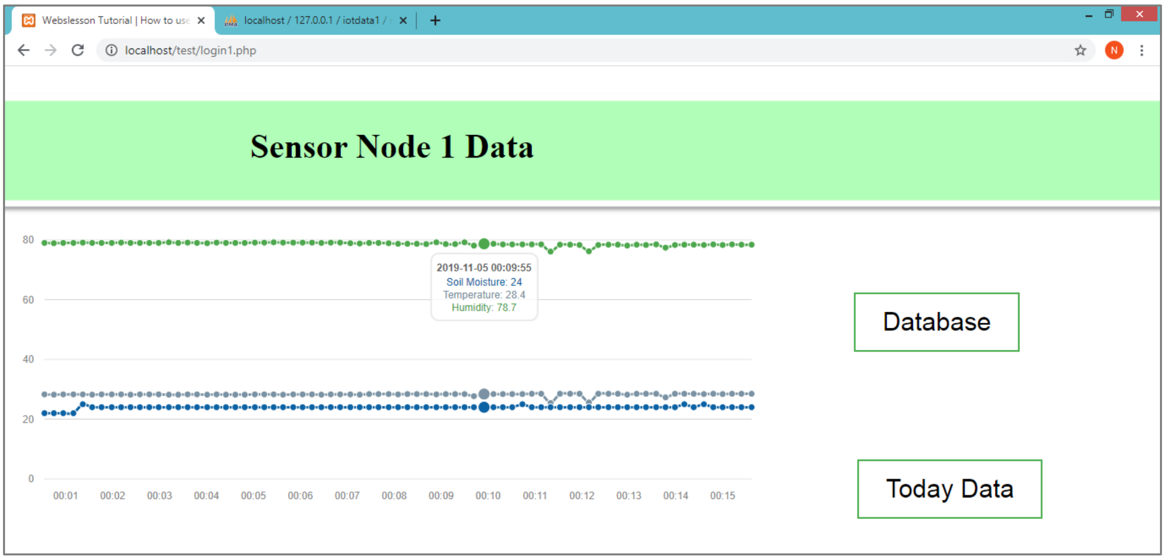


Figure 50: Sensor node data page

The database page of each sensor node presents the real-time sensor node readings in tabular form. There is a sorting method to select the number of reading values to be presented. And at the end of each column of sensor readings, the average value is calculated and displayed. Using that facility, we can calculate the average values of soil moisture, temperature, and humidity as per our preference of the number of data.

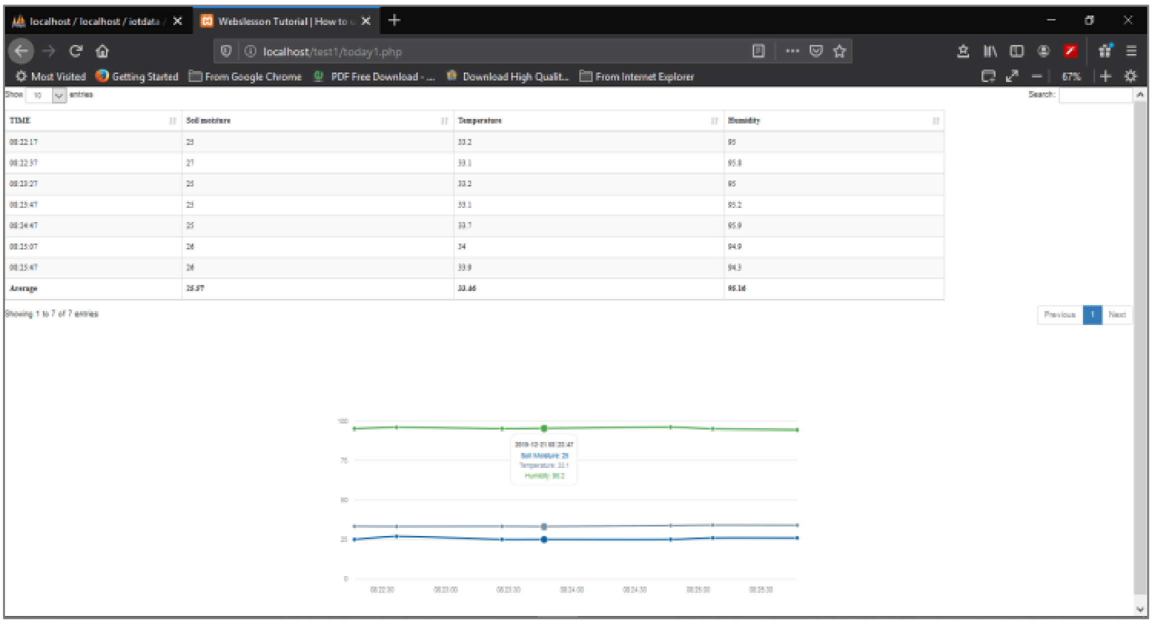


Figure 51: The data representation of sensor node readings and average values per day

As shown in Figure 50 the web page which displays today data includes only the database of the current date and graphs of soil moisture, temperature, and humidity. With the use of this page, we can observe the current date weather patterns and average values which would help in the decision making of the daily agriculture process.

4.6 PLANT DISEASE CLASSIFIER OUTPUT

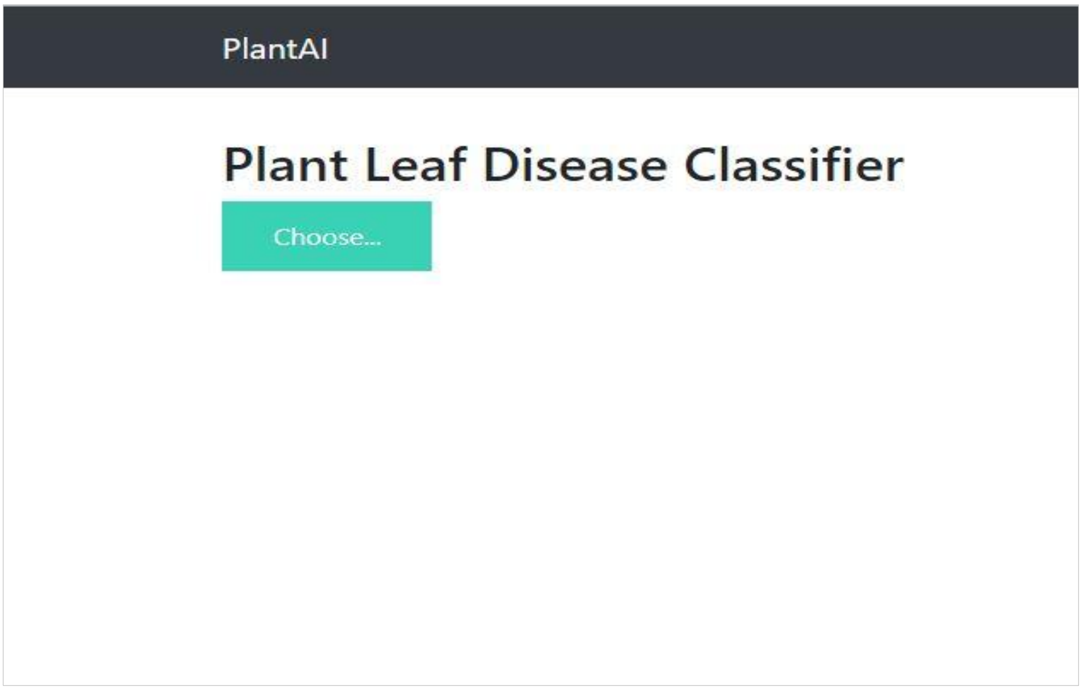


Figure 52: Web application interface

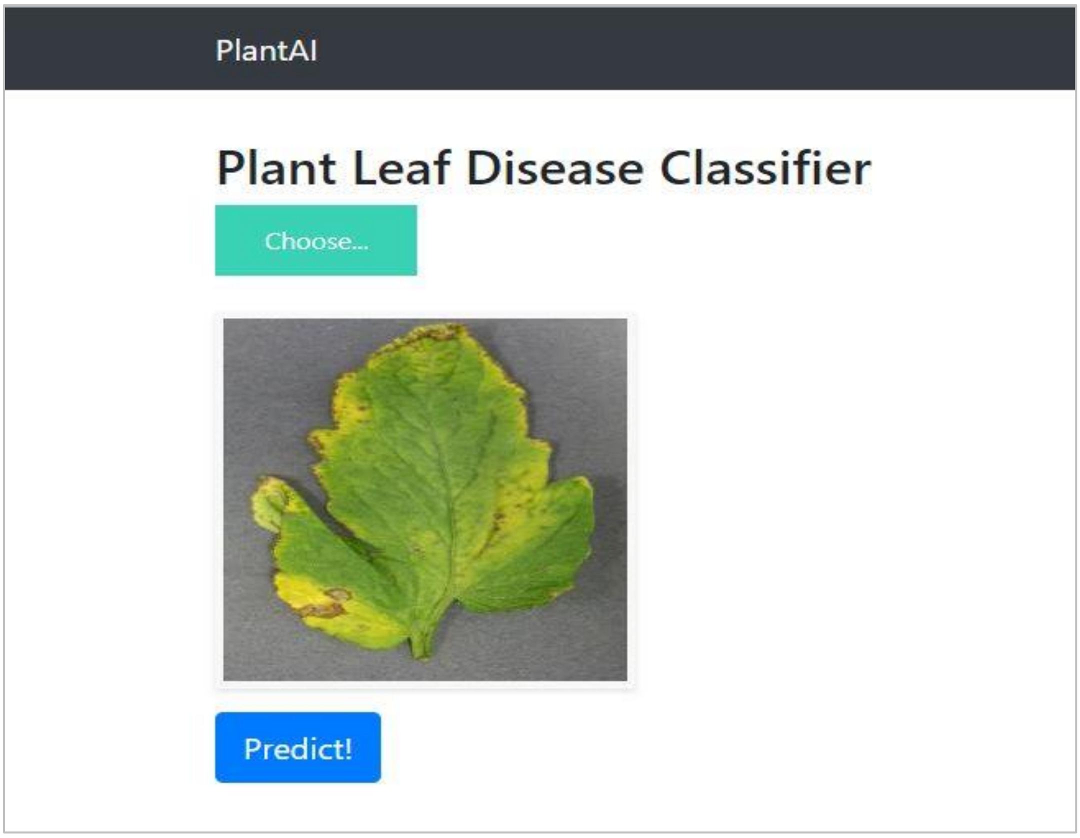


Figure 53: Displaying input image

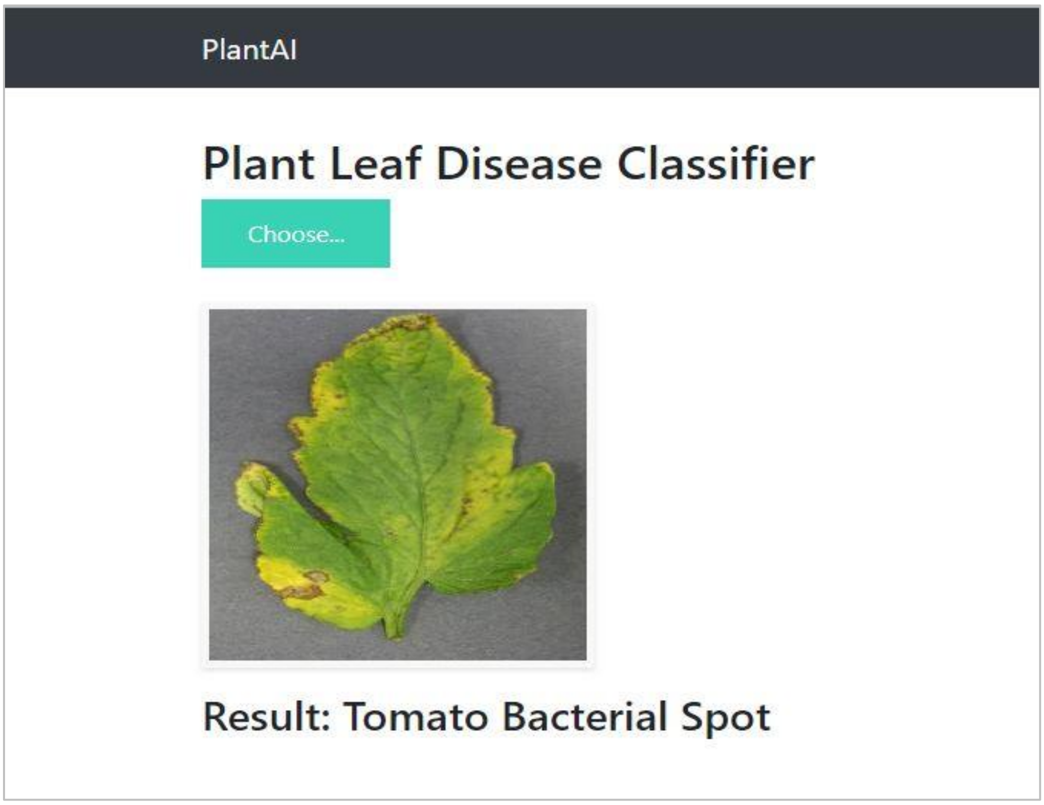


Figure 54: Results output

4.7 PROBLEMS ENCOUNTERED DURING THE PROJECT

4.7.1 Sensor Node Battery Power Issue

For the powering of the sensor node, initially, a single rechargeable battery was used. Then it was noted during the testing that there is a difficulty in connecting to Wi-Fi, inability to power up the sensors, etc. due to lack of required current from the battery. Therefore, to rectify that error two batteries were used to supply the required current.

4.7.2 Relay PCB Power Issue

We used to power up the relay circuit using the same power supply we used to power the solenoid valves. The PCB was given 12V DC and voltage was regulated to give input for both microcontroller and all four relays. During the testing, it was noted that the current requirement is not fulfilled by the above-mentioned input power. Therefore, we had to remove the PCB and power up the microcontroller and four relays separately. Then the issue was mitigated.

4.7.3 Changes to the Sensor Node Enclosure Box

As mentioned in section 3.1.2 initially we designed the sensor node enclosure box to 3D print. But the cost per sensor node enclosure box was quite expensive and there are four sensor nodes in our prototype. Instead of 3D printing the enclosure box, we used cladding material to build a suitable sensor node enclosure box. This design is quite different from what we designed using Solid Works because we add some changes to the box to make it easier to place and remove the PCB and sensors inside the box.

4.7.4 Collecting data about blister blight disease

To get better prediction we need a large set of data set with organized in a good manner. We searched it in Nayapana tea factory office and filter out the reasons for disease occurrence it makes us difficult and to develop the machine learning model we collected related data from internet.

4.7.5 Collecting image data for oil palm ripeness detection and nutrient deficiency detection on tea leaves

We planned to develop a handheld device to detect the oil palm ripeness detection and nutrient deficiency detection on tea leaves but we could not able to collect a large amount of data set. We went for the field visit and we collected a few images for different categories. But to create a deep learning model we need a large amount of data set.

4.7.6 Training the Deep learning model

Training the machine learning model using normal computers will not work because it needs high processing power. We used Google collab to train our model initial stage to it takes lots of time to get good accuracy we also tried using a computer lab computer but during the training, process power went off so it causes us to train it again.

5. CONCLUSION AND DISCUSSION

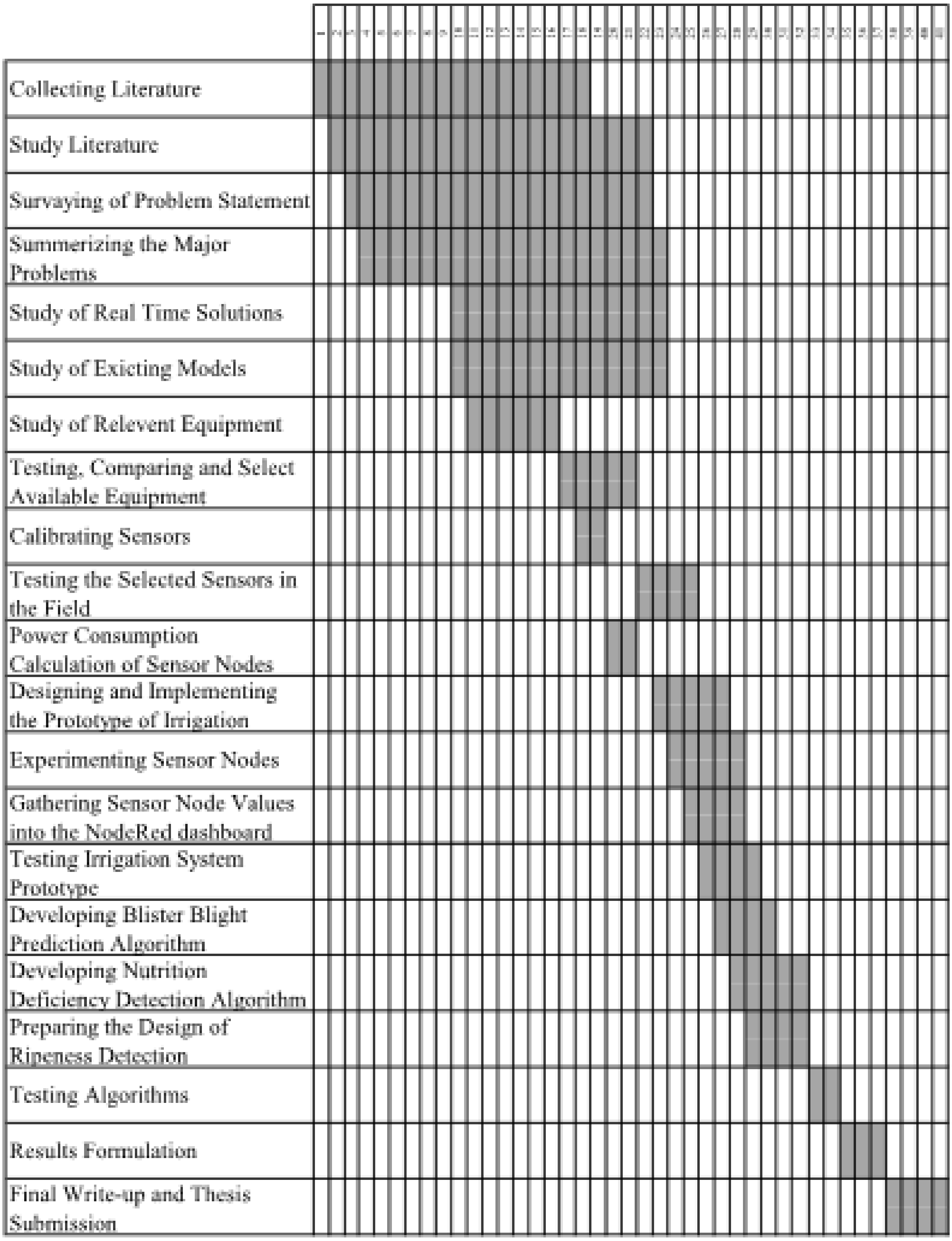
In this project, our first objective is design of an automatic drip irrigation system for tea plantations. To address the problem stated in the problem statement regarding watering the new tea plants, a precision agriculture system based on the Internet of Things technologies was proposed. As noted in the literature review, to measure the physical environment a wireless sensor network is preferred. After analyzing all the facts that we found in the literature review we have designed our prototype. The environmental parameters which found to be useful in the decision-making process of the system were soil moisture, temperature, and humidity. To monitor those parameters, we have implemented four sensor nodes in the designed prototype. Data acquisition by these sensor nodes can be sent to the central node afterward. And depending on sensed parameter values, decisions are made whether we need to apply water or not. Also, the gathered data have inserted into a database and the analytical approach, as well as accessibility to data, was obtained through a web application. One benefit of this new approach is different regions in the farmland can be analyzed in a discriminated manner. This approach is beneficial because all the plants may not need water at the same time. Therefore, by analyzing the node parameter values, now the system has the intelligence to decide where and when watering is required. The sensors in the nodes are prone to be damaged because they are directly exposed to harsh weather conditions. Therefore, a weatherproof enclosure design was made to overcome that problem. Communication is done wirelessly using Wi-Fi technology. Unlike the previous work done on this topic, here power supply and power consumption of wireless sensor nodes are considered deeply.

The second objective of our project is to design a system to predict blister blight disease occurrence in tea leaves. During our field trip to Nayapana tea estate we encountered this problem and talking with the tea staffs they have stated that they cannot predict the occurrence of the disease and because of that they are spreading the fertilizers to good healthy tea leaves. Therefore, this matter forced us to create a system to predict the disease occurrence. That is the reason behind creating a web application so the user can add the values of the features and get the output whether the disease occurred or not we hope this system will help them in future. Our third objective is to create a system to classify tomato leaf diseases so we have created a web application to detect the diseases and use proper fertilizers for the diseases.

Finally, we proposed a method to detect oil palm ripeness and nutrient deficiency classification on tea leaves we tried to found a dataset to implement the proposed methodology but unfortunately, we couldn’t find the proper dataset. Therefore, we have proposed the methodology for detecting the ripeness of the oil palm fruit to do the harvesting.

For the future work we are planning to implement the drip irrigation system in a real tea estate and market it as a product. And planning to create a mobile application to detect and classify tomato leaf diseases.

6. TIMELINE



Collecting Literature
Study Literature
Survaying of Problem Statement
Summerizing the Major Problems
Study of Real Time Solutions
Study of Exicting Models
Study of Relevent Equipment
Testing, Comparing and Select Available Equipment
Calibrating Sensors
Testing the Selected Sensors in the Field
Power Consumption Calculation of Sensor Nodes
Designing and Implementing the Prototype of Irrigation
Experimenting Sensor Nodes
Gathering Sensor Node Values into the NodeRed dashboard
Testing Irrigation System Prototype
Developing Blister Blight Prediction Algorithm
Developing Nutrition Deficiency Detection Algorithm
Preparing the Design of Ripeness Detection
Testing Algorithms
Results Formulation
Final Write-up and Thesis Submission

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APPENDIX