SMART PLANT DISORDER IDENTIFICATION SYSTEM USING COMPUTER VISION TECHNOLOGY

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Dissertation submitted in partial fulfillment of the requirements for the Bachelor of Science in Information Technology, Specializing in Software Engineering

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DECLARATION

I declare that this is my own work and this proposal does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other university or Institute of higher learning and to the best of our knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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Signature of the supervisor   Date

(Dr. Janaka Wijekoon)

ABSTRACT

Economic development of a country is highly depends on agriculture productivity. According to the criteria of economy, quality and quantity of the agricultural products are important in its trading. Farmers are expected to produce high or sufficient quantity of products with optimum quality. But, in most of the times, farmers are failing to fulfill these expectations due to various issues. Major issue is to early identification of nutrient deficiency occurs in crops prominently. Early prediction and identification of the exact nutrient element deficiency will help the farmers to prevent from disease spreading in crop. This can improve the productivity in agriculture. In present era, we are utilizing technology in different areas to get numerous benefits. Based on the research, the researcher has comes up with a solution for the above problem with the help of deep learning and image processing technique. CNN EfficientnetB0 model is the best deep learning classification algorithm which is proved to be efficient in predicting the nutrient deficiency by comparing with ResNet50 and VGG16. Final outcome of this research is a mobile application named “CropMedic Plus 2.0” which can process the image of the leaf of the plant to detect the nutrient deficiency in it accurately. Current accuracy level of the model is 88% which will be improved in the future work. Main goal of this application is to provide the cost effective and optimal solution to prevent the reduction of agricultural yields because of nutrient deficiency.

Keywords: Convolutional neural network, Micronutrients, Image processing, EfficientNetB0

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LIST OF ABBREVIATIONS

Abbreviations	Description
CNN	Convolutional Neural Network
GA	Genetic Algorithm
GDP	Gross domestic product
IDE	Integrated Development Tool
iOS	iPhone Operating System
RAM	Random Access Memory
R-CNN	Region-based Convolutional Neural Network
SDK	Software Development Kit
SVM	Support Vector Machine
UI	User Interface

1. INTRODUCTION

1.1 Introduction

Agriculture is the most important sector for the Sri Lankan economy. This sector is the only thing which provides the essential need for people. The majority of the labor force is engaged in this sector. Approximately 38 percent of the labor force was engaged in agriculture in 1999 [9]. However, during the last three decades, contribution gross domestic product of agriculture was reduced [9]. In this sector, rice is the most important activity in rural areas of people. As shown in Fig. 1.1, Currently Agriculture sector contributing 6.9 percent for the nation Gross Domestic Product and over 25 percent of people of Sri Lanka employed in this agriculture sector.

Sri Lanka GDP from Agriculture

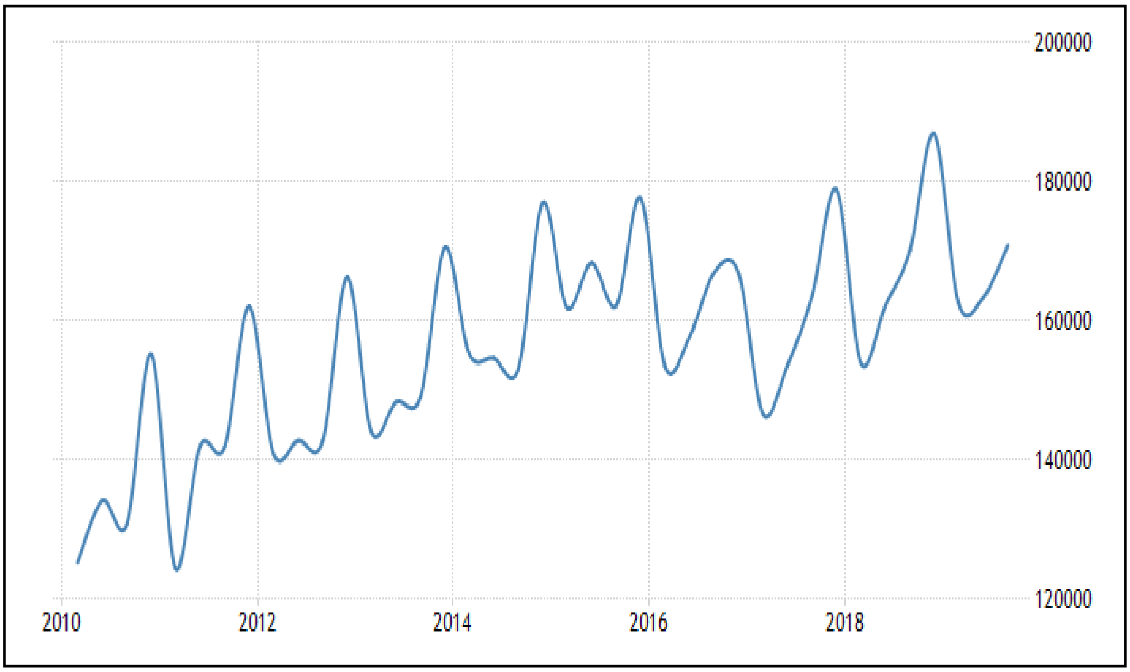


Figure 1.1: GDP Chart [3]

The production of oilseeds and fruits plays a vital role in the economy of Sri Lanka. According to Statistics in 2020, the total production of oilseeds and fruits were 349,000 MT [43] and 540,000 MT [28] annually. Groundnut is considered a "King" of oilseeds [37]. Groundnut (Arachis Hypogaea L.) is the 6th major oilseed crop in the world [31]. As shown in Fig. 1.2, it is one of the crops which contributes highly to the economy of Sri Lanka. It is grown mainly in Kilinochchi, Moneragala, and Mulathivu. Groundnut production is a vital source of economy and employment in Sri Lanka and also it's an essential component of Sri Lankan rural income. In the Fruit production 3Banana, guava, papaya, and lemon continue to impact prominently in the economy. Among those plantations, Guava and lemon seem to have been in an important place in the market [34]. The estimated Sri Lankan production for guava and lemon in 2019 was 81.74K metric tons and 5.56K metric tons [44].

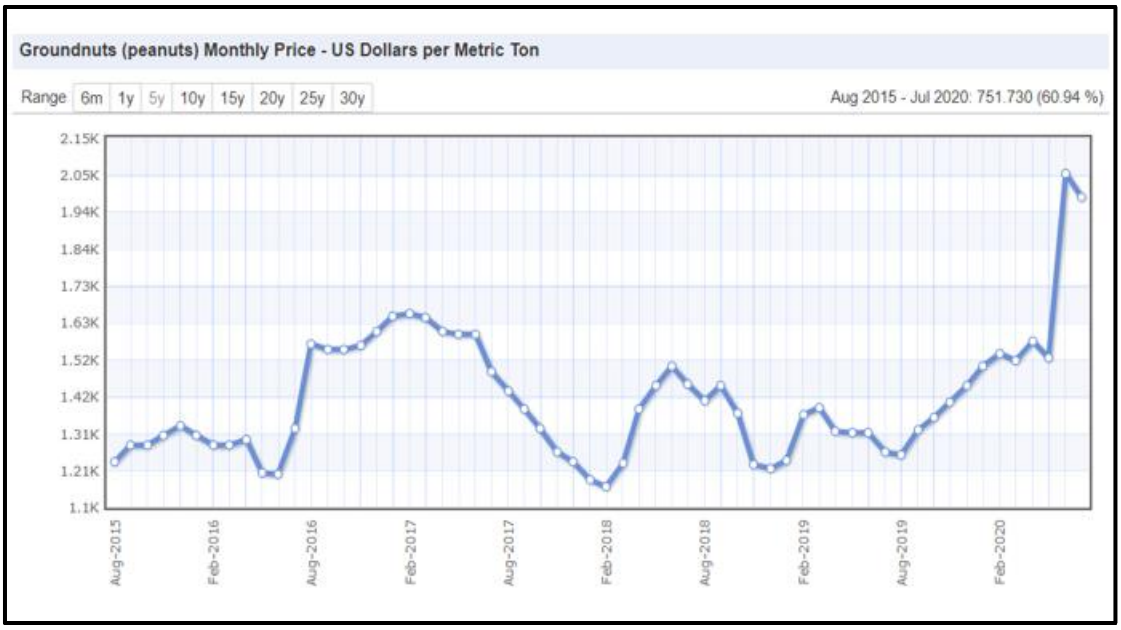


Figure 1.2: Groundnut Monthly Price range [31]

In the agriculture sector, there are many unsolved things related to cultivation. The farmers are facing lots of problems to get quality and quantity output of the cultivation effectively. Mainly they're facing problems in identifying nutrient deficiency in an early stage because different plants have different nutrient deficiencies and most of the nutrient deficiency symptoms are very similar. Usually, nutrient deficiencies will cause diseases to spread faster [8].

From the Background literature on plant nutrient deficiencies has mentioned that Nitrogen (N), Potassium (K), Phosphorus (P), and Sulfur (S) deficiencies are recorded mostly in the production of groundnut, lemon, and Guava plants. Due to the various factors such as environmental weather conditions, seasonal variation, and the spread of diseases, these plants have been found to be extremely susceptible to infection [32].

"CropMedic 2.0" is aimed to solve this issue by developing a mobile application to identify the nutrient deficiency among Nitrogen, Potassium, and Phosphorus in groundnut, guava, and lemon plants. Through this application expect that the farmers will be able to identify the nutrient deficiency with its degree.

1.2 Background Literature

1.2.1 Overview of nutrient deficiency in plants

According to the article by the Jawfer hessian, Plants need important nutrients for growth and normal functioning. Nutrient deficiency occurs when a needed nutrient isn't available in enough quantity to satisfy the needs of a plant. Nutrients can be divided in to two types [8]. Such as macronutrients and micronutrients. Macro nutrients are nitrogen (N) phosphorus (P) and potassium (K). As shown in the Fig. 1.3, Macronutrients symptoms are shown in the old leaves Micronutrients are sulfur (S), boron (B), chloride (Cl), copper (Cu), manganese (Mn), iron (Fe), and zinc (Zn). Mostly macronutrients are the nutrients affect crops abundantly [8]. In this research, our research team is mainly focusing on identifying the macronutrients such as Nitrogen, Phosphorus and Potassium in Groundnut, Guava and Citrus plants

Precautions in identifying nutrient deficiency symptoms include the following:

- Most nutrient deficiency symptoms look very similar [15]. For example, the symptoms of sulfur deficiency and nitrogen deficiency can be very similar depending on the severity of nutritional deficiency and the stage of plant growth.

- Many nutrient deficiencies can occur at the same time [8]. Multiple deficiencies in one plant, or survival of one nutrient deficiency can cause another deficiency [13] (e.g. excess P cause Zn deficiency).
- Different plant species and even for gardeners of the same species differ in their ability to show signs of nutrient deficiency [8].
- Hidden hunger. Plants might be nutrient deficient without showing symptoms directly.

In addition to the above precautions, direct observation is additionally limited by time. Between the time a plant is nutrient deficient (hidden hunger) and visual symptoms appear, crop health and productivity could also be substantially reduced.

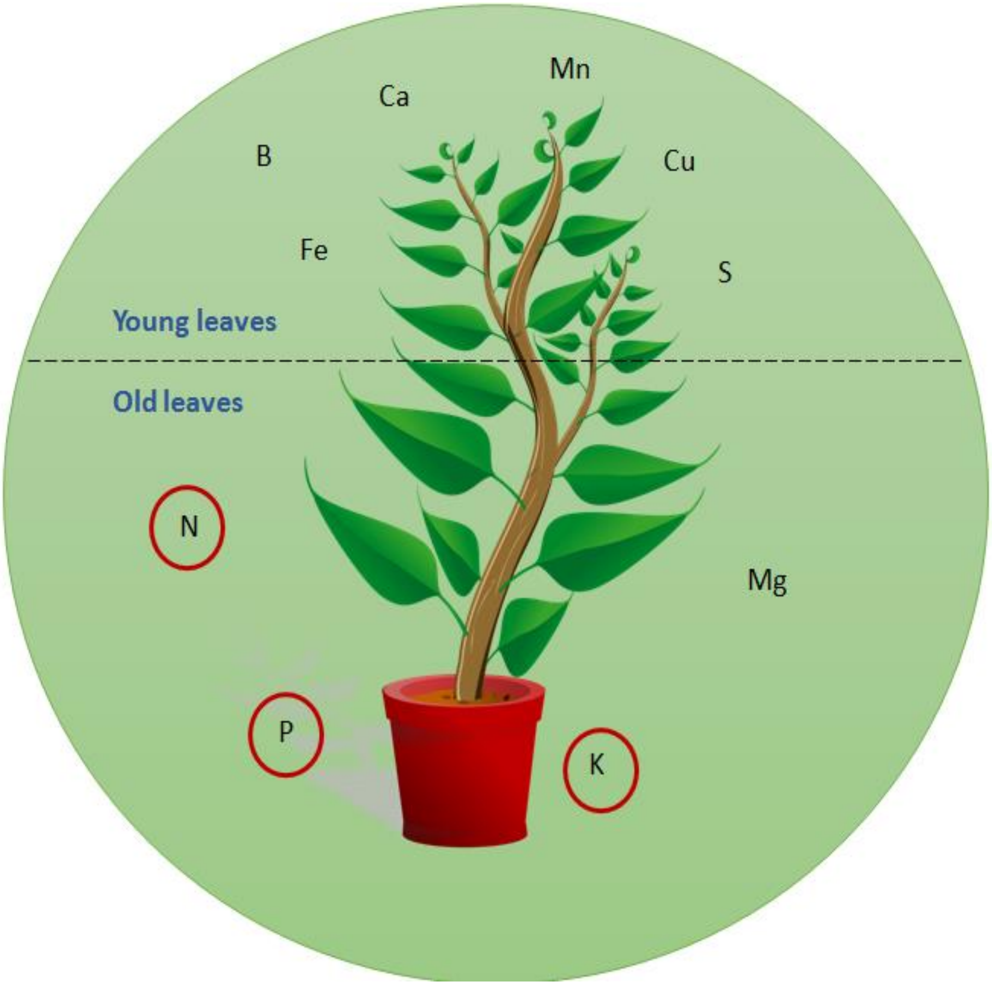


Figure 1.3:Macronutrients and micronutrients

General Key Features to Identify the of macronutrient deficiencies:

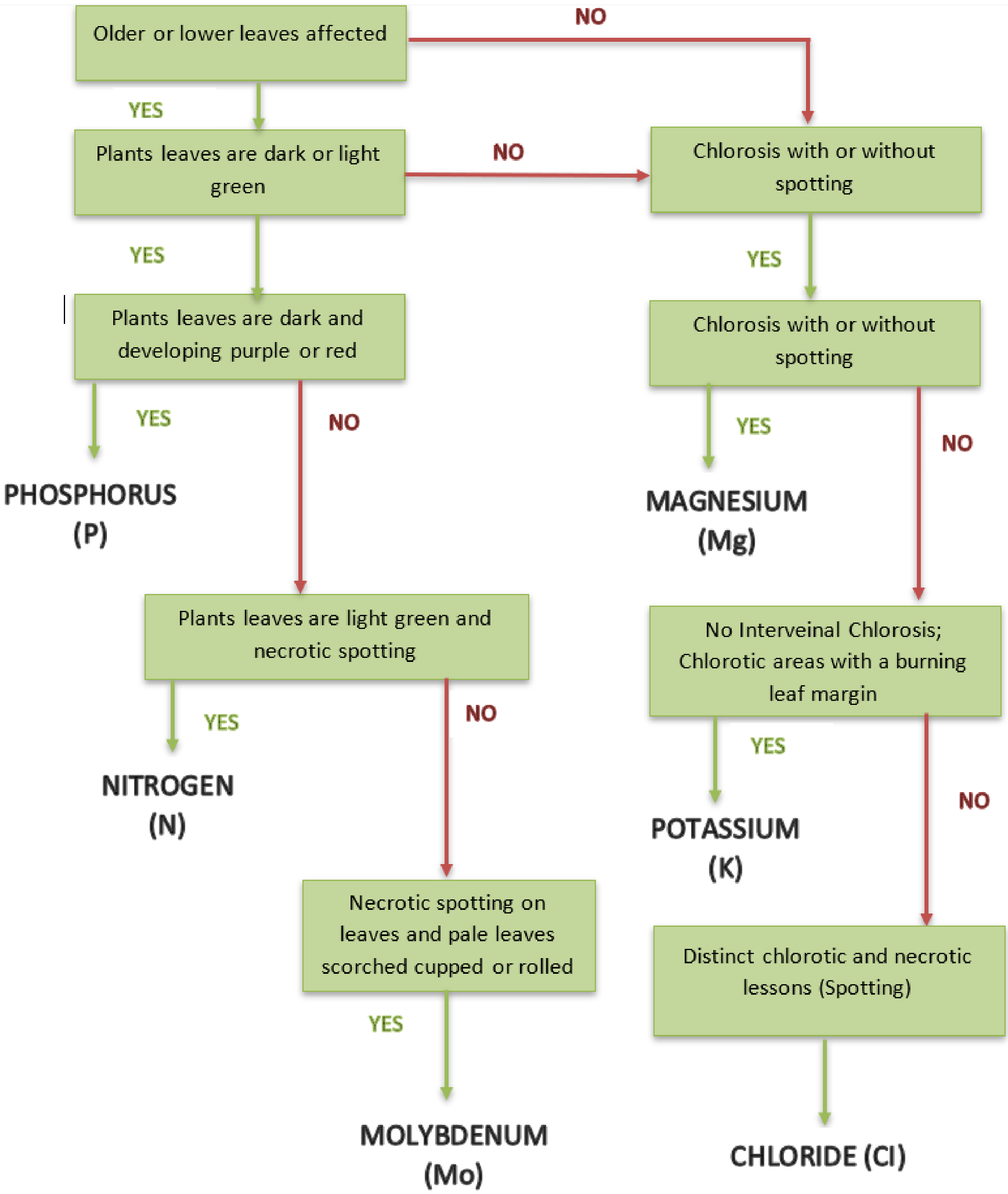


Figure 1.4: Flowchart to identify the mobile nutrients

Fig. 1.4 can be used to identify the nutrient deficiencies in plants according to the symptoms. If a statement describes the symptoms of the plants and followed along with “Yes”. It will be the nutrient disorder. If not, it followed by “No” and redirected to another deficiency symptom. This Process will continue until probability of nutrient deficiency identified. Even though, above mention key statements are the general symptoms seen in different crops. But Nutrient deficiency symptoms are differed from the types of crops and species mostly. In this research, we are mainly focus nutrient deficiencies in Groundnut, Guava and Lemon plants

1.2.2 Overview of groundnut and its nutrient deficiencies

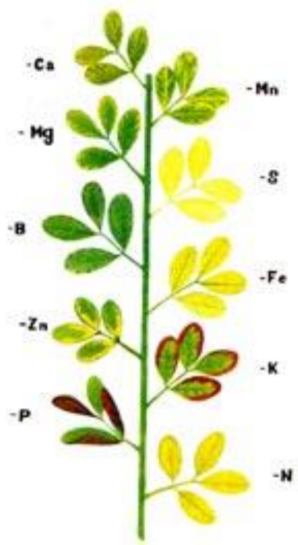


Figure 1.5:Visualization of Nutrient deficiency in groundnut

Groundnuts require more phosphorus, sulfur to be an oil seed crop and more calcium to form a proper shell and fill the pod [34]. To produce one tone of pods / hectare of groundnut requires about 58 kg, 5 kg B and 18 kg K, 11 kg Calcium, 4 kg Sulfur and 9 kg Magnesium[43]. To maintain the overall health of the soil and consistently good yields, a desirable level of organic carbon (0.3 -0.7%) should be maintained in the soil.

According to the R.Tharsiny and G.Thivahary (2015), Nitrogen and phosphorus are important for effective production of groundnut. It requires Phosphorus, nitrogen fixation, and nodule formation for growth and development [37]. Once the nitrogen needs of a crop have been mineralized, most soils can be filled with nitrogen conditioning fertilizer which assists to provide phosphorus requirements [34]. Most tropical soils lack phosphorus which causes the phosphorus deficiency [44].

Symptoms of Nitrogen deficiency in groundnut are, plant becomes stunted and turns yellow [24]. The stem of the groundnut turns thin, oval and red in color. Chlorosis first appears in the lower leaves. The upper leaves are green. Residual nitrogen migrates towards the newly growing leaves, causing the tendency of the remaining young upper leaves [31]. Fig. 1.5 illustrates all the visual symptoms of all nutrient deficiency in Groundnut plant. Phosphorus deficiency causes dark green leaves with a skin-like texture, reddish purple leaves and rims [11]. Potassium deficient plants show bleaching or browning at the edges and tips of the leaves. The leaves appear dry and charred on the edges, and the surface is irregularly chlorotic in the severe case [5]. Below Fig. 1.6 demonstrates the features of nitrogen and potassium deficiency discussed above.

Figure 1.6: Nitrogen, Potassium deficiencies in Groundnut plant

1.2.3 Overview of Guava and its nutrient deficiencies

Guava grows best in moist soils with flowing water and ambient temperatures of approximately 27°C [35]. The 33-foot-high tree copper-colored bark harvests all year round, harvesting about 80 fruits per year. However, the addition of organic fertilizers will typically result in crops targeting 200 fruits per tree[40]. According to the Fruit and management department, Currently the average area of each plantation can be less than 10 acres, but it is estimated that more than 1,200 hectares are under guava cultivation[8].

Nitrogen deficiency in guava plants causes chlorosis in leaves. first it appears on old leaves and it usually begins at the tips. Depending on the severity of the nitrogen deficiency, the chorus can be dead or can drop old leaves. Symptoms of phosphorus deficiency are stunted growth and dark green that appears on the old leaves of the plant[32]. In severity stage, leaves and stems can appear purple in color. Plants with lack of potassium grow slowly. The stem becomes weak. It reduces the size of seeds and fruits in their production[38]. Fig. 1.7 shows the symptoms of Nitrogen, Potassium and Phosphorus deficiency.

Figure 1.7:Nitrogen, Phosphorus and Potassium deficiency in Guava plant

1.2.4 Overview of Lemon plant and its nutrient deficiencies

Lemons grow on all types of soil. Well-drained and light soil is suitable for cultivation of citrus plant. Soil pH range for plantation is 5.5-7.5[17]. They can also grow in slightly alkaline and acidic soils. Well-drained soil is ideal for growing lemons. In Sri Lanka, citrus fruits are cultivated on an area of approximately 923,000 hectares, with an annual production of 8608 thousand metric tons [32].

From the literature study, Citrus plant needs regular watering. Life-saving irrigation should be given in winter and summer. Irrigation is required for flowering, fruiting and proper plant growth. Excessive watering can also lead to diseases such as root rot and collar rot. High frequency irrigation is beneficial. Salt water can be harmful to crops. Partial drying of soil in spring does not affect the plant [39].

According to an article by the A. K Srivastava, Nitrogen deficiency in lemon affects old leaves first, and then young leaves. Moreover, leaves change from pale yellow to green [36]. Mature leaves are slowly bleached into a mottled irregular green and yellow pattern. Due to the Phosphorus deficiency, the leaves become very small and thin with purple or bronze discoloration [8]. As shown in the Fig. 1.8 normally, Potassium deficient plant leaves seems broader and Yellowing in the leaves tips [42].

Figure 1.8:Nitrogen, Phosphorus and Potassium deficiency in Citrus plant

1.2.5 Image processing for the identification of Nutrient deficiency

According to Jayamala.K, Patil, Raj Kumar paper titled “Advances in image processing for detection of plant disease” [45]. This paper explains the methods which are available to study plant diseases using image processing. These methodologies were proposed by the human professionals in detecting the plant diseases to increase the throughput. The paper mainly focuses on speed and accuracy which were the main characteristics of plant disease detection using machine learning. There is space for the development of fast, effective interpreting algorithms which could help plant scientist in detecting the disease. The algorithm uses color space and co-occurrence matrix to extract short disease spot texture features and BP neural network is applied as a classifier with an accuracy of 98 % [45].

When using an image processing technique for classifying the absence of nutritional disease that occurred in oil palm leaves can only be investigated by the leaves’ surface [6]. This technique is functioning as a guide for fertilization because the trees show rapid reaction to the used fertilizers. Extreme use of fertilizers will cause harm to the trees. So, the use of fertilizers must be controlled. To examine the leaves’ surface of oil palm leaves needs high-end digital imaging devices. Based on the texture and color of the disease type, feature extraction will progress. The feature vectors will be reached acting as inputs to a fuzzy classifier [6].

Prediction of multiple nutrient deficiency in paddy leaf images has been discussed by the Mrityunjaya V Latte and Sushila Shidnal. This paper mainly focuses on the pattern analysis to identify the nutrient deficiency from extracted RGB color features. In addition, Image effective comparison were trained at various levels such as multiple color comparison, multiple pattern comparison and combination of color and pattern comparison, so that defectiveness were accurately detected for combination of deficiency like nitrogen-potassium(NK), phosphorous-potassium (KP) and nitrogen-phosphorus(NP) [21].

1.2.6 Machine Learning and Deep Learning for the identification of Nutrient deficiency

Jonilyn A. Tejada, Glenn Paul P.Gara has implemented that the LeafCheckIT, web based solution that uses Random Forest machine learning algorithm to identify the Nitrogen (N), Phosphorus (P) and Potassium (K) collectively in banana leaves. They have used 10-fold cross validation test conducted on WEKA data mining software based on the training data set. The outcome of this study resulted in 89.64% accuracy rate [22].

According to the N.Minni and N.Rehna (2016), Farmers have been practicing the manual procedure to identify the nutrient deficiency in plants. This process with a lower accuracy and throughput is proposed to be replaced with computer oriented concepts such as Image Processing and Machine Learning, with the intention of achieving speed and accuracy. Initially images of various types of leaves were captured using digital camera. The captured RGB images represented into Hue Intensity Saturation (HIS) color model. In image segmentation, the pixels which are mostly green are identified first. Then threshold value is calculated and if the pixel intensity is less than the computed threshold value, those pixels were masked. After that, In Feature extraction infected portion of the leaves are segmented to equal size. Feature extraction was done only for color separation. For color separation HIS models are representing colors of the image and denoted in color histogram. K means clustering algorithm is used for clustering the Normal leaves and deficient leaves. Here K-NN algorithm was applied to classify the particular deficiency which affects the plant leaf [3].

Leaf disease identification can be done in two phases. In the first phase, the leaf is known based on preprocessing on stages of image processing and an artificial neural network is used as a classifier throughout the phase. During the second phase kmeans, based segmentation is relayed to identify defected areas [27]. The color of 7 | P a g e leaves plays a significant role in recognizing major deficiencies such as NPK (Nitrogen, Phosphorus, and Potassium) when a crop is in the mid of its growth. To make it happen, a group of databases should be created, which includes healthy, nitrogen defected, phosphorus defected and potassium defected leaves. Color features of both healthy and defected leaves are extracted using the HSV color model [27]. Similarly, color features of test images are extracted and compared against database properties.

MATLAB 2016 was used for developing the algorithm for processing and classification of image [19]. For filtering of noise and resizing of images, Gabor filter was used. The images were transferred from the RGB to HSV (Hue, Saturation and Value) color space. They have segmented out the deficient leaves sample from the color image. Every image added to the collection and analyzed to compute a color histogram, which indicates the proportion of pixels of each color within the image. Thus, as an output 256 features were obtained for every image. The color histogram for every image is stored in the database. The results reveal that superior performance for histogram-based feature extraction compared to the other classification methods. The best classification accuracy with texture features was obtained with KNN classifier. The effect of different kernels for SVM was investigated for both the feature sets. It was seen that SVM with linear kernel gave the highest accuracy of classification in both cases. Similarly, the effect of distance metric and number of neighbors on accuracy of KNN was also checked for the feature set. It was seen that KNN with cosine metric and k value of 3 gives highest accuracy. The study can be extended to micronutrient deficiency and disease infestations also [19].

In the research article, this is based on the topic of "Use of leaf color images to identify nitrogen and potassium deficient tomatoes" [10]. This paper, it shows a novel idea based on computer vision was presented. The approaches such as percent intensity histogram, percent differential histogram, Fourier transforms, and wavelet packet can be used to extract color feature of leaves. Moreover, a Genetic Algorithm (GA) has been used to select features to receive the ideal information for diagnosing the disease. Experiments illustrated that the accuracy of this diagnostic system is above 82.5 % and it can diagnose disease about 6 to 10 days before experts could determine.

1.3 Research Gap

Table 1.1: Comparison between similar products

Features and Previous works	Mobile Application	Nutrient Deficiency Identification		Plants Used	Multiple nutrient identification	Degree of Nutrient deficiency	Suggesting fertilizer	Accuracy of Results	Technology used
		Colour Analysis	Texture Anlaysis						
1. Advances in image processing for detection of plant disease [28]	✓	Diseaes Identification		Not specified				81.94%	YCbCr, Co-occurance matrix
2. Overview of image processing approach for nutrient deficiencies detection [6]		✓	✓	Elaeis Guineensis			✓	Positive Results	Fluzzy Classifier
3. LeafcheckIT a banana leaf analyzer for identifying macronutrient deficiency [22]		✓		Banana				80.64%	WEKA Data mining
4. Use of leaf color images to identify nitrogen and potassium deficient tomatoes [23]		✓		Tomato				82.50%	GA Algorithm, Intensity Histogram
5. Detection of nutrient deficiency in plants using image processing techniques[3]		✓		Rose				Positive Results	HIS model, K-NN algorithm
6. Multiple nutrient deficiency detection in paddy leaf images [21]	✓	✓		Paddy	✓			Results with 0.67 error rate	Pattern Analysis, HIS model
7. Detection of nutrition deficiencies in plants [4]		✓		N/A				Positive Results	Expensive chlorophyll meters
Crop Medic Plus 2.0	✓	✓	✓	Groundnut, Guava, Citrus	–	✓	✓	87.63% and Positive Results	CNN – EfficientnetB0, Image Processing

With the comprehensive study of literature review mentioned above in Table 1.1, It clearly defines that a system which need to identify the nutrient deficiencies in a plant and their degrees of identified deficiency with speed and accuracy. In the past, several researches have conducted for identification of diseases with machine learning and image processing techniques but few researches has done to identify the nutrient deficiency.

There are nutrient deficiency identification researches that were done by researches still don't predict the degree of the nutrient deficiency which is most needed to identify. There is research that contains using leaf color images to identify nitrogen and potassium deficient tomatoes [23]. It is focusing only on the nutrition deficiency of the plants but those are not suggesting any solution for the crops to cure the disorder.

There are several researchers [28], who used the CNN model to diagnose the diseases in plant. But there are fewer researchers who used CNN model to the identification of nutrient deficiency in plant leaf. The main idea of this research component is depending on the Convolutional neural network, so the accuracy level of the neural model [7] identification made a huge impact. From the previous works, CNN [10] had been experimented and an accuracy of 99.53% was achieved in plant disease identification. Compared to other classification algorithm, it has very less preprocessing. Another special feature of CNN is it automates the feature extraction. These advantages and accuracy level clearly indicate the importance of the selected neural model.

The main feature which is in the research is to identify the degree nutrient deficiency of plants and suggesting suitable fertilizer for nutrient deficiency. For this purpose, it is necessary to identify the nutrient deficiency in a particular plant. "CropMedic plus 2.0" mobile application is able to fill the above-mentioned gaps which are left by the past researchers and give facilities to the targeted customer.

“CropMedic Plus 2.0” application gives following functionalities to targeted users:

- Available in Low Cost: Cost is a major concern for the average user of the application. If it is a high cost version, it will be very expensive for users to buy it. Also, since the main users are rural farmers, our research team has planned to make the main features free.

- Simple and user-friendly interface: All interfaces are designed in a simple and user-friendly manner as the main users of this system are rural farmers and most of them have no experience with Android applications.

- Accuracy: Machine learning techniques are used to provide more accuracy to the user in predicting the nutrient disorder.

- Portable: According to our country there is no existing system which can detect the nutrient deficiencies with its degree and give suggestion for fertilizer in mobile device. “Crop Medic Plus 2.0” is an android application, which is easy to carry around and able to identify the nutrient disorder by capturing the image of the leaf.

1.4 Research Problem

According to the criteria of economy, quality and quantity of the agricultural products are important in its trading. Farmers are expected to produce high or sufficient quantity of products with optimum quality. But, in most of the time farmers are failing to fulfill their expectations due to various issues. Major issue is the nutrient deficiency in crops. Different conditions of weather, soil, water and land causes' different disease conditions in crops.

Possibilities of spreading of disease are increase with time [17]. Nutrient deficiency cannot be identified early by direct observation because same plant may deficit in many nutrients. Sometimes, same symptoms are produced in different nutrient deficiency. Inability of farmers to detect the nutrient deficiency early in crops is the major problem identified[18]. For example, deficiency of sulphur and nitrogen can produce same symptoms [8]. So, early and precise detection of nutrient deficiency in crops are the major problems for farmers in increasing productivity of agriculture.

The current methods used in identifying plant nutrition disorders is very expensive and highly cumbersome for field use. Currently satellite imagery and expensive Chlorophyllmeters are used for the identification of such nutrition disorders [5]. These methods require high funding which most of the farming communities cannot afford. For example, 49% of the population in Sub-Saharan Africa live on less than 1$ a day, 10 years back [6]. Sub-Saharan Africa accounted roughly of a third of the overall growth within the period of 1993 – 2005 [6] showing how heavily involved the country's labor force is in the agricultural industry. Expecting farmers from such regions to use the existing systems for identification of plant nutritional disorders is far from being pragmatic.

Until now, in Sri Lanka there are no implemented method, the agricultural sector keeps some raw data on its website, but farmers should have a proper knowledge to make decision from raw data. Most of the rural level farms have less exposure to industry and lack of knowledge modern era to solve a problem. Getting profit from the cultivation is more important for a farmer but several factors impacts on market their products for reasonable price due to less production. Experience plays a major role in cultivation since they are not digitalized yet. It is exceedingly difficult to start farming for a fresh farmer without an experience thus there is no guidance for them. Farmers usually detect the plant with their eye which makes them take tough decision on which fertilizer to use. It requires detailed knowledge and lots of experience need to make sure the actual disorder detection. Since most of the disorders have similar symptom. Rural farms affect because rural farmers do not know about nutrient deficiency and fertilizer.

Research and new findings can be helpful to stable the position of cultivation in the society. In recent times, rural youth have stated that access to data, lack of financial stable, and negative perceptions about agriculture are the main reasons why they leave cultivation. Higher percentage of youth unemployment is the major problems presently affecting youth in Sri Lanka. When young people cannot find proper jobs in societies, they think to emigrate from rural areas for chances in large cities and in other countries facing an uncertain future. Young people have numerous innovative concepts but are often omitted from the planning and policy procedures of the future of rural areas. They are usually less interested in jobs in this area because of the perception that agriculture is outdated and unprofitable.

A lot of evidence shows that agriculture provides a viable way to succeed in a sustainable future. It is a must to motivate young people and encourage them to involve in cultivation. “Crop Medic Plus” is aimed to solving the above-mentioned problem by introducing a smart intelligent system for identification of nutrient deficiency and its degree. Through this, it is expected that the farmers will be able to increase the yield of cultivation.

1.5 Research Objective

1.5.1 Main Objective

The main aim of this component is to provide an intelligent solution to identify the crops and nutrient deficiency in a crop with speed and accuracy to farmers. First "CropMedic 2.0" is expected to identify whether it is a healthy leaf or unhealthy leaf and further it will identify which nutrient deficiency type affects the crop specifically. From our system, User can upload an image of a crop leaf suspicious to have been affected with a nutrient deficiency, and the system should be able to perform the diagnosis with the help of a well-trained convolutional neural model.

1.5.2 Specific Objective

- Data Collection: Datasets were collected through online resources and field visits

- Data Handling: Required datasets collected from the real fields and online in the format of image.

  Collects the images of datasets for training the model from real fields, agricultural departments and online. Totally, 8754 images have collected for training model.

- Data Preprocessing: Image processing is used to preprocess the datasets. It has done to remove the complexity in the datasets.

- Main users of this application are farmers, so mobile application should be user friendly and more understandable.

- Our whole system is fully depended on datasets. Therefore, developing suitable algorithm for training those datasets with more accuracy.

2. RESEARCH METHODOLOGY

2.1 Methodology

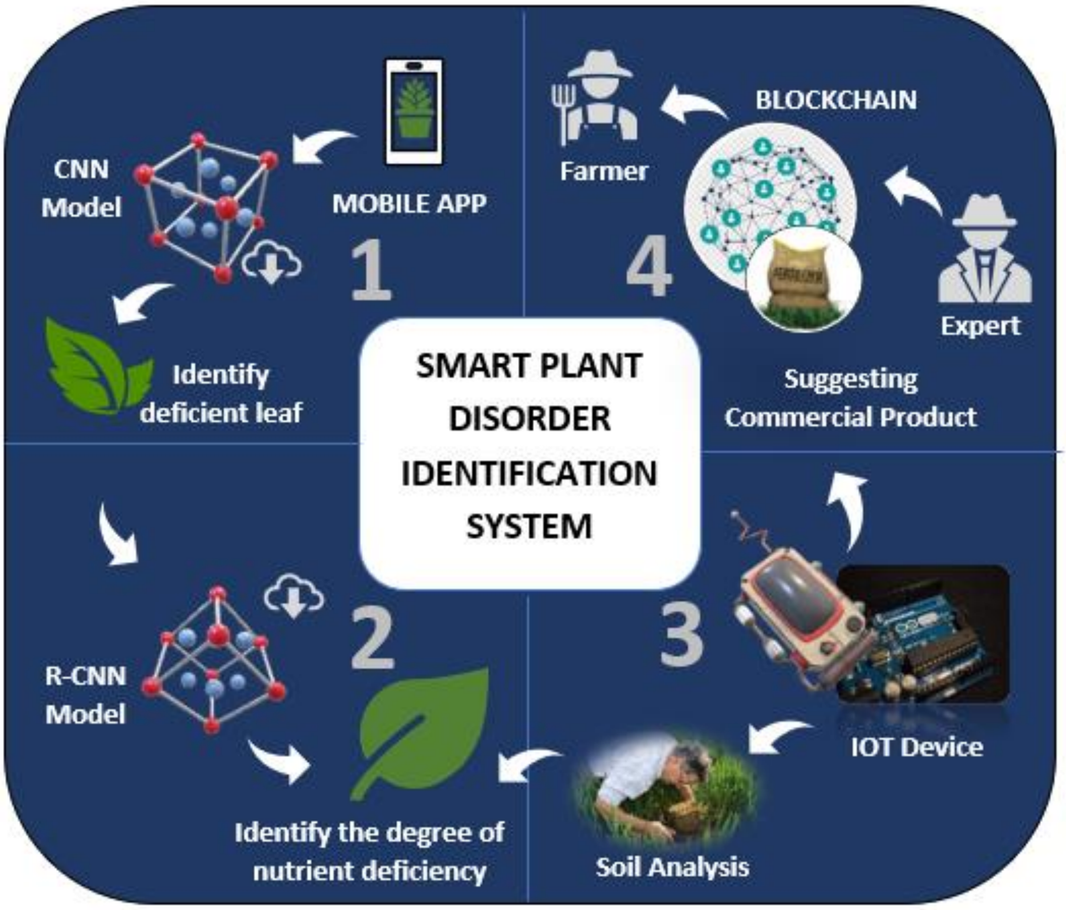


Figure 2.1:Overall diagram of our System

As shown in the Overall diagram Fig. 2.1 our mobile application consists of four components. Such as

1. Accurate identification of nutrient deficiency (among N, P and K)
2. Identification of the degree of Nutrient deficiency and recommendation of suitable remedy.
3. Soil analysis using IoT to provide accurate degree of nutrition deficiency in soil and recommendation

4. Implement a secure and distributed platform for identifying best commercial product for deficiency based on diagnosis

The outcome of the system is expected to come in the form of a mobile application that can be able to identify the crop nutrient deficiency and its degree with more accuracy and speed. Special Feature of CropMedic 2.0 is to identify the degree of nutrient deficiency using the RCNN. And our system is enabled farmers and expert to communicate efficiently and securely within the private ledger blockchain. Target user of this application is Farmers, Experts and vendors. Farmer are expected to identify the nutrient deficiency and its degree. Vendors can able to provide the suitable details of the fertilizer for the nutrient deficiency. Experts are supposed to share the most adequate fertilizer with the purchasing quality and instructions.

Below Fig. 2.2 shows the high-level architecture of the entire system:

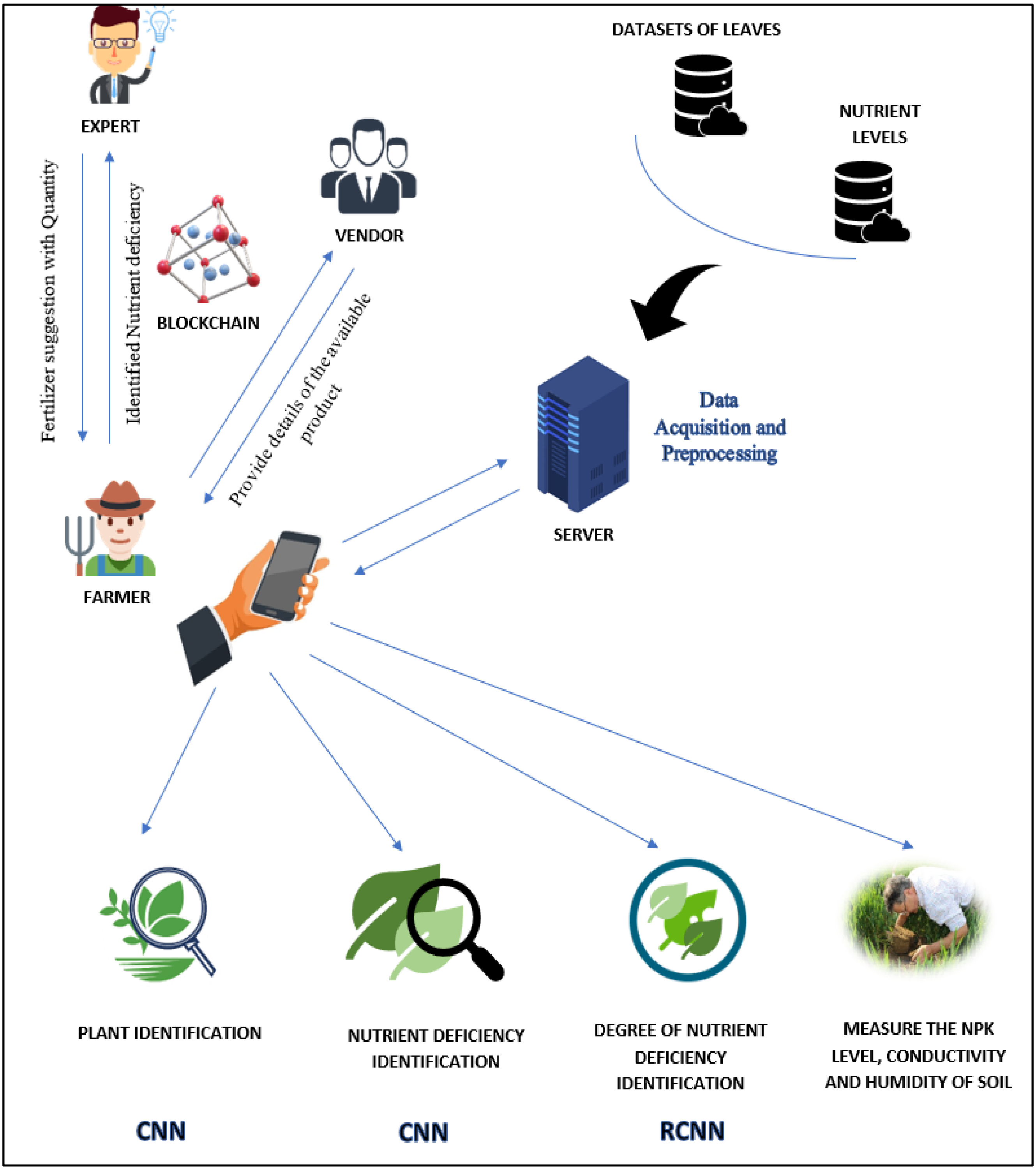


Figure 2.2:Hight Level Diagram of System

Identification of Nutrient Deficiency using Image Processing and Machine Learning

This sub research component focuses on identifying plant and nutrient deficiency using image processing and machine learning. If the leaf shows a symptom of a nutrient disorder which is denoted under the scope of this research, it will be sent to the trained model and do further analysis. After that, results of the analysis will be sent to the mobile app. A user can upload an image of a crop leaf suspected to be infected with a nutrient disorder and system should identify the disorder with the help of a well-trained neural model.

Based on the flow of the diagram, this individual component can be further divided into the following sub-tasks shown in the Fig. 2.3.

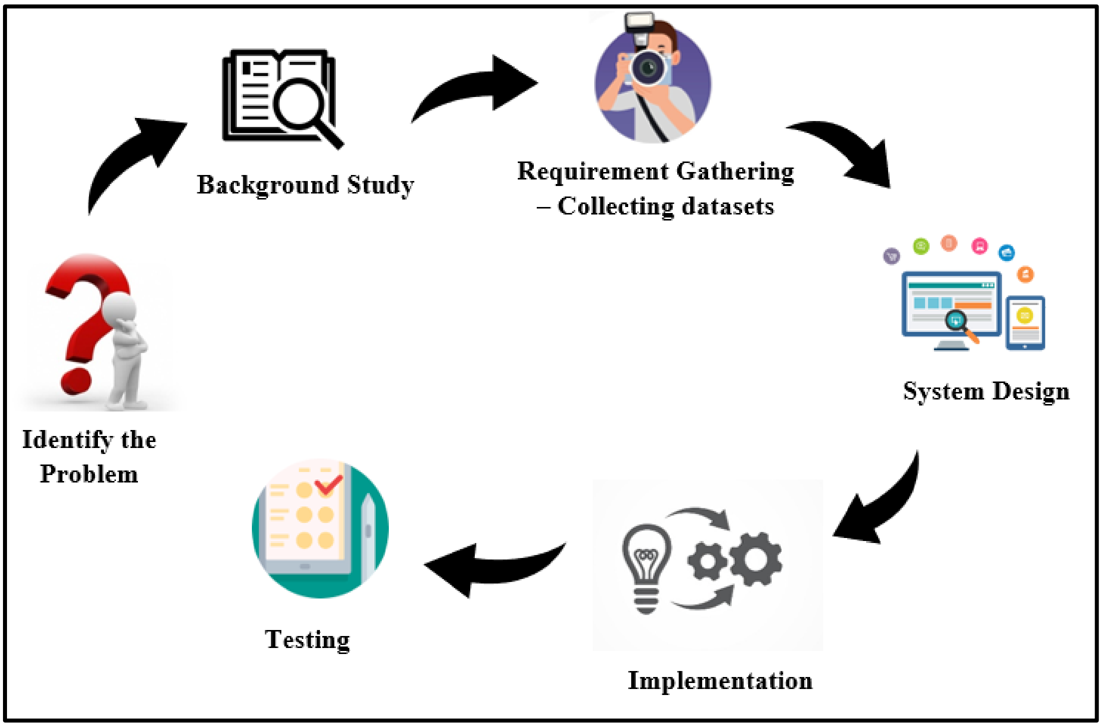


Figure 2.3: Sub tasks for the Crop nutrient deficiency prediction

2.1.1 Identify the Problem

Early detection of nutrient deficiency is important because possibilities of spreading of disease are increase with time. Nutrient deficiency cannot be identified exactly by direct observation because same plant may deficit in many nutrients. Sometimes, same symptoms are produced in different nutrient deficiency. Inability of farmers to detect the nutrient deficiency early and identify its degree precisely in crops is the major problem identified. Through a survey of the background literature referred in Section 1.2 above, it was identified that it is very important to implement a system that can detect nutritional deficiencies and its degree.

In order to identify the degree of nutrient deficiency in every stage, first we need to identify which nutrient deficiency affects the plant. This component is primarily intended to implement the first half of the system that makes the initial diagnosis of an image uploaded by the user. Once the initial detection of nutrient deficiency is identified in this component, Component two will identify the degree of nutrient deficiency.

2.1.2 Background Study

I. Study about Nutrient Deficiencies

Covered in Section 1.2.1 above

II. Study about Neural Models

A comprehensive analysis of the use of various neural models and their application in the literature review of this research study was conducted. Moreover, Those models needed to be narrow down to a few neural models and choose the one that best fits the requirements of the project.

In this research, CNN has chosen to train the neural network model. This is because, like a human brain, it can automatically extract features from images[7]. Compared to other networks, CNN automatically adjusts the pixel value to pooling through the convolution effectively[28]. Softmax layer used for layer prediction In terms of performance, CNN trains the model automatically without any data loss. According to past studies[23], the CNN model was recorded as a successful architecture and achieved an accuracy of 99.53%. This level of accuracy clearly defines the importance of the selected neural network for image classification.

According to the several background study, there are many CNN architectures used previously. Such as EfficientnetB0, Inception-V3, GoogLeNet, ResNet and VGG. According to the comprehensive literature review EfficientB0, ResNet and VGG has stated as top three architecture in CNN[10]. In this research, Comparison has done among ResNet, EfficientnetB0, and VGG architectures and the Model which got highest confidence level has selected to the identification of nutrient disorder in plants

2.1.3 Requirement Gathering

Since it was decided during the feasibility study stage of the project, it was expected to use a neural model to identify the disorders, which could classify images based on a trained image data pool. It was essential to collect images of each nutrient deficiency type for each plant type. The following methods has followed to collect the datasets.

1. Collected the images from online

   Few Nutrient deficiency images has collected from various websites of agricultural departments and blogs websites.

2. Manually captured through the field visits.

   The collection process of data was not limited to obtained from online data sources. Images were collected through the field visits where these three crops such as groundnut, guava and Citrus were grown. Camera is used to capture the images. Following are the field visits conducted during this research.

Field visit 01 – Regional Agriculture Research center, Kahagolla

After the discussion with the Deputy Director of the Regional Agriculture Research and Development Centre located at Kahagolla. we have decided to grow the plants in the control environment to get more accuracy and feasibility in results. They have suggested three methods to grow the plants in control environment. Such as,

1. Reduce each nutrient level in a plant and prevent the absorption of nutrients individually through the Standard protocol. This method is not feasible because it is very expensive to apply.

2. Soil and tissue analysis of crops which grown under the field condition. The most problem with this method is to differentiate the diseases symptom and disorder symptom in a plant leaf prominently.

3. Nitrogen, Potassium, Phosphorus are absorbed via soil. So, Apply the various ratio amount of fertilizers to each plant and able to see the symptoms of nutrients visually. To identify the nutrient deficiency in a plant, if urea can be applied to that plant less than the recommended level, symptoms can be identified. This method is more feasible to identify the nutrient deficiency symptom prominently.

According to the third method, we have planned to grow the plant in control environment because of the Covid19 Situation, our research team could not able to cultivate the plants in above mentioned methods and also, this research needed the comprehensive knowledge about the plants disorder and symptoms. As shown in the below Fig. 2.4, the Deputy director Mr.K.P Somachandra and his assistant was provided the full support to explain about feasible methods to conduct this research.

Figure 2.4: Field Visit 01 – Regional Agriculture Research Center Bandarawela.

In this 1st Field visit, from discussion with relevant officials in Agriculture Research Institute and as well as small and medium scale farmers, it was accepted that, mostly Macro nutrients such as Nitrogen, Potassium, Phosphorus affects the production of crops frequently. Nutrients are limited as Nitrogen, Potassium, Phosphorus to identify deficiency in three types of plants.

<u>Field visit 02 - Regional Agriculture Research Centre, Kilinochchi</u>

The Fig. 2.5 shows the second visit to the research center which was scheduled for the 1st of August 2020 and held under the support and guidance of Additional Director Dr. S.J. Arasakesary. The main purpose of this visit was planned to capture the images of nutrient deficiencies in Groundnut, Guava.

During this visit, In the discussion with the local farmer community, they're still using the traditional methods of nutrient disorder prevention and treatment are being practiced around that area. Direct observation of different fertilizer-based treatments was carried out on the plants affected by potassium deficiency. Groundnut and Guava nutrient deficiencies were directly observed and captured the pool of images for the datasets. As shown below Fig. 2.5 images were captured using the camera with the black background.

Figure 2.5:Field Visit 02 – Regional Agriculture Research Center Kilinochchi.

At the end of every field visits, we were able to collect a significant amount of leaf images for our dataset. The dataset contained healthy images and nutrient deficient image of plants.

The below images show the dataset contained 300 images of healthy groundnut leaf and 300 images of nitrogen deficient groundnut leaf

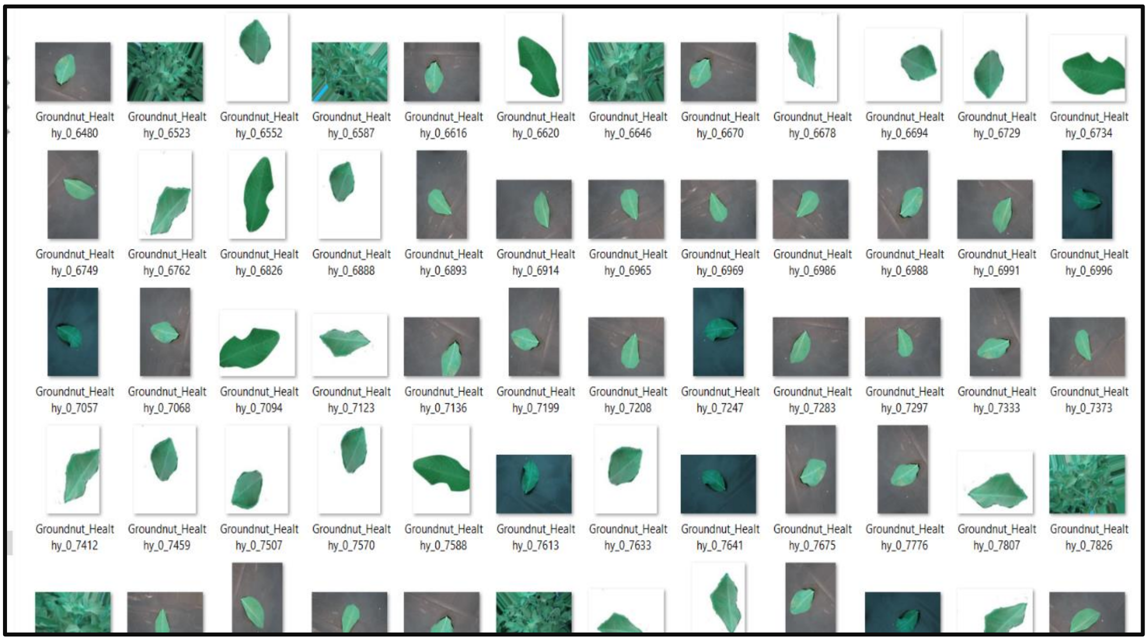


Figure 2.6:Snapshot of Healthy groundnut leaf dataset

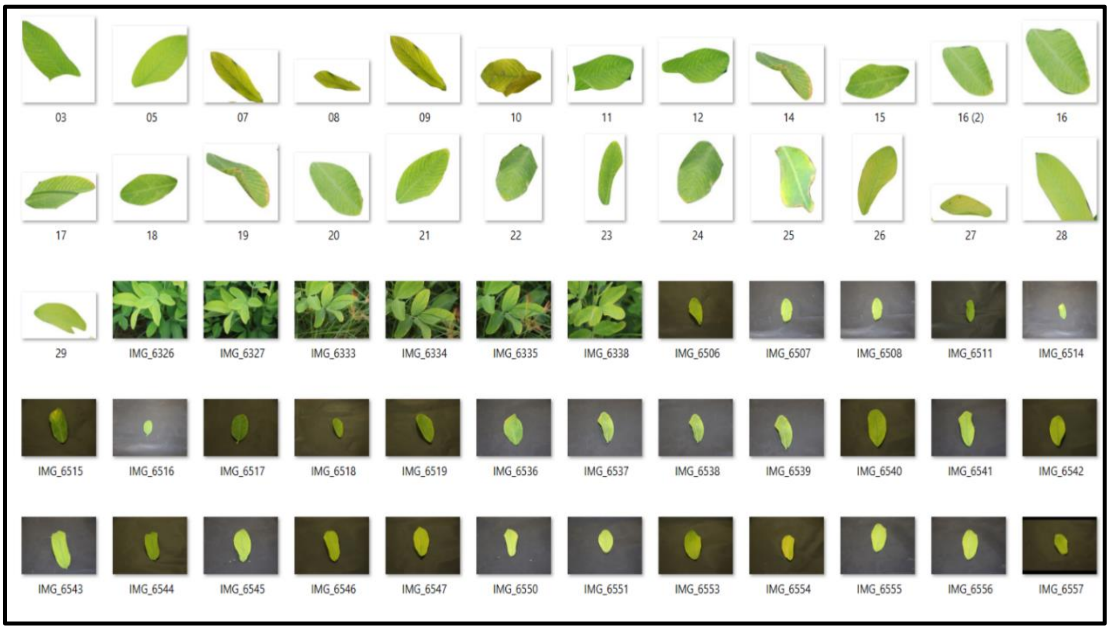


Figure 2.7: Snapshot of Nitrogen deficient groundnut leaf dataset

The below figures demonstrate the dataset contained 300 images of potassium deficient groundnut leaf and 300 images of Sulfur deficient groundnut leaf

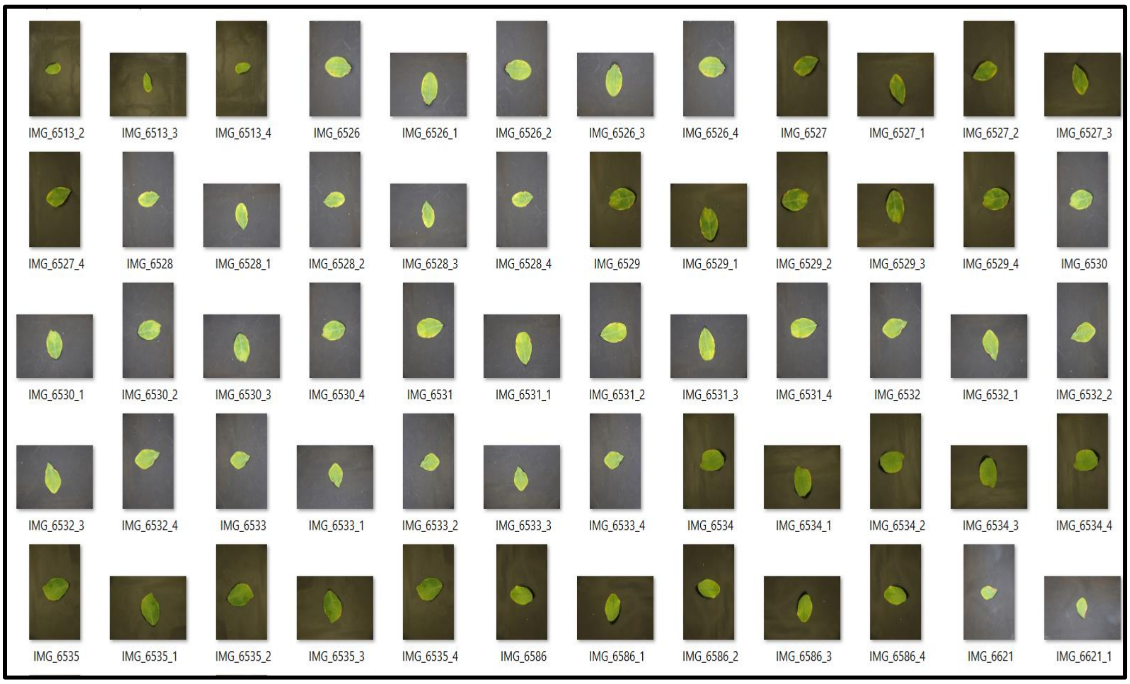


Figure 2.8:Snapshot of Potassium deficient groundnut leaf dataset

Figure 2.9:Snapshot of Sulfur deficient groundnut leaf dataset

The below figures show the dataset contained 3000 images of guava healthy leaf and 300 images of nitrogen deficient guava leaf

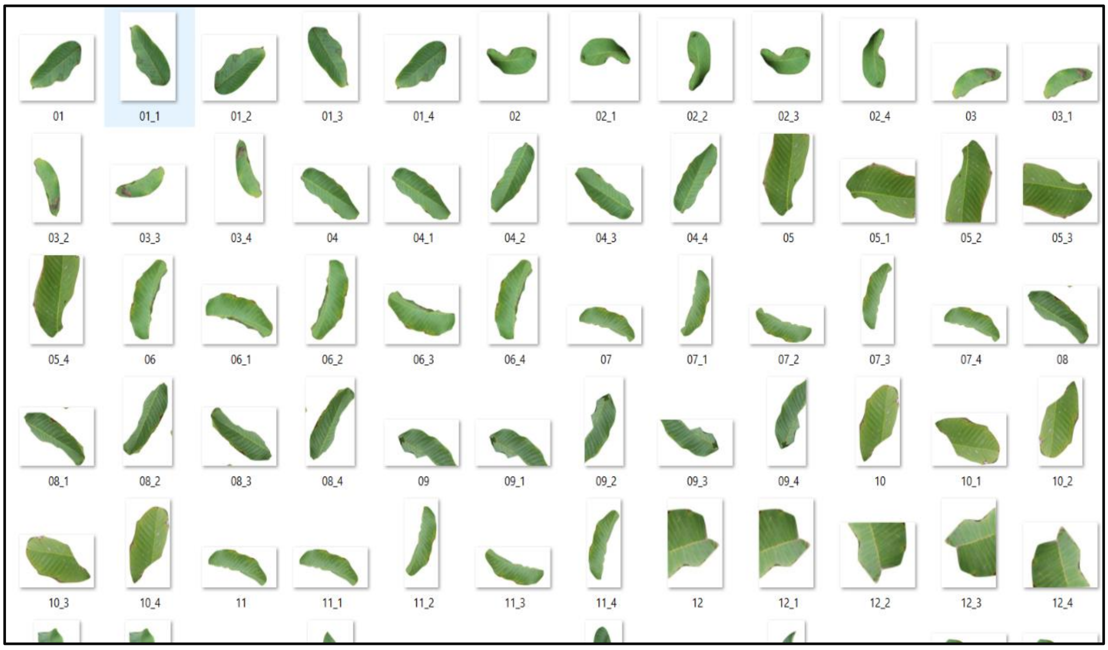


Figure 2.10:Snapshot of healthy guava leaf dataset

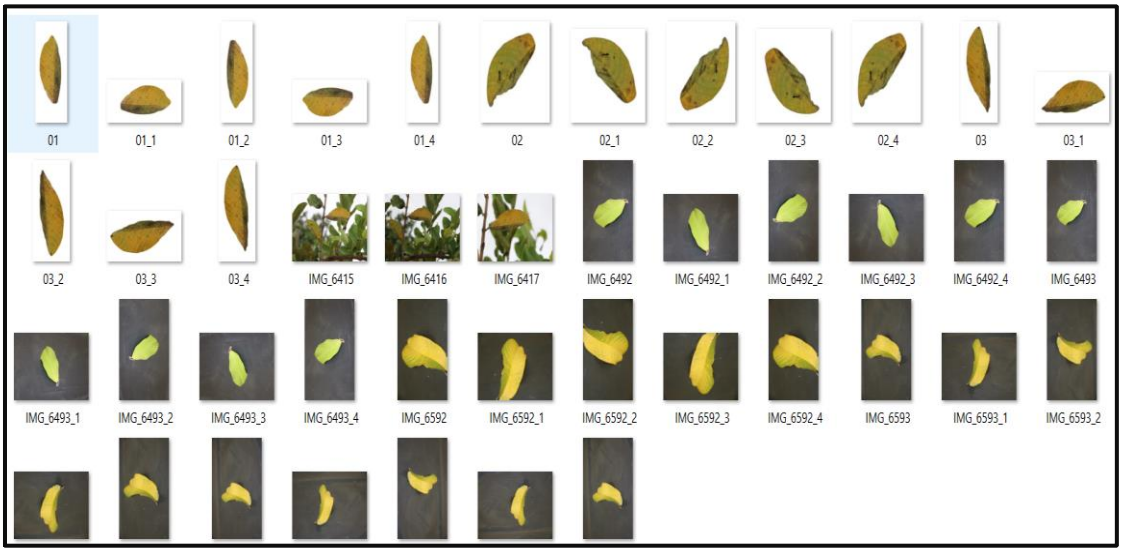


Figure 2.11: Snapshot of nitrogen deficient guava leaf dataset

The below figures show the dataset contained 300 images of guava Potassium deficient leaf and 300 images of citrus healthy leaf

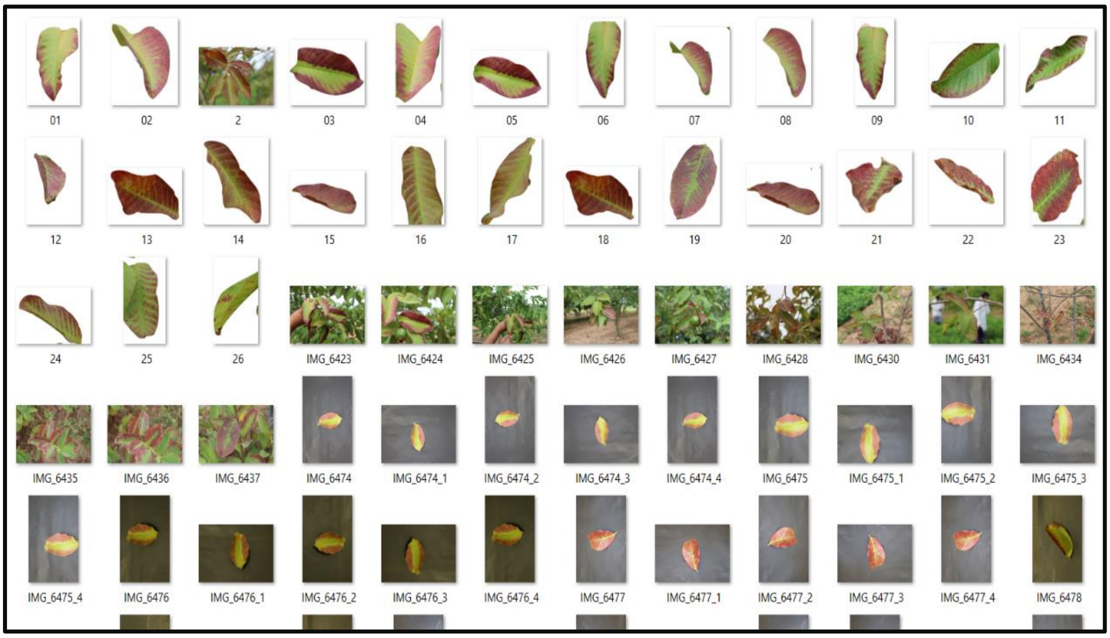


Figure 2.12: Snapshot of Potassium deficient guava leaf dataset

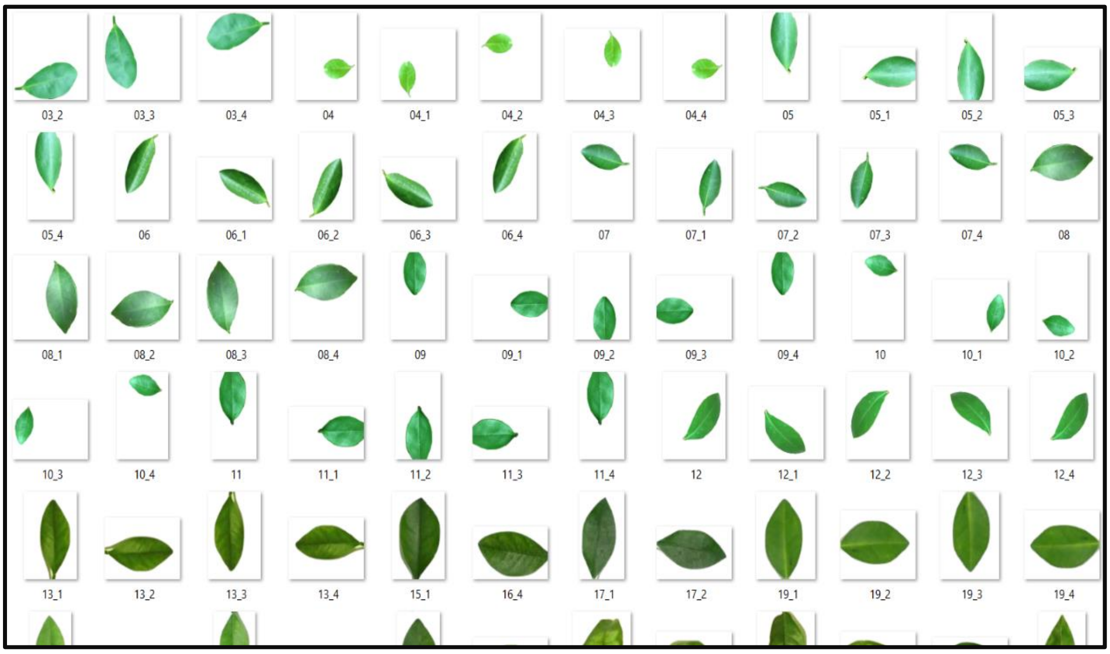


Figure 2.13: Snapshot of Healthy citrus leaf dataset

The below figures show the dataset contained 300 images of Citrus Nitrogen deficient leaf and 300 images of citrus Phosphorus deficient leaf

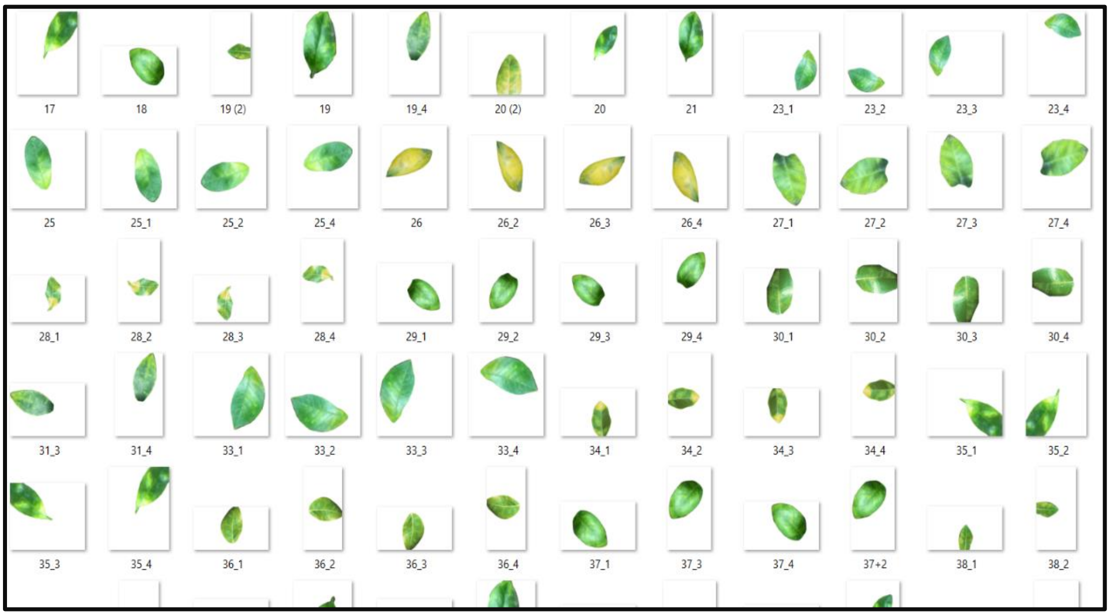


Figure 2.14: Snapshot of citrus nitrogen deficient leaf dataset

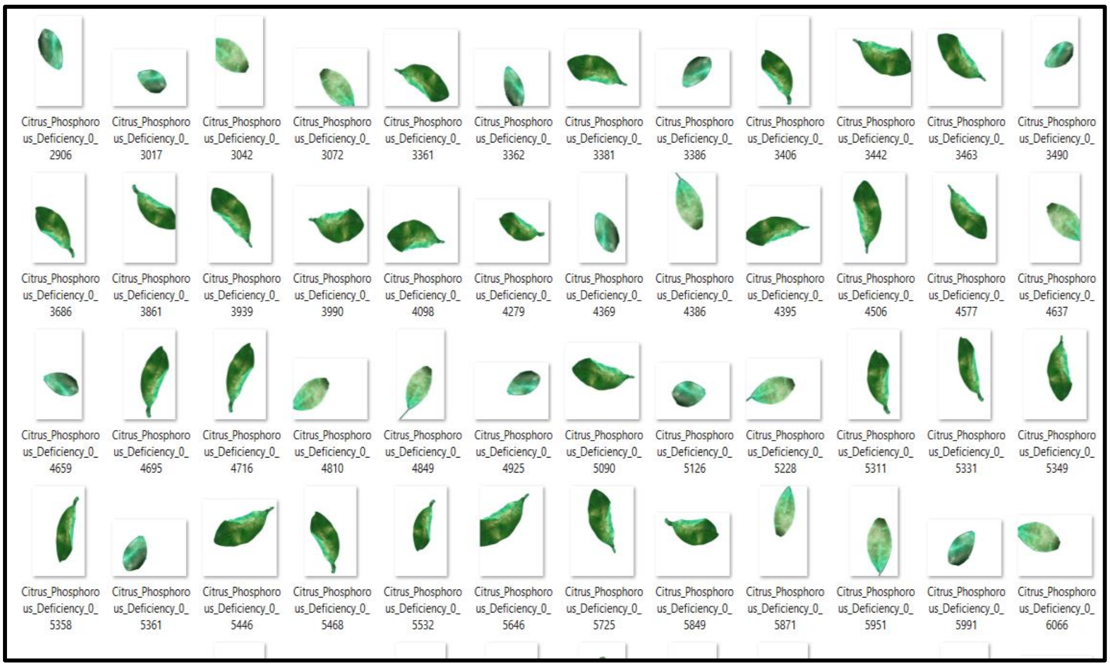


Figure 2.15: Snapshot of citrus Phosphorus deficient leaf dataset

The below Fig. 2.16 shows the dataset contained 300 images of Citrus Potassium deficient leaf

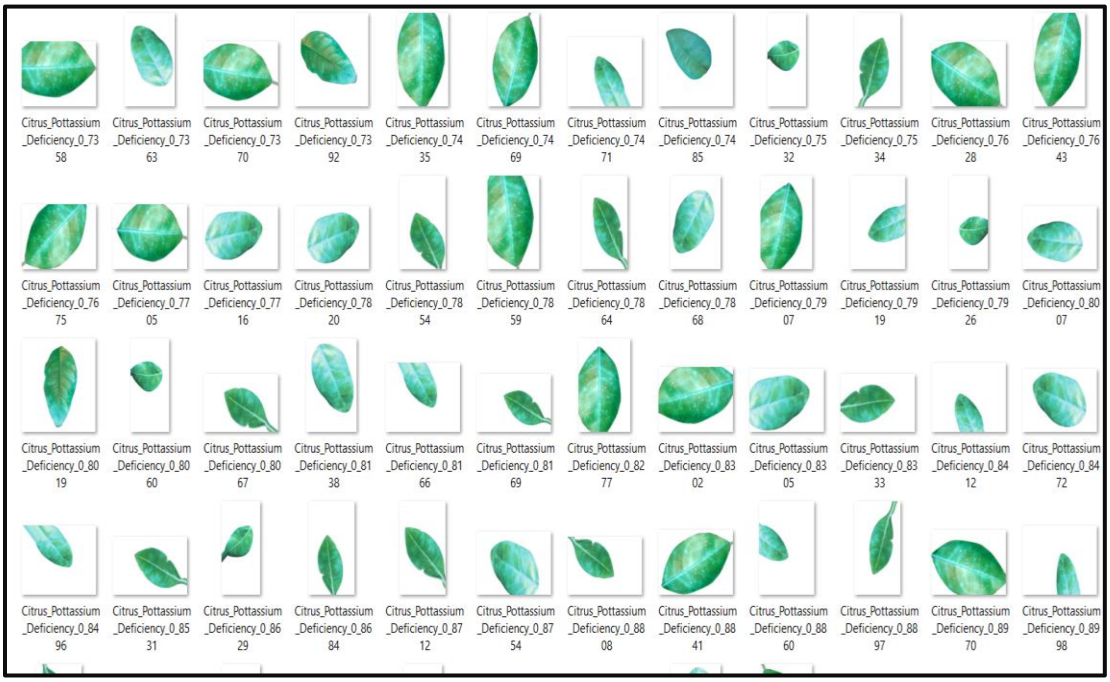


Figure 2.16: Snapshot of citrus Potassium deficient leaf dataset

2.1.4 System Design

Nowadays, everyone uses the mobile for all day to day activities. It was decided to implement a mobile based solution for the problem identified in the above phase. It is expected to encourage the young farmers to engage in agriculture using mobile solution.

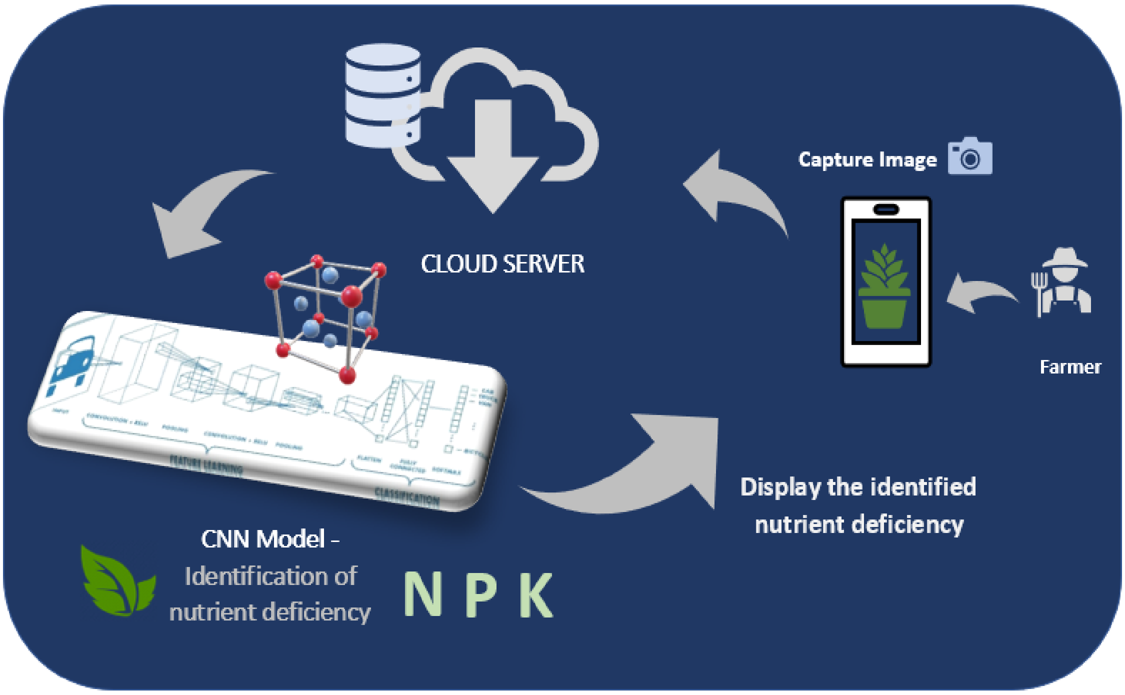


Figure 2.17: High Level diagram of research component 01

As shown in the above Fig. 2.17, Suspected leaf will be uploaded to the mobile application by the user. These images are sent to Deep learning model which will predict the nutrient deficiency. In the prediction, datasets are moved with various stages like Normalization of data, Model training, Model testing and Model validation.

Following Fig. 2.18. illustrates the Architectural Diagram for the Component 01

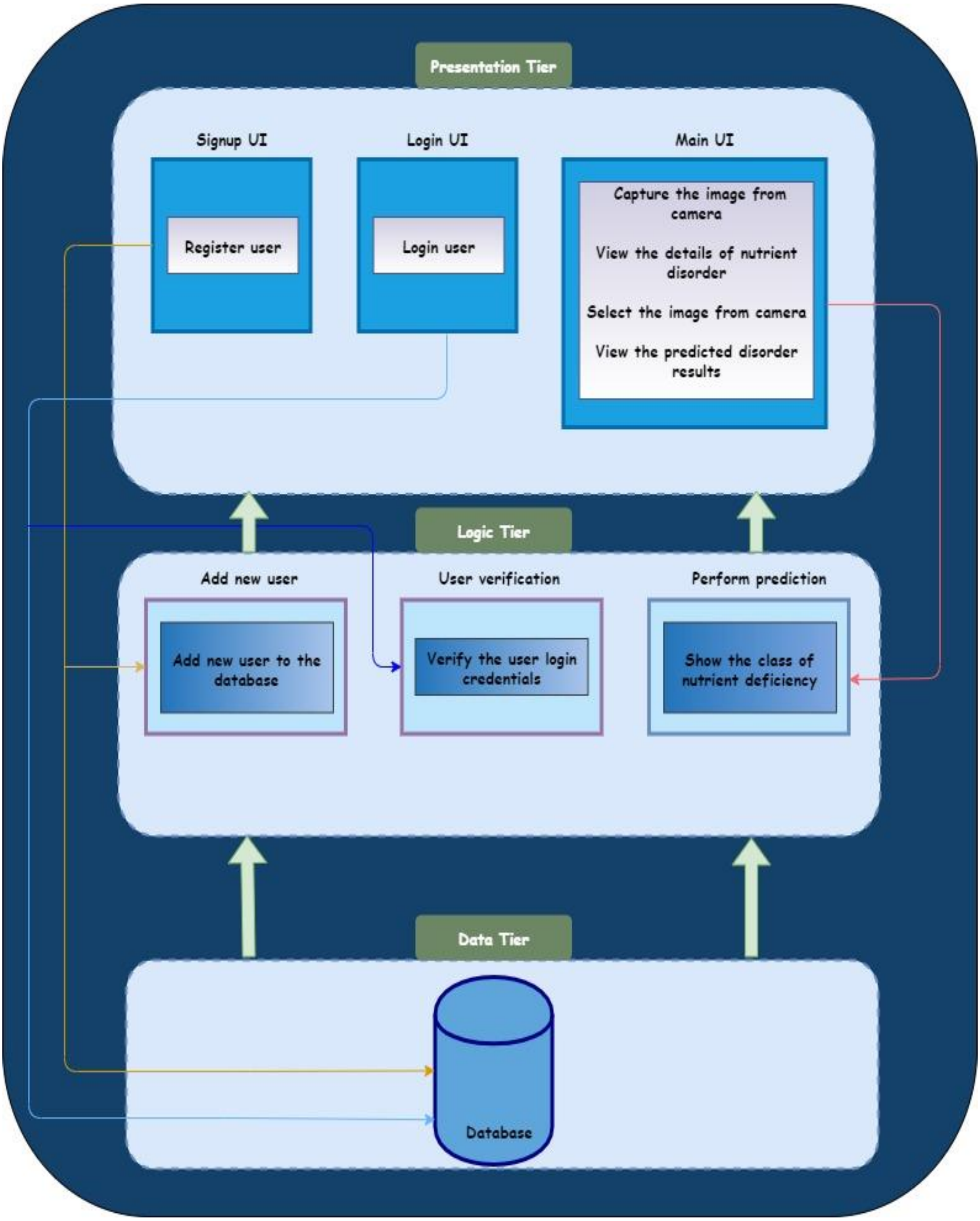


Figure 2.18: Architectural diagram

Following Fig. 2.19. shows Sequence diagram for Component 01

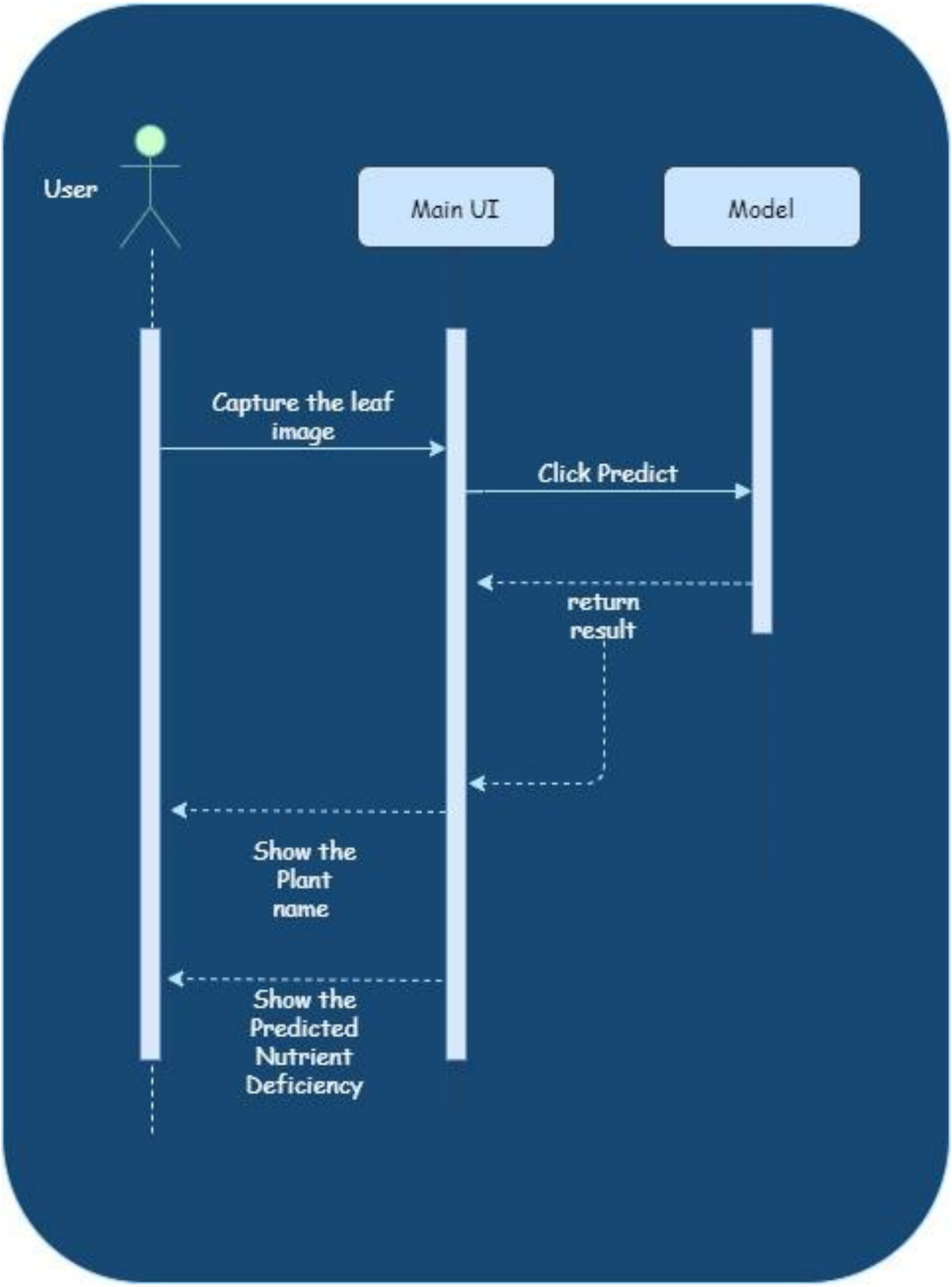


Figure 2.19: Sequence Diagram

Flow of the Nutrient deficiency prediction is shown below in the Fig. 2.20.

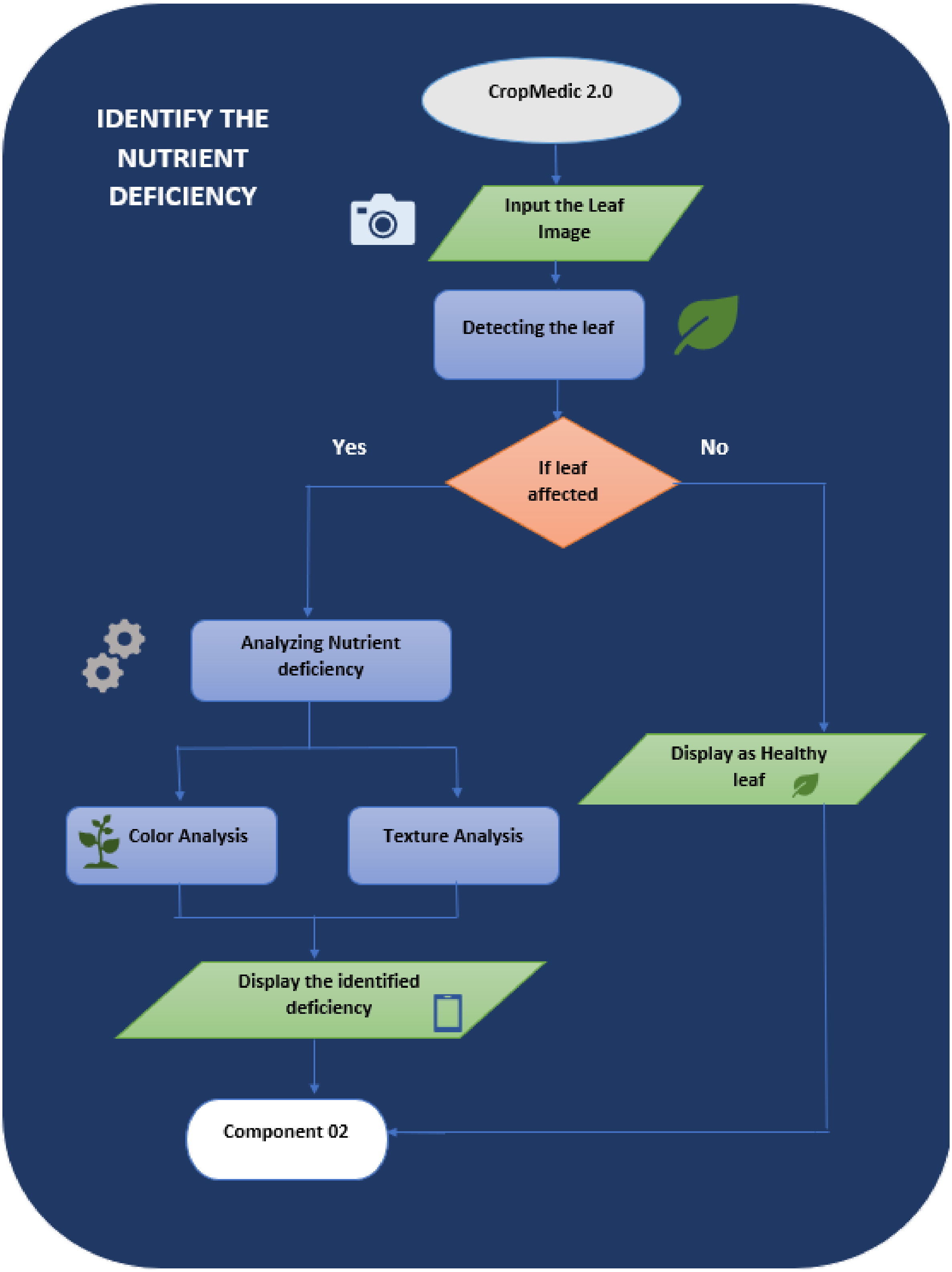


Figure 2.20: Flow chart of Nutrient deficiency Prediction

Following Fig. 2.21, shows use case diagram for the Nutrient Deficiency Prediction:

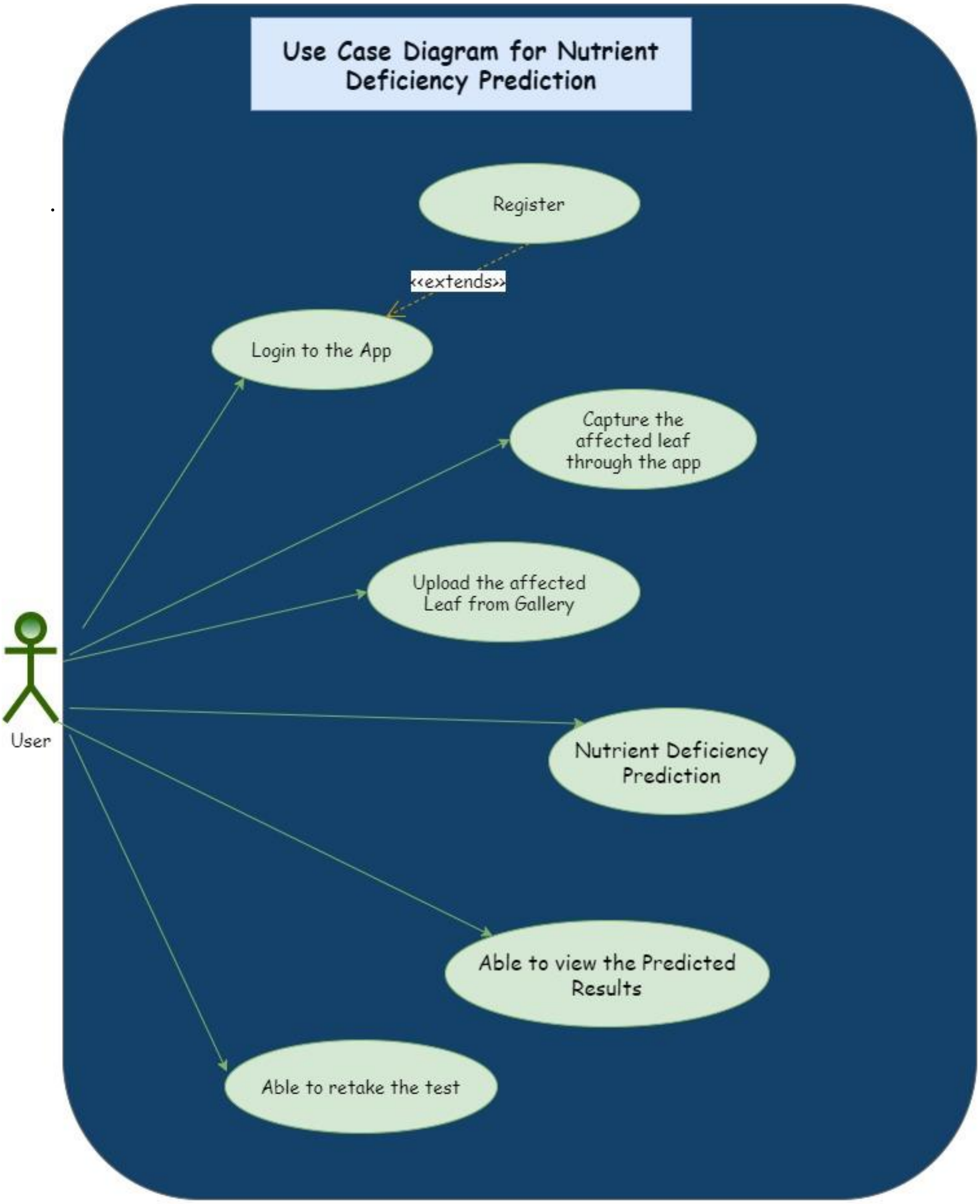


Figure 2.21: Use case diagram for the nutrient deficiency prediction

As shown in the above usecase diagram, functionalities and requirements were identified and listed as follows:

1. User should have the ability to capture the affected leaf through the mobile application.
2. User must be able to select the affected leaf image from the gallery through the app.
3. User should have the ability to view the predicted results according to their input image.
4. User must be able to retake the analysis of nutrient deficiency.

According to the above requirement, wireframes were designed in this system design phase. Following images shows the wireframe of the design

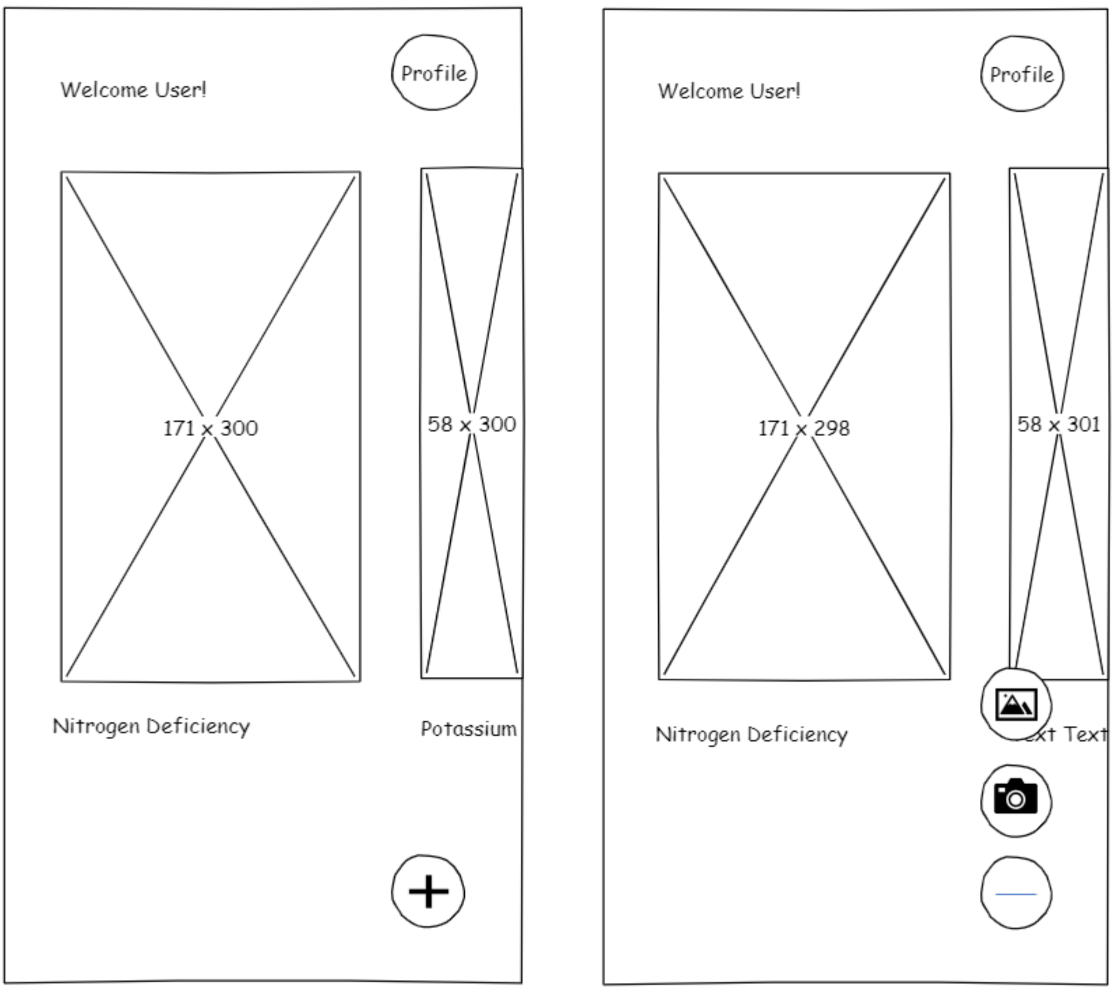


Figure 2.22: Wireframes for main screen of mobile application

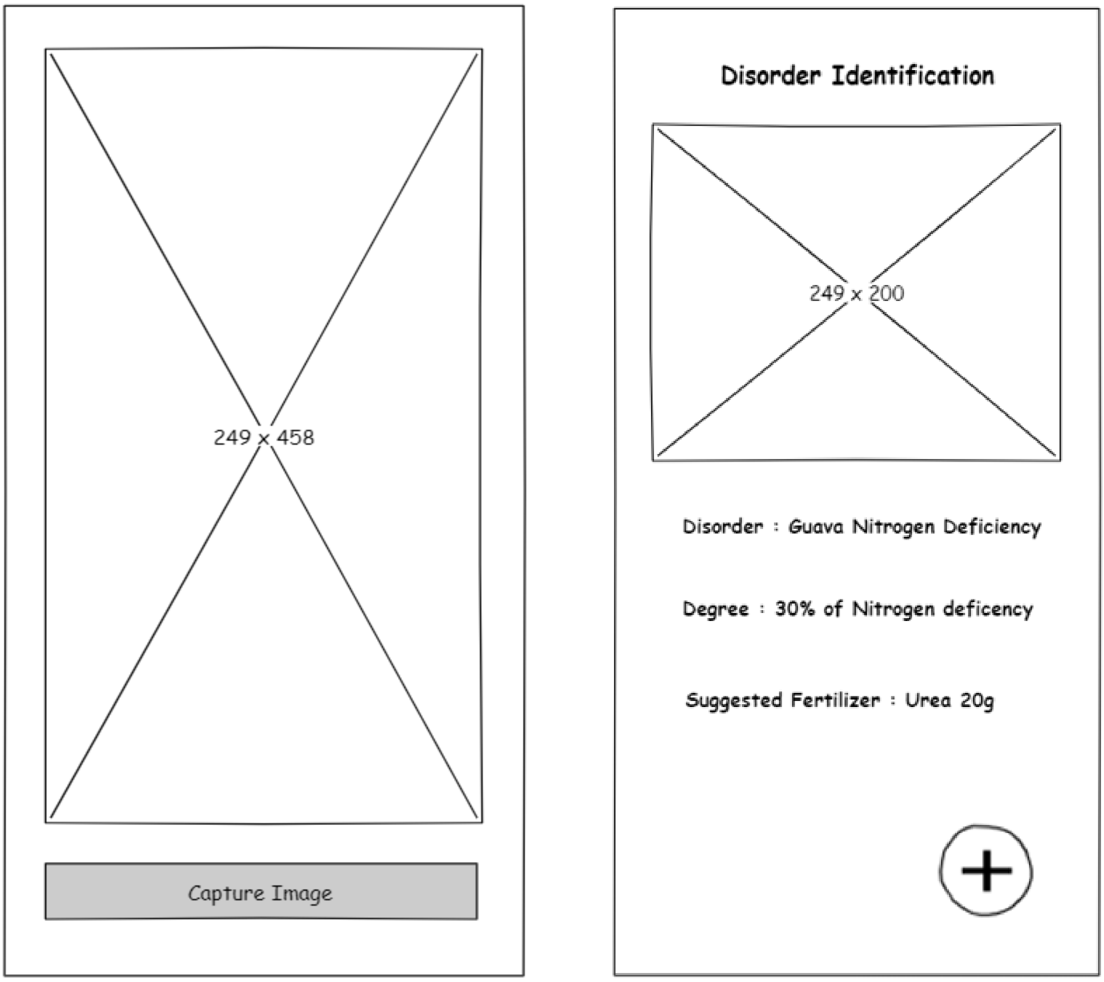


Figure 2.23: Wireframes for Capture the Image and deficiency prediction

2.2 Implementation

According to the implementation phase of the application, it can be divided into two parts.

- Backend Implementation
- Frontend Implementation

2.2.1 Backend Implementation

I. Dataset Description

As covered in the requirement gathering section, nearly 8000 images of plant leaves were collected and classified into 11 classes. Below Fig. 2.24, demonstrates the classes of datasets. From the whole datasets, 80% of the data is divided as the training dataset, the remaining 20% of the data contributing to the test dataset.

```
# The view the name of the classes in dataset
trainGenerator.class_indices

{'Citrus_Healthy': 0,
 'Citrus_Nitrogen_Deficiency': 1,
 'Citrus_Phosphorous_Deficiency': 2,
 'Citrus_Pottassium_Deficiency': 3,
 'Groundnut_Healthy': 4,
 'Groundnut_Nitrogen_Deficiency': 5,
 'Groundnut_Pottassium_Deficiency': 6,
 'Groundnut_Sulfur_Deficiency': 7,
 'Guava_Healthy': 8,
 'Guava_Nitrogen_Deficiency': 9,
 'Guava_Pottassium_Deficiency': 10}
```

Figure 2.24: Name of the Classes

II. Data Preprocessing

After collecting the images, to feed these images into the training model, it needs to be in standardization form and have clear data. Preprocessing was done to increase accuracy and reduce the complexity of the dataset.

```
# Preprocessing of Image.
print('Image Preprocessing')
training_datagenerator=ImageDataGenerator(
                rescale=1./255,
                zoom_range=0.2,
                shear_range=0.2,
                validation_split=0.2,
                horizontal_flip=True
                )
testing_datagenerator=ImageDataGenerator(rescale=1./255)
```

Figure 2.25: Preprocessing the Images

While converting the color image to grayscale is an accepted preprocessing technique, we employed Image standardization. For this, first the data has rescaled in the range of 0 to 1. This is called Normalization. Next, each training dataset image pixel should be transferred from 0 to 255. Reason behind this is, some images in the dataset would have high pixels and some would have low pixels. It is necessary to treat the Images at the same level. We need this data preprocessing. If not, high pixel images can get more loss than low pixel images and it may need more learning ratings. Above Fig. 2.25, shows the code for preprocessing of image.

III. Retraining the model

Overview of CNN Model

Among many neural networks, convolutional neural networks are considered as the main categories which can perform image classification and recognition [20]. Commonly neural networks transfer the input data through the hidden layers. Each layer has made up with neurons and each neuron are fully connected with each other [7] but Convolutional Neural network is little different from common neural network because the layers in this network has three dimensions such as height, depth and width [25]. However, A layer neurons are not connected with next layer neurons. The prediction output would be able to minimize to a vector scores probability with its depth dimension

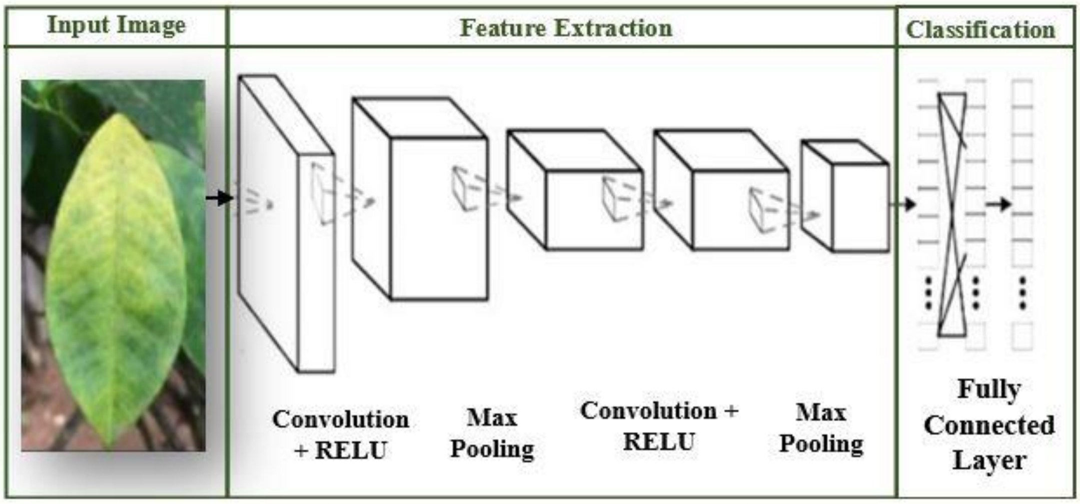


Figure 2.26: CNN Architecture

As shown in the Fig. 2.26, Theoretically, Convolutional Neural network mainly has two section. They're Feature extraction and Classification. When training the model, Convolution layer is the first layer which help to perform the extraction of feature in the input image using the Filter/Kernel. It learns the features of the images by keeping the relationship between the image pixel [10]. The below Fig. 2.27, illustrates that the mathematical formula which includes two inputs. They are image matrix and filter.

- An Image Matrix (Volume) of dimension $(h * w * d)$
- A filter $(f_h * f_w * d)$
- Outputs a Volume dimension $(h - f_h + 1) * (w - f_w + 1) * 1$

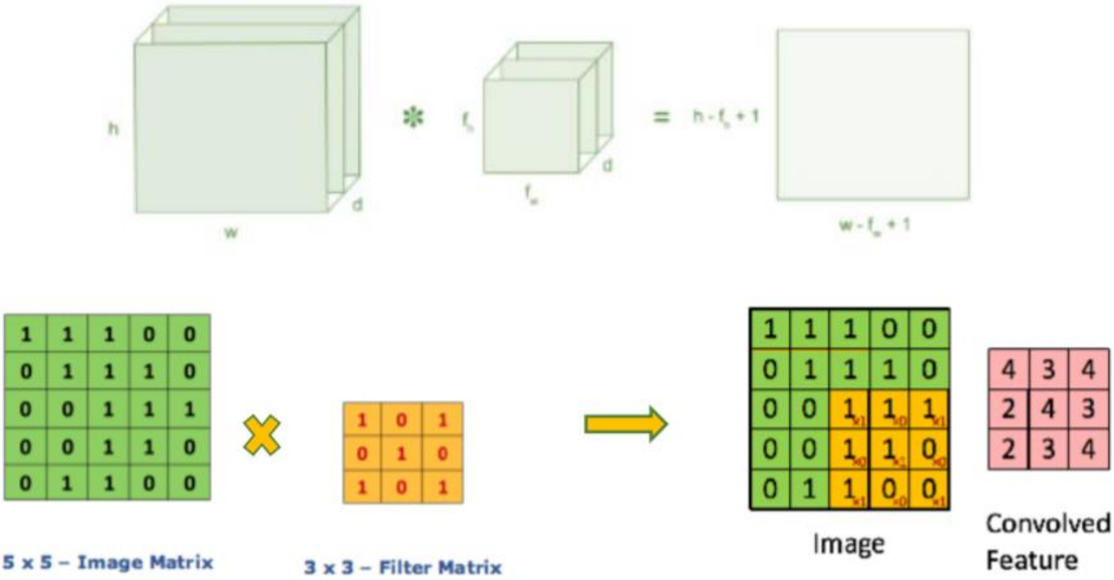


Figure 2.27: Matrix of the Image multiplies by the Matrix of filter [10]

Sometimes the input images are not filtered very well in the 1st layer. The output images from the first layer will be passed through the activation function. It is used in ReLu which stands for Rectified Linear Unit for a non-linear operation. It will convert the negative values into zero. Instead of ReLU, sigmoid or tanh can be used. These two functions are also non linear function. But mostly researchers and scientists recommend the ReLU because its performance is good when comparing with other two non linear functions [16].

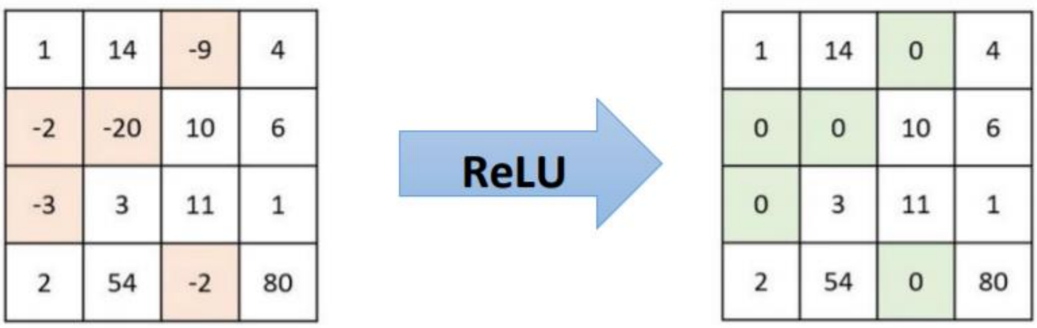


Figure 2.28: Feature Extraction with ReLU

As like Convolutional Layer, pooling layer is used to minimizing the spatial size. It will reduce the dimension of image (when the images are very large) which helps to minimize the computational power for the data processing. Main advantages of this layer are helping to extract the features in a rational way, and it helps to reduce the time of training the model. Fully connected layer is the final layer which helps to classify the images. This layer gets the input from previous layers such as Convolutional layer and Pooling layer. It flattens the input and convert it into single vector. That vector will be the input for the next step. This layer will be gone for the backpropagation process to increase the accuracy of weights [3]. As shown in the CNN architecture, every neuron gains the weights to get more accurate label for input images. The label which get more neurons will be the output for the classification with help of Softmax technique. InceptionV3, LeNet-5, ResNet50, VGG16 and EfiicientNetB0 are some CNN architectures.

Reasons for selecting CNN

After several background studies, CNN model builds for prediction of nutrient deficiency. This model extracts the color and texture features of leaf from input images and classifies them based on the features as Nitrogen(N), Potassium(K), Phosphorus(P) deficiency through the Convolution, max pooling layers. These convolution layers have different types of filters and that can be added as required until the requirement is satisfied. Moreover, the CNN model can do the feature extraction automatically. Transfer learning allows retraining the SoftMax layer of an existing model, ensuing in a noteworthy decrease in not only training time, also the dataset size required. Convolutional layer helps to perform the extraction of features. For example, Color extraction, edge detection, and gradient orientation

IV. Transfer Learning

Nutrient deficiency detection was implemented through the adapted CNN architecture and trained the model in the transfer learning mode of feature representation. A pre-trained VGG-16, EfficientNet-B0 and ResNet50 were used as the effective feature extractor. All these architectures were pre-trained with the help of huge dataset of images. However, it has learned to represent the low-level features such as edges, rotation, shapes, spatial and lighting in an effective manner. These features can be passed to activate the knowledge transfer and represents as a feature extractor for new dataset of images. As in our case, the new dataset of images has various categories than from original dataset. However, based on the principles of transfer learning, a pretrained model is applied to extract appropriate features from the images. Below Fig. 2.29, illustrates the architecture of transfer learning with the backbone of convolution.

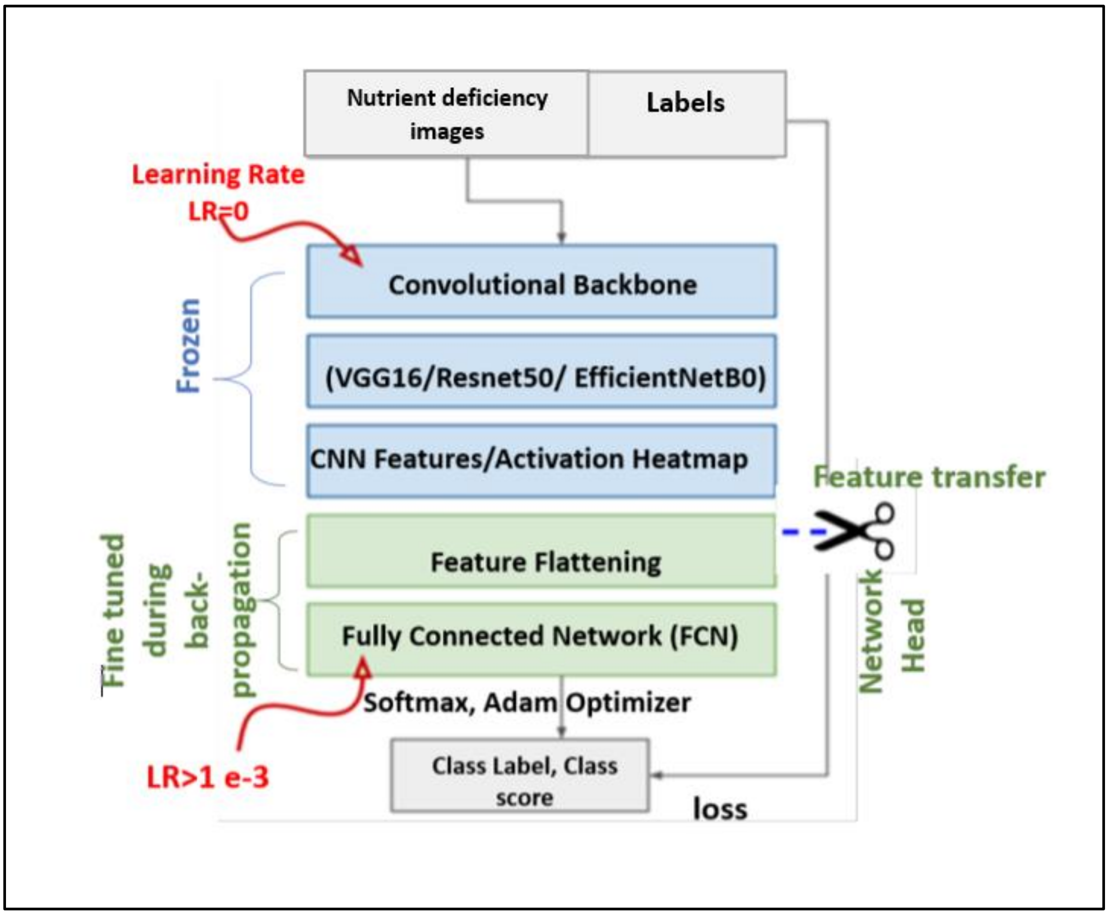


Figure 2.29: Architecture of Transfer learning through convolutional backbone

During the research, Loss function change was experimented for the three convolutional architecture models. Each model was trained with 50 epochs. The model was trained using the collected dataset of deficient leaf with 11 classes. The VGG-16 model trained using categorical crossentrophy and reached the accuracy of 0.43. it took longest time while training the model.

Further improvement is made when model was trained with ResNet50 and EfficientNetB0, EffiecientNetB0 is much faster compared to other two models. It should be noted that each epoch for the given training datasets of images took approximately 15 minutes and a learning rate of 0.001. EfficientNetB0 achieved highest accuracy of 0.88 with comparison of ResNet50 and EfficientNetB0.

V. Training Loss and Accuracy

For training the model, split the preprocessed dataset into two parts and 80% for training and 20% for testing purpose are used. Fig. 2.30 shows changes in the loss function of the three convolutional models compared during this study.

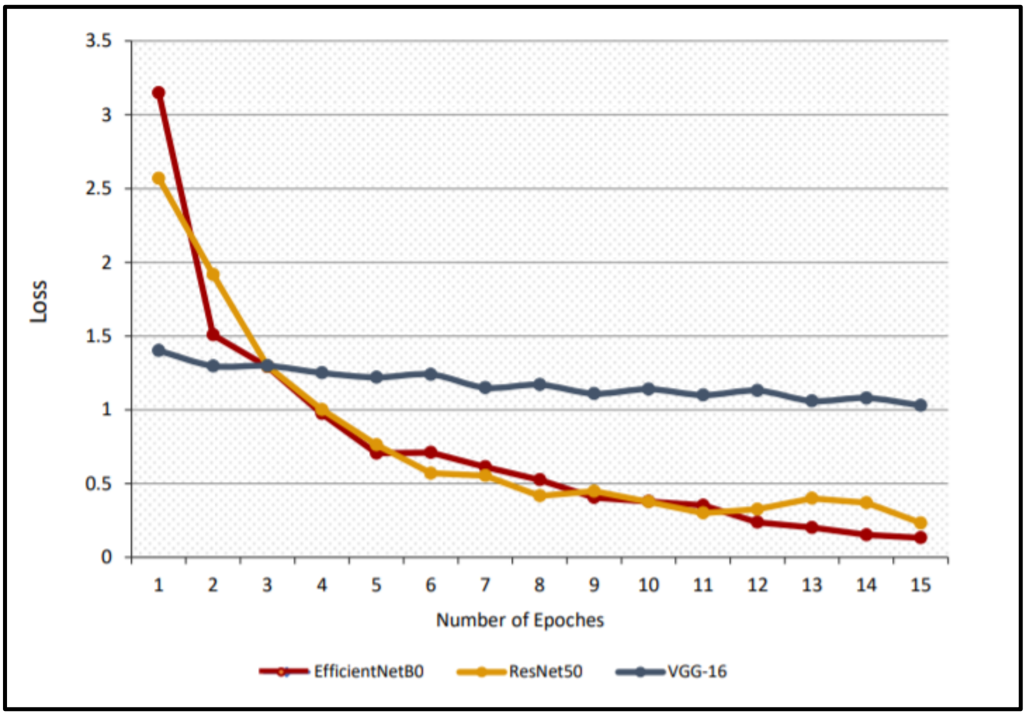


Figure 2.30: Comparison of loss function

VI. Model Testing

Model testing is used to test the accuracy of a model. Predictions are made against known results to see how accurately the algorithm predicts the desired data. Prediction results has covered in the section 2.3.

2.2.2 Frontend Implementation – Mobile application

The System “Crop Medic Plus 2.0” is a mobile application where user can able to predict the nutrient deficiency and its degree by capturing the image of suspected leaf. Moreover, it was developed using the flutter framework with Dart language. Flutter is an SDK from google to make cross platform application that can run on IOS and Android with a single code base. Firebase is used for the database to store the prediction results. Android studio is used as a development environment. Below Fig. 2.31 shows the project structure of the system.

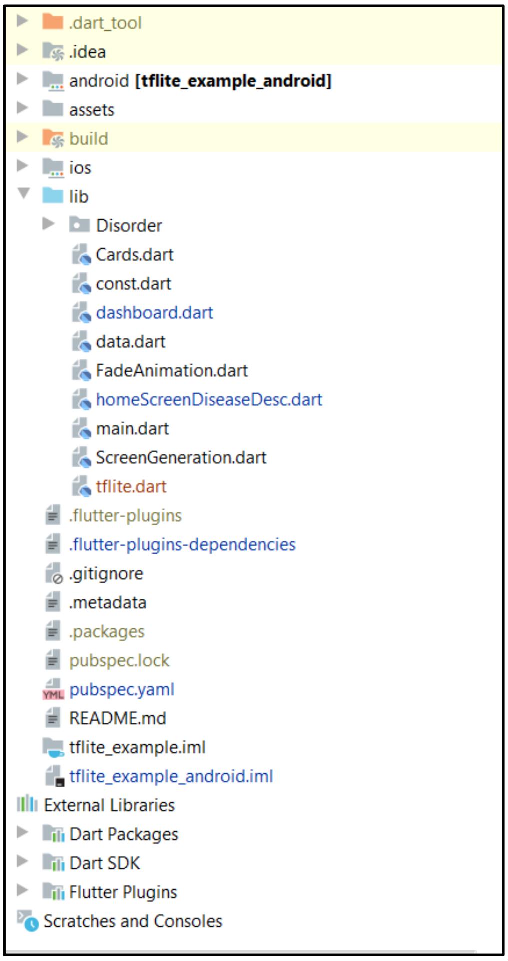


Figure 2.31: Project structure in flutter

As a first step, flutter project was set up in the Android studio including the installation of required plugins. The user interface layout was developed using the Dart language. As demonstrates in the Fig. 2.32 and 2.33, the "Lib" directory contains the all the dart files and the "assets" directory consists all the images and assets used in the projects.

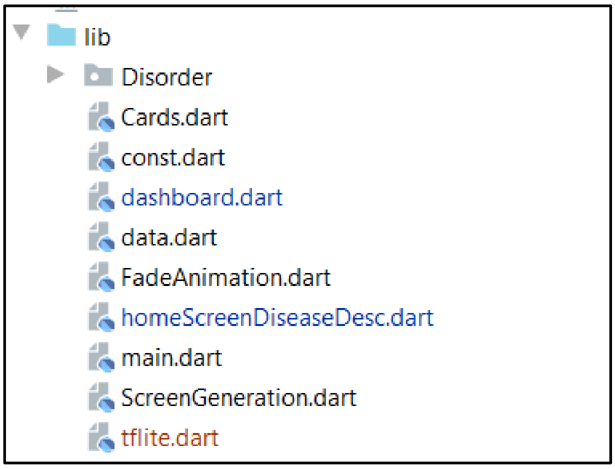
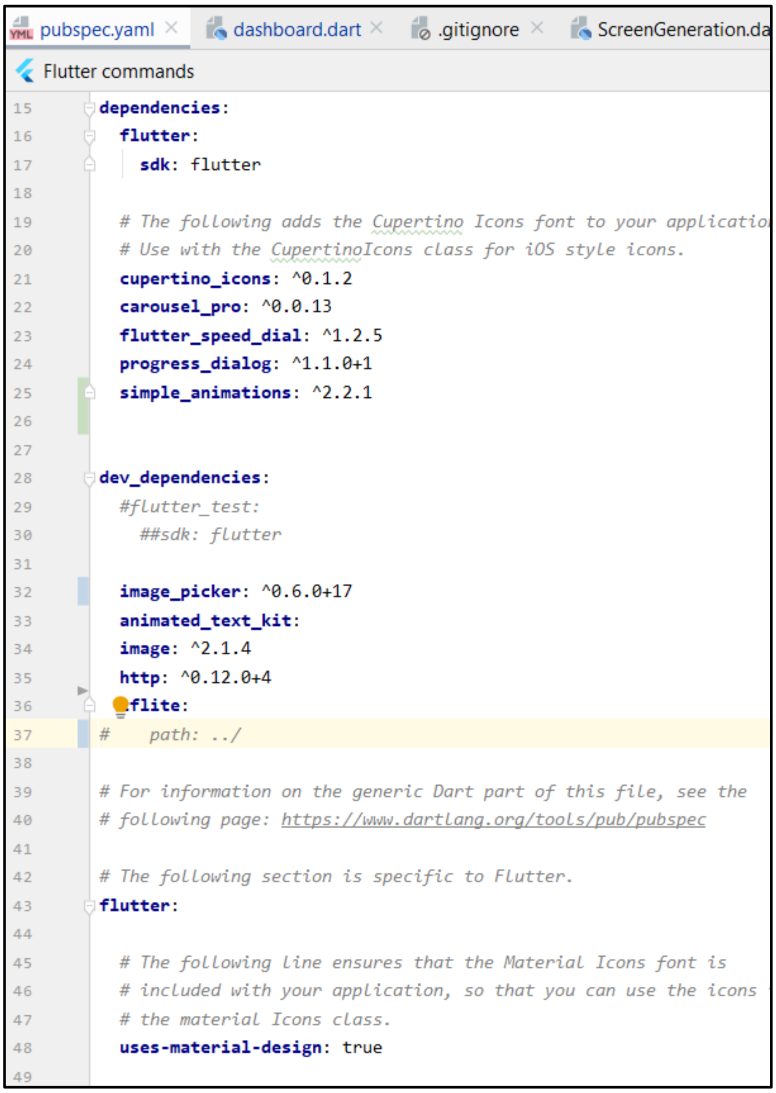


Figure 2.32: Lib Folder with dart files

Figure 2.33: Assets Folder

In flutter development, “pubspec.yaml” file contains all necessary dependencies and packages which is needed to the project such as camera, firebase, cloudstore and image picker shown in the Fig. 2.34 below




```yaml
dependencies:
  flutter:
    sdk: flutter

  # The following adds the Cupertino Icons font to your applicatio
  # Use with the CupertinoIcons class for iOS style icons.
  cupertino_icons: ^0.1.2
  carousel_pro: ^0.0.13
  flutter_speed_dial: ^1.2.5
  progress_dialog: ^1.1.0+1
  simple_animations: ^2.2.1


dev_dependencies:
  #flutter_test:
    ##sdk: flutter

  image_picker: ^0.6.0+17
  animated_text_kit:
  image: ^2.1.4
  http: ^0.12.0+4
  flite:
#     path: ../

# For information on the generic Dart part of this file, see the
# following page: https://www.dartlang.org/tools/pub/pubspec

# The following section is specific to Flutter.
flutter:

  # The following line ensures that the Material Icons font is
  # included with your application, so that you can use the icons
  # the material Icons class.
  uses-material-design: true
```

Figure 2.34: Pubspec file with all dependencies

Following are the images of User interface designed using flutter.

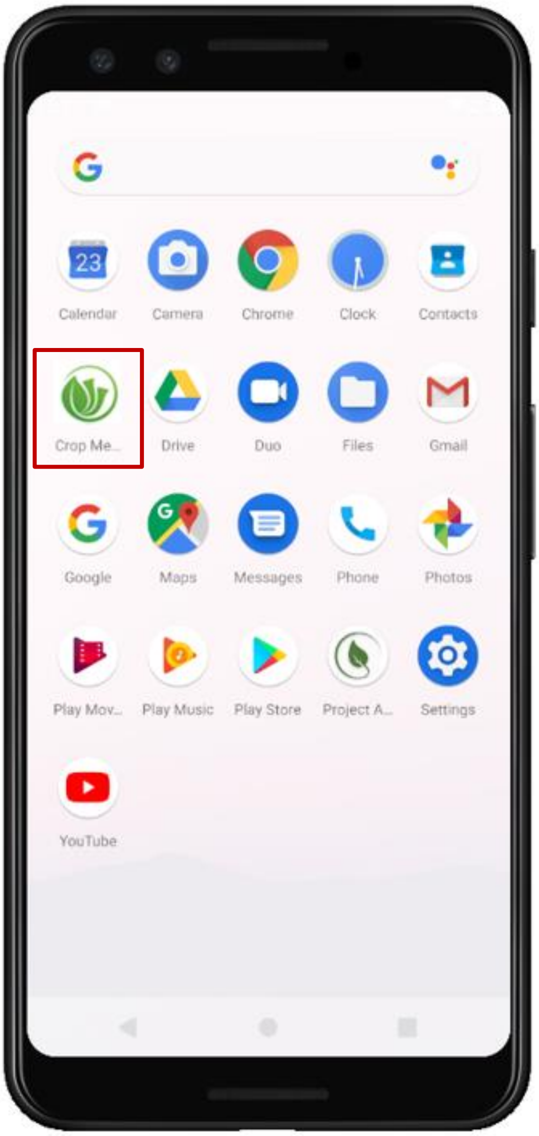


Figure 2.35: App Icon

Figure 2.36: Splash Screen

Figure 2.38: Home Page

Figure 2.37: Trending disorder and their Symptoms

Figure 2.39: Select the images from gallery or Camera

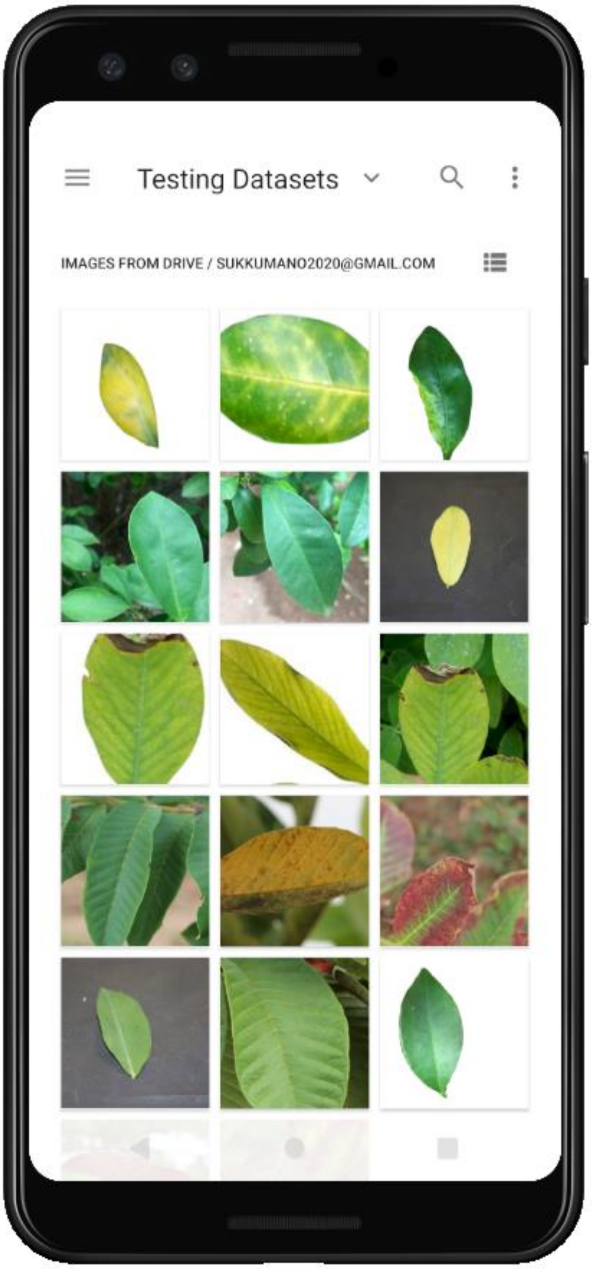


Figure 2.40: Select the image from gallery

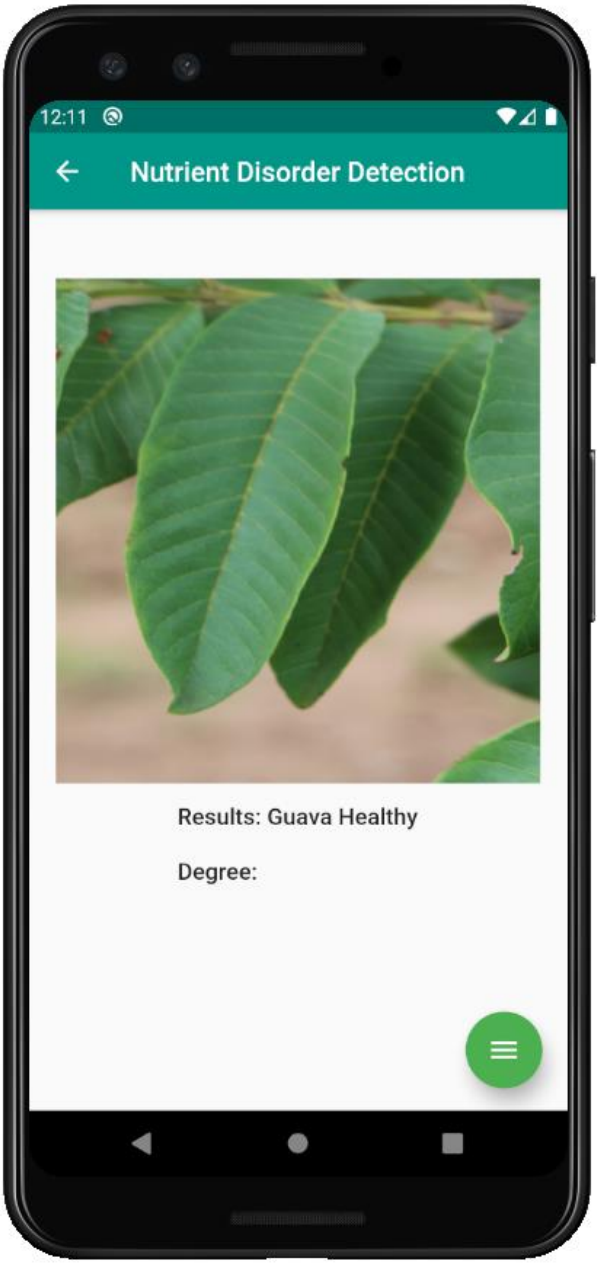


Figure 2.41: Prediction Results

2.3 Testing

Testing an application is a complex and important component of application development. The main components of application testing include performance, ease of use, security, non-functional and functional testing devices, multiple platforms and browsers. It is also very important to ensure product quality. There are many levels of this process, including design testing, unit testing, module testing, integration testing, and acceptance testing.

2.3.1 Design Testing

In this phase, the application design was tested to ensure that the application had the required functionality. It also tests if the interface is responsive, and the app responds properly to touch controls. Moreover, all UI designs have tested to see if they provide a better user experience. Following are some testcase performed to ensure that the flutter app user interfaces are performing well as expected.

Table 2.1: Testcase to check the UI functionality - Capture the Image

Testcase ID	TU_01
Testcase Scenario	Capture the image of affected leaf using the app camera
Pre-Conditions	User should a login into the system
Input Data	Press the camera button on the app
Expected Results	User should able to capture the image within the app
Actual Results	User captures the image using the mobile app
Pass/Fail	Pass

Table 2.2: Testcase to check the UI functionality - Select the image from Gallery

Testcase ID	TU_02
Testcase Scenario	Select the image of affected leaf from the gallery
Pre-Conditions	User should a login into the system
Input Data	Press the gallery button on the app
Expected Results	User should be able to select the image from gallery
Actual Results	User selects the image from the gallery
Pass/Fail	Pass

2.3.2 Unit Testing

Unit testing is a phase of testing that takes place after each module or function has been executed. Each function is tested individually to ensure it is working properly. This is done individually for each member.

2.3.3 Module Testing

Module testing can be done by checking each and every class, file and component and subsystem. It is reviewed by another group member which means the owner does not test his/her own module.

2.3.4 Integration Testing

After completing the unit testing, each module is integrated with other sub modules. This integrated system will be tested during this phase. This test was done individually by the members of the group to ensure that the integrated system was working properly.

2.3.5 System Testing

The entire system has been tested to ensure that is working properly. This can be done by any group member.

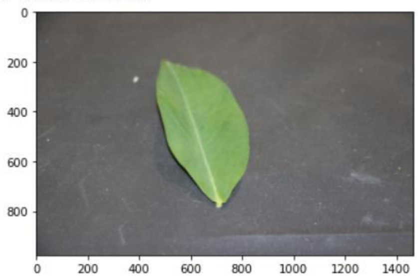
2.3.6 Acceptance Testing

In this phase, the acceptability of the system is tested. The purpose of this testing is to evaluate the functionality of the system as well as the value of the business.

Following are some testcases which was tested for the nutrient deficiency prediction:

Table 2.3: Testcase to detect the healthy leaf

Testcase ID	T_01
Testcase Scenario	Detection of healthy groundnut leaves
Pre-conditions	Trained the model with 8000 Images of dataset
Input Image	
Expected Output	To be identified as Groundnut Healthy

Actual Output	`output = model.predict_classes([prepare('/content/drive/My Drive/Datasets/testingData`
	`disorder=image.load_img('/content/drive/My Drive/Datasets/testingData/Groundnut_Healt`
	`plt.imshow(disorder)`
	`print(Classes[int(output)])`
	
	Groundnut_Healthy
	

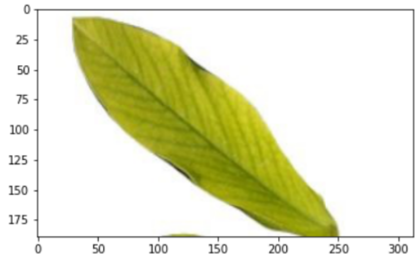
Pass/Fail	Pass

Table 2.4: Testcase to detect the healthy leaf

<table>
<tr><td>Testcase ID</td><td>T_02</td></tr>
<tr><td>Testcase Scenario</td><td>Detection of Nitrogen deficient groundnut leaves</td></tr>
<tr><td>Pre-conditions</td><td>Trained the model with 8000 Images of dataset</td></tr>
<tr><td>Input Image</td><td></td></tr>
<tr><td>Expected Output</td><td>To be identified as Groundnut Nitrogen deficiency</td></tr>
<tr><td>Actual Output</td><td>

```
output = model.predict_classes([prepare('/content/drive/My Drive/Datasets/testingData/
disorder=image.load_img('/content/drive/My Drive/Datasets/testingData/Groundnut_Nitroge
plt.imshow(disorder)
print(Classes[int(output)])
```

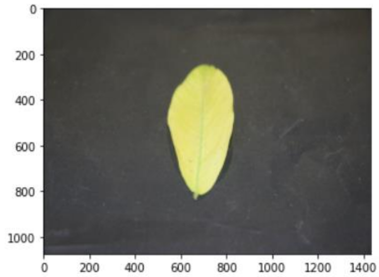
Groundnut_Nitrogen_Deficiency



</td></tr>
<tr><td>Pass/Fail</td><td>Pass</td></tr>
</table>

Table 2.5: Testcase to detect the Sulfur deficient groundnut leaf

Testcase ID	T_03
Testcase Scenario	Detection of Sulfur deficient groundnut leaves
Pre-conditions	Trained the model with 8000 Images of dataset
Input Image	
Expected Output	To be identified as Groundnut Sulfur Deficiency

Actual Output	`output = model.predict_classes([prepare('/content/drive/My Drive/Datasets/testingData/G`
	`disorder=image.load_img('/content/drive/My Drive/Datasets/testingData/Groundnut_Sulfur_`
	`plt.imshow(disorder)`
	`print(Classes[int(output)])`
	
	Groundnut_Sulfur_Deficiency
	

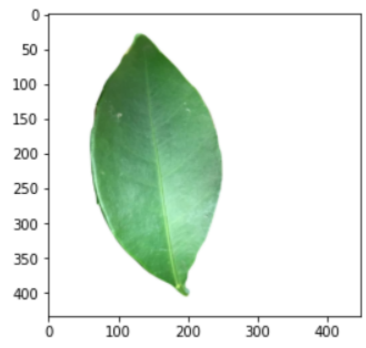
Pass/Fail	Pass

Table 2.6: Testcase to detect the Potassium deficient groundnut leaf

Testcase ID	T_04
Testcase Scenario	Detection of Potassium deficient groundnut leaves
Pre-conditions	Trained the model with 8000 Images of dataset
Input Image	
Expected Output	To be identified as Groundnut Potassium deficiency
Actual Output	
Pass/Fail	Pass

Table 2.7: Testcase to detect the citrus healthy leaf

Testcase ID	T_05
Testcase Scenario	Detection of healthy Citrus leaves
Pre-conditions	Trained the model with 8000 Images of dataset
Input Image	
Expected Output	To be identified as Citrus Healthy

Actual Output	`output = model.predict_classes([prepare('/content/drive/My Drive/Datase`
	`disorder=image.load_img('/content/drive/My Drive/Datasets/testingData/C`
	`plt.imshow(disorder)`
	`print(Classes[int(output)])`
	
	`Citrus_Healthy`
	

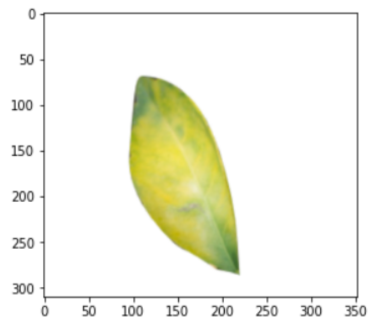
Pass/Fail	Pass

Table 2.8: Testcase to detect the Nitrogen deficient Citrus leaf

<table>
<tr><td>Testcase ID</td><td>T_06</td></tr>
<tr><td>Testcase Scenario</td><td>Detection of Citrus Nitrogen deficient leaves</td></tr>
<tr><td>Pre-conditions</td><td>Trained the model with 8000 Images of dataset</td></tr>
<tr><td>Input Image</td><td></td></tr>
<tr><td>Expected Output</td><td>To be identified as Citrus Nitrogen Deficiency</td></tr>
<tr><td>Actual Output</td><td>

```
output = model.predict_classes([prepare('/content/drive/My Drive/Datasets/test
disorder=image.load_img('/content/drive/My Drive/Datasets/testingData/Citrus_N
plt.imshow(disorder)
print(Classes[int(output)])
```

Citrus_Nitrogen_Deficiency



</td></tr>
<tr><td>Pass/Fail</td><td>Pass</td></tr>
</table>

Table 2.9: Testcase to detect the Phosphorus deficient Citrus leaf

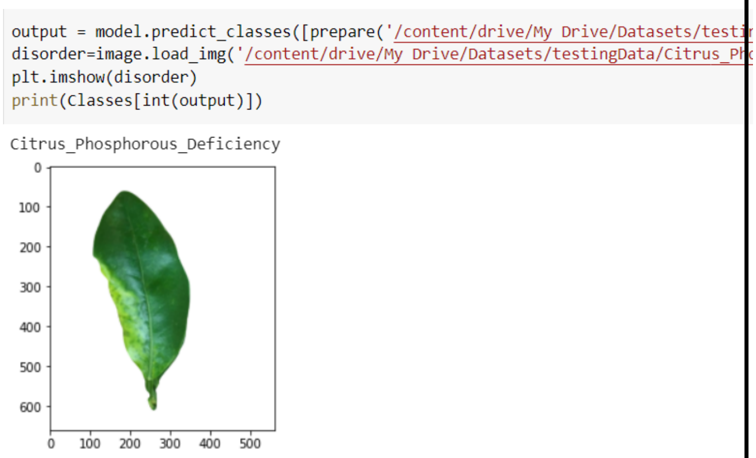
Testcase ID	T_07
Testcase Scenario	Detection of Citrus Phosphorus Deficient leaves
Pre-conditions	Trained the model with 8000 Images of dataset
Input Image	
Expected Output	To be identified as Citrus Phosphorus deficiency
Actual Output	
Pass/Fail	Pass

Table 2.10: Testcase to detect the Potassium deficient Citrus leaf

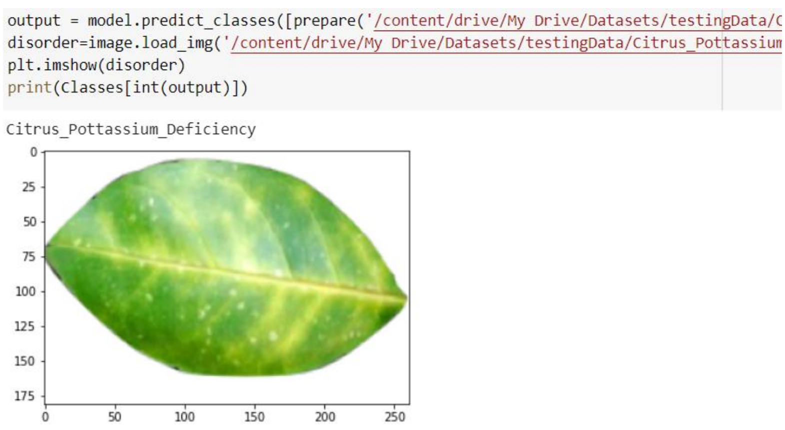
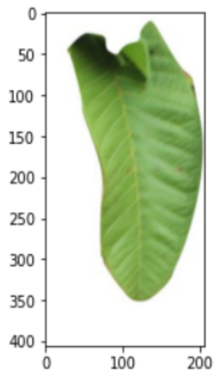
Testcase ID	T_08
Testcase Scenario	Detection of Citrus Potassium deficient leaves
Pre-conditions	Trained the model with 8000 Images of dataset
Input Image	
Expected Output	To be identified as Citrus Potassium Deficiency
Actual Output	
Pass/Fail	Pass

Table 2.11: Testcase to detect the guava healthy leaf

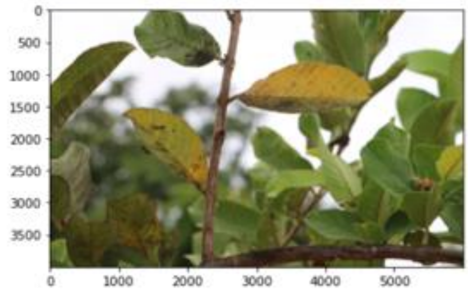
Testcase ID	T_09
Testcase Scenario	Detection of healthy Guava leaves
Pre-conditions	Trained the model with 8000 Images of dataset
Input Image	
Expected Output	To be identified as Guava Healthy

Actual Output	`output = model.predict_classes([prepare('/content/drive/My Drive/Datasets/`
	`disorder=image.load_img('/content/drive/My Drive/Datasets/testingData/Guav`
	`plt.imshow(disorder)`
	`print(Classes[int(output)])`
	Guava_Healthy
	

Pass/Fail	Pass

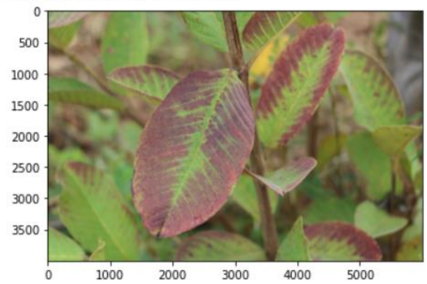
Table 2.12: Testcase to detect the Nitrogen deficient guava leaf

Testcase ID	T_10
Testcase Scenario	Detection of Guava Nitrogen Deficiency leaves
Pre-conditions	Trained the model with 8000 Images of dataset
Input Image	
Expected Output	To be identified as Guava Nitrogen Deficiency

Actual Output	`output = model.predict_classes([prepare('/content/drive/My Drive/Datasets/testingData/`
	`disorder=image.load_img('/content/drive/My Drive/Datasets/testingData/Guava_Nitrogen_D`
	`plt.imshow(disorder)`
	`print(Classes[int(output)])`
	
	Guava_Nitrogen_Deficiency
	

Pass/Fail	Pass

Table 2.13: Testcase to detect the Potassium deficient Guava leaf

Testcase ID	T_11
Testcase Scenario	Detection of Guava Potassium Deficiency leaves
Pre-conditions	Trained the model with 8000 Images of dataset
Input Image	
Expected Output	To be identified as Guava Potassium Deficiency
Actual Output	output = model.predict_classes([prepare('/content/drive/My Drive/Datasets/testingData/Guav disorder=image.load_img('/content/drive/My Drive/Datasets/testingData/Guava_Pottassium_Def plt.imshow(disorder) print(Classes[int(output)]) Guava_Pottassium_Deficiency 
Pass/Fail	Pass

2.4 Commercialization of product

This final deliverable is mainly targeting the farmers. According to the Department of Census statistics, 180,790 has been stated as the population of farmers in 2019, which is considered as our main target users. Main intention of this research is to help the farmers, therefore this application would give the services in free of charge. Other target users of this application are vendor and agricultural experts. Through this application vendors provide the details of the available fertilizer products to farmers. However, vendors are advertising their products through this application. Our research team have planned to charge monthly subscription fee from the vendor. They also got benefit from our app. This will make both parties more comfortable dealing. Below Fig. 2.42 shows the benefits from all target user of this project.

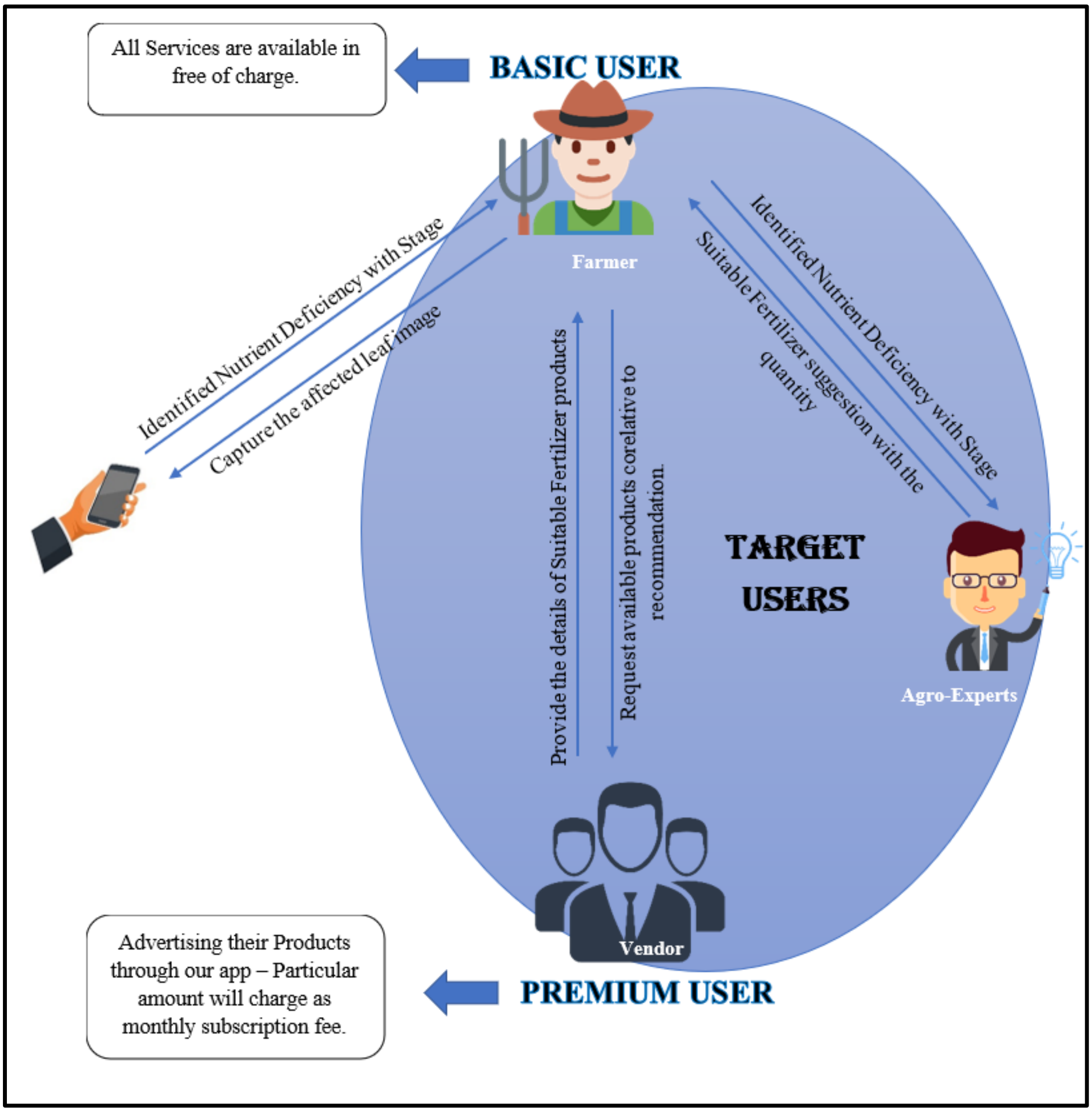


Figure 2.42: Commercialization of Product

3. RESULTS AND DISSCUSSION

3.1 Results

3.1.1 Model Evaluation Metrics

Deep learning is applied to detect nutrient deficiency. That shows its promising results. In this research, experimentation has done with a lightweight convolutional network architecture (VGG-16, ResNet50, and EfficientNetB0) for detecting nutrient disorder and associated with its symptoms in leaves of plants.

Our results show reasonable overall accuracy of 88.3%, 43.8%, and 56.1% to the detection of nutrient deficiency using EfficientNetB0, VGG16 and ResNet50 backbones through dataset set of 8000 images, respectively. The Fig. 3.1 shows a graphical plot of the three backbone models under consideration. The row corresponds to three architectures of the CNN model and the columns correspond to the accuracy of each model. EfficientNetB0 achieved the best accuracy for the prediction of nutrient deficiency in plants compared to ResNet50 and VGG16.

Table 3.1: Comparison results with different architectures of CNN

Model	**Accuracy**
EfficientB0	0.88
VGG-16	0.43
Resnet50	0.56

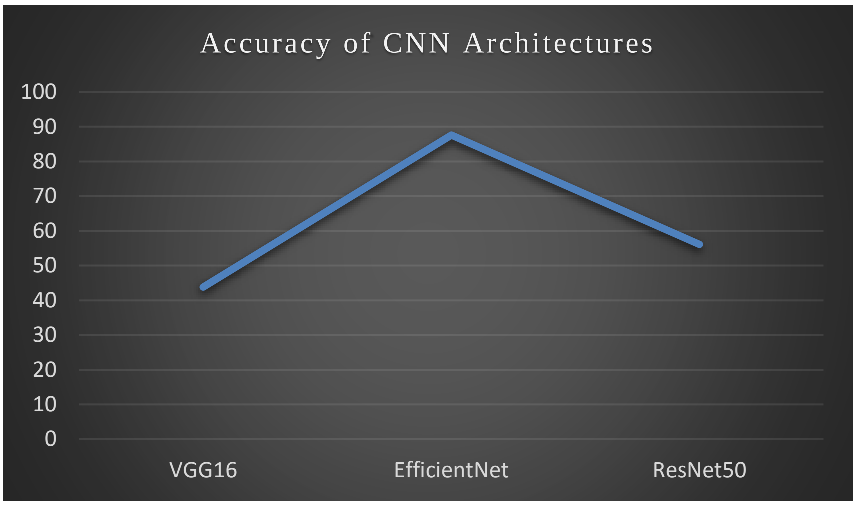


Figure 3.1: Graph for overall accuracy of three Architectures

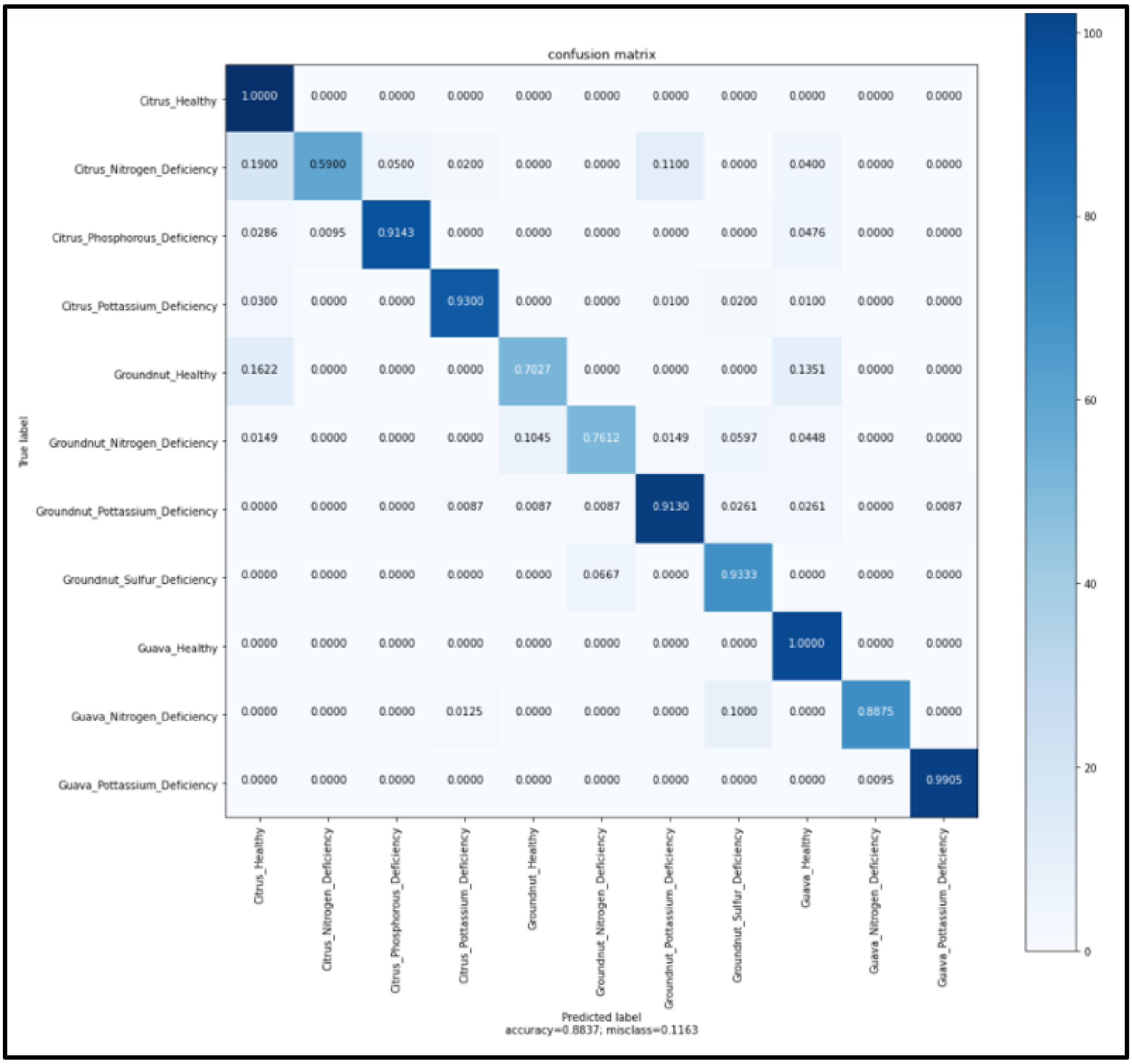


Figure 3.2: Confusion Metrics of the EfficientB0

Evidences

Following images demonstrates the training and its accuracy results of CNN model Architectures.

- EfficientNetB0

```
model1 = efn.EfficientNetB0(include_top=True, weights=None, classes=len(classes))
model1.compile(optimizer='adam',loss='categorical_crossentropy',metrics=['accuracy'])
es = EarlyStopping(monitor='accuracy', mode='min', verbose=1, patience=5)
history = model1.fit(train_generator, epochs=50)
model1.save("/content/drive/My Drive/deficiency classification/efficientnet.h5")

Epoch 1/50
 2/73 [..............................] - ETA: 5s - loss: 3.1023 - accuracy: 0.4062WARNING:tensorflow:Ca
73/73 [==============================] - 251s 3s/step - loss: 2.2499 - accuracy: 0.6279
Epoch 2/50
73/73 [==============================] - 11s 153ms/step - loss: 0.8754 - accuracy: 0.7225
Epoch 3/50
73/73 [==============================] - 11s 152ms/step - loss: 0.8837 - accuracy: 0.7493
Epoch 4/50
73/73 [==============================] - 11s 151ms/step - loss: 0.6845 - accuracy: 0.8040
Epoch 5/50
73/73 [==============================] - 11s 153ms/step - loss: 0.3974 - accuracy: 0.8630
Epoch 6/50
73/73 [==============================] - 11s 152ms/step - loss: 0.3418 - accuracy: 0.8682
Epoch 7/50
73/73 [==============================] - 11s 154ms/step - loss: 0.3001 - accuracy: 0.9107
Epoch 8/50
73/73 [==============================] - 11s 155ms/step - loss: 0.2663 - accuracy: 0.9289
Epoch 9/50
73/73 [==============================] - 11s 156ms/step - loss: 0.1737 - accuracy: 0.9367
Epoch 10/50
73/73 [==============================] - 11s 155ms/step - loss: 0.3730 - accuracy: 0.9341
Epoch 11/50
73/73 [==============================] - 11s 155ms/step - loss: 0.4307 - accuracy: 0.8933
Epoch 12/50
```

Figure 3.3: EfficientNetB0 Model Training

```
model = load_model("/content/drive/My Drive/deficiency classification/efficientnet.h5")

from sklearn.metrics import accuracy_score
print ('accuracy', end = ' = ')
print (accuracy_score(image_pred.classes, Y_predicted_class_indices))

accuracy = 0.8837209302325582
```

Figure 3.4: EfficientNetB0 Accuracy Result

- VGG-16

```
from keras.applications.vgg16 import VGG16
from keras.models import Model
from keras.layers import Dense , Flatten, GlobalAveragePooling2D, Dropout

model2 = VGG16(weights= None, include_top=False, input_shape=(244,244,3))
output_vgg16_conv = model2.output

#Add the fully-connected layers
x = Flatten(name='flatten')(output_vgg16_conv)
x = Dense(4096, activation='relu')(x)
x = Dense(len(classes), activation='softmax')(x)

model2 = Model(inputs=model2.input, outputs=x)

model2.compile(optimizer='adam',loss='categorical_crossentropy',metrics=['accuracy'])
es = EarlyStopping(monitor='accuracy', mode='min', verbose=1, patience=5)
model2.fit(train_generator, epochs=50)
model2.save("/content/drive/My Drive/deficiency classification/vgg16.h5")
```

```
Epoch 1/15
 2/73 [..............................] - ETA: 14s - loss: 2.3415 - accuracy: 0.4688WARNING:tensorflow:Call
73/73 [==============================] - 16s 217ms/step - loss: 1.0716 - accuracy: 0.5637
Epoch 2/15
73/73 [==============================] - 16s 217ms/step - loss: 0.9644 - accuracy: 0.5690
Epoch 3/15
73/73 [==============================] - 16s 219ms/step - loss: 0.9647 - accuracy: 0.5690
Epoch 4/15
73/73 [==============================] - 16s 220ms/step - loss: 0.9623 - accuracy: 0.5690
Epoch 5/15
73/73 [==============================] - 16s 221ms/step - loss: 0.9611 - accuracy: 0.5690
Epoch 6/15
73/73 [==============================] - 16s 221ms/step - loss: 0.9647 - accuracy: 0.5690
Epoch 7/15
```

Figure 3.5: VGG16 Model Training

```
model = load_model("/content/drive/My Drive/deficiency classification/vgg16.h5")

print ('accuracy', end = ' = ')
print (accuracy_score(image_pred.classes, Y_predicted_class_indices))
```

```
accuracy = 0.4383561643835616
```

Figure 3.6: VGG16 Accuracy result

- ResNet50

```
from keras.applications.resnet50 import ResNet50
base_model = ResNet50(weights= None, include_top=False, input_shape= (244,244,3))

x = base_model.output
x = GlobalAveragePooling2D()(x)
x = Dropout(0.9)(x)
predictions = Dense(len(classes), activation= 'softmax')(x)
model3 = Model(inputs = base_model.input, outputs = predictions)

model3.compile(optimizer='adam',loss='categorical_crossentropy',metrics=['accuracy'])
es = EarlyStopping(monitor='accuracy', mode='min', verbose=1, patience=5)
model3.fit(train_generator, epochs=50)
model3.save("/content/drive/My Drive/deficiency classification/resnet50.h5")
```

```
Epoch 1/20
73/73 [==============================] - 14s 188ms/step - loss: 1.0457 - accuracy: 0.7927
Epoch 2/20
73/73 [==============================] - 13s 183ms/step - loss: 0.5014 - accuracy: 0.8439
Epoch 3/20
73/73 [==============================] - 13s 183ms/step - loss: 0.3601 - accuracy: 0.8968
Epoch 4/20
73/73 [==============================] - 13s 184ms/step - loss: 0.2690 - accuracy: 0.9176
Epoch 5/20
73/73 [==============================] - 13s 184ms/step - loss: 0.1473 - accuracy: 0.9532
Epoch 6/20
73/73 [==============================] - 13s 184ms/step - loss: 0.2901 - accuracy: 0.9271
Epoch 7/20
73/73 [==============================] - 13s 184ms/step - loss: 0.1558 - accuracy: 0.9532
Epoch 8/20
73/73 [==============================] - 13s 185ms/step - loss: 0.1923 - accuracy: 0.9410
Epoch 9/20
73/73 [==============================] - 13s 185ms/step - loss: 0.2345 - accuracy: 0.9332
Epoch 10/20
73/73 [==============================] - 13s 185ms/step - loss: 0.0853 - accuracy: 0.9766
```

Figure 3.7: ResNet50 Model Training

```
model = load_model("/content/drive/My Drive/deficiency classification/resnet50.h5")

print ('accuracy', end = ' = ')
print (accuracy_score(image_pred.classes, Y_predicted_class_indices))
```

```
accuracy = 0.5616438356164384
```

Figure 3.8: ResNet50 Accuracy Result

3.1.2 Model Prediction Results

Below Fig. 3.9 show some results of prediction with the EfficientB0.

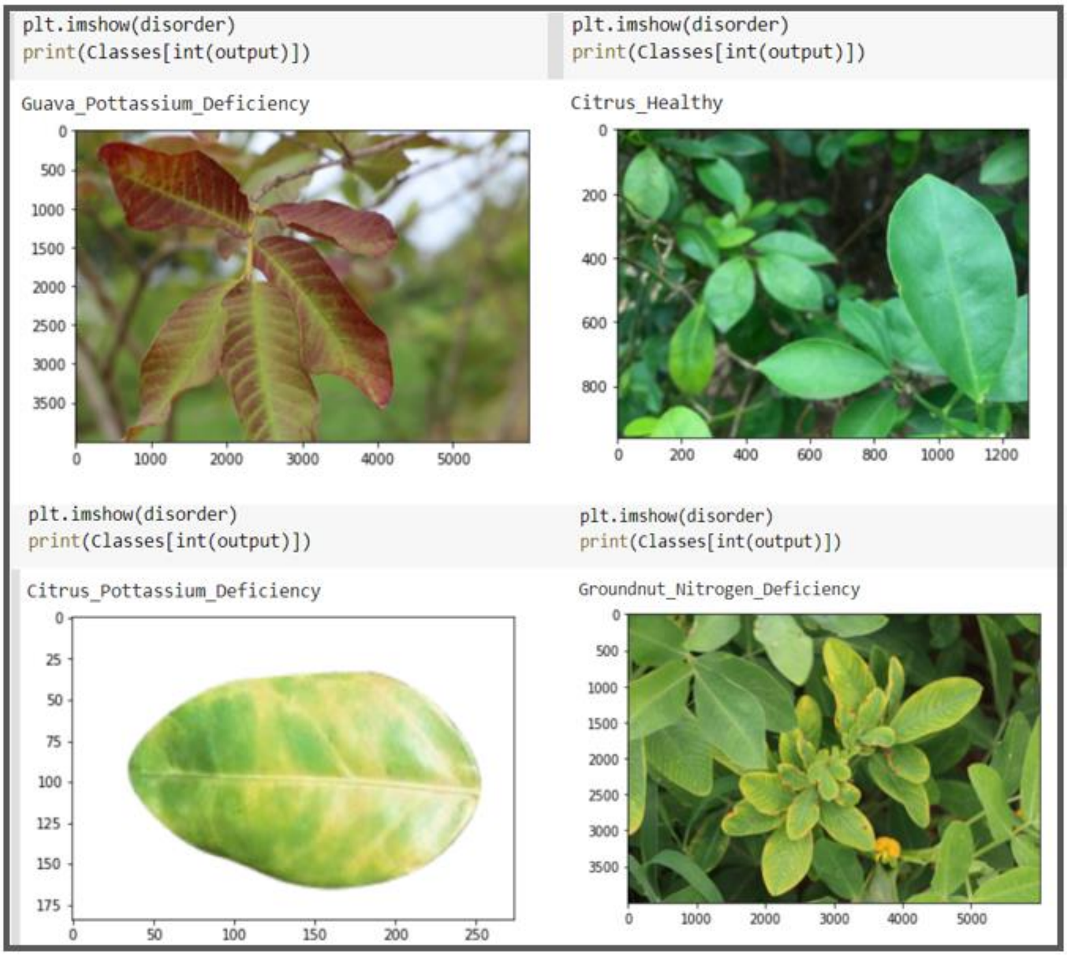


Figure 3.9: Sample results for the Prediction of Nutrient deficiency

3.1.3 Sample prediction results through the mobile app

Below images show the prediction output through the Crop Medic Plus 2.0 Mobile app.

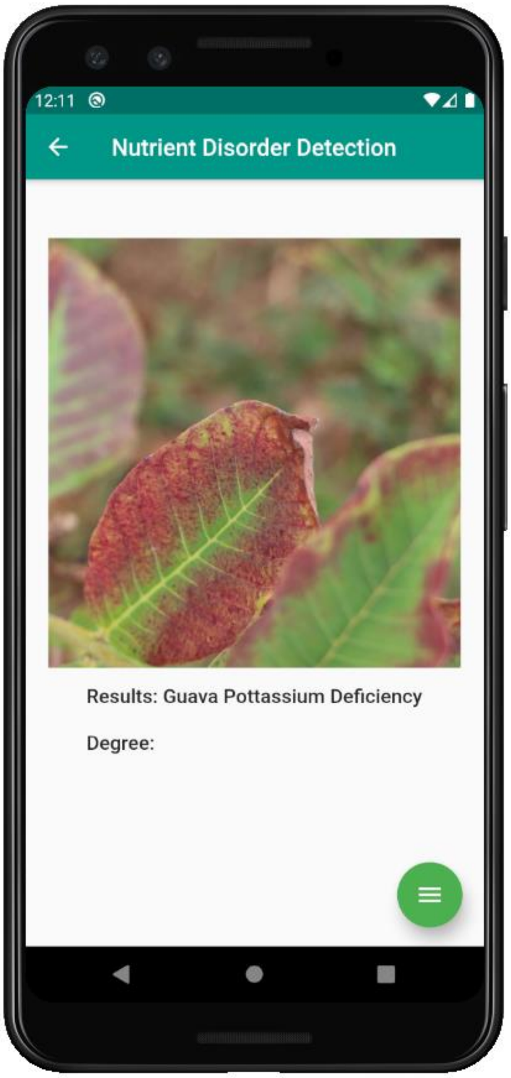


Figure 3.10: Prediction result of guava potassium deficiency

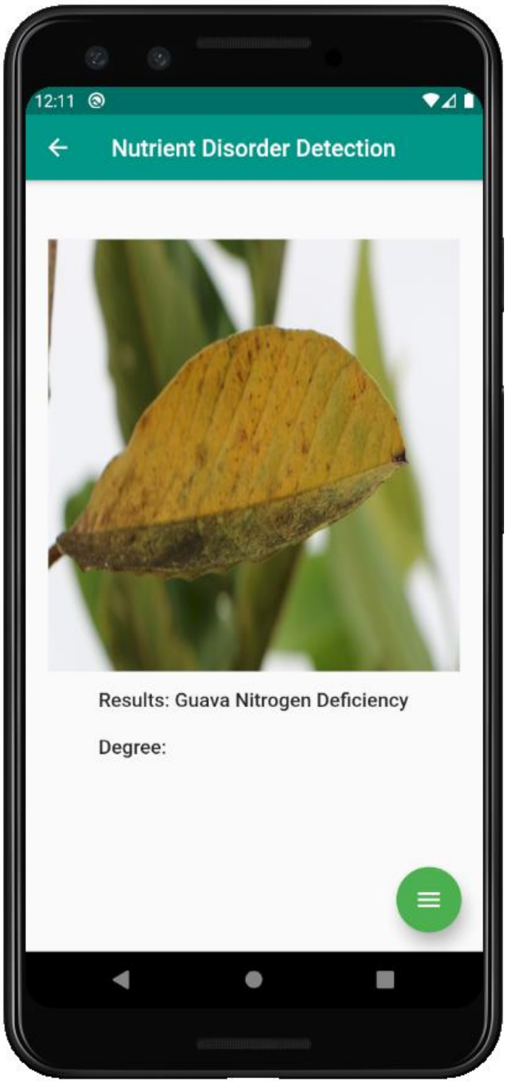


Figure 3.11: Prediction result of guava Nitrogen deficiency

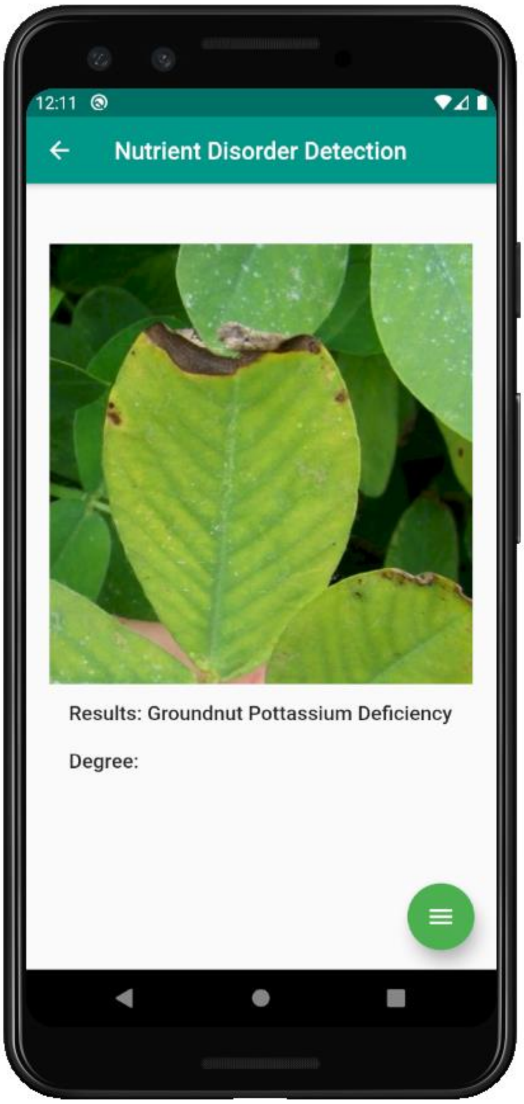


Figure 3.13: Prediction result of Groundnut potassium deficiency

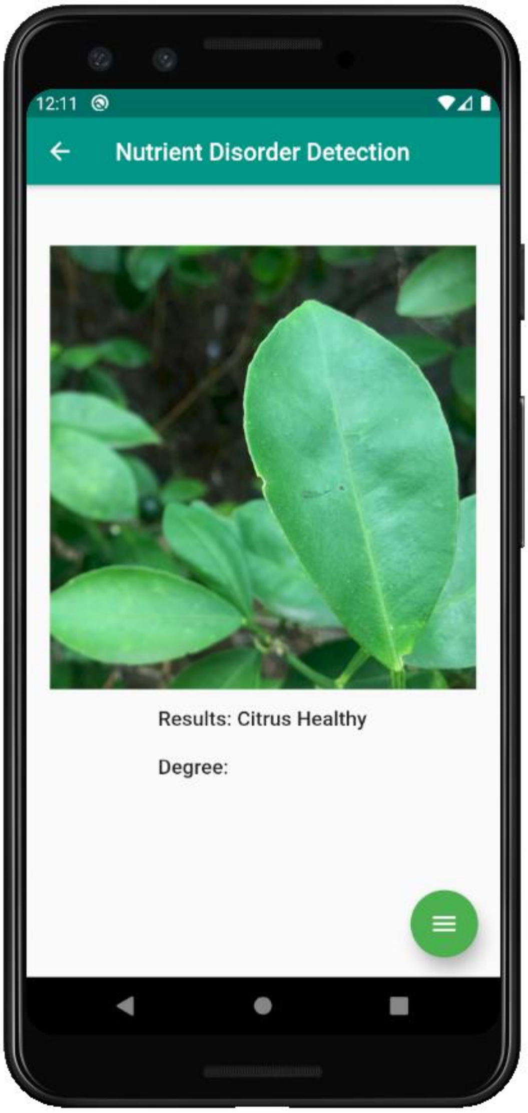


Figure 3.12: Prediction result of Citrus Healthy leaf

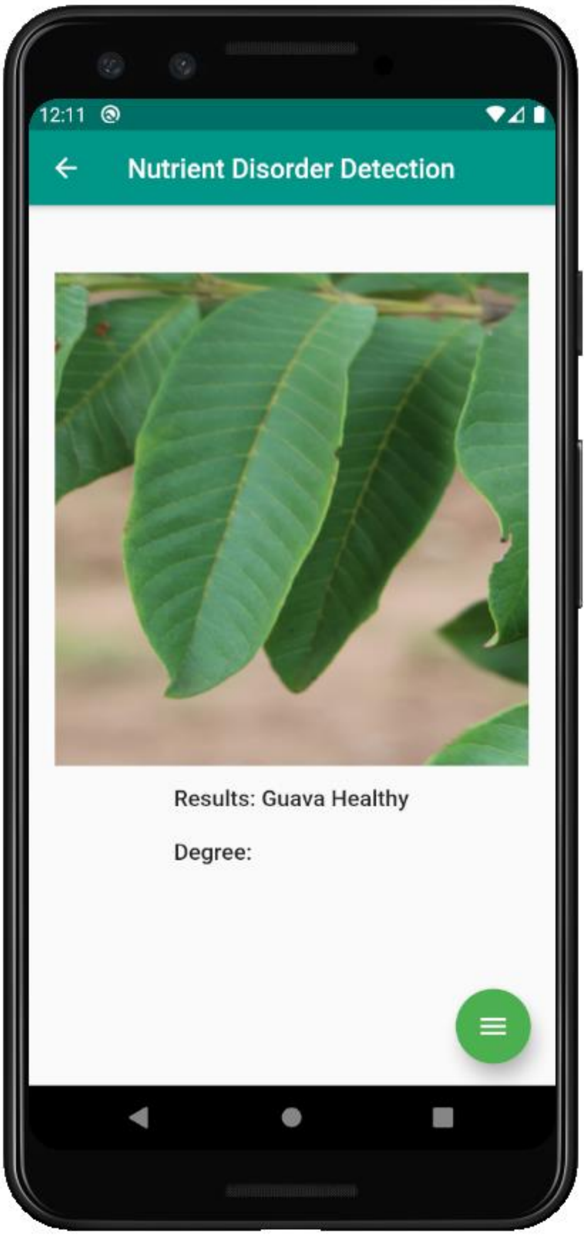


Figure 3.15: Predict Results of the Guava healthy leaf

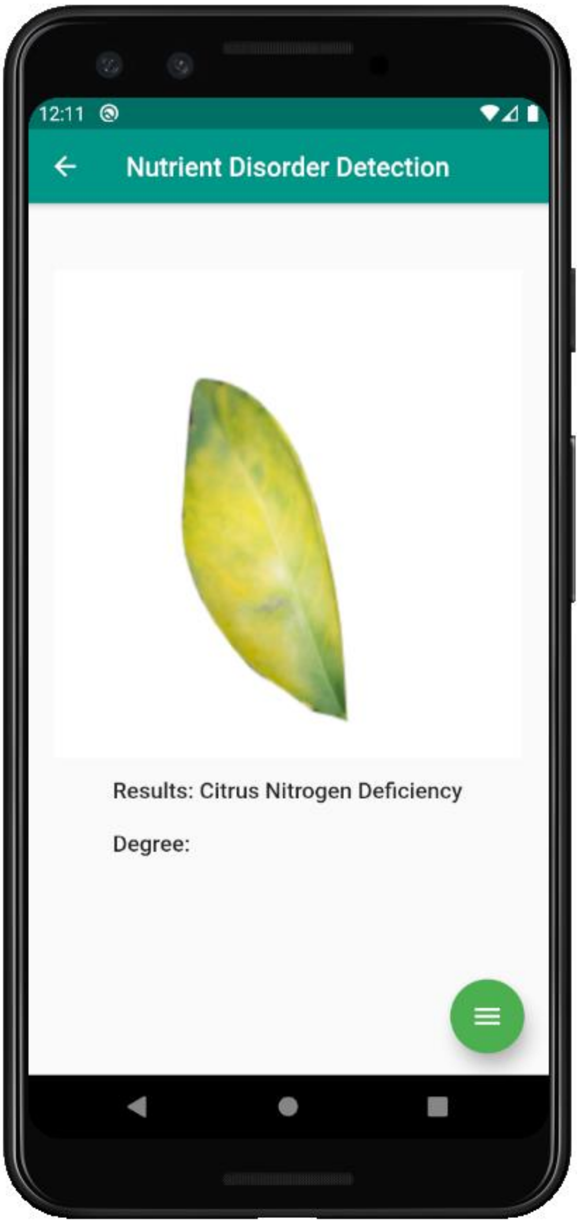


Figure 3.14: Prediction result of Nitrogen Groundnut deficiency

3.2 Research Finding

Through the comprehensive literature studies, it was clear that similar approaches and products have been adopted in the past to implement smart system that can identify plant nutritional disorders. However, all of them are limited to only to detect some micronutrients or doesn't able to identify nutritional disorders based on their severity level.

According to the literature review and throughout the research, some facts was identified about the nutrient deficiencies. Such as symptoms of nutrient disorders are appear different from the ideal disorder systems, different plant species and even for farmers of the same species differ in their ability to show signs of nutrient deficiency.

Through this research study, it was confirmed that a well-trained neural model can be used for more accurate nutrient deficiency image classification. Experimentation has done with a convolutional network architecture (VGG-16, ResNet50, and EfficientNetB0) for detecting nutrient disorder and associated with its symptoms in leaves of plants. EfficientNetB0 achieved the best accuracy for the prediction of nutrient deficiency in plants compared to ResNet50 and VGG16. Even though, with the limited number of nutrient deficiency images as datasets, Promising results were achieved for all three models.

From this research, a fact has emphasized that the Training, Sensitivity, and prediction rates can be improved with more dataset images of nutrient deficiency leaves in plants. Our results evidenced that the application of generative adversarial network-based enhancement techniques that can contribute to improved accuracy and generate more generalized and robust models.

Throughout the research, the main expectation was to implement the system in an extensible way to support other crop types or other nutrient deficiency types in the future. Therefore, a strategy was used to meet this requirement. All implementations related to machine learning are separated from the front-end operation, so future requirements for other crop and nutrient disorder types, changes need to be done in the back-end neural model without interrupting the front-end operation.

3.3 Discussion

Prior research conducted for the deficiency detection mechanisms have certain setbacks, several of them being research limited to a specific task, pursuing costly methodologies/approaches, and the lapse of practicality on implementation in a real-world perspective. For example, satellite imagery and chlorophyll meters have been employed with Machine Learning techniques [5] for plant deficiency identification which is a costly and time-consuming approach.

Another critical fact is that certain deficiencies have similar symptoms which prompt the need for accurate identification system. So, Farmers randomly use fertilizers without knowing the disorder and its degree [7]. Administration of the incorrect fertilizer based on an erroneous judgement of deficiency could have detrimental effects [13]. This is where deep learning has been utilized to play a critical role. Deep learning is a subcomponent of machine learning where the ANN algorithm is produced by a human expert. It will learn from the huge number of datasets automatically with less cost. For the purposes of this research, Convolutional Neural Network (CNN) is used for the detection of the exact disorder with less cost through the hidden layers.

Moreover, the current research work done is to predominantly study the applicable technologies in identifying the disorders rather than utilizing an existing technique to identify the degree of the disorder and provide a practical solution. And mostly, past researchers have employed color analysis to identify the nutrient disorder using ML algorithms [5]. Here we have enhanced the approach to use edge detection, colour analysis and texture analysis which can be done automatically through CNN. Overall, with this amalgamation of techniques for identification of nutrient deficiencies, a predicted result of higher accuracy can be obtained.

In machine learning, data collection and preprocessing are of critical importance. As we progressed with the research datasets with relevance to the mechanisms and system were not readily available or accessible, due to the COVID-19 pandemic situation surging globally. Hence, the algorithms were trained on sample datasets obtained via controlled and progressive capture of deficiencies in homegrown lemon plant. Those datasets were verified by the agricultural expert. And other two plants datasets (Guava and Groundnut) were collected from the field visits. Necessary proceedings were made.

While training the deep learning algorithm with a large dataset, mostly Jupyter notebook gives “Memory error”. And also, in our machines, we don’t have access to limitless computational powers. Because of this issue, Google colab, a free cloud service offers with 12GB ram were used to train our model with speed and more efficiency.

The final product of the research was introduced and to be release as a mobile application for smartphones, that was aimed to drawing the attention of the younger generation of the agricultural community towards agriculture. The application is expected to minimize overuse of chemical fertilizers by applying the correct amount of fertilizer to nutrient disorders.

4. SUMMARY OF STUDENT CONTRIBUTIONS

Table 4.1: Summary of Student Contribution

Name	Task
M.Sukanya	▪ Literature Review Previous researches were reviewed which are relevant to identify nutrition deficiency by using image processing and Machine learning ▪ Requirement Gathering and analysis Symptoms and the respective disorders were discussed with farmers and Agriculture department. Gathered the datasets of disorder plants through the Field visit ▪ System Design System architecture design, Database design, usecase design and Wireframes design were designed according to the requirement. ▪ Function Implementation The following steps were implemented to identify the nutrient deficiency.

	✓ Insert the image. Affected leaf can be captured through the app or else uploaded from the phone storage. Frontend Implementation was done ✓ Pre-processing of the image The uploaded image pre-processed to enhance the quality of image, resize the image with the dimension as training ✓ Selected the suitable Architecture of CNN from (EfficientNetB0, VGG16, ResNet50) ✓ Build and Train the model ✓ Predict the output ▪ Testing ▪ Documentation

5. CONCLUSION

5.1 Conclusion

The smart disorder identification system was implemented for the local farmers with the latest technologies to provide a solution to detect the nutrient disorders in plants. The agriculture fields currently possess a high market for the application of ICT. Topics on the applicability of machine learning and image processing for identifying nutritional disorders were investigated to assist farmers who are inexperienced in identifying crop nutrient disorder and to provide a decision support system in identifying nutrient disorders for experienced user. A scope was set up to identify micronutrients found on the leaf surface of citrus, peanut, and guava plants. Images of symptomatic leaves were acquired for analysis, and the use of deep learning practices were very effective in providing a very accurate prediction with the well-trained neural networks.

Machine learning and deep learning practice was applied in the nutrient disorder identification has been showing promising results. In this research, three pretrained convolutional network architecture such as VGG-16, ResNet50, and EfficientNetB0 was experimented for detection of nutrient disorder in plant. Among those three architectures, EfficientNetB0 was achieved the best accuracy for the nutrient disorder detection.

The end product was a flutter mobile application that could be deployed on android and ios operating system platforms. The farmer has the ability to capture an image of an affected plant leaf through the app or select an image by navigating through the device's gallery. Once the user uploads the image, the system will predict the nutrient disorder.

Finally, CropMedicPlus 2.0 application efficiently gives maximum solution for farmer's problem. We highly expect this system will help farmers to increase their productivity and that will maximize profit.

5.2 Future work

For future improvement, Farmer can have the ability to be capture many images of the affected leaf at once and predict the exact disorder. Identification of nutrient disorder can be extended by adding support to all types of disorders and more crops. Also, This application will facilitate with three languages which will help farmers who have language barriers.

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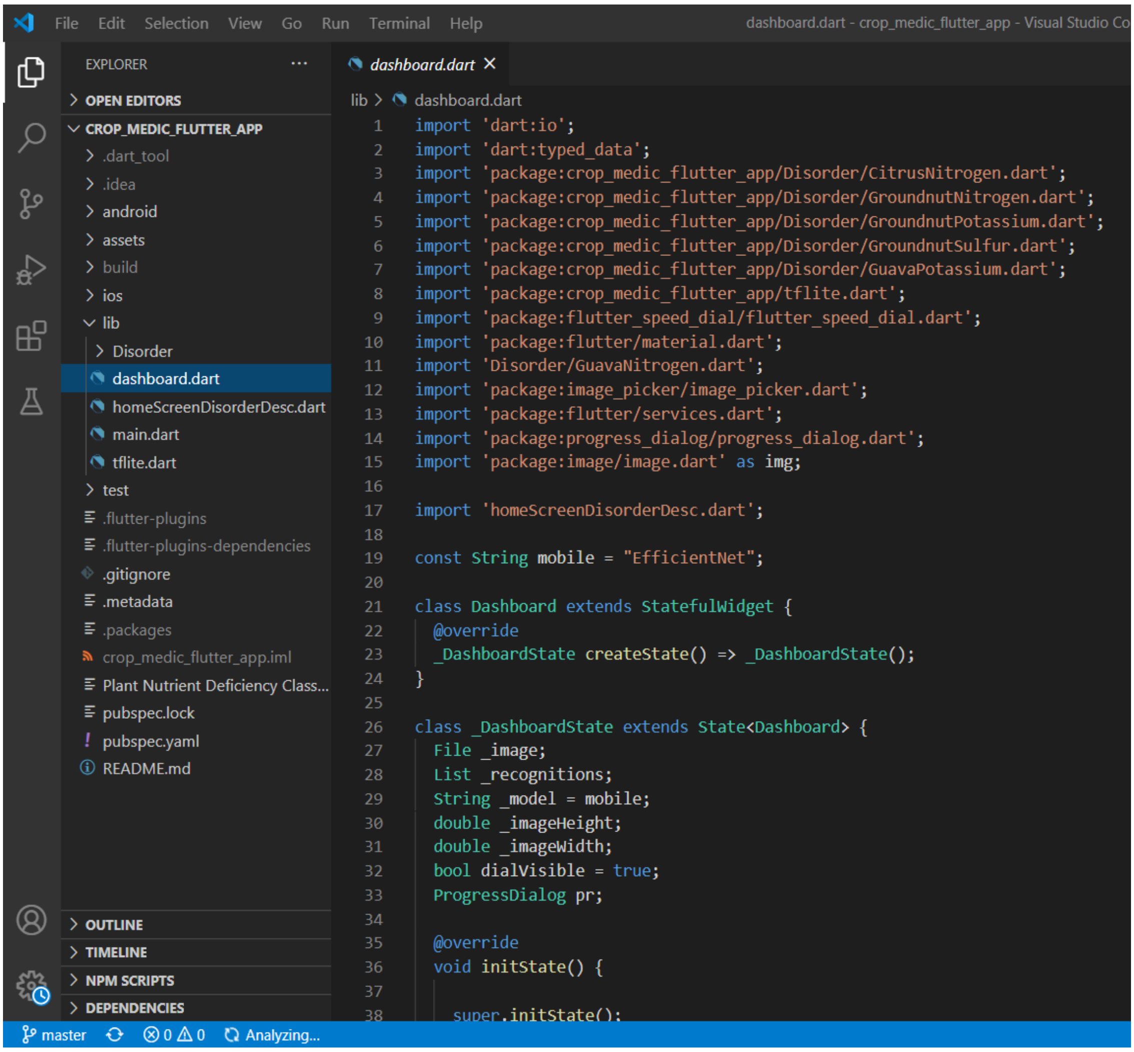
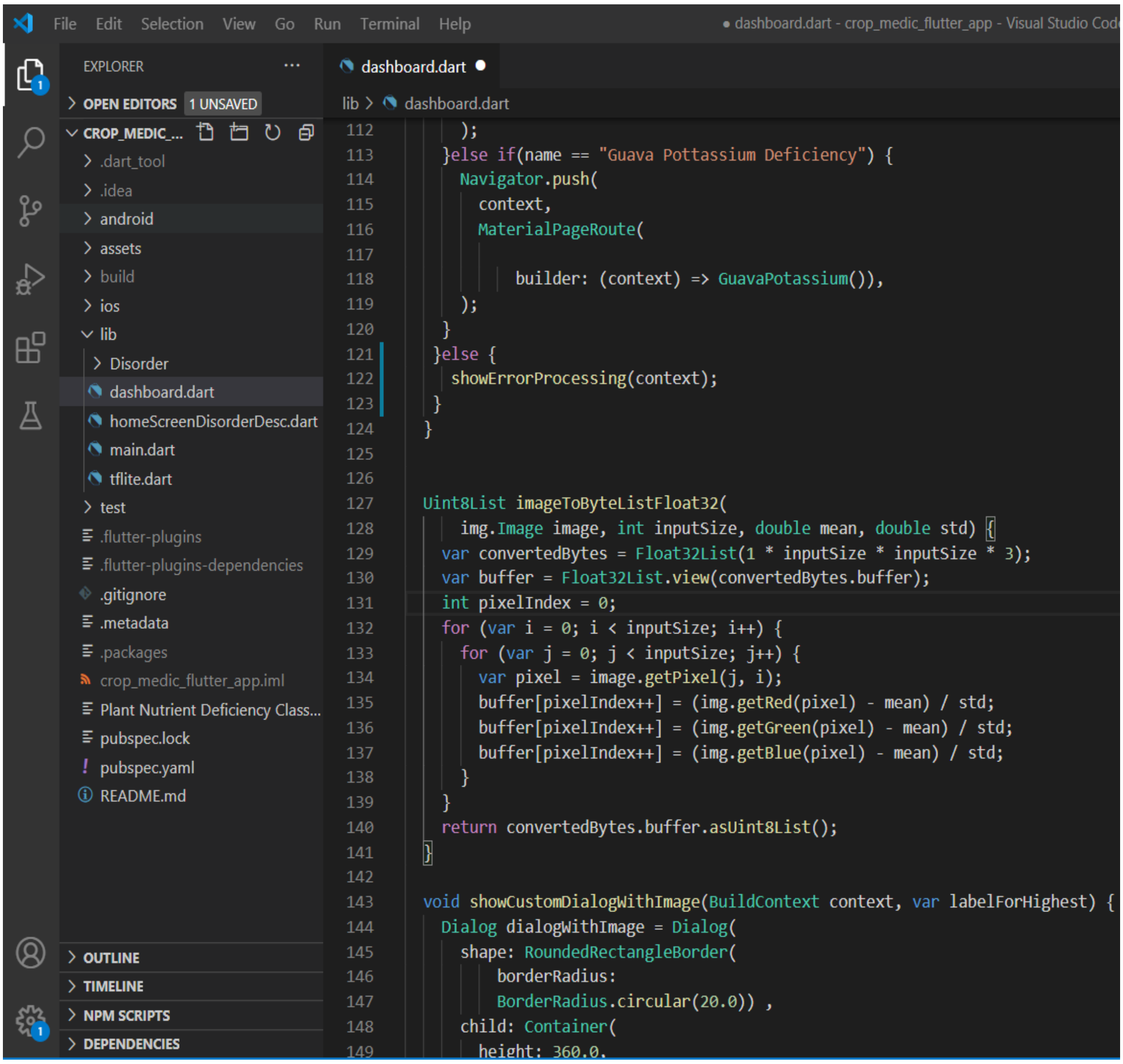
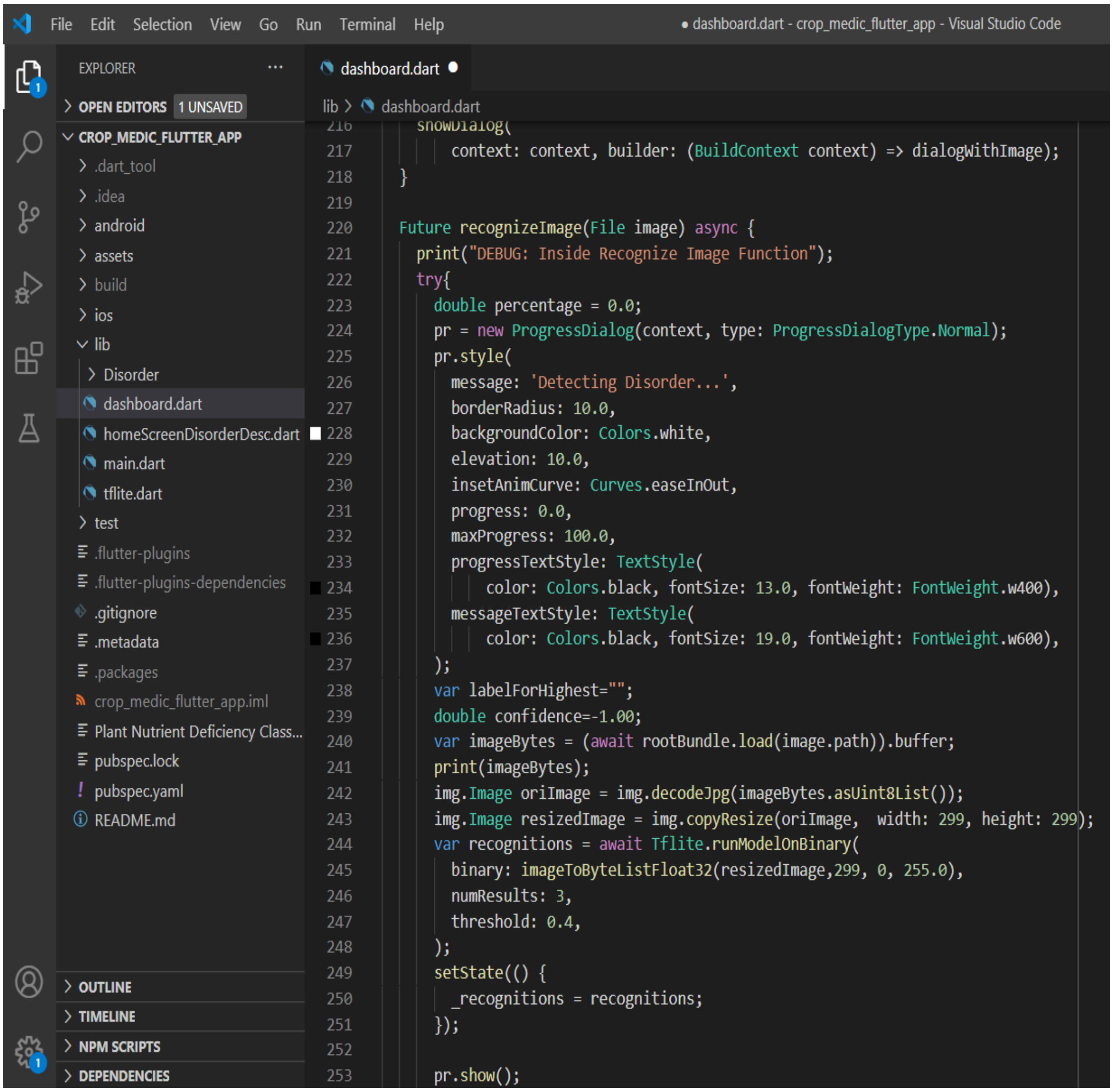
APPENDICES

Appendix A- Dashboard of mobile application

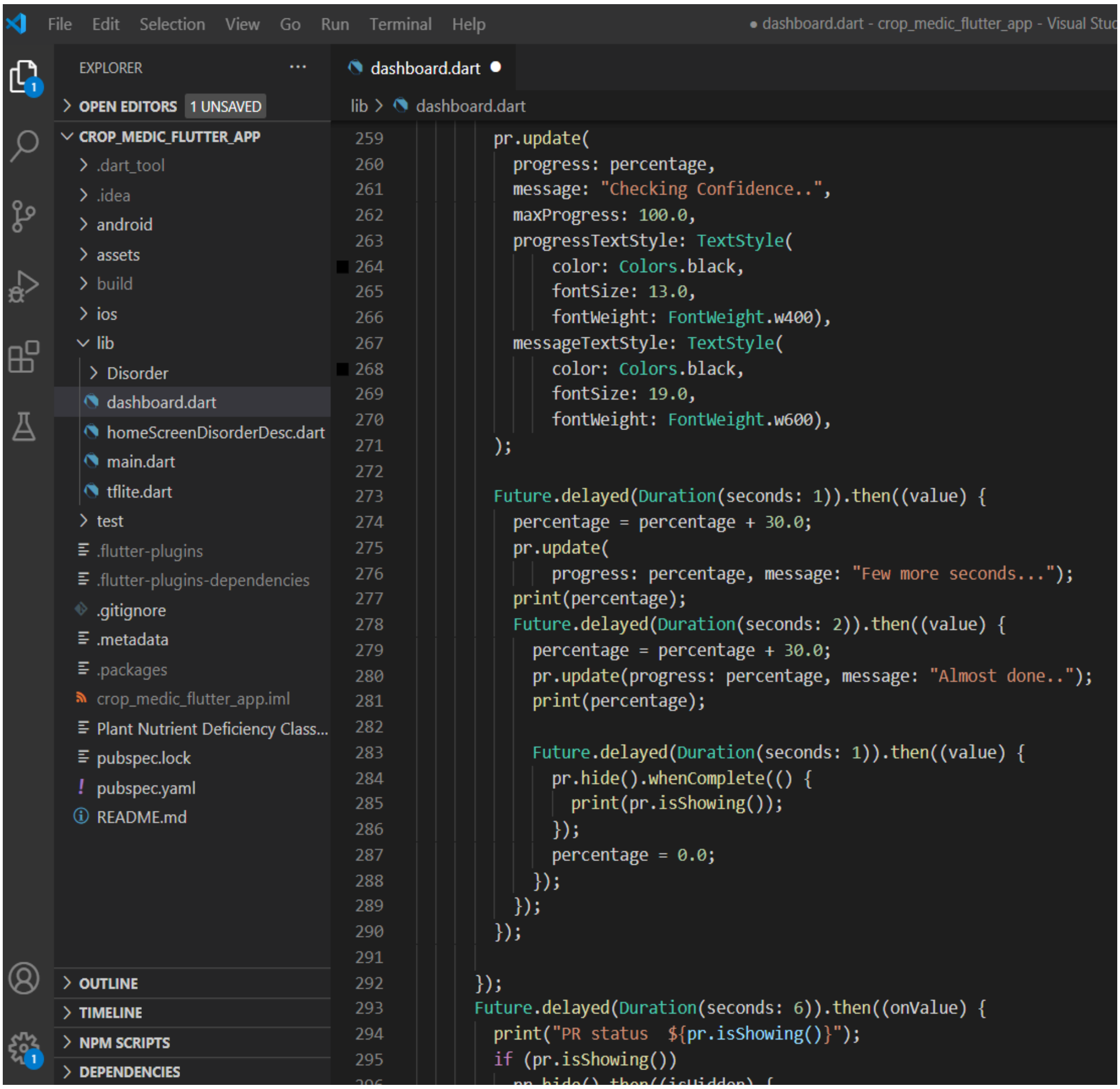



File Edit Selection View Go Run Terminal Help
● dashboard.dart - crop_medic_flutter_app - Visual Studio Code
EXPLORER
OPEN EDITORS 1 UNSAVED
CROP_MEDIC_...
.dart_tool
.idea
android
assets
build
ios
lib
Disorder
dashboard.dart
homeScreenDisorderDesc.dart
main.dart
tflite.dart
test
.flutter-plugins
.flutter-plugins-dependencies
.gitignore
.metadata
.packages
crop_medic_flutter_app.iml
Plant Nutrient Deficiency Class...
pubspec.lock
pubspec.yaml
README.md
OUTLINE
TIMELINE
NPM SCRIPTS
DEPENDENCIES
dashboard.dart
lib > dashboard.dart
);
}else if(name == "Guava Pottassium Deficiency") {
Navigator.push(
context,
MaterialPageRoute(
builder: (context) => GuavaPotassium()),
);
}
}else {
showErrorProcessing(context);
}
}
Uint8List imageToByteListFloat32(
img.Image image, int inputSize, double mean, double std) {
var convertedBytes = Float32List(1 * inputSize * inputSize * 3);
var buffer = Float32List.view(convertedBytes.buffer);
int pixelIndex = 0;
for (var i = 0; i < inputSize; i++) {
for (var j = 0; j < inputSize; j++) {
var pixel = image.getPixel(j, i);
buffer[pixelIndex++] = (img.getRed(pixel) - mean) / std;
buffer[pixelIndex++] = (img.getGreen(pixel) - mean) / std;
buffer[pixelIndex++] = (img.getBlue(pixel) - mean) / std;
}
}
return convertedBytes.buffer.asUint8List();
}
void showCustomDialogWithImage(BuildContext context, var labelForHighest) {
Dialog dialogWithImage = Dialog(
shape: RoundedRectangleBorder(
borderRadius:
BorderRadius.circular(20.0)) ,
child: Container(
height: 360.0,



File Edit Selection View Go Run Terminal Help
● dashboard.dart - crop_medic_flutter_app - Visual Studio Code
EXPLORER
OPEN EDITORS 1 UNSAVED
CROP_MEDIC_FLUTTER_APP
.dart_tool
.idea
android
assets
build
ios
lib
Disorder
dashboard.dart
homeScreenDisorderDesc.dart
main.dart
tflite.dart
test
.flutter-plugins
.flutter-plugins-dependencies
.gitignore
.metadata
.packages
crop_medic_flutter_app.iml
Plant Nutrient Deficiency Class...
pubspec.lock
pubspec.yaml
README.md
OUTLINE
TIMELINE
NPM SCRIPTS
DEPENDENCIES
dashboard.dart
lib > dashboard.dart
    context: context, builder: (BuildContext context) => dialogWithImage);
}
Future recognizeImage(File image) async {
  print("DEBUG: Inside Recognize Image Function");
  try{
    double percentage = 0.0;
    pr = new ProgressDialog(context, type: ProgressDialogType.Normal);
    pr.style(
      message: 'Detecting Disorder...',
      borderRadius: 10.0,
      backgroundColor: Colors.white,
      elevation: 10.0,
      insetAnimCurve: Curves.easeInOut,
      progress: 0.0,
      maxProgress: 100.0,
      progressTextStyle: TextStyle(
          color: Colors.black, fontSize: 13.0, fontWeight: FontWeight.w400),
      messageTextStyle: TextStyle(
          color: Colors.black, fontSize: 19.0, fontWeight: FontWeight.w600),
    );
    var labelForHighest="";
    double confidence=-1.00;
    var imageBytes = (await rootBundle.load(image.path)).buffer;
    print(imageBytes);
    img.Image oriImage = img.decodeJpg(imageBytes.asUint8List());
    img.Image resizedImage = img.copyResize(oriImage, width: 299, height: 299);
    var recognitions = await Tflite.runModelOnBinary(
      binary: imageToByteListFloat32(resizedImage,299, 0, 255.0),
      numResults: 3,
      threshold: 0.4,
    );
    setState(() {
      _recognitions = recognitions;
    });

    pr.show();


File Edit Selection View Go Run Terminal Help
● dashboard.dart - crop_medic_flutter_app - Visual Stud
EXPLORER
OPEN EDITORS 1 UNSAVED
CROP_MEDIC_FLUTTER_APP
.dart_tool
.idea
android
assets
build
ios
lib
Disorder
dashboard.dart
homeScreenDisorderDesc.dart
main.dart
tflite.dart
test
.flutter-plugins
.flutter-plugins-dependencies
.gitignore
.metadata
.packages
crop_medic_flutter_app.iml
Plant Nutrient Deficiency Class...
pubspec.lock
pubspec.yaml
README.md
OUTLINE
TIMELINE
NPM SCRIPTS
DEPENDENCIES
dashboard.dart
lib > dashboard.dart
pr.update(
progress: percentage,
message: "Checking Confidence..",
maxProgress: 100.0,
progressTextStyle: TextStyle(
color: Colors.black,
fontSize: 13.0,
fontWeight: FontWeight.w400),
messageTextStyle: TextStyle(
color: Colors.black,
fontSize: 19.0,
fontWeight: FontWeight.w600),
);
Future.delayed(Duration(seconds: 1)).then((value) {
percentage = percentage + 30.0;
pr.update(
progress: percentage, message: "Few more seconds...");
print(percentage);
Future.delayed(Duration(seconds: 2)).then((value) {
percentage = percentage + 30.0;
pr.update(progress: percentage, message: "Almost done..");
print(percentage);
Future.delayed(Duration(seconds: 1)).then((value) {
pr.hide().whenComplete(() {
print(pr.isShowing());
});
percentage = 0.0;
});
});
});
});
Future.delayed(Duration(seconds: 6)).then((onValue) {
print("PR status ${pr.isShowing()}");
if (pr.isShowing())

<u>**Appendix B- Model integration with mobile application**</u>