DETECTION OF MAJOR RICE AND POTATO DISEASES USING TENSORFLOW AND MACHINE LEARNING

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DETECTION OF MAJOR RICE AND POTATO DISEASES USING TENSORFLOW AND MACHINE LEARNING

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CERTIFICATE

This is to certify that the thesis entitled, **"DETECTION OF MAJOR RICE AND POTATO DISEASES USING TENSORFLOW AND MACHINE LEARNING"** *submitted to the Department of Plant Pathology, Faculty of Agriculture, Sher-e-Bangla Agricultural University, Dhaka, in partial fulfillment of the requirement for the degree of* **MASTER OF SCIENCE IN PLANT PATHOLOGY** *embodies the results of a piece of bona fide research work carried out by bearing* **ABDULLAH AL JUBAIR** *Registration No.* **14-06058** *under my supervision and guidance. No part of the thesis has been submitted for any other degree or diploma, elsewhere in the country or abroad.*

I further certify that such help or sources of information, as have been availed of during the course of this investigation has duly been acknowledged.

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DEDICATED

TO

MY BELOVED PARENTS

AND

SUPERVISOR

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ABSTRACT

Rice and potato are the staple food for over half the world's population. Early and quick detection of rice and Potato diseases are crucial important for our agricultural industry. Several studies focused this issue, and their findings varied depending on their methods. The approach used in this piece of research to identify the four common diseases of rice and two potato diseases including Rice leaf blast, Rice leaf blight, Rice brown spot, Rice leaf smut, Potato early blight and Potato late blight using TensorFlow machine learning technique. The disease samples were collected and sample pictures were captured while visiting the crops field. The causal organisms of rice blast and Bacterial leaf blight of rice were isolated and identified as *Magnaporthe oryzae* and *Xanthomonus oryzae pv. oryzae*. The rest of the selected diseases were identified as per the typical symptoms. In this piece of research, the prediction model is built using TensorFlow's Keras API and the AlexNet CNN. The machine learning model was created using the open-source TensorFlow platform. Following the creation of the TensorFlow Tflite model, this is transformed into the Core ML model, which is then used in the android app to predict diseases. TensorFlow functions by using thousands of plant disease leaf images by converting the input data to Core ML model through Adam optimizer. The model was developed based on the label dataset collected from farmer's field, research field and online domain. TensorFlow machine learning techniques found to be effective showing 99% accuracy by image augmentation. This concept could be used in the creation of mobile applications that aid farmers in identifying rice and potato diseases and suggesting the suitable solution to the farmers. Thus, to prevent the production losses of rice and potato crops due to the diseases mentioned, the model are suggested to practice by the concerned growers.

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CHAPTER I

INTRODUCTION

Bangladesh has huge potential in the field of agriculture. According to the national census data and World Bank report, 2020, Bangladesh has 16.5 million farmers families and 37.75 % active population working on farming sector. Agriculture contributes 19.3% of the gross domestic product of Bangladesh (Bangladesh Finance Bureau, 2014).

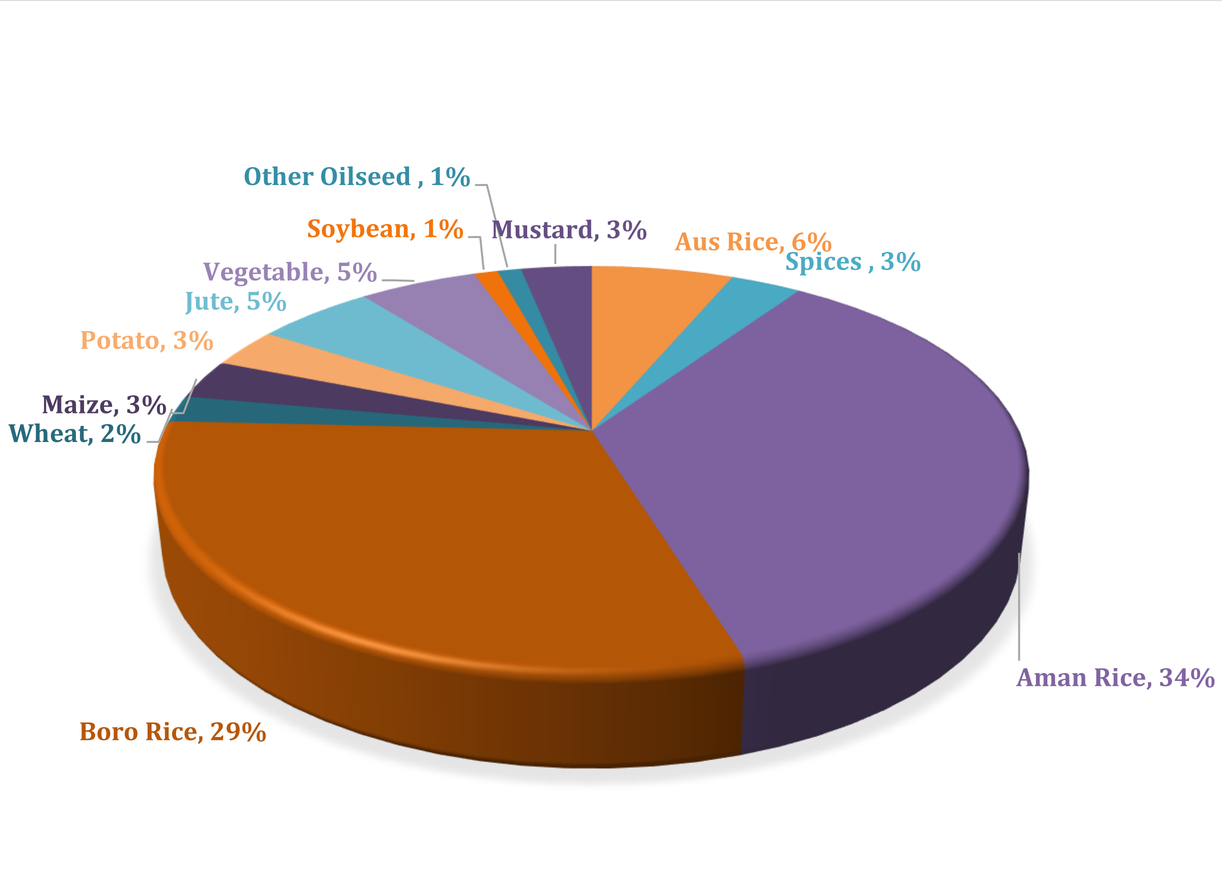


Figure 1: Rice comprises 69% of total crops Production in Bangladesh

Rice is grown well throughout Bangladesh except southeastern coastal areas. The country's agro - climatic conditions are ideal for cultivating rice round the year. Though, the average production of rice in the country is substantially lower (2.94 t/ha) than those of other nations that cultivate rice (BBS, 2012). About 156 million people in the world eat rice as their primary food. About 2 million people are added to the population every year in Bangladesh. If the population grows at this rate each year, by 2050, there will be 238 million people live in the country. Within similar period, the total cultivable land is reducing at the rate of 1% per year due to heavy industrialization, houses and development (Hossain *et al*., 2013) .

To feed this ever-growing population, total rice production must increase. However, due to climate change rice cultivation is facing various adverse conditions such as drought, flood, salinity, extreme temperature stress and higher intensification of pest and diseases (Shelley *et al*., 2016).

A research conducted during 1979-81 in Bangladesh found 20 rice diseases, including two viral, two bacterial, 13 fungal and one micronutrient lacking difficulty. Some diseases are classified as major including bacterial blight, bacterial leaf streak, sheath blight, brown spot, stem rot and leaf scald. It is evident that periodically a disease outbreak or epidemic occurred in the country such as Rice blast. Under critical epidemic situation around 98% yield loss occur due to spread of blast. Field survey indicated that 65.4% yield loss from severely infected field with the disease. Another major rice disease named false smut disease has become emerging in Bangladesh during T. Aman season for the last five years (Miah *et al*., 2008).

In a survey Nazifa *et.al.* (2021) found a variation in blast incidence and severity of rice under different field sites and different varieties. Rayhan *et.al*. (2019) also found varying incidence on severity of rice blast in different location of Bangladesh.

In both of these studies they identified several isolates with different growth and cultural characteristics on different media. The pathogen was very destructive and highly changeable in genetic makeup and able to arrive as a new race or variants. So, continuous monitoring on different isolates in different rice growing region is utmost important.

Potato is one of the major potential cereal crops in subcontinent as well as in the world. It is a significant crop that has the potential to provide food for millions of people, particularly in developing nations. Only by controlling crop-affecting illnesses will the crop's full potential be fulfilled. Severe bacterial diseases including soft rot, common scab, bacterial wilt, and brown rot as well as major fungal diseases like late blight, early blight, black scurf, fusarial wilt/dry rot, wart, powdery scab, and charcoal rot significantly reduce potato production both in the field and elsewhere. While illnesses like black scurf, wart, powdery scab, and common scab deform the tubers and lower their market value, diseases like late blight, early blight, fusarial wilt, and black leg mostly damage the crop and foliage. While certain tuber diseases, like dry rots, only affect stored tubers, others, like soft rot, damage potato tubers at every stage—in the field, storage, and transit—and can result in significant loss in some circumstances. With regard to their identification, symptoms on potato plants or tubers, type of the pathogen involved, epidemiology, management techniques, etc., the major fungal and bacterial diseases impacting potato crop are covered on our research (Khurana *et al*., 2004). Among various abiotic factors affecting rice, rice blast is the most disastrous, causing 70-80% yield loss. It infects all the developmental stage of plant and produce symptoms on the leaf, collar, neck, panicle, and even in the glumes (Kapil Simkhada, 2021). Rice false smut caused by *Ustilaginoidea virens* is a destructive inflorescence disease threatening rice production worldwide. The disease is emerging in many rice growing countries including India. Therefore, an investigation was conducted in farmers' field of Odisha during kharif 2017. The disease incidence, chaffiness and yield loss for 20 rice genotypes were assessed following a standard method (Baite, 2020). Early blight of potatoes, causal agent *Alternaria solani,* causes major yield losses in most potato growing areas of the world. Leaf symptoms are characteristic dark brown to black lesions with concentric rings (J E van der Waals, 2001). Late the blight of potato is a devastating and one of the economic diseases of potato and other plants belonging to family Solanaceae. Late blight, caused by *Phytophthora infestans,* is one of the most threatening pathogenic diseases which not only results in direct crop losses but also cause farmers to embrace huge monetary expenses for disease control and preventive measure (Tiwari, 2021). Bacterial leaf blight of rice is among the most devastating pathosystem of rice in nearly all the rice growing localities in tropical and temperate regions especially in Asian countries (Naqvi, 2019). Among the major fungal diseases of rice, brown spot occupies not only an important position, but also historical interest (Chakrabarti, 2001).

Modern technology in field of agriculture

The rapid development of new technology and the shifting landscape of the online world (e.g. Internet of Things, AI, Cloud-based solutions) presents a unique opportunity for the development of automated and robotic systems for urban farming, agriculture, and forestry. Machine vision, global positioning systems, laser technologies, actuators, and mechatronics advancements have enabled the development and implementation of robotic systems and intelligent technologies for precision agriculture (Panpatte, 2018). Integrating IOT and WSN (Wireless Sensor Network), Machine Learning and AI have been deployed and implemented in agriculture for automated and robot farming. In addition to planting, watering, weeding, pruning, and harvesting, intelligence technologies utilizing machine vision have been developed. For smart farming management, we need to focus important aspects of Machine Learning, IoT, Artificial Intelligence, and Big data. The global population is projected to surpass nine billion by 2050, necessitating a 70% increase in agricultural production to meet the need. Utilizing cutting-edge technical advancements to increase agricultural productivity remains one of the greatest demands.

Significance of Artificial Intelligence in agriculture

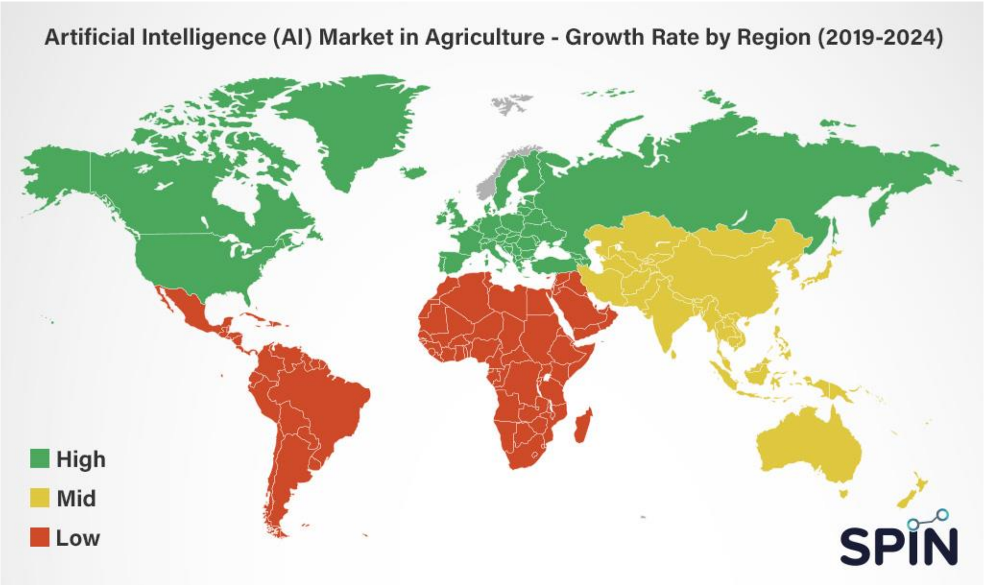


Figure 2: Artificial Intelligence market in Agriculture

A solution powered by AI could assist farmers in producing high-quality goods with minimal effort. Consequently, it is recommended to apply a digital solution helped by artificial intelligence to improve the living conditions of the exploited farmer community, while simultaneously creating a new opportunity for businesses and entrepreneurs by enabling smart farm as a service.

Massive amounts of structured and unstructured data are generated every day as a result of the Internet of Things. These include information on historical weather patterns, soil reports, fresh studies, precipitation, pests, infestations, drone and camera images, etc. Cognitive IoT solutions are capable of sensing all of this data and delivering actionable insights to boost yield.

Proximity sensing and distant sensing are two advanced technologies largely employed for intelligent data fusion; soil testing is one application of this high-resolution data.

In contrast to remote sensing, which requires sensors to be installed on airborne or satellite systems, proximity sensing requires sensors to be installed on the ground. The IoT-enabled sensors must be put at the specified locations in the field. These sensors are the transducers that collect data on climate conditions, soil moisture and fertility, root and shoot growth, abundant leaf growth, photoperiod monitoring, flowering and seed setting, insect and disease symptoms as important growth factor symptoms, and harvest readiness.

Using Big Data

By assessing and correlating data regarding the weather, types of seeds, soil disease risk, historical data, market trends, and prices, farmers will be able to make more informed decisions. Drone-based photos can facilitate in-depth field analysis, crop monitoring, and field scanning. Combining computer vision, IoT, and drone data enables farmers to take swift response. Data collected from drone images can create real-time alerts to expedite precision farming. Businesses such as Aerial tronics have integrated the IBM Watson IoT platform and the visual recognition APIs into commercial drones for real-time image processing.

Computer Vision technology has applications for disease detection

Preprocessing of pictures ensures that leaf images are split into categories such as background, non-diseased portion, and diseased portion. The diseased portion is then removed and sent to distant diagnostic labs for additional analysis. In addition, it aids in pest identification and nutrient shortage recognition.

Crop readiness identification

Images of various crops captured under white/UVA light to evaluate how ripe the green fruits are. Farmers can construct several degrees of crop/fruit category readiness and put them to separate stocks before sending them to market (Panpatte *et al*., 2018).

Machine learning for plant disease detection

Plants are constantly attack by the pathogen, which lead significant loss of economical crop worldwide. Many scientists and artificial intelligence expert developed image processing through TensorFlow machine learning to detect plant disease within shortest period. Previously scientists typically applied large-scale genetic screening and genomic process to identify genes and proteins of interest. However, today's advancements in machine learning algorithms, a group of analytical techniques that automate the process of building models and iteratively learn from data to gain insights without explicitly programming, offer more effective and powerful tools to not only identify genes/proteins involved in plant-pathogen interactions but also to classify plant diseases from images of infected leaves (Xin Yang *et al.*, 2019). Here, we evaluate works that use machine learning to identify plant diseases and understand how plants interact with pathogens . To get expected outcome, we have appropriately classify and detect the rice leaf and potato diseases and apply appropriate treatment to reduce the loss. In our nation, rice disease and potato disease detection is typically done manually, followed by expert diagnosis and then approval of the appropriate course of action. These task sequences are quite difficult for large farms. Additionally, it requires a lot of work and a lot of time. Contrarily, taking images of the infected area of the rice leaf and validating them using a learning scheme offers a more accurate method for detecting rice leaf illnesses than a manual scheme. This research work shows how to correctly detect rice leaf and potato leaf diseases using Tensor flow machine learning. But the TensorFlow lite cannot identify the disease image by small dataset. It need large datasets like ImageNet and we use an extremely efficient machine learning model like AlexNet. A leading architecture for any object-detection task, AlexNet is a highly effective technique that can achieve high accuracies on very difficult datasets (Mohanty *et al.*, 2016). It has a wide range of applications in artificial intelligence problems involving computer vision, and sooner or later it might be used more frequently for picture tasks than convolutional neural networks. For this reason, the AlexNet approach was used to find diseases in rice and potato leaves (Matin et al., 2020). We obtained good results using the AlexNet technique, which utilized 90% of the photos in our dataset as training data. These images were divided into three object classes, including Rice leaf blast, Rice leaf smut, Potato early blight and Potato late blight. We got the satisfactory result and 99.9% accuracy to detect desire plant diseases.

Android application and treatment of diseases

Now we developed Image detection application inputting data to the Tensor flow lite of android studio. It has gallery or camera functionality. Farmers can take photo through the app camera or input the disease affected leaves from gallery to the app. Then the app can detect disease and provide immediate result displaying the screen with percent of accuracy. Then farmer can click the below button to know the remedy of the diseases through the app. Thus, the present investigation was undertaken to detect selected rice and potato diseases by using TensorFlow machine learning and image processing technique.

Objectives:

-To detect selected rice and potato diseases by using TensorFlow machine learning and image processing technique.

CHAPTER II

REVIEW OF LITERATURE

Many researchers worked on machine learning TensorFlow to detect plant diseases and found satisfactory result. As diseases are natural in crops so that early detection of disease is need to improve plant health status and quality production. Initial development of plant diseases can be detected by using image processing techniques (Kumari, 2019). The use of computers in agriculture is having remarkable success in several areas, including the early diagnosis of many plant diseases. The automation of agriculture has become the primary focus of practically all nations in an effort to increase precision and accuracy and meet the world's growing food demand. Plant disease identification is one of the biggest problems in agriculture and has a considerable impact on how well crops are grown. Plant diseases have a negative impact on the quality of grains, legumes, fruits, and vegetables as well as cause significant production losses and economic losses. Therefore, there is a need for quick and accurate methods for identifying and assessing plant diseases (Harjeet Kaur, 2019). One of the key components of precision agriculture for tracking incidence and assessing the severity of variations in crops is image-based plant disease identification. 60% to 70% of the variabilities, as opposed to the stem and fruits, are linked to diseases brought on by pathogens, and 70% to 80% of these diseases affect the leaves (Aliyu M. Abdu, 2020). The most difficult difficulty for all agricultural formers is identifying the diseases that plague a certain crop and their causes. Some diseases spread quickly and easily, which can lead to disaster in the targeted production of that time period. To address this issue, it is best to identify the diseases at an early stage (Roopa, 2021). Agriculture that promotes sustainable development must conduct health surveillance and identify plant illnesses. Manually keeping track of plant diseases is exceedingly challenging. It necessitates extensive professional experience, knowledge of certain plant diseases, and lengthy processing times. Thus, plant disease detection uses image processing. Acquisition, picture pre-processing, image segmentation, feature extraction, and classification are a few of the procedures involved in disease detection (Ramsanthosh, 2021). The conventional methods of disease classification and detection require a great deal of time, hard work, and continuous farm monitoring. Diseases brought on by bacteria, viruses, and fungus can frequently be prevented by applying disease detection techniques. Crop protection is essential for maintaining agricultural products. To recognize the impacted leaf photos, machine learning techniques are frequently applied. The different machine learning techniques that are used to assess if a plant is diseased or not. There were several procedures taken, including the acquisition of the image, feature extraction, classification of the sickness, and result display (Varshney, 2022). In more recent years, Artificial intelligence and machine learning are used to providing information for disease diagnosis online, consolidating the higher internet penetration worldwide.

Even more recent time, app based plant detection technology on android have proliferated, taking advantage of the historically unprecedented rapid global adoption of mobile phone technology. Because of their computer power, high-resolution displays, and comprehensive built-in accessory sets, such as powerful HD cameras, smartphones in particular offer very unique techniques to aid in the identification of diseases. By 2020, it is predicted that there will be between 5 and 6 billion smartphones worldwide. Mobile broadband coverage was available to 69% of the world's population by the end of 2015, while mobile broadband penetration reached 47% in 2015, a 12-fold increase since 2007 (Mohanty *et al*., 2016). Deep learning models with an inception layer, like GoogleNet and InceptionV3, have a superior ability to extract the features and deliver higher performance results than other deep learning models (Hassan, 2022).

Machine Learning Tensor flow

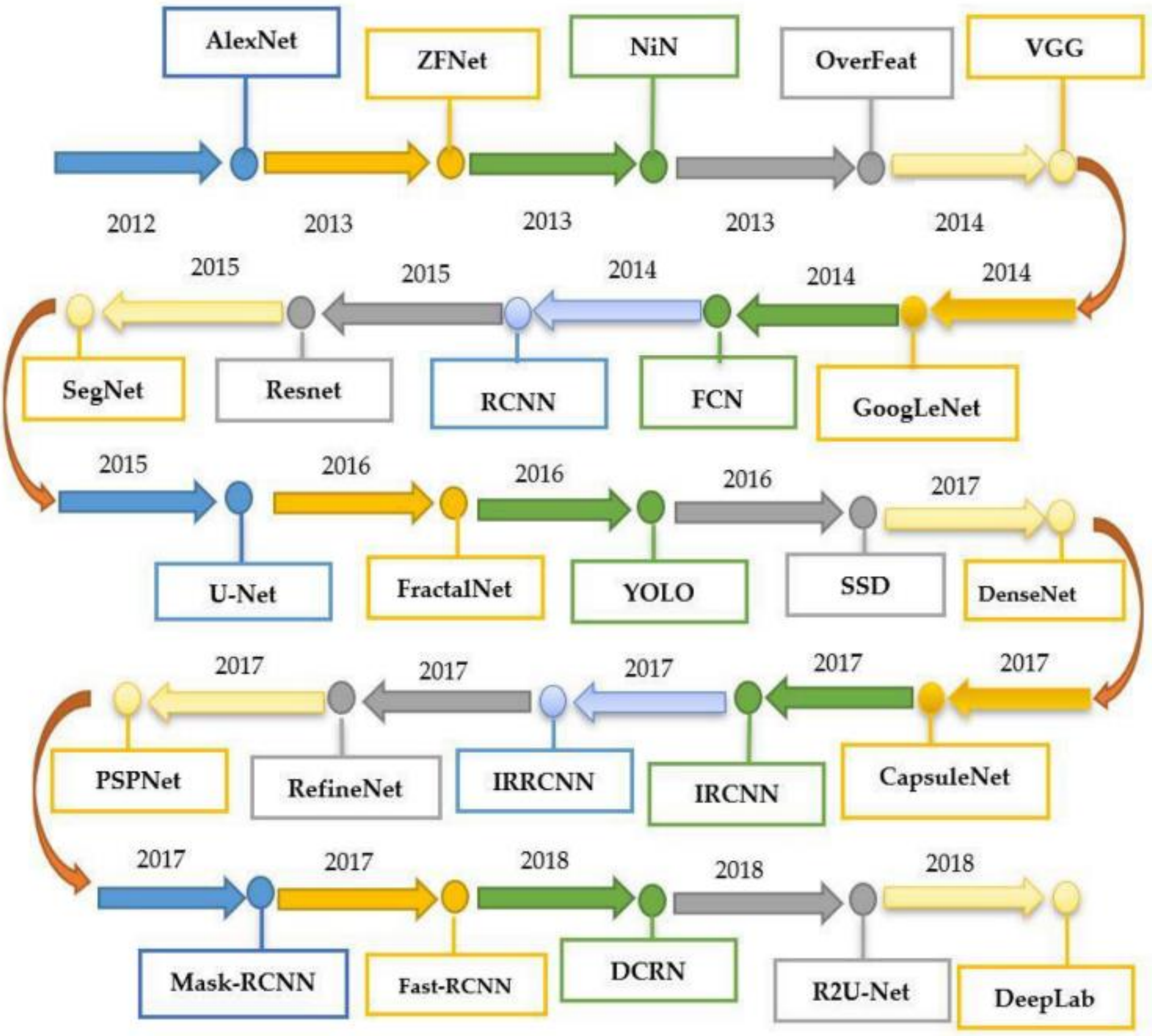


Figure 3: Summary of the evolution of various deep learning models from 2012 until now.

TensorFlow is a machine learning system that works in diverse situations and scale is evolving starting from 2012(figure 5). Tensor Flow employs dataflow graphs to express computation, shared state, and the operations that alter that information. AlexNet has 60 million parameters known as the first modern CNN. It has best image recognition performance at its period. ZFNet has 42.6 million parameters. It reduced weights by considering 7 * 7 kernels and improved accuracy. GoogLeNet has 7 million parameters. It has fewer number of parameters as compared to AlexNet model but better accuracy at its time. ResNet has 25.5 million parameters. It is vanishing gradient problem have better accuracy than VGG and GoogLeNet models. DenseNet has 7.1 million parameters. It reduced number of parameters with better accuracy. It distributes the nodes of a dataflow graph among numerous machines in a cluster and among various computing units within a single system, such as multicore CPUs, general-purpose GPUs, and specially created ASICs known as Tensor Processing Units (TPUs).

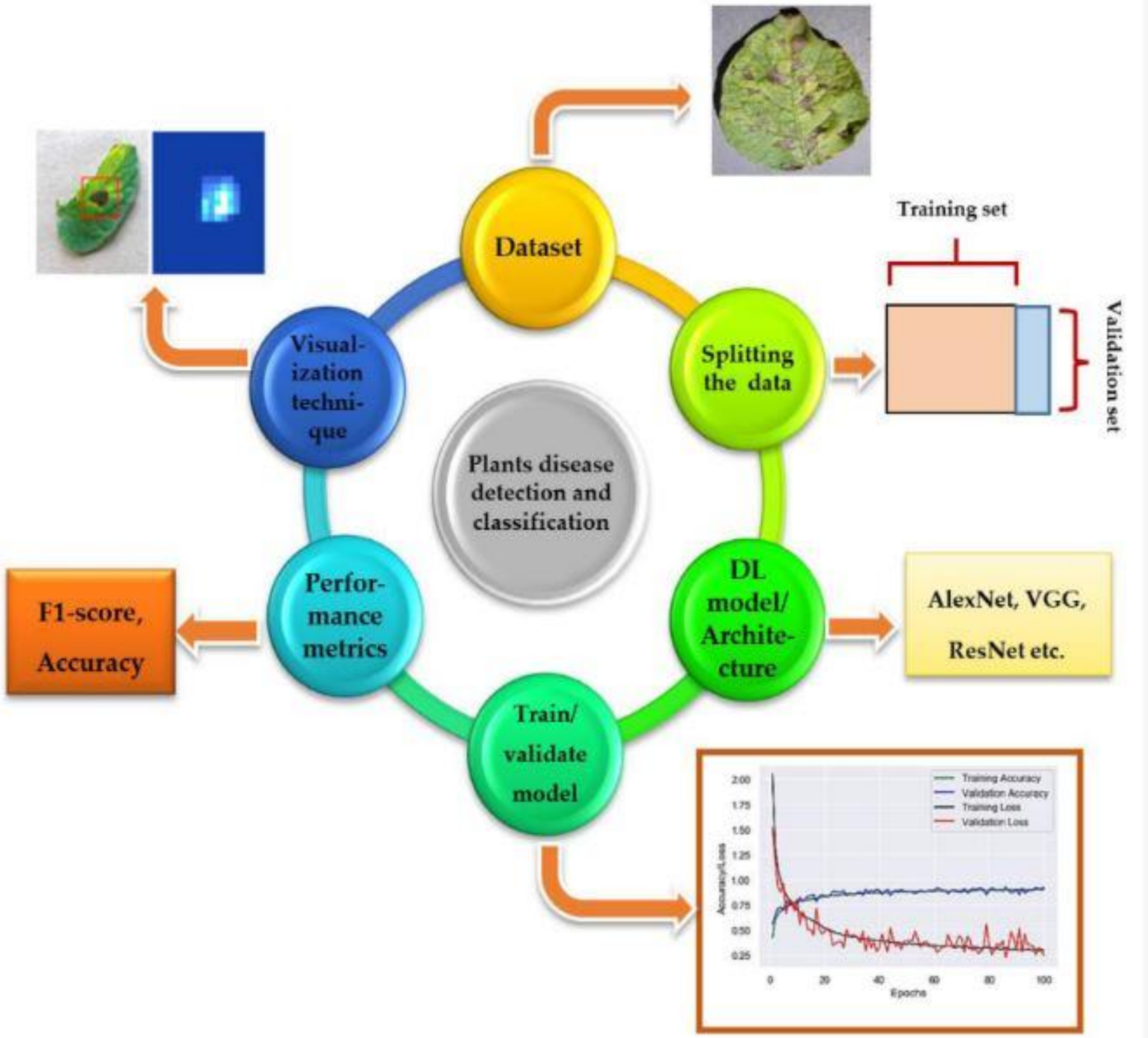


Figure 4: TensorFlow working process to detect plant diseases (2022)

This architecture allows the application developer flexibility because, unlike earlier "parameter server" systems, which managed shared state internally, TensorFlow enables developers to test out cutting-edge optimizations and training techniques. TensorFlow supports a wide range of applications, with a focus on deep neural network training and inference (Abadi *et al*., 2016)

CHAPTER III

MATERIALS AND METHODS

3.1. Sample Collection

I collected 20 rice blast disease samples , 50 bacterial leaf blight and 20 late blight of potato sample from Bangladesh Rice Research Institute, Gazipur; regional Bangladesh Rice Research Institute, Barishal: Bangladesh Agricultural Research Institute, Gazipur and Central Farm of Sher e Bangla Agricultural University, Dhaka. The disease samples were collected in polythene sheet to keep the samples moist. The collected samples were kept in normal refrigeration for isolation of organisms involved. The sample collection was conducted during during December, 2022-January, 2023.

Figure 5 : Rice disease samples collecting from BRRI, Barishal

Figure 6: Visiting BRRI and BARI for disease samples collection

Figure 7: Rice disease samples collected from SAU central farm

Figure 8: Rice blast disease samples collected from the field

A B

Figure 9: Collected rice bacterial leaf blight samples (A. Leaf and B. Field views)

Figure 10: Collected typical symptoms of Late blight of potato

3.2. Preparation of culture media

3.2.1. PDA media preparation

The standard Potato Dextrose Agar (PDA) media (200g of peeled potatoes, 20 g of dextrose, and 20 g of agar and 1000 ml of distilled water). Cleaned and peeled potato tubers were sliced into pieces. Then the pieces were boiled in distilled water to collect the extract by sieving with a fine piece of cloth. Dextrose and agar were dissolved in the potato extract and the volume was made up to 1000 ml by adding distilled water. After preparation, the media was poured into 500 ml Erlenmeyer flasks, plugged with cotton and wrapped with aluminum foil. The flasks containing media were sterilized in the autoclave at 121°C under 15 pound per square inch (psi) for 20 minutes. The media were acidified with 30 drops of lactic acid per 250 ml medium to inhibit the growth of bacteria. 20 ml of medium was poured into each petri dish (9 cm diameter) inside Laminar Air Flow (LAF) with proper cautions and then allowed to solidify.

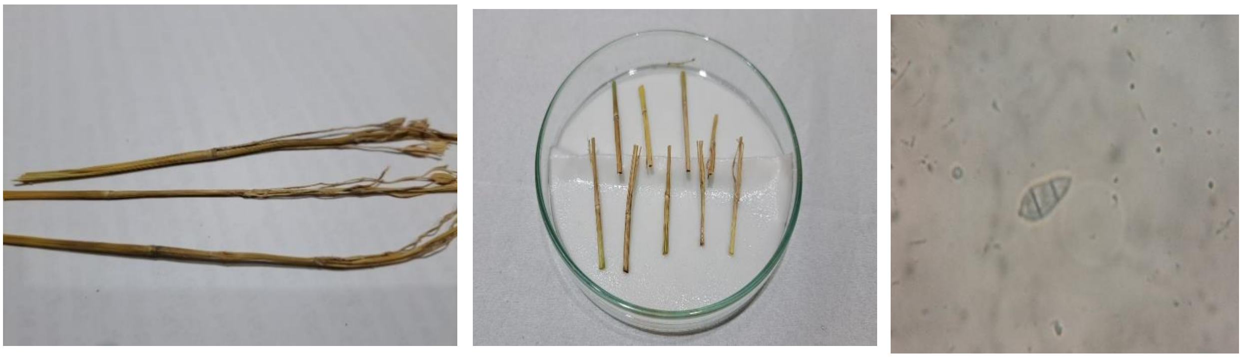
3.2.2. NA media preparation

28g nutrient agar powder was dissolved in one liter of distilled water and mixed thoroughly. The suspended media was then sterilized by autoclaving at 121°C for 15 minutes. The sterilized and liquid nutrient agar media was then **p**oured into the petri dishes and wait for the medium to solidify. After solidification of the media the Nutrient agar is ready to use.

Figure 11: PDA and Nutrient Agar media preparation

3.2.3. Isolation and identification of *Magnaporthe oryzae*

Isolation of *Magnaporthe oryzae* was done by tissue planting method. Infected neck portions of the panicle, which were collected from the field were sterilized by the surface disinfectant Clorox (1%) for 3 minutes. After sterilization, the infected necks were washed three times with sterile water. Then placed on moist sterile blotter paper and placed in incubation chamber for 2 days at 25 ±1°C. Conidia grown on infected neck portions were transferred on PDA media after observation in the stereomicroscope. After 30 days of incubation, the fungi was grown on culture media. A portion of culture was taken on slide and observed under compound microscope and identified the pathogenic fungi as *Magnaporthe oryzae*. Observing 3-celled pyriform conidia (figure 12)

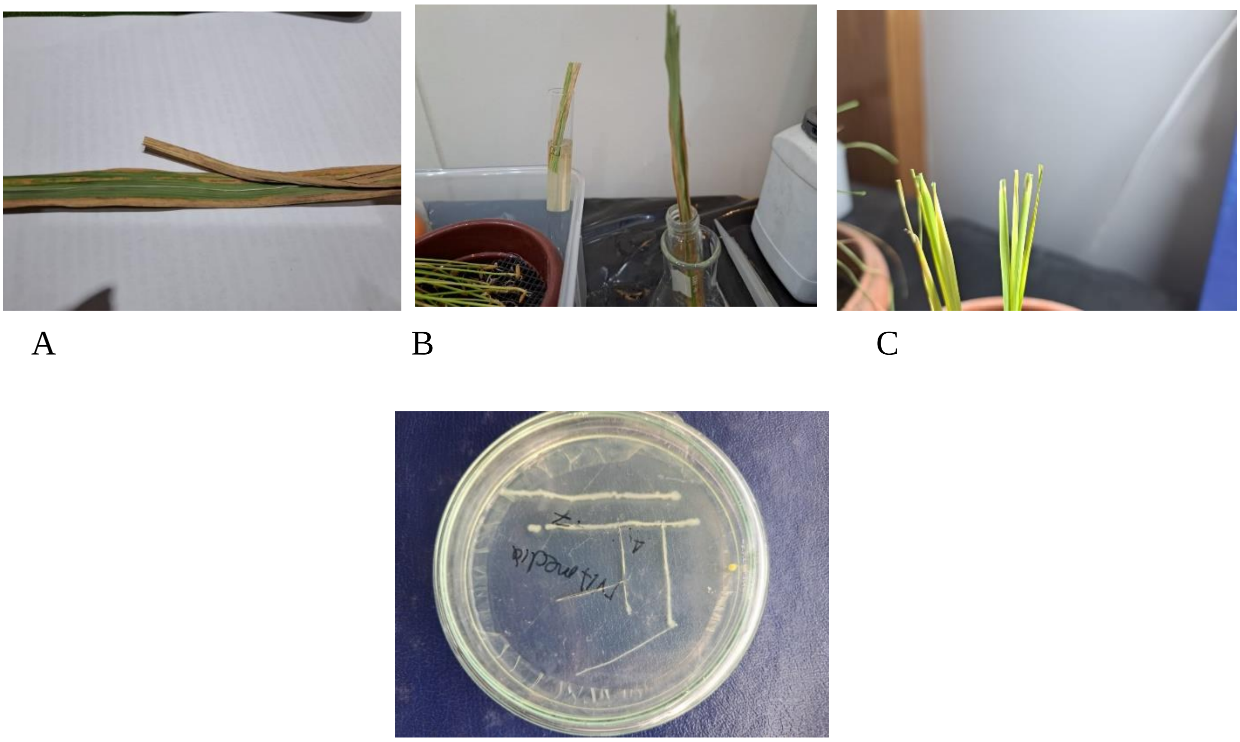


A B C

Figure 12: Isolation and identification of *Magnaporthe oryzae***.** A. Infected neck. B. Infected neck placed on moist filter paper and C. Conidium (100x).

3.2.4. Isolation and identification of *Xanthomonas oryzae pv. oryzae*

For isolation of *Xanthomonas oryzae pv. oryzae*, infected leaf portion was clipped by sterile scissor and cut portion was emerged in the sterile distilled water in a sterilized test tube and kept for 24 hrs. Nutrient agar were then shocked by bacterial suspension using sterile tooth pick and incubated for 3 days at 25 ±1°C. To confirm Xanthomonas Oryzae pv. Oryzae leaf clipping inoculation methods was performed. Sterile scissor was emerged in bacterial suspension and leaf tips were cut by bacteria adhered scissor. The inoculated seedlings were kept in incubation room and BLB symptoms were appeared after five days of inoculation.



A B C

D

Figure 13: Isolation and identification of *Xanthomonas oryzae pv. oryzae.* A. infected leaf observing BLB symptom. B. Leaf clipping of infected leaf and placed in the sterile distilled water. C. Isolation of *Xanthomonas oryzae pv. oryzae* by streaking method from water sample. D. Development of BLB after leaf clipping method using sterile scissors emerged in the *Xanthomonas oryzae pv. oryzae* water suspension.

3.2.5. TensorFlow Machine learning process

A comparative analysis of frameworks that can be utilized for model generation has been undertaken, and the resulting model can be used in the Android project.

It is an Algorithm for Image Classification. TensorFlow is a popular framework for deep learning, and Keras is its official high-level API. TensorFlow combines many methods and models, allowing us to create a deep learning neural network for tasks such as image identification and classification and natural language processing. Keras was created with modularity and usability in mind. Keras simplifies as much as possible the implementation of the numerous powerful but difficult functions of TensorFlow. It is designed to work with the Python programming language. Advantage of the TensorFlow framework over other frameworks used in the project work is that it has a very simple implementation using the Keras library APIs. TensorFlow framework supports numerous programming languages, which makes it popular. In addition, Google created this framework, thus it is regularly updated with the most recent ML algorithms and libraries (Kumar *et al.*, 2022).

3.3. Image classification

Classification of images is a supervised learning technique. It identifies the set of target classes and trains a model to recognize those using labeled images, where each label corresponds to a preset class. If there is a single class, then the task is known as image recognition, but a task involving many classes is known as image classification (Hortizuela *et al*., 2020).

3.3.1. Feature extraction

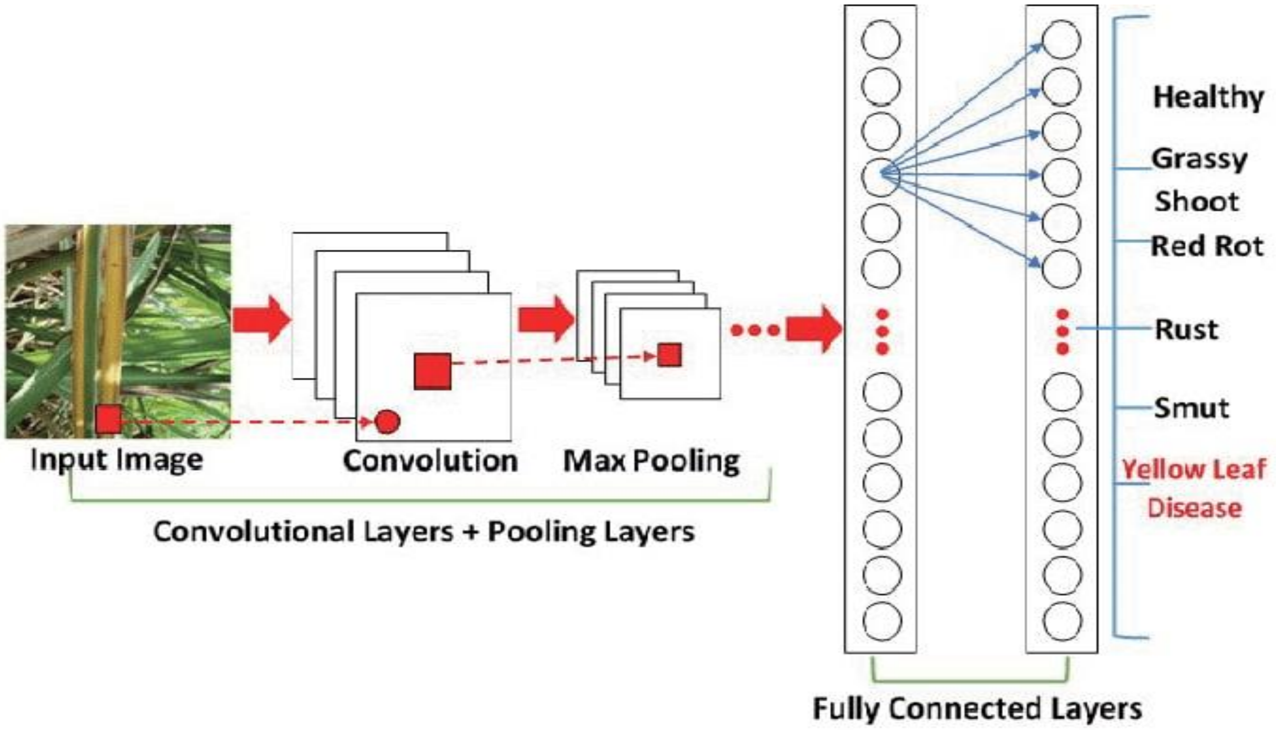


Figure 14: Feature extraction flowchart

Features are the data pieces that was transmitted across the network. In specialized image recognition, the features are the group of pixels, such as edges and points that the network analyze for the pattern.

3.3.2 Feature recognition

It is the process of extracting relevant features from an input image in order to analyze them. The procedure of obtaining visual features utilizing a convolutional layer to accomplish this, and this layer creates the representational component of the image. The result of these calculations is a feature map. This procedure is usually performed using many filters, which helps to maintain the sophistication of the image.

3.3.3. Activation function

Following the creation of the image's feature map, the image's values are sent via the activation layer. Since the pictures are already nonlinear, this layer increases their nonlinearity. Primarily, the ReLU (rectified linear unit) activation function was utilized. Collecting layers reduces the size of the image by compressing the information it conveys. The practice of pooling makes the network more adaptable and adept at detecting images based on their pertinent characteristics. This layer of a CNN will abstract away the unimportant elements of the image while retaining the more important parts. This aids in preventing overfitting of the model, which occurs when the network learns too many elements of the training case and fails to generalize to fresh data.

3.3.4. Flattening

This is the final layer of the CNN, the tightly connected layers, which involves compression of the vector data. The values are compressed into a lengthy vector or column of consecutively arranged numbers.

3.4. Machine Learning process

We discovered the image classification technique used in the machine learning procedure to construct and train the model. The procedure consists of four distinct steps. These steps are collecting data, preparing data, choosing a model, training the model.

```
import tensorflow as tf
from tensorflow.keras import models, layers
import matplotlib.pyplot as plt
```

Figure 15: Machine Learning process

3.4.1. Data set preparation

Images of rice and potato diseases were captured in an actual rice and potato crop field under varying weather conditions. It adds variability to the dataset, which facilitates the development of more accurate models. The photographs are labeled with their respective disease's features and placed in the appropriate folder. Operations and data were manually prepared. Which is utilized in the preparation of models. There are seven label classes viz. i. Potato_Early-blight, ii. Potato_Late_blight, iii. Potato_healthy, iv. Rice_Bacterial_leaf_blight, v. Rice_Leaf_blast, vi. Rice_Brown_spot and vii. Rice_Leaf_smut. To improve the model's precision, the number of photos inside each image class is kept nearly constant. 2282 pictures were utilized to create the model. The ratio of training data to test data is maintained at 80:20.

3.4.2. TensorFlow Model creation

TensorFlow lite is an open-source framework for machine learning that can be executed on the device. The following are some of TensorFlow lite's important features:

```
dataset = tf.keras.preprocessing.image_dataset_from_directory(
    "image_data",
    shuffle = True,
    image_size = (IMAGE_SIZE, IMAGE_SIZE),
    batch_size = BATCH_SIZE
)
```

```
Found 2282 files belonging to 7 classes.
```

```
class_names = dataset.class_names
```

```
class_names
```

```
['Potato___Early_blight',
 'Potato___Late_blight',
 'Potato___healthy',
 'Rice_Bacterial_leaf_blight',
 'Rice_Brown_spot',
 'Rice_Healthy',
 'Rice_Leaf_smut']
```

Figure 16: Disease detection by TensorFlow

Since there is no round trip to the server, there is no latency. Internet connectivity is optional Minimized model size Low power consumption of the device no personal information leaves the device.

Multiplatform support like iOS, Android, Linux, and microcontroller Multiple programming languages, including Java, Swift, Objective C, C++, and Python, are supported. High performance with device hardware for app development is achieved by preparing an image classification model. Using the Tensorflow lite model creator library, a Tflite model with a custom data set was created. The model was developed using a proprietary dataset.

The model creator library simplifies the creation of a new model using a custom dataset. It employs transfer learning to decrease the required training time and amount of training data. The open-cv dependency is required to check the valid image format in the dataset; if any image is not in an acceptable format, it is removed from the dataset. This prevents the error from occurring if any of the picture formats are incorrect and model generation fails. The zip file contains the training data with labels. The Keras utils module extracts the zip dataset from the specified file location and places it in the temp folder for further processing. Now, the exact path to the root of the dataset has been prepared by concatenating the folder name. To eliminate invalid photos from the collection, the authorized image extension names (jpg, jpeg, and png) are extracted. The "check images" function examines the images in the entire dataset and deletes any faulty images that are discovered. Therefore, the remaining photos in the dataset are legitimate following this function call. The data loader module then loads data from the specified folder location. These data are now separated into train data and test data. The "image classifier" object invokes the "create" function to generate the TensorFlow model from "train data" This method produces the Tflite extension model.

3.4.3. Model education

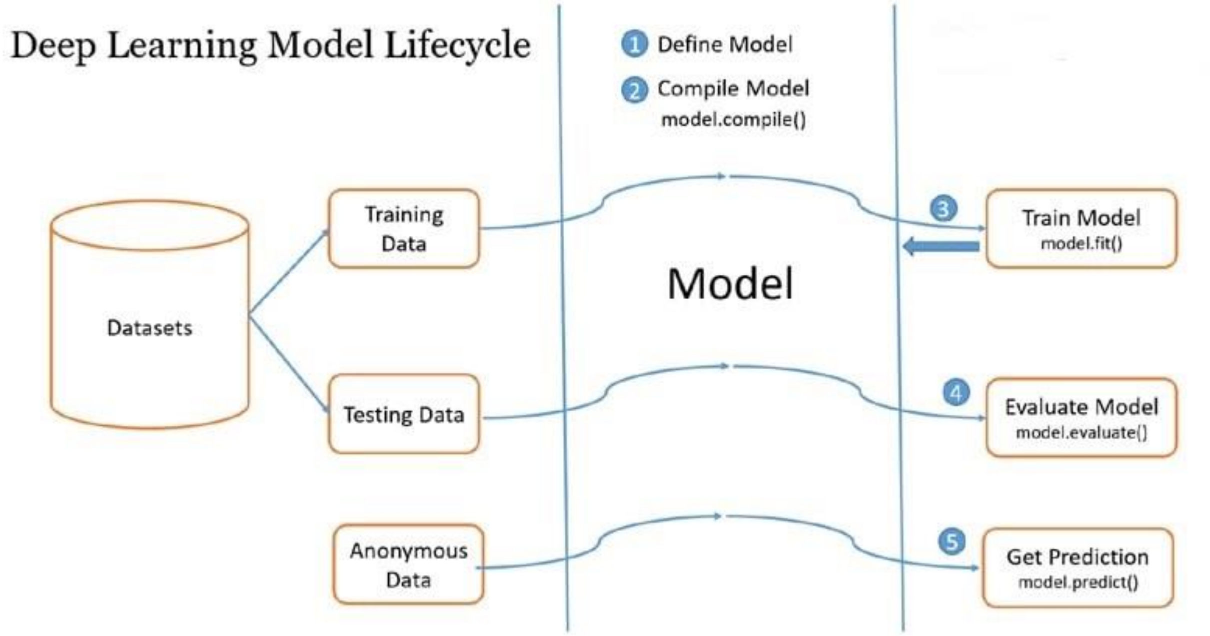


Figure 17: Deep Learning model lifecycle

Once the model instance is established, the data must be fitted. The entire process is time-consuming while the dataset gets trained. In general, the longer we train the model, the better its performance, but excessive training epochs run the danger of overfitting the model. Therefore, we must select the value of the training epochs with great care. To reduce the effect of overfitting the data set is further augmented.

Data augmentation takes the approach of generating additional training data from your existing examples by augmenting those using random transformations that yield believable-looking images. This helps expose the model to more aspects of the data and generalize better.

Data augmentation has been used by the following Keras preprocessing layers: tf.keras.layers.RandomFlip, tf.keras.layers.RandomRotation, and tf.keras.layers.RandomZoom.

The TensorFlow model parameters utilized internally during model training. As indicated in the figure above, the model employs seven label classes: Potato_Early-blight,Potato_Late_blight,Potato_healthy,Rice_Bacterial_leaf_blight, Rice_Brown_spot, Rice_Leaf_blast, Rice_Leaf_smut.. In addition, it displays the trainable and untrainable characteristics.

```
train_ds = train_ds.cache().shuffle(1000).prefetch(buffer_size=tf.data.AUTOTUNE)
val_ds = val_ds.cache().shuffle(1000).prefetch(buffer_size=tf.data.AUTOTUNE)
test_ds = test_ds.cache().shuffle(1000).prefetch(buffer_size=tf.data.AUTOTUNE)
```

```
resize_and_rescale = tf.keras.Sequential([
    layers.experimental.preprocessing.Resizing(IMAGE_SIZE, IMAGE_SIZE),
    layers.experimental.preprocessing.Rescaling(1.0/255)
])
```

```
data_augmentation = tf.keras.Sequential([
    layers.experimental.preprocessing.RandomFlip("horizontal_and_vertical"),
    layers.experimental.preprocessing.RandomRotation(0.2),
])
```

```
input_shape = (BATCH_SIZE, IMAGE_SIZE, IMAGE_SIZE, CHANNELS)
n_classes = 7
model = models.Sequential([
    resize_and_rescale,
    data_augmentation,
    layers.Conv2D(32,(3,3),activation='relu', input_shape=input_shape),
    layers.MaxPooling2D((2,2)),
    layers.Conv2D(64, kernel_size = (3,3), activation='relu'),
    layers.MaxPooling2D((2,2)),
    layers.Conv2D(64, kernel_size = (3,3), activation='relu'),
    layers.MaxPooling2D((2,2)),
    layers.Conv2D(64,(3,3),activation='relu'),
    layers.MaxPooling2D((2,2)),
    layers.Conv2D(64,(3,3),activation='relu'),
    layers.MaxPooling2D((2,2)),
    layers.Conv2D(64,(3,3),activation='relu'),
    layers.MaxPooling2D((2,2)),
    layers.Flatten(),
    layers.Dense(64, activation='relu'),
    layers.Dense(n_classes, activation='softmax'),

])

model.build(input_shape=input_shape)
```

Figure 18: TensorFlow model training process

3.4.4. Model training:

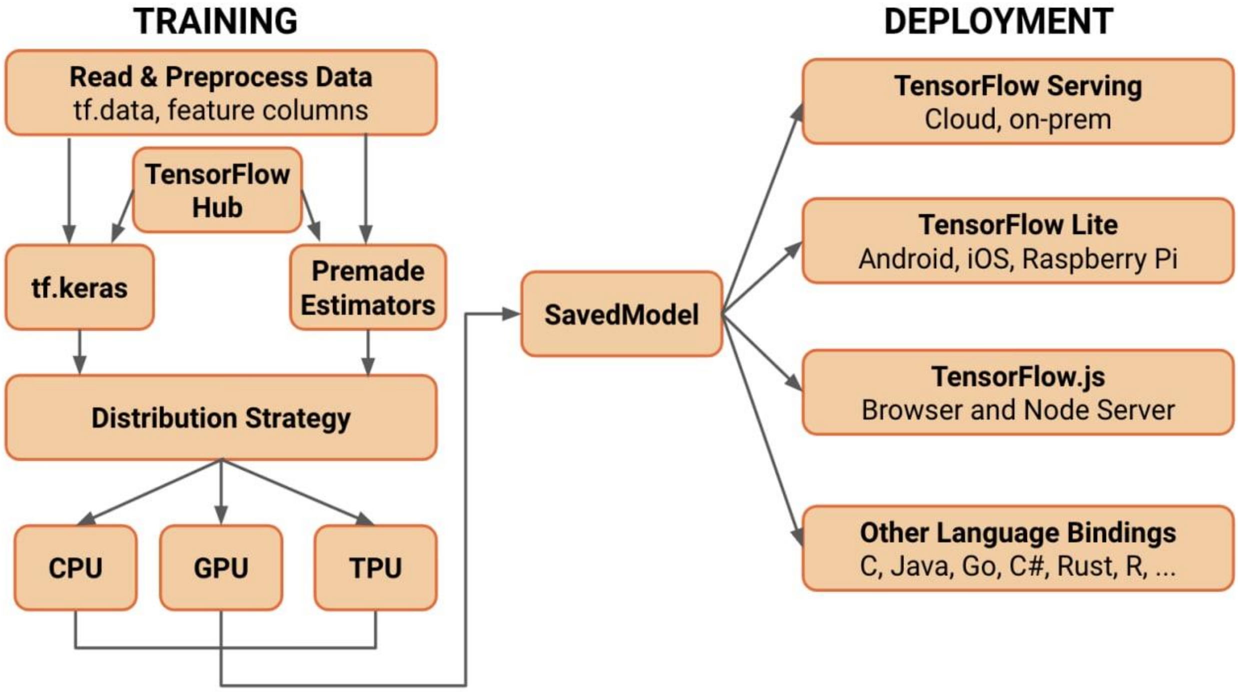


Figure 19: TensorFlow model training and deployment

After model education For this tutorial, choose the tf.keras.optimizers.Adam optimizer& tf.keras.losses. Sparse Categorical Cross entropy loss function. To view training and validation accuracy for each training epoch, pass the metrics argument to Model.compile. Then Train with the model for 50 epochs with the Keras Model.fit method:

```
model.compile(
optimizer = 'adam',
loss= tf.keras.losses.SparseCategoricalCrossentropy(from_logits= False),
metrics = ['accuracy']
)
```

```
history = model.fit (
    train_ds,
    epochs = EPOCHS,
    batch_size = BATCH_SIZE,
    verbose = 1,
    validation_data = val_ds
)
```

Figure 20: Model validation

3.4.5. Model evaluation

Now, the model is further examined with test data, and its accuracy and loss are evaluated. The model is exported using the "export" function, and the Tflite extension model is saved within the specified directory path. On the basis of an analysis of the model's accuracy metrics, adjustments can be made to improve the metric data. It displays the model's properties during training. The model was trained over the course of five iterations. The model is compact and 4 MB in size. This paradigm is used for development across several platforms.

```
loss, accuracy = model.evaluate(test_ds)
```

```
8/8 [==============================] - 6s 233ms/step - loss: 0.0365 - accuracy: 0.9883
```

```
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

loss = history.history['loss']
val_loss = history.history['val_loss']
```

Figure 21: Model evaluation

3.4.6. Tflite Model conversion

The Tflite extension model cannot be utilized directly in the android app development project. The TensorFlow convertor must be utilized to convert this model into a Tflite model. Then, the arguments are supplied to the "convert" function, which accepts all the necessary parameters and changes the model into a Tflite model. This ML model is subsequently utilized in the construction of an android app to detect potato and rice illnesses.

```
import os
model_version=max([int(i) for i in os.listdir("models/") + [0]])+1
model.save(f"../models/{model_version}")
```

```
INFO:tensorflow:Assets written to: ../models/1\assets
```

```
model.save('models/model1.h5')
```

```
import tensorflow as tf
model=tf.keras.models.load_model("model1.h5")
converter = tf.lite.TFLiteConverter.from_keras_model(model)
converter.experimental_new_converter = True
tflite_model = converter.convert()
open("converted_model1.tflite", "wb").write(tflite_model)
```

```
INFO:tensorflow:Assets written to: C:\Users\Aman\AppData\Local\Temp\tmp76jf2sur\assets
WARNING:absl:Buffer deduplication procedure will be skipped when flatbuffer library is not properly loaded
742056
```

Figure 22: Tflite Model conversion

While creating a new model or retraining an existing model with a custom dataset, this TensorFlow library internally uses several benefits from other dependent libraries, such as Keras, NumPy, and Matplotlib. This makes the library more versatile and usable for a variety of reasons. It also provides the ability to employ alternative algorithms for improved performance and precision. Now, the converted T model is used in the android app development project. APIs from the Tflite framework are used to interface with the model in order to detect rice and potato leaf disease. This consequence of the sickness is displayed in the app for the farmer. This model is lightweight and simple to incorporate into the application.

3.5. App development

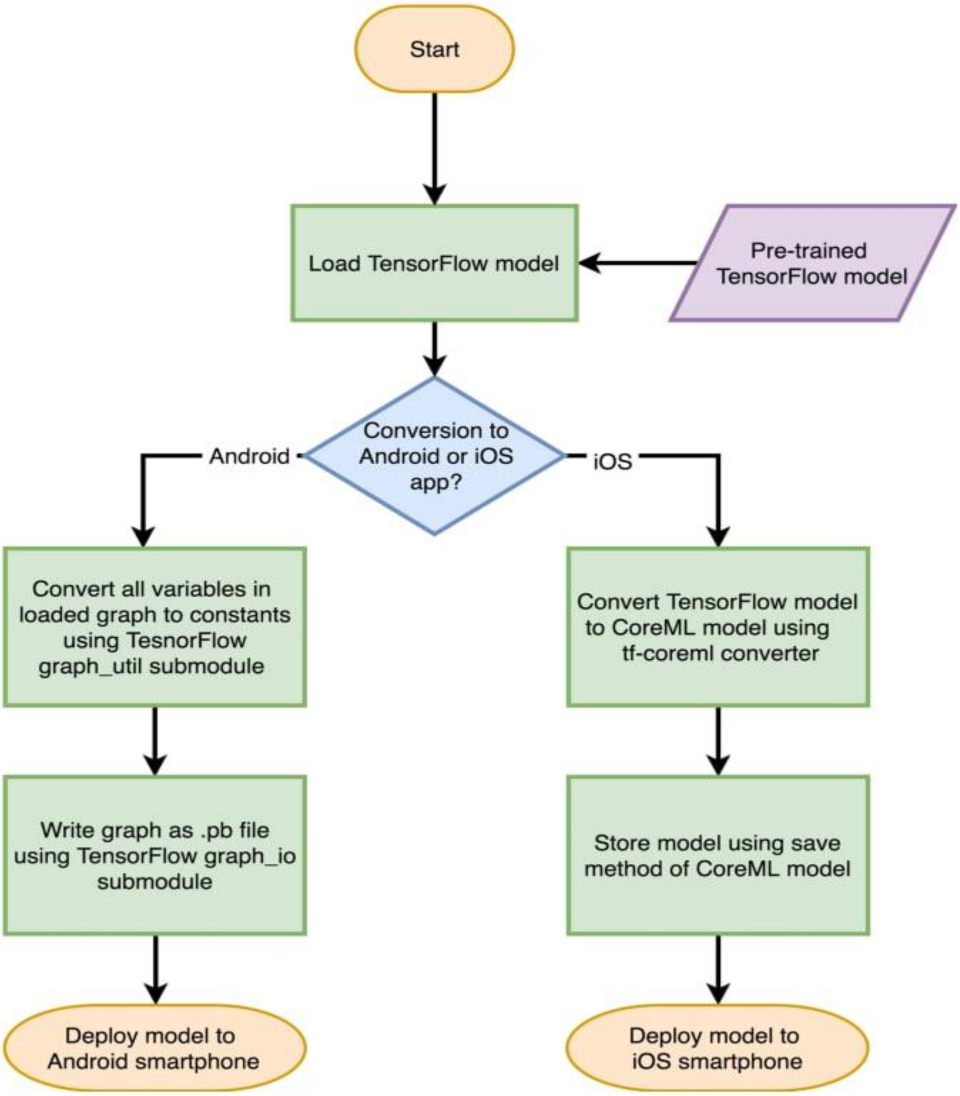


Figure 23: App development flowchart

Project Configuration This mobile application development is performed on a windows using the android IDE. This work was accomplished with the java programming language. Java is an open-source programming language for Android platform. The application is created primarily for android. The program uses a Core Data local database to store disease data locally.

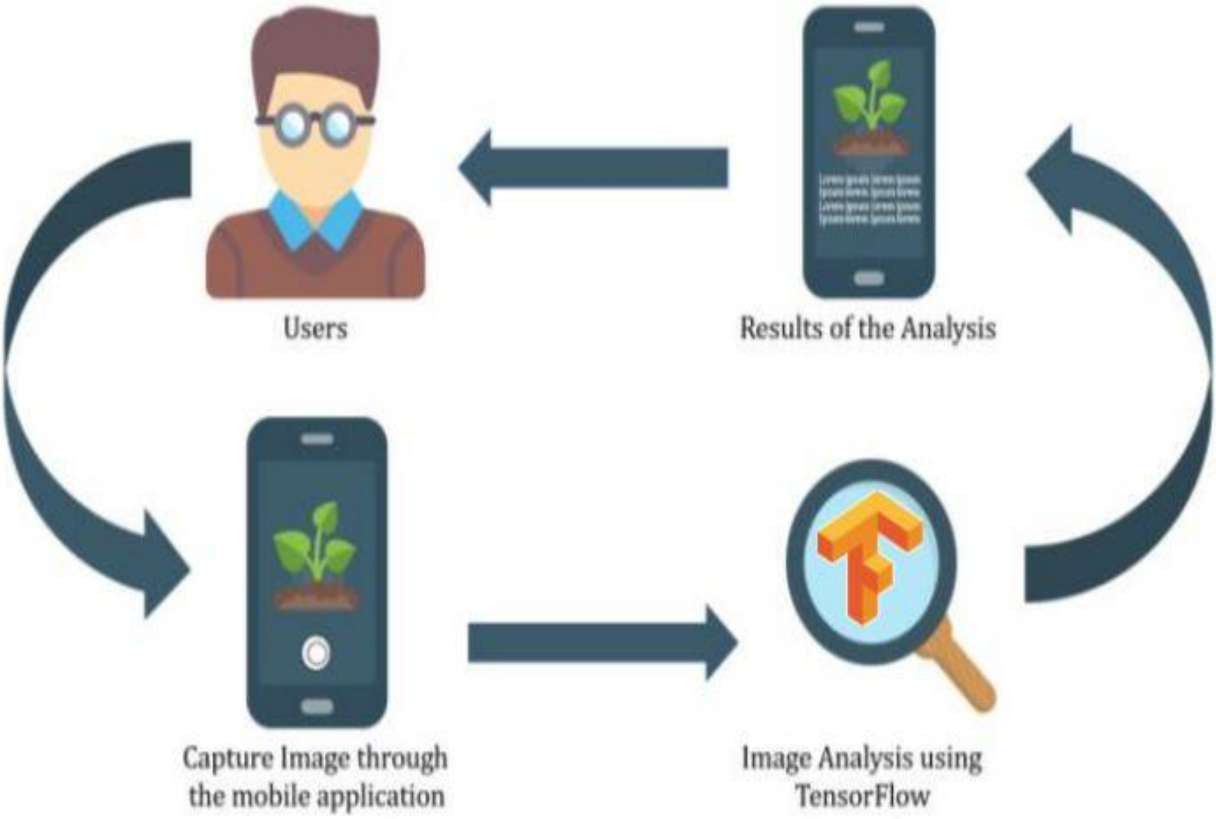


Figure 24: Conceptual framework for users

3.5.1. Architecture of applications:

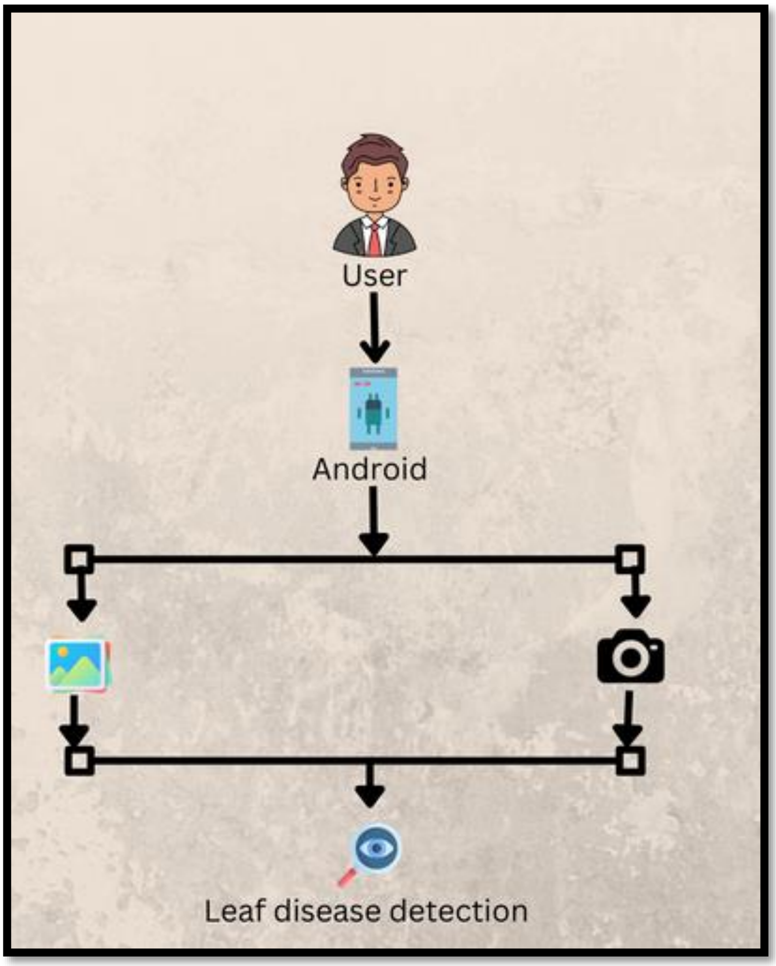


Figure 25: System architecture

This design pattern is comprised of the interactor, view, presenter, router, and entity layers. These five tiers have distinct individual responsibilities, in accordance with the idea of concern segregation. According to the principle of separation of concerns, each layer has its own responsibility, and no two layers may share a responsibility. This makes it simple to spoof the layers while constructing test cases. These layers are loosely coupled, and if necessary, any layer can be removed or altered at any time, making the application more scalable. According to this architecture, the view layer is responsible for rendering the UI components and preparing the screen for the user. This presenter manages all the functionality associated with the view that is visible to the user, such as accepting touches, button clicks, etc., and passing it on to the next required layer. The interactor layer manages the application's business logic, data manipulations, algorithms, etc. The router layer is responsible for app animation during navigation. The final entity layer binds data from the server or the local database and prepares the model utilized by the remainder of the application.

This study shows how important plant disease detection is now. This model was created using Deep Learning in Python. 20% images from the PlantVillage dataset were used to check the accuracy of this model. These pictures are for 7 different classes. 20% of each class are chosen at picked for testing. Some real-time pictures were also used. Those pictures were taken in the local environment. They do it not belong to any class that is present in dataset. But model gives us more than 99% accuracy on those images as well, by telling whether a leaf is healthy or unhealthy.

This is the app's home screen or landing screen. When an application is launched, farmers will see this screen. Figure 8 depicts the inspect disease screen, where the farmer picks the rice and potato disease image and then inspects the illness using the selected disease photos. When an image is not selected and the "Check Disease" button is clicked, the application will prompt the farmer to select the rice and potato image with a pop-up message. When a farmer selects an image and then clicks the "Check Disease" button, the software navigates to the next screen. On the subsequent screen, the farmer can view the disease details, if any, or the image of healthy rice and potato. Figure 9 represents the disease detail display. This screen displays a model forecast based on machine learning. The label of more confidence is displayed first, followed by the label of lesser confidence. These disease-related advice are also displayed on the same screen. This will assist the farmer in taking preventative measures against the disease. This increases crop productivity, and farmers will receive a substantial income from rice and potato cultivation. This "Save" button is located in the navigation bar's upper-right corner. When this button is selected, all crop details, including image and illness information, are saved to the device's local database. This will aid the farmer in reviewing the Disease History Module. This module displays the stored disease information. The statistics are retrieved from the local database of the device. On this screen, all historical disease data are displayed. By clicking on any row on this screen, the farmer can view the disease's specifics. These results will assist farmers in comprehending what types of diseases are occurring at what times. By examining the illness's past, farmers can use the appropriate pesticide to prevent the disease from returning to the land. This would save the farmer time and money. The farmer can remove the record at any time by sliding the screen to the left. A red delete button appears, which, when clicked helps to delete the disease images.

CHAPTER IV

RESULT

4.1. Image processing to detect Rice and Potato diseases

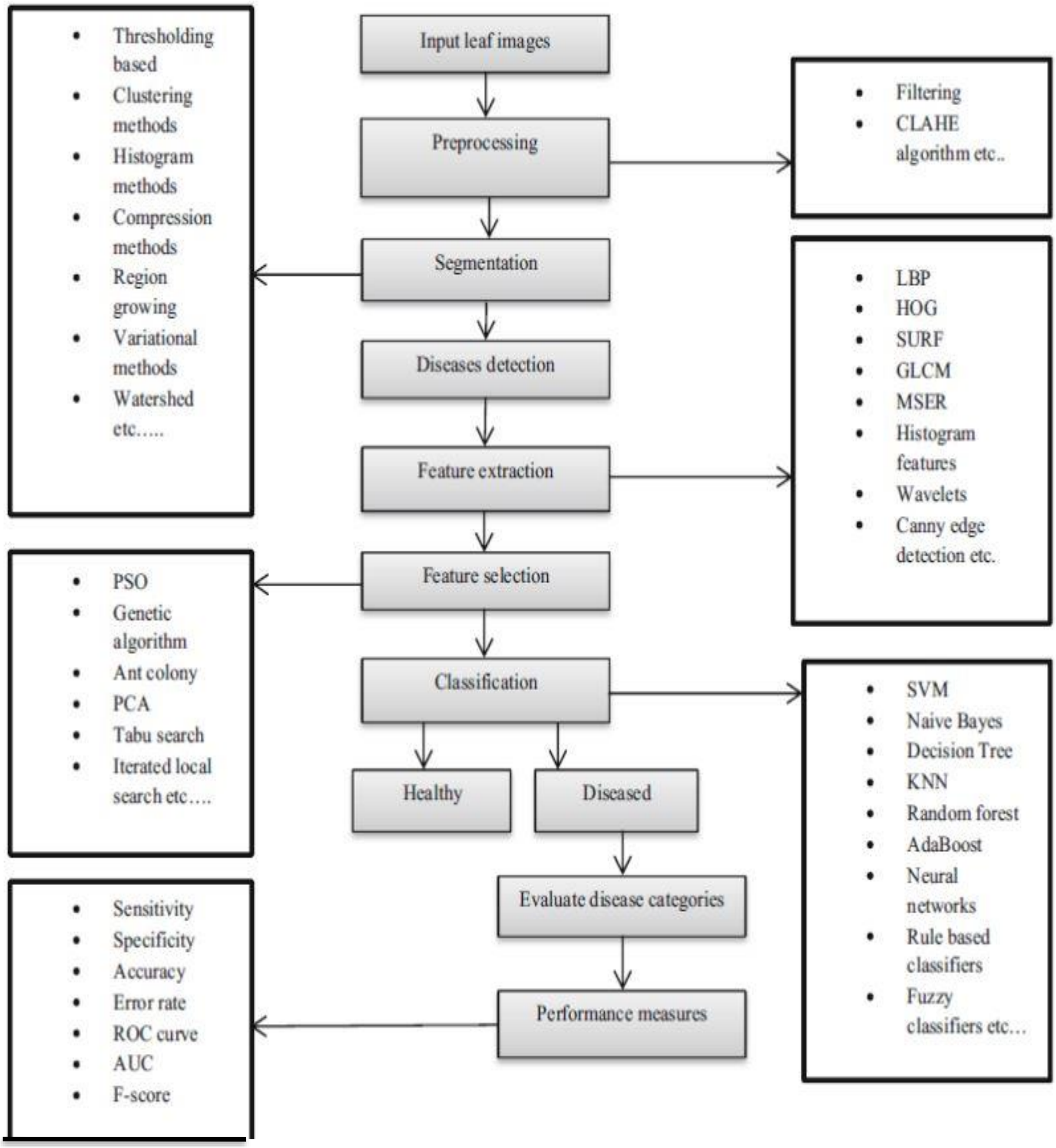


Figure 26: General structure for disease detection and classification of leaves by TensorFlow

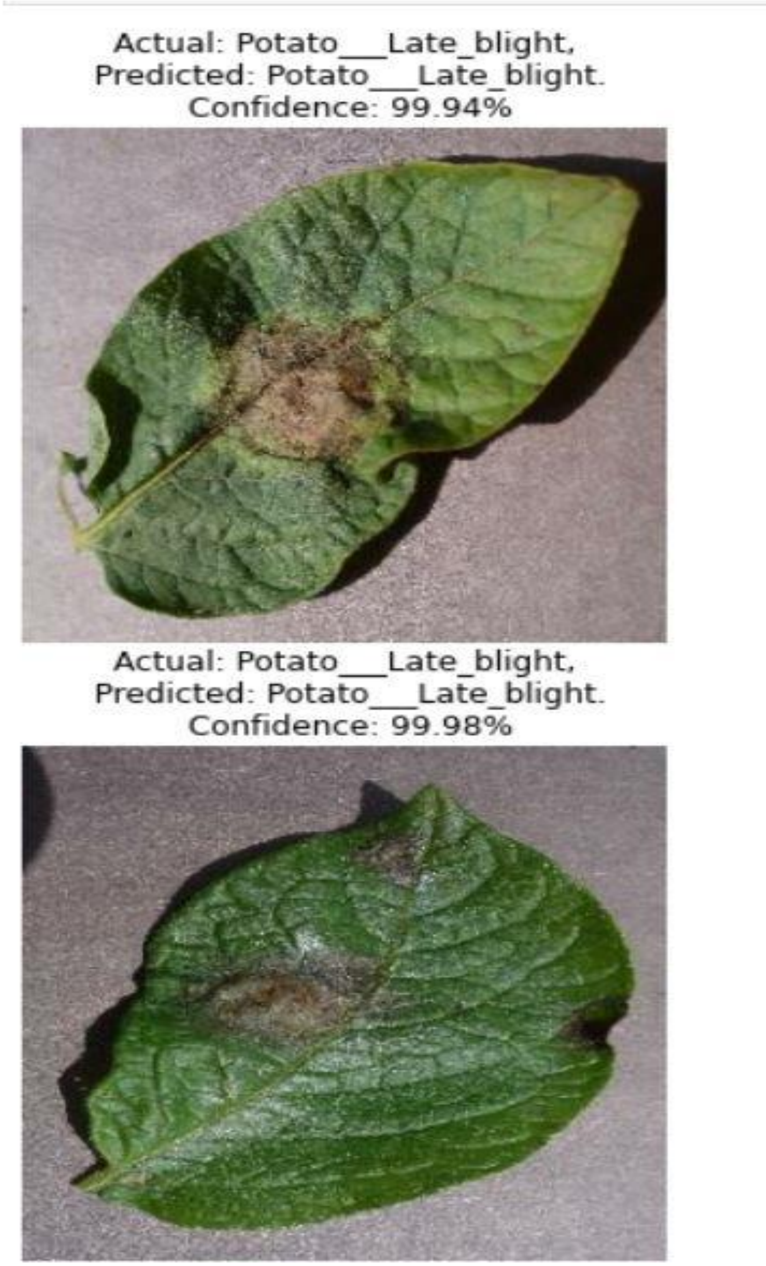


Figure 27: Disease image detection by Machine Learning

Figure 28: Disease image detection by Machine Learning

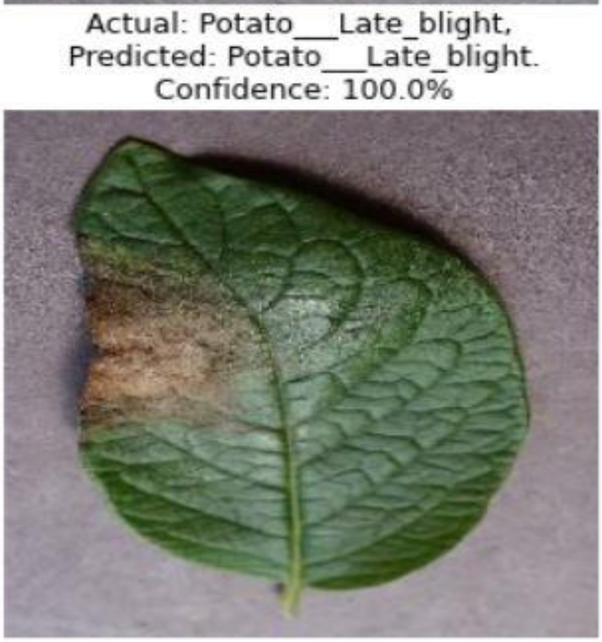


Figure 29: Late blight of potato, early blight of potato and rice smut disease detection with accuracy

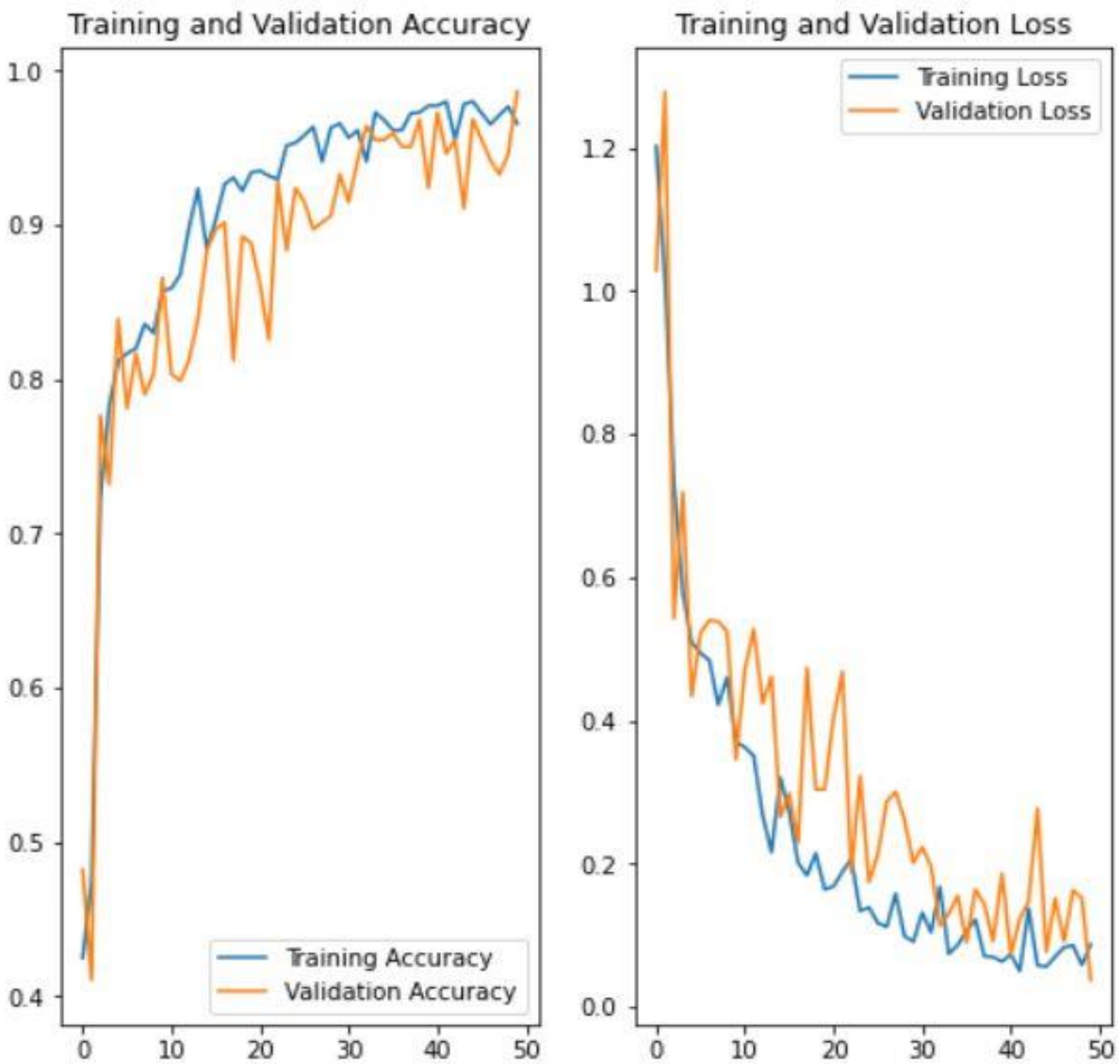


Figure 30: Training and validation accuracy and loss

Different types of diseases are detected using different machine learning techniques, but these approaches are mostly server-based where logic is implemented on the server side. We have written a program, which leverages the existing algorithms to prepare the ML model and embedded them on the mobile apps. First, the TensorFlow lite model was prepared using the TensorFlow open-source library. Now, this model is further converted into the CoreML model. The CoreML model is compatible with the android apps and is used in the development of the app. The ML model is successfully created using the TensorFlow framework. The accuracy of the model was 98%.

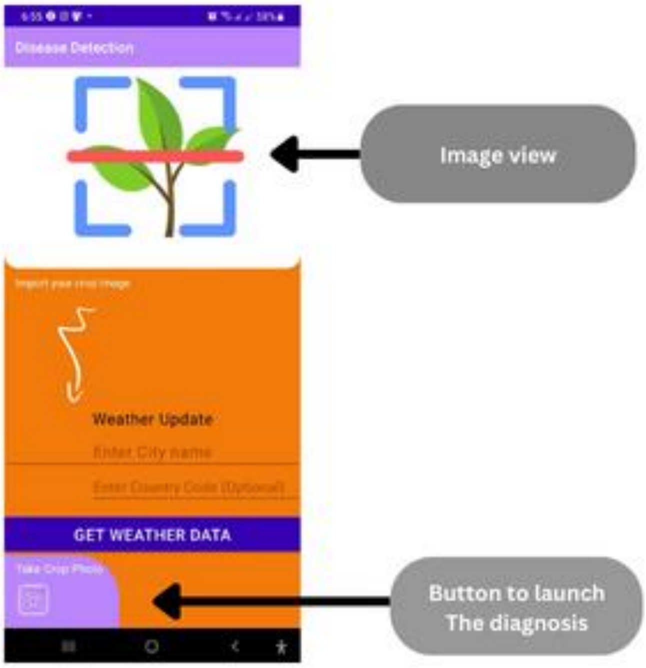


Figure 31: The app development common framework

The model detects the Potato_Early-blight,Potato_Late_blight, Potato_healthy, Rice_Bacterial_leaf_blight, Rice_Brown_spot, Rice_Healthy, Rice_Leaf_smut. The model also predicted healthy leaves. Using the converted ML model, an android app was successfully developed which detects the cotton plant diseases. The TensorFlow library internally used the neural network algorithm to train the image classification model. It works for the training and validation accuracy are close to each other , which indicates that the model is balanced and works more accurately.

4.2. Rice blast

Rice blast caused by a fungus named *Magnaporthe grisea* causes lesions to form on leaves, stems, peduncles, panicles and even seeds. It is so destructive that it ranked top position as the most important plant diseases among them (TeBeest *et al*., 2012).

4.2.1. Symptoms and signs of affected Rice leaves

The symptoms on the leaves can vary depending on the environmental conditions, the age of the plant, and the resistance levels of the host cultivars. Lesions on susceptible cultivars may appear gray-green and water-soaked at first, with a darker green border, and they can quickly grow to several centimeters in length. On susceptible cultivars, older lesions frequently develop a light tan color with necrotic borders. Lesions on resistant cultivars are often small (1-2 mm) and brown to dark brown in color (Wrather *et al.*, 2009).

4.2.2. Rice blast disease management

Rice farmers are recommended to utilize practical methods that are part of cultural initiatives to control this disease. Crop rotation is one straightforward and efficient method that is strongly advised for the simple reason that it offers a mechanism for separating viable spores in crop leftovers from the sprouting seedlings. Rice farmers are recommended to think about fertilizing each of the many cultivars appropriately as a second strategy. The excessive application of nitrogen fertilizers, as demonstrated above, increases the amount of rice blast in the fields yet frequently has no effect on yields. Maintaining an appropriate flood level for the rice to flourish is a third approach that is frequently disregarded or challenging to use in some areas. In fields or some areas, rice blast is known to be particularly severe. As a result, rice blast is frequently severe in fields that were not rotated, have inadequate irrigation, and have excessive fertilization. Finally, it is always advised to plant using high-quality, disease-free seed since infected seeds left on the soil's surface act as an inoculum for epidemics (TeBeest *et al*, 2012).

4.2.3. Rice leaf smut

Rice leaf smut disease caused by *Ustilaginoidea virens* is an emerging threat to rice cultivation worldwide due to its heinous effects on grain yield and quality. During the Kharif season of 2016, a roving survey was conducted in the state of Karnataka, India, and it found that the severity of the false smut disease ranged from 4.44 to 17.22%. In addition, the pathogenicity and morphometric diversity of 15 distinct pathogen isolates, each of which came from a different habitat, were investigated. The most virulent strain, Uv-Gvt, was chosen from the 15 strains that were investigated for whole genome sequencing on an Illumina NextSeq 500 platform utilizing 2 x 150 bp sequencing chemistry (Pramesh D, 2020).

4.2.4. Rice false smut disease management

The application of chemical pesticides is by far the most prevalent strategy for the management of plant diseases. It is likely well-liked by farmers because it is simple to obtain and effective in a short amount of time. Fungicides are the primary tool utilized in the management of rice false smut. They are, however, detrimental to the environment and raise the expense of cultivation, and as a result, their use is strongly prohibited whenever it is at all possible. Because of this, it need to be utilized prudently as a preventative step, but not as a therapeutic one. The timing of the application of fungicides as well as the dose that is used are both essential factors in disease control. When the correct timing of the application of the fungicide is not done or when an insufficient concentration of the material is applied, crop loss is prevalent (Baite *et al.*, 2021).

4.2.5. Rice bacterial leaf blight disease management

Bacterial blight is one of the most serious diseases of rice. The earlier the disease occurs, the higher the yield loss.Yield loss due to bacterial blight can be as much as 70% when susceptible varieties are grown, in environments favorable to the disease. When plants are infected at booting stage, bacterial blight does not affect yield but results in poor quality grains and a high proportion of broken kernels. Planting resistant varieties has been proven to be the most efficient, most reliable, and cheapest way to control bacterial blight.

4.2.6. Rice brown spot disease management

Brown spot is a fungal disease that infects the coleoptile, leaves, leaf sheath, panicle branches, glumes, and spikelets. Improving soil fertility is the first step in managing brown spotIts most observable damage is the numerous big spots on the leaves which can kill the whole leaf. When infection occurs in the seed, unfilled grains or spotted or discolored seeds are formed.

4.2.7. Potato early blight

One of the most common leaf diseases of potatoes is early blight. It is thought to be a disease that is hard to control. Recent studies in Colorado have shown that fungicides can be used to control early blight if they are applied before the fungus makes spores and spreads further in the field (Venette *et al*., 1970).

4.2.8. Potato early blight disease management

Early blight can be kept to a minimum by making sure the plants have the best growing conditions, such as the right amount of fertilizer, water, and control of other pests. Grow later maturing, longer season varieties. Fungicides should only be used when a disease starts early enough to cause economic loss (Nuñez *et al*., 2019) .

4.2.9. Potato late blight

Late blight is caused by an oomycete pathogen called Phytophthora infestans. Potato is the main host for this pathogen, but P. infestans can also infect tomatoes, petunias, and hairy nightshade, which are all solanaceous plants. These infected pathogen can spread the disease to potatoes (Robinson *et al*., 2022)**.**

Potato late blight disease management

Late blight can be control by getting rid of cull piles and volunteer potatoes, harvesting and storing potatoes the right way, and using fungicides when needed. It is important to let air flow so that the leaves can dry each day. When conditions aren't ideal, overhead sprinkler irrigation can make late blight worse. In Tule Lake of USA, solid set sprinklers make conditions better for late blight to grow, but nighttime irrigation should not recommended (Nuñez *et al*., 2019).

CHAPTER V

DISCUSSION

A research conducted during 1979-81 in Bangladesh found 20 rice diseases, including two viral, two bacterial, 13 fungal and one micronutrient lacking difficulty. Some diseases are classified as major including bacterial blight, bacterial leaf streak, sheath blight, brown spot, stem rot and leaf scald. It is evident that periodically a disease outbreak or epidemic occurred in the country such as Rice blast. Under critical epidemic situation around 98% yield loss occur due to spread of blast. Field survey indicated that 65.4% yield loss from severely infected field with the disease. Another major rice disease named false smut disease has become emerging in Bangladesh during T. Aman season for the last five years (Miah *et al*., 2008).

However, today's advancements in machine learning algorithms, a group of analytical techniques that automate the process of building models and iteratively learn from data to gain insights without explicitly programming, offer more effective and powerful tools to not only identify genes/proteins involved in plant-pathogen interactions but also to classify plant diseases from images of infected leaves (Xin Yang *et al.*, 2019).

This research shows that how significant to plant disease detection now. This model created using Machine Learning TensorFlow of Python framework. About 20% plant images collected from the PlantVillage dataset (an online open source database for plant disease images) to check the accuracy of the model framework. These disease affected leaves. These pictures are for seven different classes. 20% of each class are chosen at picked for testing. Some real time images were also used. These images are taken in the local environment. The examined model gives us more than 99% accuracy on those images as well, by tellling whether a leaf is healthy or unhealthy. The investigation was conducted utilizing a collection of 2282 open source images and 100 real time photographs from experimental conditions and the actual surroundings. The framework attained an overall testing accuracy of 99% on datasets from collected plant disease affected leaves. The accuracy of CNN model suggests that it is ideally suited for automatic plant detection and diagnosis. Finally this model output can integrated with the android app using android studio extension to detect plant diseases by mobile set. Despite being trained on a dataset from Plant Village (an open source disease dataset platform) including only 7 classes, this system is able to determine whether a plant has a disease or not because symptoms are similar across all plant species. This app Can detect Potato_Early_blight, Potato_Late_blight, Potato_healthy, Rice_Leaf_blast, Rice_Bacterial_leaf_blight, Rice_Brown_spot, Rice_Leaf_smut. Then the database should connected with the Tflite model. The project to construct an android app cannot directly use the Tflite extension model. This model has to be transformed into a Tflite model using the TensorFlow convertor. The "convert" function then receives the arguments and converts the model into a Tflite model by accepting all required parameters. This machine learning model is then used to create an android app that can identify infections in rice and potatoes.

While creating a new model or retraining an existing model with a custom dataset, this TensorFlow library internally uses several benefits from other dependent libraries, such as Keras, NumPy, and Matplotlib. As a result, the library is more adaptable and useful for a range of purposes. It also provides the ability to employ alternative algorithms for improved result. The framework uses a core Data local database to store disease data locally.

CHAPTER VI

SUMMARY AND CONCLUSION

The present research work employed the capabilities of deep learning to develop an autonomous plant disease detection system. This method is built on a basic categorization process that takes advantage of CNN's feature extraction capabilities. Finally, the model uses fully connected layers for prediction. The investigation was conducted utilizing a collection of 2282 publicly accessible photos and 10 photographs from experimental conditions and the actual surroundings. The system attained an overall testing accuracy of 99% on datasets available to the public and performed well on photos of Plant Village dataset. The accuracy of CNN suggests that it is ideally suited for automatic plant detection and diagnosis. This method can be implemented with android app to identify plant diseases in agricultural areas in real time.

Despite being trained on a dataset from Plant Village (an open source disease dataset platform) including only 7 classes, this system is able to determine whether a plant has a disease or not because symptoms are similar across all plant species.

This app can detect, Potato_Early_blight, Potato_Late_blight, Potato_healthy, Rice_Bacterial_leaf_blight, Rice_Leaf_blast, Rice_Brown_spot, Rice_Leaf_smut.

It is possible to increase the model's precision by utilizing a variety of distinct methods, including modifying the by introducing more diverse photos to the training dataset, modifying a few input parameters and utilizing algorithms. In the future, this system will adopt top 10 crop diseases detection such as Rice, potato, Tomato, Onion and many more. The constructed app need to be uploaded in app store and to make it available for the farmers or crop growers for quick detection of disease and it’s solution.

CHAPTER VII

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