IMPLEMENTATION OF AN IMPROVED CNN MODEL FOR DETECTION AND PREVENTION OF PLANT DISEASES USING DEEP LEARNING IN AGRICULTURE

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APPROVAL

This Researched Based Project titled **"Implementation of an Improved CNN Model for Detection and Prevention of Plant Diseases Using Deep Learning in Agriculture"**, submitted by Md. Mahfuzur Rahman, ID No: 191-15-12378, Arko Roy Badhon, ID No: 191-15-12399 and Md. Zahirul Islam Mehadi, ID No: 191-15-12223 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on *24 january 2023*.

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We hereby declare that, this project has been done by us under the supervision of **Afsara Tasneem Misha, Lecturer** Department of CSE Daffodil International University. We also declare that neither this Research work nor any part of this study has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

Plant growth is a crucial requirement for framers since it provides a pathway for their livelihood. Plant damage and growth are correlated with one another. Healthy crop cultivation is a priority for framers. It has long been a source of worry that plant diseases all around the world annually cause huge crop output losses. To prevent crop damage from pathogen infection during crop development, harvesting, and post-harvest processing of the produce, new technology for prompt plant disease detection must be developed and used. This will increase crop yield and ensure the sustainability of agriculture. among the many methods for identifying plant disease. However, appropriate application of such procedures is highly difficult because it necessitates expensive equipment and demands a deep understanding of technology to determine and resolve unusual errors or lab results. The use of detecting plant disease has been thoroughly illustrated in this study, along with its benefits and drawbacks. For tracking and evaluating the crop variance plant disease based on images identification is one of the most important precision agricultural tasks. Prior to recently, the majority photo processing techniques methods some of which still are making use of what some have referred to as ML architectures. In the fields of image recognition and pattern analysis, the DL network is quickly taking the lead as the standard. However, there are few studies on its use in identifying diseases in plant leaves. Software program tells us the identity of a species of plants, its confidence level, and the treatment that may be used to treat it. Since the suggested technique combines statistical ML and picture processing algorithms, it is substantially less costly and takes less time to predict than other DL based systems. The proposed system's accuracy, which is based on Python, is around 90% up. We used the CNN model to build the potato model where accuracy is 98%. We used the VGG-19 model with the accuracy 99% to build the tomato model . Again, we used the CNN model to build the rice model and the accuracy is 93%.

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CHAPTER 1
INTRODUCTION

1.1 Introduction

Food is in higher demand due to rising population. Plant diseases made it challenging to fulfill the demand. There are numerous fertilizers available to boost productivity and identify diseases. However, it can be challenging to identify the current illness and provide the best treatment for it. Therefore, Our goal is to create a model system that will diagnose a sickness and provide the best treatment, helping to boost productivity and meet rising demand.

The issue of effective disease prevention is strongly related to the topic of sustainable farming. Overuse of pesticides may cause diseases to acquire enduring resistance, which significantly reduces their ability to fight back [1]. precise and on time among the fundamental elements of accuracy Plant disease detection is part of agriculture. In order to attain wholesome production in this evolving climate change, it is crucial to reduce unnecessary loss of finances and other assets. Suitable and timely illness Diagnosis and timely treatment are more important now than ever significant. There are various methods for identifying diseases in plants [2]. When a disease has no outward signs or when its effects become apparent It is too late to act; a thorough investigation is necessary. However, as most diseases have minimal visual signs, an eye exam conducted by a qualified professional is the main procedure utilized in practice for disease detection. A plant pathologist must have outstanding observational abilities to recognize distinctive signs and arrive at accurate disease diagnoses. Variations in the symptoms sick plants exhibit might lead to a misdiagnosis since novice landscapers and amateur plant pathologists may have more difficulty identifying it. Amateurs who are new to gardening and skilled experts as a confirmation mechanism for detecting diseases may benefit greatly from an automatic system created by using the plant's outward appearance and visible symptoms, to discover plant illnesses [3]. Vast amount of literature and results, it was discovered that the majority of times, intensity measurements by image analysis did not closely match actual values. The great majority of research that have been published in the area of measuring plant disease intensity and detecting it have not provided actual values for reliability comparison.

1.2 Motivation

Around the world, crop diseases have an impact on crop yields. Farmers must possess specialized knowledge and rigorous training in order to identify the early signs of plant illness and take prompt action to stop the disease's progress. In addition to promoting economic growth, disease control can also assist combat hunger, poverty, and the harmful effects of chemical fertilizers on the environment [4]. The main causes of plant diseases are pathogens and environmental factors. The aim of this project is to automate the cognitive process of visual inspection-based detection and identification. Since most diseases are mirrored on the leaves, the availability of photographs of the plant or various plant components makes this possible. In Bangladesh, agriculture is the main industry. In terms of global agricultural output, Bangladesh comes in fourth. Farmers in Bangladesh grow a wide range of different crops [5]. The production of crops is influenced by a number of variables, including the climate, the soil, various diseases, etc. The only method currently used to identify plant diseases is by naked-eye inspection., which demands additional manpower, adequately outfitted labs, pricey gadgets, etc. Inadequate disease diagnosis can also result in inadequate application of pesticides, which can reduce a crop's capacity for self-defense and result in the growth of long-term disease opposition. By observing the infection on the plant's leaves, the plant disease can be identified as illness-detection leaves.

1.3 Rationale of the Study

Plant disease detection has previously been the subject of a lot of research. But in our country so, far no such work has been implemented in any website or app. Around the world, plant viruses are known to significantly reduce crop productivity, plant quality, and plant-based goods. They present a special concern because they are challenging to find and distinguish. But in our country there haven't any fully satisfied webserver. The foundation of Bangladesh's economy is agriculture. Due to a lack of information and experience, our generation no longer practices traditional farming methods. By automating the procedures involved, technological advancements open the door for a shift from conventional farming practices to smart agriculture. Current agricultural issues include soil nutrient depletion, pest-caused diseases that reduce output, irrigation issues, soil erosion, a lack of storage facilities, a lack of high-quality seeds, a lack of transportation, bad marketing, etc. The prediction of illnesses continues to be one of the biggest issues in agriculture that have to be resolved. The conventional method of farming relies on visual inspection to identify diseases, which requires expertise and experience to manage.

1.4 Research Questions

This research-based project has research questions. We selected some target questions and below is the solutions of these questions -

A. How many crops are implemented in this Project?
    - Four crops are implemented
B. How many diseases are implemented in this project?
    - around six diseases are implemented
C. Is it possible to add more crops and diseases?
    - Yes, in future more crops and diseases are can be implemented
D. Which datasets are used to build this project?
    - plant village dataset are used

1.5 Expected Output

Through data patterns, we have attempted to demonstrate the scope of the plant disease issue. We thus applied the ML model. It is used to calculate the number as a percentage and to submit an application. This study's target webpage is in –

- To create a system that can reliably identify crop disease and pest.
- Establish a pesticide database for the appropriate disease and pest.
- To offer treatment for the disease that has been identified.
- Our website will provide the upazila-based agricultural extension office's address.
- Our website will provide the address of pesticide dealers.
- To assist the farmers, we shall appoint one local representative.
- We'll strive to offer assistance via live chat every day of the week.

- Growth stunting: Plant diseases can often be identified by their presence in plants.
- Spots on leaves – Infections can result in patches (black spot) on leaves.
- Areas of decay: In some places, leaves can rot and decompose.
- Growths - the plant may develop strange lumps and growths.
- Pest presence - If pests are found close to a plant crop, infection has probably already taken place.

1.6 Project Management and Finance

This is a research-based project so it has three parts of working. They are Web Programming, Algorithms built with machine learning and report writing. All tasks are divided into team members. To successfully build this project, there are several investments needed. Because this is a web-based project so it needs domain and hosting. Which are made cost for this project. This cost is totally divided into three parts as our team member number is three.

1.7 Report Layout

This chapter covers the introduction, including the detection of plant diseases, as well as the reasons for conducting the study, its objectives, and its results. The format of the report will come next. In chapter 2, we will talk about the history of our research topic.
We will talk about our study's research methodology in chapter 3.
We will talk about testing and implementation in chapter 4.
We will talk about the design specification in chapter 5.
We will talk about the result discussion in chapter 6.
We will talk about the conclusion and future in chapter 7.

CHAPTER 2
BACKGROUND

2.1 Introduction

Many studies with the plant have been conducted prior to this. Either supervised learning or unsupervised learning can be used in machine learning. Using a collection of captioned images of ill pairs, the system is trained and instructed using supervised learning. That information has previously been correctly classified as having an illness or not. The accuracy of machine learning increases with dataset size. Machine learning and traditional classifier techniques to classification are the two main methods used in real-world applications. A neural network classifier in machine learning employs a number of cognitive processing steps that are organized in layers and in a pyramid. These layers are then used for feature learning, analysis, and pattern categorization. The database that is downloaded from the Internet is correctly segmented, the various plant species are named and identified to create a proper database, and then a test database is generated that contains a variety of plant diseases is used to assess the project's accuracy and confidence level. The output will be predicted with the highest level of accuracy after our classifier has been trained using training data.

2.2 Related Works

Investigated the spectral properties of wheat and showed how to use the RELIEF-F algorithm to create new spectral indices (NSIs). This approach did not include routine crop inspections [6]. A method that describes the creation and evaluation of an aerial system for hyperspectral digital photography for applications in distant perception. Four high-resolution CCD cameras make up the system. The expense of maintaining this system is high [7]. For the Canopy spectral properties of wheat with an aphid infestation, A methodical approach, although this approach required time-consuming calculations, ML methods for diagnosing rust on leaves illness along with an analysis of size of the training sample and the illness symptoms' impact on estimation methods. The effectiveness of GPR, v-SVR, and PLSR is compared to that of PRI and NBNDVI in this study. Complex spectra are produced by many illness symptoms in combo at different disease severity levels, which lower the accuracy of PRI and NBNDVI while having no detrimental effects on the capabilities. The accuracy of the GPR is higher than that of other techniques because of its performance with a smaller training data set [8]. To determine the location of the disease's lesion, P. Revathi, et al. suggested two phases. The proposed HPCCDD Algorithm is used for image analysis and disease classification after segmentation using the Edge detection technique. In order to identify illness spots, this research developed based on RGB features algorithms where in the collected images are initially processed before picture separation in color is performed. Using the Sobel and Canny filter, the edge characteristics are retrieved to locate the illness areas [9]. A demonstration of the application in the use of image fusion process of identifying plant maladies. The spectrums of the visible (VNIR) and (SWIR) were used in this investigation. The methodology k-means method at broad frequencies was employed by the authors for the segmentation of leaves. They have introduced a new method for removing grids with the aim of removing the grid from hyperspectral photos. The authors' overall spectrum accuracy was 93%, with an accuracy of 83% for their greenery indicators in the spectral region of VNIR. However, the proposed method had a higher accuracy, it required use a multispectral camera with 259 spectral bands, which made the remedy is very pricey [10]. Developed the Blight to microorganism detection System for the Blackberry Plant, considering traits like color, edges, correlation, entropy, variance, uniformity, and standard deviation etc. The authors divided the area of interest in utilizing separation to capture and chop the picture. The edges of the photo were extracted using Canny edge detector. The degree of plant disease may now be exactly predicted by the authors' technique [11].

2.3 Comparative Analysis and Summary

SVM-based Multiple Classifier System for Recognition of Wheat Leaf Diseases, color features are encoded in RGB to HIS by using GLCM, and form parameters are seven invariant moments. They employed an SVM classifier with MCS, used for offline disease detection in wheat plants. Illustrates how different plant diseases can be classified and identified. Because it saves time, money, and effort, a machine learning-based recognition system will prove to be very advantageous for the Indian economy. The technique recommended in this for feature set extraction is the color co-occurrence method. To automatically identify diseases in leaves, neural networks are used. While needing less computational labor, the recommended method can significantly help with the accurate detection of leaves and looks to be a critical strategy in cases of steam and root infections [12]. They used the appropriate methods to incorporate all the hybrid aspects of a leaf's color, texture, and shape. PlantVillage is an online platform that focuses on crop health and crop illnesses. It is a tool for crop health. Experts in plant pathology wrote the text, which accurately reflects that the data was taken from academic publications [13]. They are used in conjunction with various picture preprocessing techniques to improve feature extraction. By using the appropriate management technique’s such the use of fungicides, genetic disorder harsh chemicals, and chemical sprays for control methods, one can acquire advance warning signs of illness and plant health. This could improve productivity and aid in the management of diseases [14]. The paper's authors [15] emphasize the necessity of developing a quick, inexpensive, and trustworthy health-monitoring sensor that aids in agricultural advancements. Several image processing techniques for identifying plant diseases in their study. Authors looked into the ability to identify plant sickness using color and textural attributes. They evaluated their algorithms using the 95 RGB image database. The features obtained for characterization included the GLCM characteristics, the photo’s average and standard deviations after applying the Gaussian filter, as well as the RGB and YCbCr means and standard deviations. For identification, the support vector machine predictor was employed. [16].

2.4 Scope of the Problem

If anyone can catch the real problem then it's not much complicated to finds out the scope of that problem. Because if anyone learns how to find the scopes of a problem then the problem can become a benefit for him. Problem of Crop disease prediction and finding its complicated curing solutions make a perfect system which will have benefited a whole nation or a country. This is also useful for technicians and agriculturists to develop a better system with better environment (community) for the farmers. Which is connected to the farmers and experts.

2.5 Challenges

Actually, it is very hard to complete a research-based project without challenges. This project is not different from that. To build this project there are various challenges. First of all, algorithm and dataset matching is the first challenge of this project. datasets are organized in different ways to gain better accuracy. Because all types of datasets are not perfectly working with this project's algorithm. Another challenge is to implement algorithms with this web application.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Research Subject and Instrumentation

With this essay, we suggest a brand-new classification a plan for plant disease identification. The suggested mechanism, as depicted fig 1, will have the ability to identify and categorize six different classes, includes bacterial leaf blight, healthy, leaf blast, leaf scald, and thin brown spot. One of the few systems in the existing literature that can categorize 6 different types is the one proposed. Most articles in the currently published literature have among 3-5 classifications. The photos will endure preprocessing stages where they will be subjected to background removal, scaling, and augmentation in the suggested deep CNN acquisition attempting to learn the technique. To make the dataset bigger, data augmentation is also done. Despite the fact that The writers' failure to discuss the possible difficulties with overfitting, which were discussed in the literature review, the bulk of articles as in available writings employ tiny information and it can result in overfitting. We employ, data augmentation in this work, whereby merely makes a few little adjustments to the source photographs to create fresh, new images. Translation, scale-in/scale-out, and rotation are examples of the subtle adjustments. Following that, In order to get the features, VGG19 and VGG16 are used. The diminished feature is carried out when flattening, VGG19 has trained model, compact layers. The classification is carried out using the VGG19's final layers. The following metrics are used to assess our suggested strategy: accuracy, precision, and F1-measure, recall.

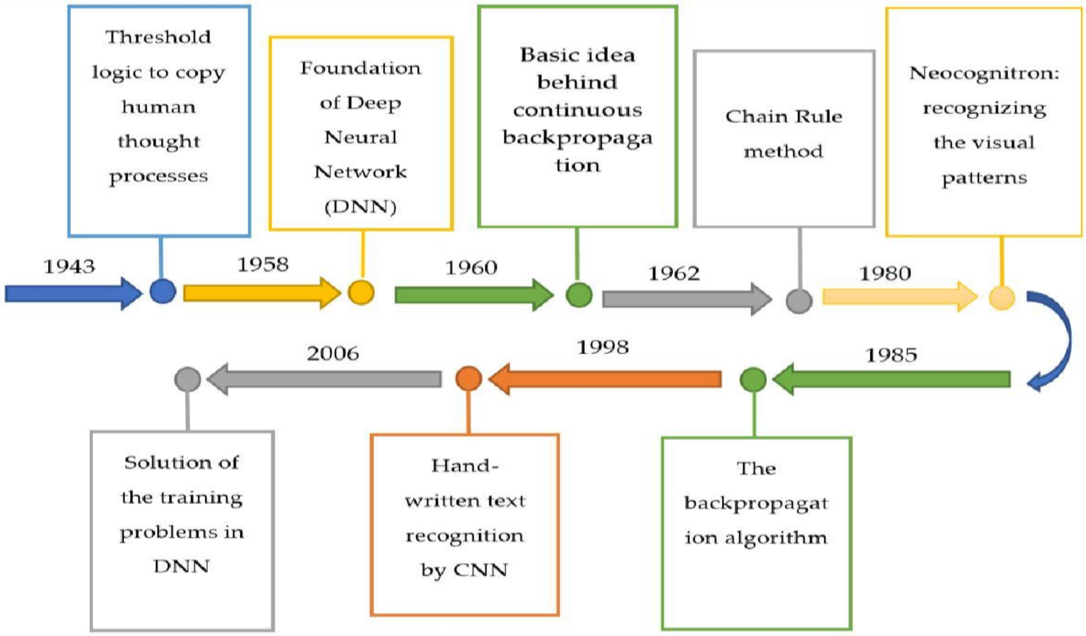

Figure 1. An overview of deep learning's development.

3.2 Data collection procedure/Dataset Utilized

After selecting an image capture sensor for the project, it's crucial to choose a data gathering platform. The datasets for the studies in this review that employed Machine learning to identify plant diseases were obtained using a variety of techniques. Using online tools to gather datasets is a frequent strategy employed by researchers. Images of plant diseases from Google and Ecosia [17] were carefully chosen for the PlantDoc collection presented in Section 2. Using photos of corn diseases obtained from Google and the PlantVillage collection, diseases were also detected [18]. Then, for disease diagnosis in maize and peach, pictures of publicly accessible databases, Google, and privately gathered data sets were used [19]. Although researchers with little access to crops can quickly acquire datasets using photos from internet sources, these datasets contain undesirable noise because of factors such as climate, place, picture size, sensor quality, and others. As a result, Scientists are more likely to obtain information about a particular area in certain places utilizing a variety of frameworks. Using a portable sensor is a typical method for gathering datasets. Using a portable imaging equipment, a small dataset of 300 pictures representing six disorders was collected. A picture of a 17 plant disease were captured a 30 cm height above the plant using an Oneplus 9 with and 48 MP resolution. To lessen the impact of reflection, the photographs were taken in the shadow without using a flash. Handheld photos of coffee leaf diseases were taken using a variety of smartphone cameras, including those on the Samsung Galaxy S8, iphone xi pro, Motorola A2, and Xiaomi mi A2 lite. In Espirito Santo, Brazil, pictures were captured out of the leaf's inner side. With white backgrounds, the conditions for taking the pictures were relatively controlled. Additional research has made advantage of portable imaging platforms [20]. While each image from handheld sensors is perfect for training machine learning models, personally scouting a field and gathering individual leaf photos takes a lot of effort. Furthermore, because the sensor's position and angles cannot be controlled with handheld photography, the data may be highly variable. Booms are used to support cameras and sensors to adjust parameters like height and angle in order to overcome this limitation posed by handheld photos

Since its release [21], the Plant Village dataset has grown in popularity as the most popular data set for instruction and building based on models using machine learning to find plant illnesses and estimating their severity [22]. There are 54,309 photos in the entire Plant Village dataset. The 38 distinct illnesses that impact 14 crops are shown by different images. The majority of the pictures were taken in a lab setting with uniform backgrounds and regulated lighting. Utilizing machine learning models trained to recognize diseases photos from the Plant Village dataset could not generalize more precisely to photographs taken in the field because these images are not typical of real-field situations [23].

Table 1: Summaries for the Plant Village Dataset

Crop	Disease	Images
Grape	Leaf Spot	1162
	Black Rot	1,180
	Black Measles	1,383
	Healthy	378
Corn	Healthy	1,162
	Leaf Spot	513
	Blight in the north	1,192
	Rust	985

Cherry	Healthy Particle Mildew	854 1,052
Blueberry	Healthy	1,502
Apple	Scab Healthy Brown Rot Ceder Rust	1,645 621 275 630
Orange	Citrus	5,507
Peach	Healthy Fungal	360 2297
Potato	Healthy Early Blight Late Blight	180 1,015 1,030
Raspberry	Healthy	385
Soybean	Healthy	6035

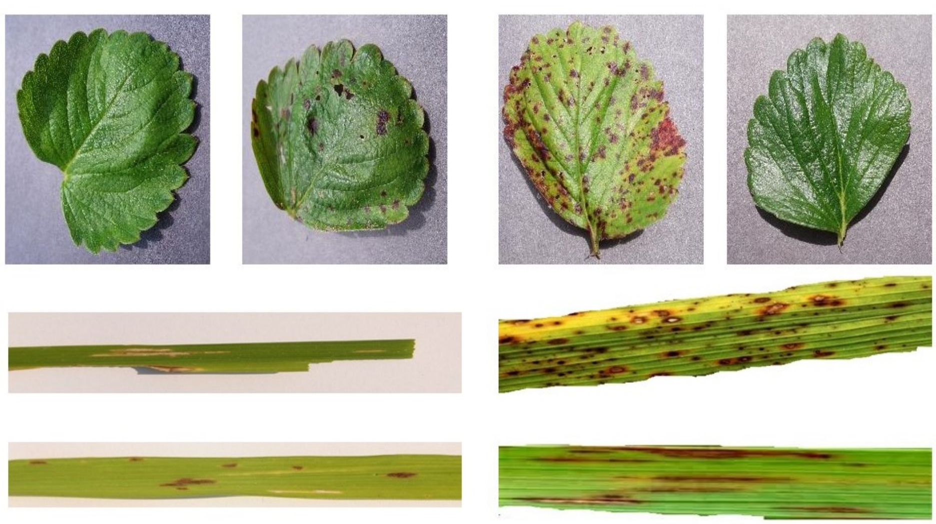

Figure 2: Strawberry and rice leaf plant village data sample

Figure 3: Corn and Peach leaf plant village data sample

Digipathos, a new huge plant disease dataset with 46,513 photos spanning 23 different crops are affected by 181 illnesses. 2326 out of the photos in this collection depict leaf illnesses that were either observed in outdoor settings with complicated backgrounds or in controlled lab settings having consistent backdrops, as shown Fig 4 and Fig 5. As seen in Fig. 5, the remaining 43,145 pictures are trimmed versions of illness lesions (c). In light of this, it is evident that a majority of the images in this collection (more than 92%) do not show plant illnesses in their natural environment. Nevertheless, numerous research have used the Digipathos dataset to pinpoint disorders.

Figure 4: Pepper and Potato leaf Digipathos Data sample

Figure 5: Tomato leaf Digipathos Data sample

Recent acquisitions include the smaller PlantDoc plant disease dataset, which has 2598 photos spanning 17 illnesses affecting 13 distinct crops. As can be seen in Fig. 6, the majority of the photographs were taken in the field, although some of them also had homogeneous backgrounds. Robust deep learning-based illness identification models can be trained by varying the image acquisition settings. However, several images in our dataset contain numerous sick leaves or whole crops Fig. 7, which makes it harder for deep learning algorithms to pick up on crucial disease traits. The PlantDoc collection is also imbalanced and offers a few pictures in each category. Table 2 display an overview of the PlantDoc data. Table 2 displays a description of the PlantDoc dataset.. It is challenging to develop precise models for identifying diseases using deep learning because this dataset is far from ideal. Due to the fact that just two of the examined studies in this survey employed it the detection of plant diseases, its application in the scientific community is limited.

Table 2: Summaries for the Plant Doc Dataset

Crop	Disease	Images
Apple	Healthy	90
	Scab	95
	Rust	88
Bell Pepper	Perfect	66
	Spot in leaf	78
Blueberry	Healthy	157
Cherry	Healthy	59
Corn	Rust	185
	Leaf Spot	69
	Leaf Blight	186
Grape	Healthy	70
	Black Rot	68

Peach	Healthy	182
Potato	Early Blight	125
	Late Blight	158
Raspberry	Healthy	135
Soybean	Healthy	69
Squash	Powdery Mildew	150
Strawberry	Healthy	90
Tomato	Healthy	69
	Mosaic Virus	120
	Yellow Virus	89
	Bacterial Spot	151
	Septoria Leaf Spot	90
	Early Blight	11
	Late Blight	94
	Leaf Mold	86
	Spider Mite	3

Figure 6: Wheat leaf Plant Doc Data sample

Figure 7: Potato leaf Plant Doc Data sample

Employing UAS-based airborne photography handheld, photography, and putting a boom-mounted camera, a dataset made up of 15,158 field photos of maize with Northern Leaf Blight infection was obtained. According to Table 3 below, Real-field pictures with 115,859 lesion annotations make up the NLB dataset. This dataset only contains pictures of maize leaves that have one illness; it cannot be used to distinguish between different diseases. The ideal use of this dataset is to train ML to distinguish between ill and perfect maize Identifying and locating NLB lesions or plants using object detection. Additionally, this dataset can offer test photos to evaluate how well DL models generalize across databases to find diseases. Fig 8 and 9 below shows examples of handheld, boom, and UAS-based photos.

Table 3: Summaries for the NLB Dataset

Platform	Images	Annotations
Drone	8000	55000
Boom	1,787	8,769
Handheld	7,877	54,818

Figure 8: Wheat and Pepper leaf NLB Data sample

Figure 9: Tomato and Strawberry leaf NLB Data sample

3.3 Statistical Analysis

The effectiveness of various machine learning approaches can be assessed using a variety of indicators. The performance of the suggested method is assessed using the most popular Seven metrics: F1 score, loss function, recall, specificity, accuracy, precision, recall, and confusion matrix . Mean Average Precision governs the framework's ability to recognize objects (mAP). It serves as the fundamental unit of measurement for all classes of items.

The mean average precision is obtained by dividing the total amount by properly detected photos by the total number of wrongly detected images for each class. The mean average precision is seen for several parameter types. These settings include the minimum batch size, the image scale that is also the picture's short edge, and the maximum pixel size of the scaled input picture. The mean average precision is calculated for each category or object found in the picture.

Using the formula below, average precision determines the average precision for recall value for the range of 0 to 1.

P= No of True detection / (No of True Detection + No of False Detection)

Another parameter that is important in assessing CNN's performance is the loss function. When making predictions given a constrained collection of outcomes known as classes, the classification loss function is employed. Cross-Entropy is a classification loss function, commonly referred to as logarithmic loss.

Table 3 displays the formulas and reasons for the different measurements to create this work. It is important to remember that True Positive, True Negative, False Positive, and False Negative are all abbreviated as Tp, TN, FP, and FN respectively.

Table 3: Equation in Metrics and Justification

Metric	Equation	Measure
Specificity	$\frac{TN}{TN+FP}$	The percentage of the actual negative cases that were accurately classified.
Precision	$\frac{TP}{TP+FP}$	True positive instances as a percentage of all categorized positive cases
F1-Score	$\frac{2Tp}{2TP+FP+FN}$	The harmonic average of the recall and precision

Accuracy	$\frac{Tp + TN}{TP + TN + FP}$	A measurement of the proportion of all accurate classifications to all classifications
Recall	$\frac{TP}{TP + FN}$	The percentage of real positive cases that were accurately classified.

3.4 Proposed Methodology/Applied Mechanism

Deep learning's concept of transfer learning is the process of using previous models to tackle a brand-new problem or difficulty. Not a specific form of DL algorithm, Flow learning is an approach to learning that approach used while exercise images. It is necessary to reuse knowledge from previous training to finish a new project. The specific task will be related in some way compared to that which was used; for example, This could include going to label items into a specific formats. Obsolete training model frequently involves a large degree it is broad to adapt to the new, unseen input. This transfer learning method, which uses fewer resources while providing superior accuracy from its pretrained weights, has been used to create three separate deep learning algorithms in this case.

i) CNN: A subset of extensive neural networks Fig-10 with an emphasis on image recognition, have advanced significantly in a variety of industries recently, including agriculture. Using consecutive blocks of fully connected, pooling, and convolutional layers, CNN builds Construct flexible and self-optimizing spatial-temporal hierarchies of characteristics. The fundamental goal of CNN is to create a stronger connection with a lot fewer elements. As with any other conventional neural network model, CNN is composed of neurons arranged in layers, including a first input layer and a final layer, and connected by ingrained weights and biases. In order for a CNN to produce patterns, there must be at least one hidden layer in the convolutional layers. These hidden layers change the input's feature space to match the output's. CNN, on the other hand, does not necessitate manual feature extraction, in contrast to other archaic approaches that do. These qualities can be instantly learned.

The convolutional layer, as its name suggests, is essential to the functioning of the CNN. It does this by employing flexible kernels (padding, size, and number), which have a tiny size but can spread throughout the whole network's depth. Convolution is performed on the input layer by this layer, and the outcome is then transmitted to the subsequent layer, where a nonlinear function like ReLU is used. Additionally, the layer leaking, often referred to as down sampling, only reduces the input's amount of convolved features on a dimensional level. By reducing the amount of pixels in an image, this action reduces the computer power required to process the data. Because of this, despite the reduction in space, the training must still be effective, accurate, and non-overfitted. Finally, there is the completely connected layer (FC), which consists of of neurons that are directly coupled to one another. In the classification process, it produces a class score.

Additionally, all of the CCN's parameters must be fixed prior to the convolutional layer and pooling layer training process, whereas During training, the kernel weights are acquired. As a result, a good activation function speeds up learning and lowers the loss function, which measures the discrepancy between actual and anticipated results. Utilizing optimization techniques like gradient descent or various gradient descent versions created using the loss function, the weights are updated. In contrast, there is less risk of overfitting when the data set is expanded and regularized (i.e., some activations are omitted at random).

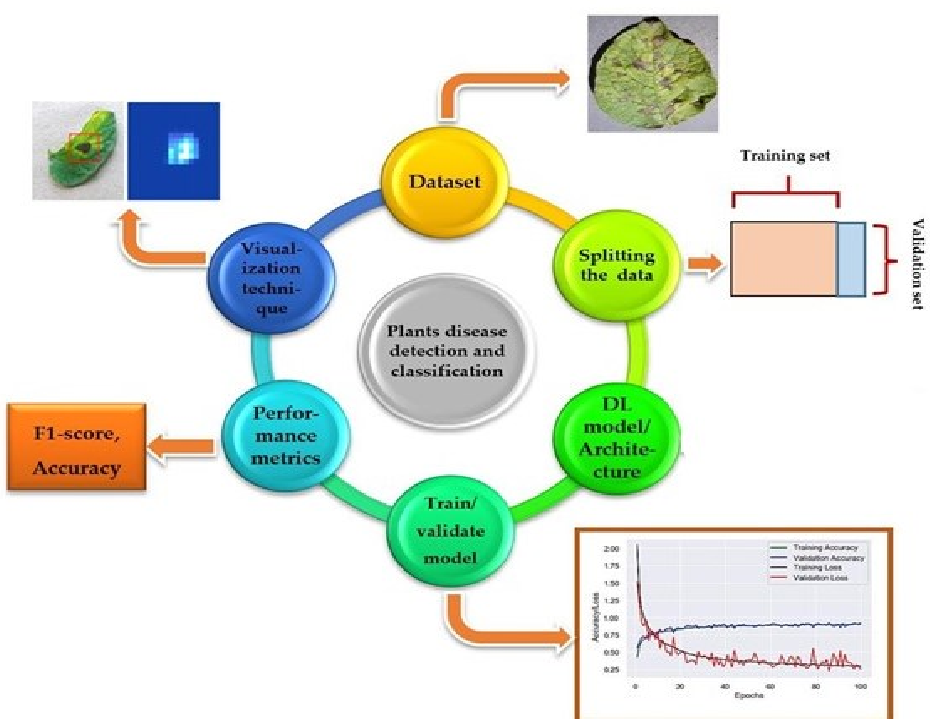

Figure 10: CNN Working Procedure

ii) VGG19: The VGG19 model is a modification inside the VGG paradigm with 19 elements, 16 convolution layers, 3 completely linked layers, and 5 MaxPool levels, and one Augmented Dataset when using VGG19 by default, the input shape is (224*224), which is not ideal for classifying our plant disease detection. As a result, we altered the input shape to (448*448), which produced a (598,668,4) in column vector inside the layer of input in the network. The predictions of plant disease detection following the model's training using a tailored layer of input were 166 and 146 correct and 11 erroneous, indicating the model's accuracy as 96.59%. When three models for deep learning VGG19, CNN (Keras), and VGG16 are used and compared, it becomes clear that VGG16 performs along with 3 algorithm's best accuracy., making it the network we should use for our study on plant disease identification.

iii) VGG16: CNN, a subset of which is referred to as VGG16, is among the most advanced models for object recognition available today. The network versions that have been studied, their increased complexity, and the arrangement of exceedingly small (5*5) convolutional separates show an important improvement over current systems. A total of 138 learnable parameters were generated when the depth was increased to 17–20 weight layers.. For better understanding, we also altered the input layer in this case and used photos that were (448*448) in size and had a (448,448,3) matrix form. On the test dataset, the accuracy score was 97.52%..

3.5 Implementation Requirements

The initial dataset's quality was improved using image enhancement, and its size was increased using augmentation. Flattening and improving the contract of the photos are produced by smoothing and enhancing image detail. This is accomplished by adjusting the locally aware edge contrast. By specifying a minimal optimum intensity amplitude as a criterion value, this method preserves the strong edges. The threshold and enhancement value in this study were both set at 0.15 and 0.5 respectively. The approach for reducing contrast uses an filter for anisotropic diffusion. The Fourier transform is used to move the a zero-frequency element of the middle of the range. In any machine learning project, it is crucial that the researchers make every effort to avoid overfitting. To overcome these concerns, the authors of suggested a number of strategies, includes augmentation, early stopping, dropout approach, stochastic pooling, L1 and L2 regularization, and dropout regularization. We suggest using data augmentation to expand the dataset, which will lessen the likelihood of overfitting. Data augmentation is a straightforward procedure that involves making little adjustments to the source photos to create new ones. To encompass techniques using scale-in/scale-out, rotation, and translation, we employ the following techniques in this work. These three straightforward techniques result in brand-new photos that are virtually identical to the originals.

There were few images still in the dataset after preprocessing. While keeping in mind that drastically the amount of photos will increase result in oversampling, we had to make some alterations to the raw photos in order to increase the amount of the Fig 11. Set up a dataset such that the example works exactly as intended. The photos were rotated between -15 and +15 degrees, cleaved within such a frequency of 0.2, and blown in and out inside one range of 0.2, in addition to being flipped both vertically and horizontally. Then, to guarantee that the generated images were consistent, the fill type for the ImageDataGenerator function was set to constant were black and did not have any degraded areas. Then, a brightness range of between 0.5 and 1.5 was chosen, within which the images will indeed fluctuate at random.

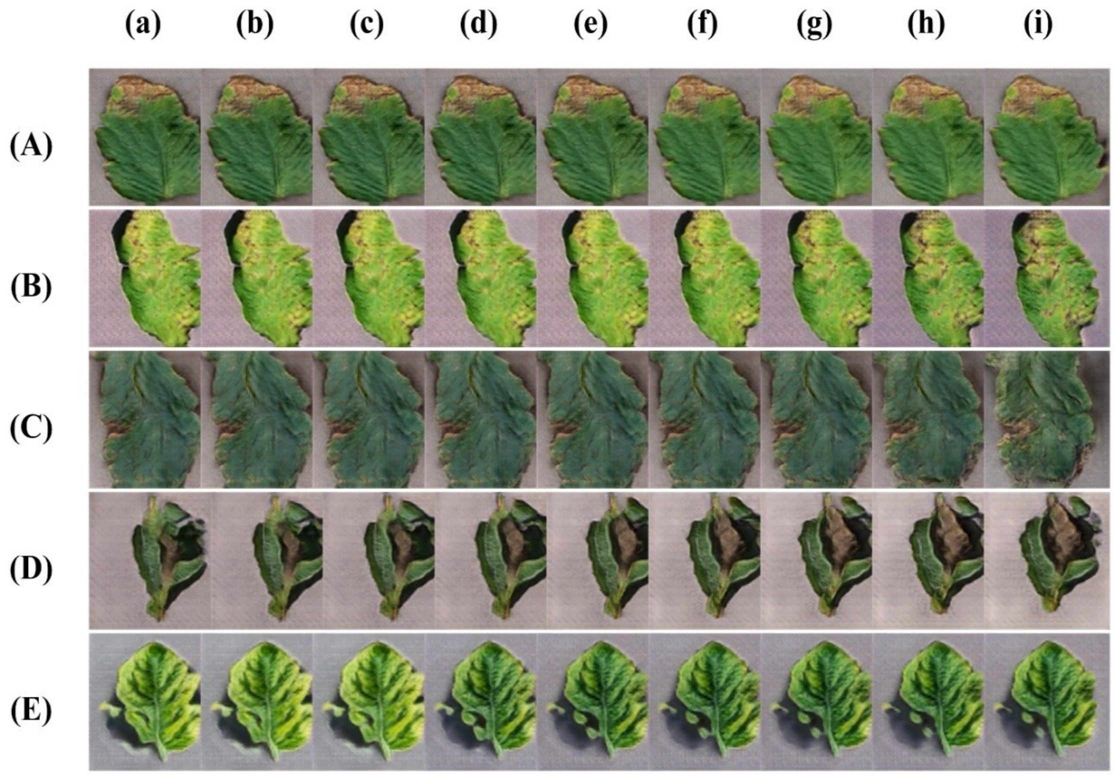

Figure 11: Data Augmentation

CHAPTER 4
EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Experimental Setup

The database utilized for this study comprises healthy rice leaves as well as crops images including brown patch, leaf burst, narrow brown spot, leaf spots blight, as well. The breakdown of training and testing images of crops leaves for various crops illnesses is displayed in Figure 12. Among the most hazardous illnesses that can have a disastrous effect on a growing crop is brown spot, and it is represented by the first dataset label. The "Late Blight" fungus is the cause of the sickness. Brownish to grayish dots first form within the leaf's center, encircled by green tips. The spots may alter in size and color as the condition worsens, but they will almost always be spherical in shape. As a result, it has the potential to reach an extreme point at which all of the leaves would deteriorate and pass away. Brown spot disease consequently causes crops to lose both quantity and quality. The healthy labeled dataset, on the other hand, displays disease-free rice that is in good health. Let's move on to Hispa, a disease that is caused by the "Early_Blight" a medium-sized, black bug. Whether it is an adult or a grub, this species of insect is harmful. This illness starts when the insect's female lays her eggs singly at the leaf end's abdominal region. When the grub emerges later, it has the characteristic of excavating they cut into a leaf for consume the tissues found among its layers. The leaf becomes white and membranous as a result of the excavation, and dies. Last but not least, the dataset shows leaf blast, a disease that develops from the fungus “Magnaporthe Oryzae”. All of the rice plant's visible above-ground parts are negatively impacted by this disease. The earliest signs of its impact are white to gray markings with red borders on the leaf. Their characteristic shape is a diamond with sharp edges. The spots may eventually kill the entire leaf as they grow larger.

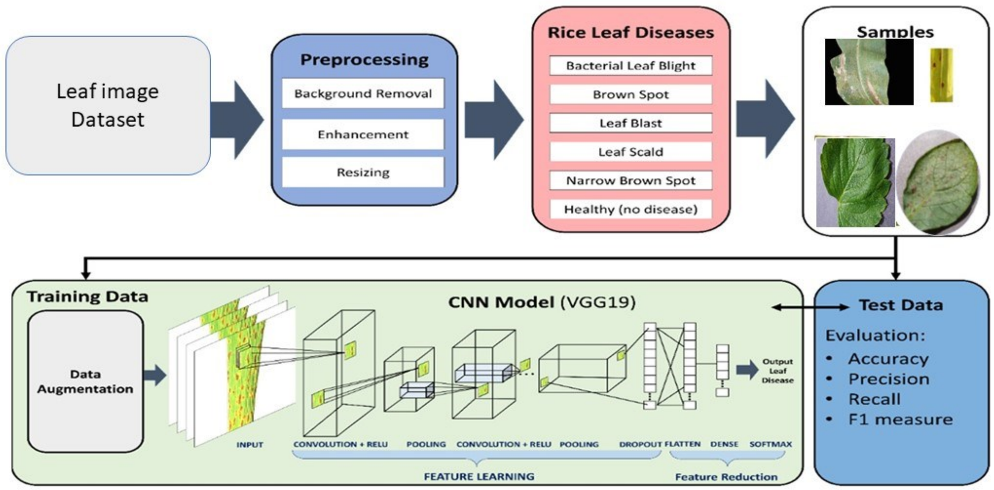

Figure 12: DL Work Flow

4.2 Experimental Results & Analysis

Performances Indices For Rice Model

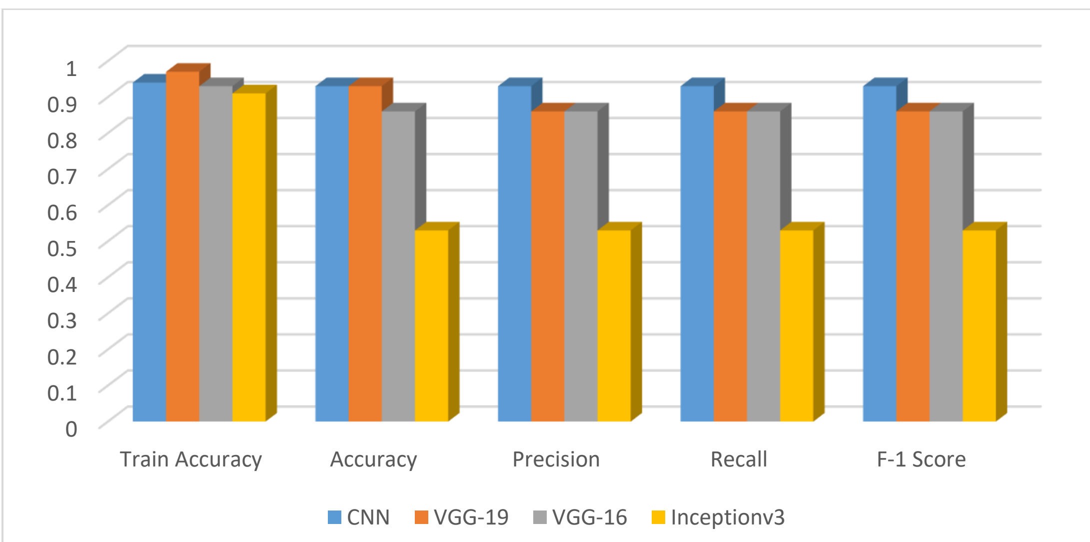

Figure 13: Comparing DL Model's Performance for Rice

The train accuracy precision recall F-1 score for the implemented DL Model is shown in the fig-14 above VGG-19 scores highest for train accuracy 0.97, whereas Inceptionv3 scores lowest 0.91. The greatest score for Precision CNN and VGG-19 is 0.93, while the lowest value for Inceptionv3 is 0.53. Inceptionv3 displays the lowest number as it did before, whereas CNN has the greatest value 0.93. CNN has the greatest score for F-1 Score, while Inceptionv3 has the lowest value once more. Finally, CNN provides us with the highest accuracy 0.93, followed by VGG-16 and VGG-19 gives 0.86, and Inceptionv3 0.53, which provides us with the lowest accuracy.

In the below curve for CNN shown in fig-13.1, the trainings and validation loss curve is seen to stay almost near to each other indicating a good fit of the dataset. So, we can take this for build our main model. While the training and validation accuracy shown in fig-13.2 also shows similar properties by increasing over the time maintaining a symmetry over all of the epochs.

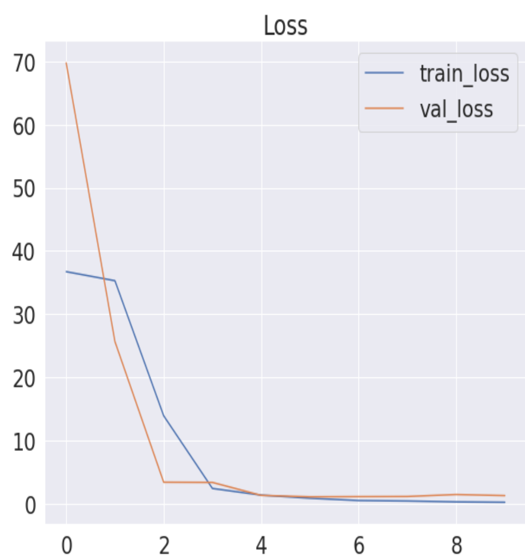

Figure 13.1: Train_loss Vs Val Loss

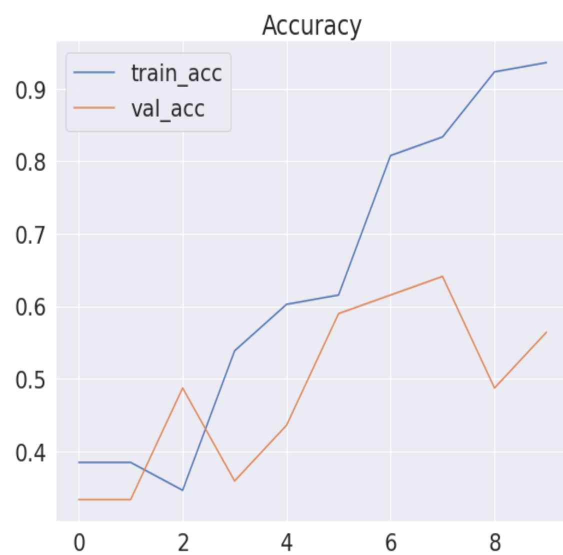

Figure 13.2: Train_acc vs Val acc

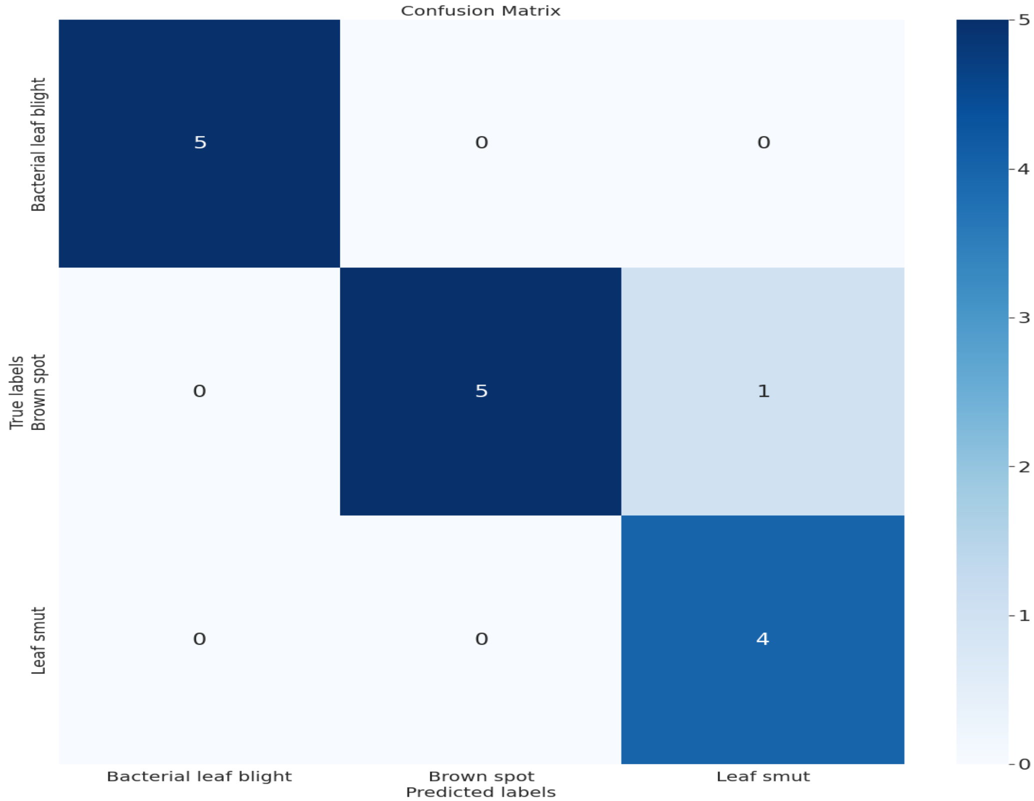

Figure 13.3: Confusion Matrix

In the test dataset, the CNN Confusion Matrix shown in fig-13.3 for Bacterial Leaf Blight fared better than all other diseases and correctly predicted 5 out of 5 images. Additionally, it was effective against the sickness Brown spot out of 5 it correctly predicted 5 out of 5. The prediction accuracy for Leaf Smut was good, although somewhat less than for the Brown Spot predict accurate 4 out of 5.

In the Below curve for VGG-19 shown in fig-13.4, the trainings and validation loss curve is seen to stay almost near to each other indicating a good fit of the dataset. But the validation loss shown in fig-13.5curve slightly high. While the training and validation accuracy also shows similar properties by increasing over the time maintaining a symmetry over all of the epochs.

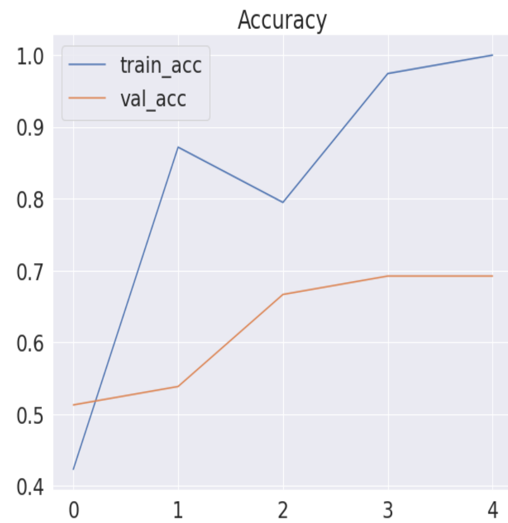

Figure 13.4: Train_loss Vs Val Loss

Figure 13.5: Train_acc vs Val acc

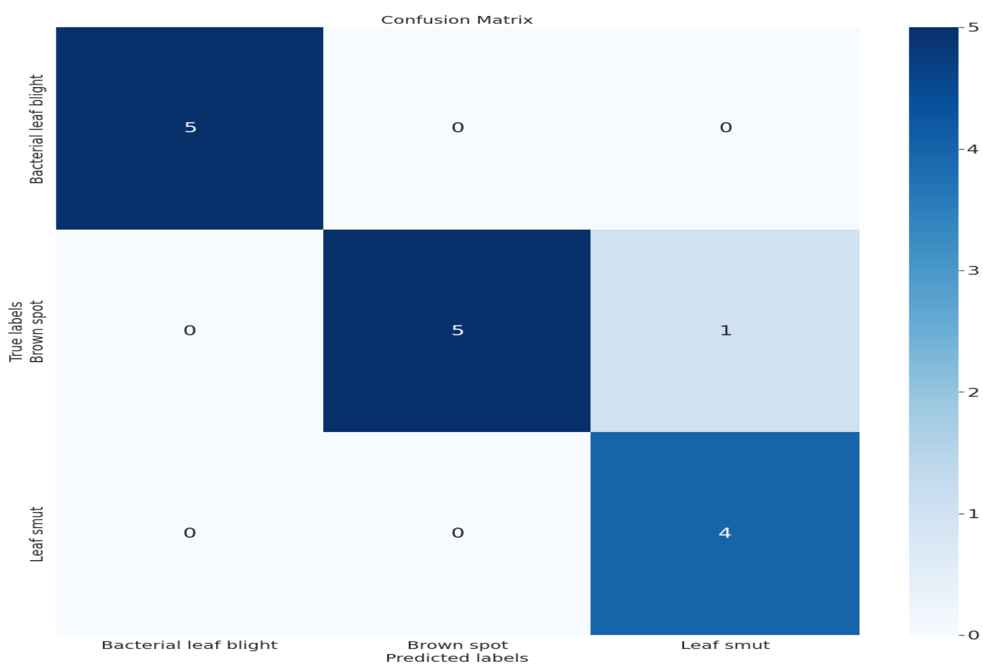

Figure 13.6: Confusion Matrix

In the test dataset, the VGG-19 Confusion Matrix shown in fig-13.6for Bacterial Leaf Blight fared better than all other diseases and correctly predicted 5 out of 5 images. Additionally, it was effective against the sickness Brown spot out of 5 it correctly predicted 5 out of 5. The prediction accuracy for Leaf Smut was good, although somewhat less than for the Leaf smut predict accurate 4 out of 5.

In the below curve for VGG16 shown in fig-13.7, the trainings and validation loss curve is seen that not staying near to each other indicating a over fit of the dataset. But the validation loss curve shown in fig-13.8 slightly high. While the training and validation accuracy shows dissimilar properties by increasing over the time maintaining a symmetry over all of the epochs. So it shows the dataset over fit.

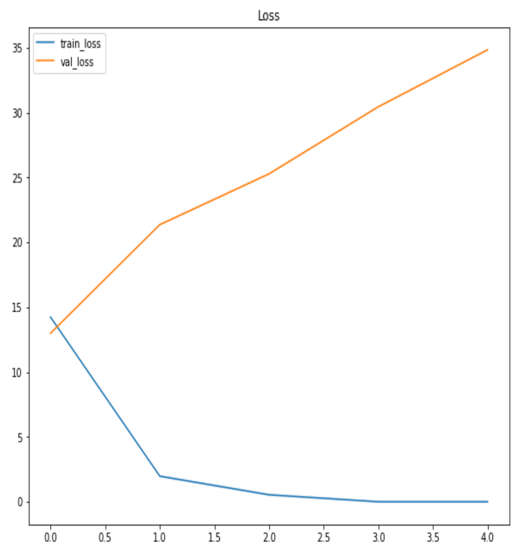

Figure 13.7: Train_loss Vs Val Loss

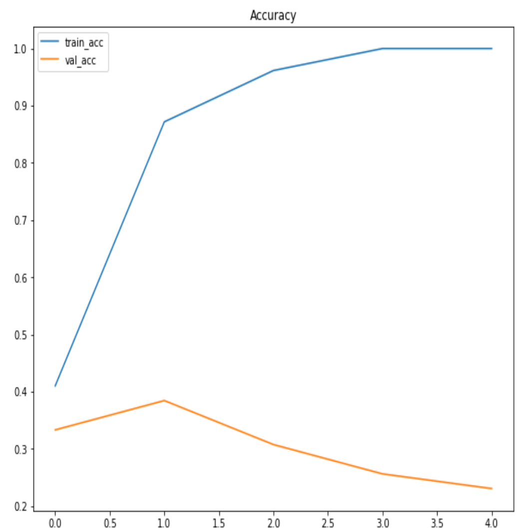

Figure 13.8: Train_acc vs Val acc

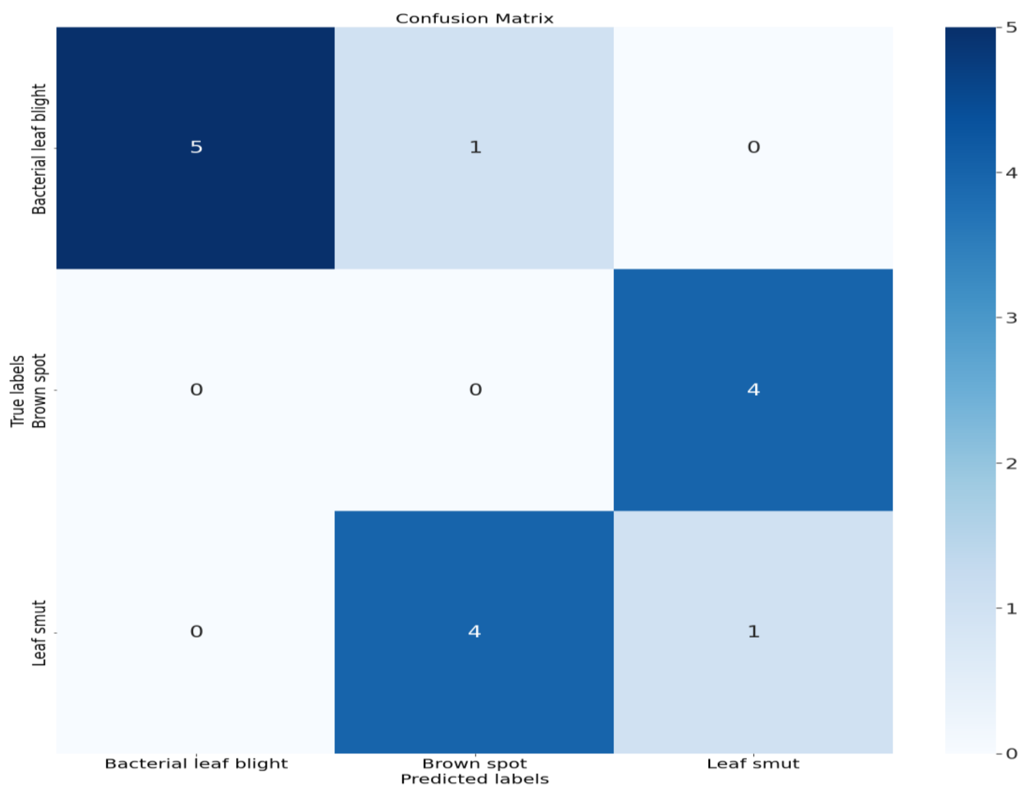

Figure 13.9: Confusion Matrix

In the test dataset, the VGG-16 Confusion Matrix shown in fig-13.9 for Bacterial Leaf Blight fared better than all other diseases and correctly predicted 5 out of 5 images. Additionally, it was effective against the sickness Brown spot out of 5 it correctly predicted 5 out of 5. The prediction accuracy for Leaf Smut was good, although somewhat less than for the Leaf smut predict accurate 4 out of 5.

In the below curve For InceptionV3 shown in fig-13.10, the trainings and validation loss curve is seen that not staying near to each other indicating a over fit of the dataset. They are running like linear. While the training and validation accuracy shown in fig-13.11 dissimilar properties by increasing over the time maintaining a symmetry over all of the epochs. So it shows the dataset over fit.

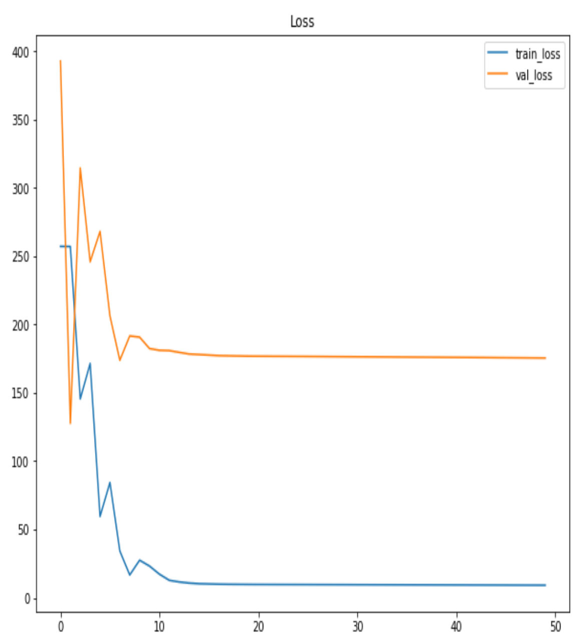

Figure 13.10: Train_loss Vs Val Loss

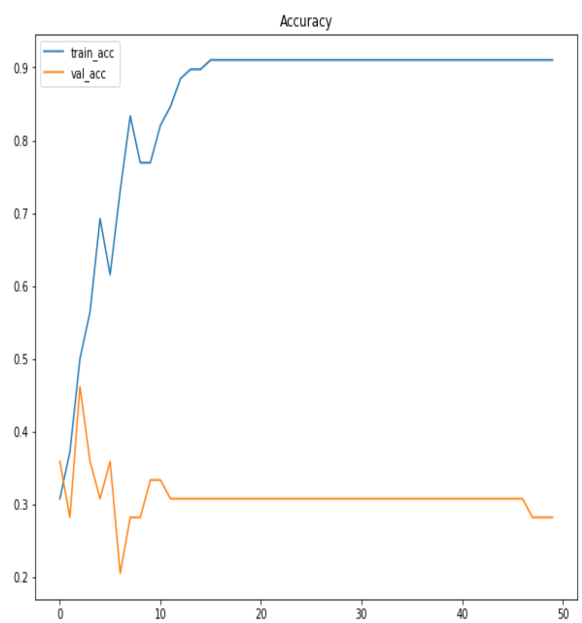

Figure 13.11: Train_acc vs Val acc

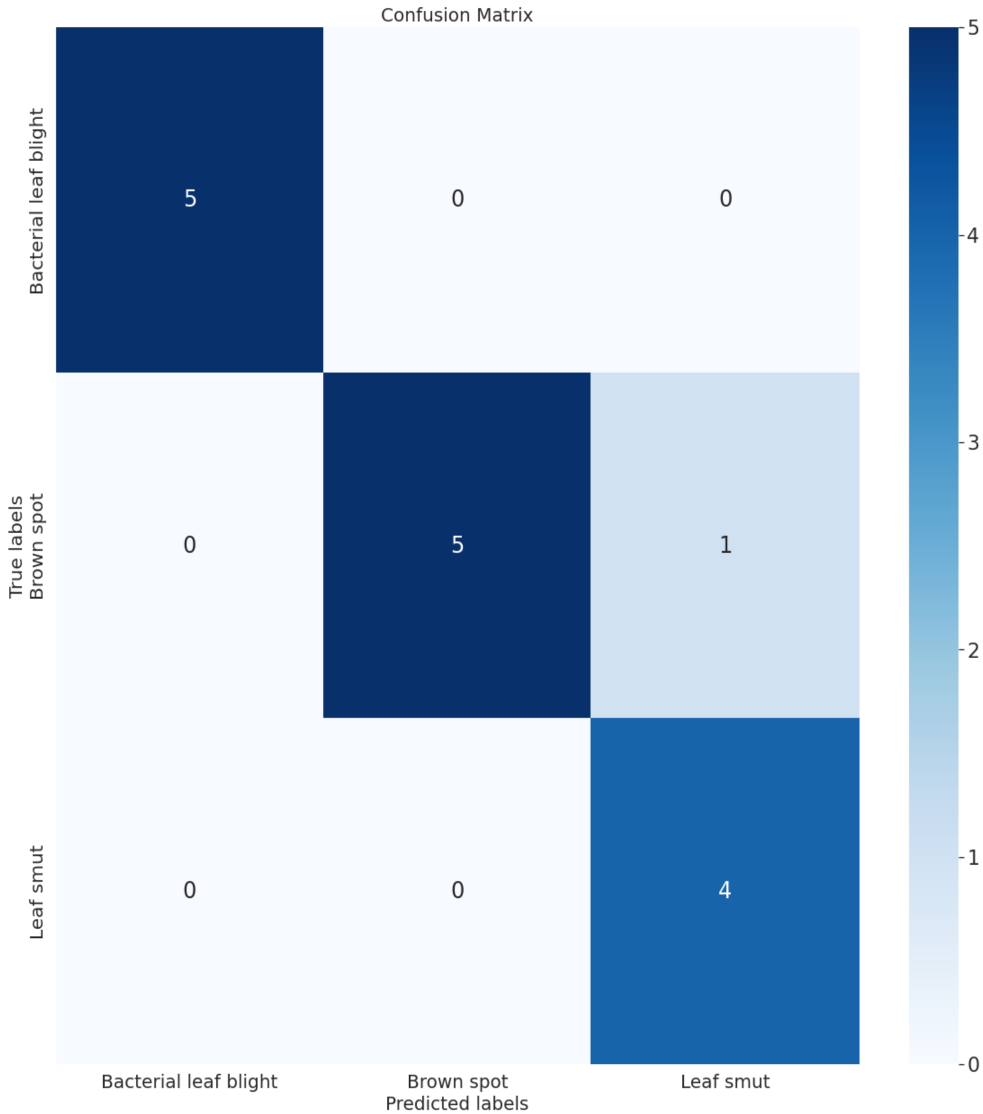

Figure 13.12: Confusion Matrix

In the test dataset, the Inceptionv3 Confusion Matrix shown in fig-13.12 for Bacterial Leaf Blight fared better than all other diseases and correctly predicted 5 out of 5 images. Additionally, it was effective against the sickness Brown spot out of 5 it correctly predicted 5 out of 5. The prediction accuracy for Leaf Smut was good, although somewhat less than for the Leaf smut predict accurate 4 out of 5.

Performances Indices For Potato Model

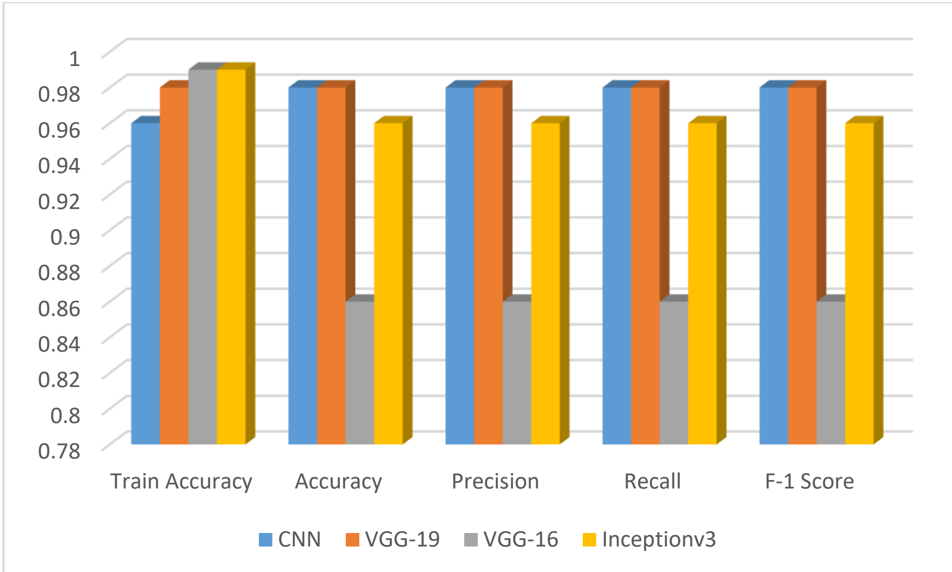

Figure 13.13: Comparing DL Model's Performance for Potato

Here above fig-13.13 shows us the train accuracy precision Recall F-1 score for implemented DL Model. For train accuracy, VGG-19 and Inceptionv3 gives the highest 0.99 and CNN gives the lowest of 0.96. For Precision CNN and VGG-19 has the highest value 0.98 and VGG-16 shows the lowest value 0.86. In Recall CNN and VGG-19 have the highest value 0.98 and VGG-16 shows the lowest value as it before. For F-1 Score shows the highest value for CNN and VGG-19 and for VGG-16 shows the lowest again. And Finally CNN and VGG-19 gives us the best accuracy 0.98 and second and third position takes Inceptionv3 and VGG-16, 0.96 and VGG-16 gives us lowest accuracy that is 0.86.

In the Below curve for CNNshown in fig-13.14, the trainings and validation loss curve is seen to stay almost near to each other indicating a good fit of the dataset. So, we can take this for build our main model. While the training and validation accuracy also shown in fig-13.15 similar properties by increasing over the time maintaining a symmetry over all of the epochs.

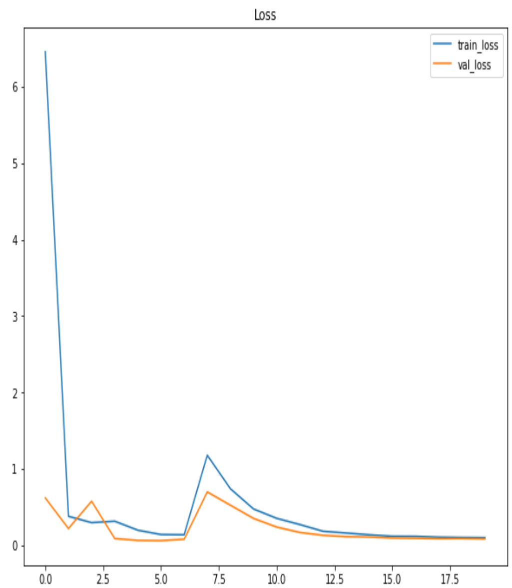

Figure 13.14: Train_loss Vs Val Loss

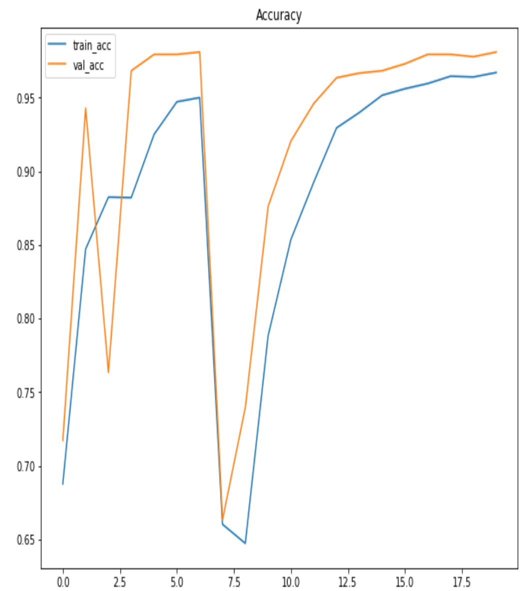

Figure 13.15: Train_acc vs Val acc

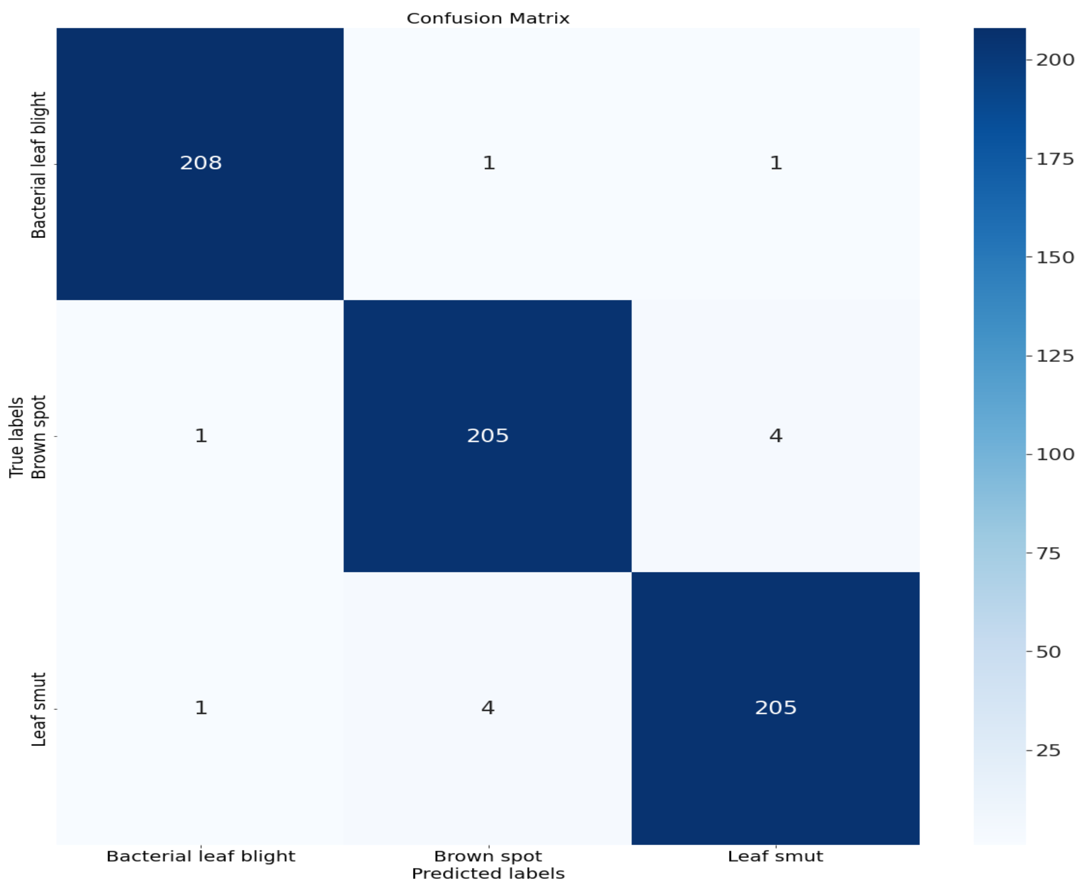

Figure 13.16: Confusion Matrix

In the test dataset, the CNN Confusion Matrix shown in fig-13.16 for Bacterial Leaf Blight fared better than all other diseases and correctly predicted 208 out of 210 images. Additionally, it was effective against the sickness Brown spot out of 210 it correctly predicted 205 images. The prediction accuracy for Leaf Smut was good, although somewhat less than for the Leaf Blight predict accurate 205 out of 210.

In the below curve For VGG-19 shown in fig-13.17, the trainings and validation loss curve is seen to stay almost near to each other indicating a good fit of the dataset. While the training and validation accuracy also shown in fig-13.18 similar properties by increasing over the time maintaining a symmetry over all of the epochs.

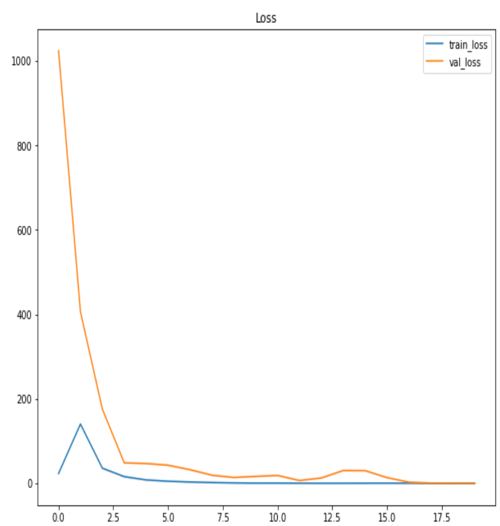

Figure 13.17: Train_loss Vs Val Loss

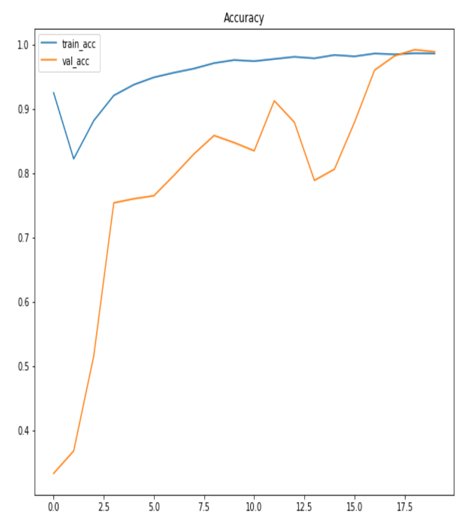

Figure13.18: Train_acc vs Val acc

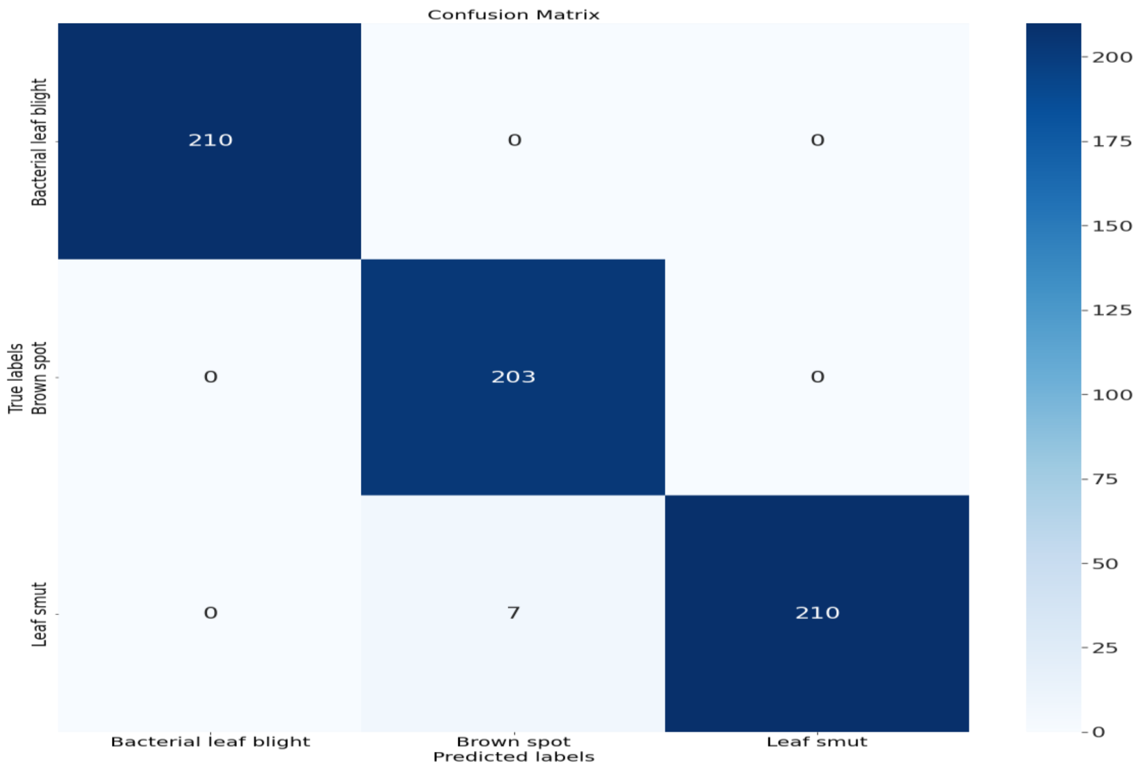

Figure 13.19: Confusion Matrix

In the test dataset, the VGG-19 Confusion Matrix shown in fig-13.19 for Bacterial Leaf Blight fared better than all other diseases and correctly predicted 210 out of 210 images. Additionally, it was effective against the sickness Brown spot out of 203 it correctly predicted 210. The prediction accuracy for Leaf Smut was good for the Leaf smut predict accurate 210 out of 210.

In the below curve for VGG-16shown in fig-13.20, the trainings and validation loss curve is seen to stay almost near to each other indicating a good fit of the dataset. While the training and validation accuracy also shown in fig-13.21 similar properties by increasing over the time maintaining a symmetry over all of the epochs. But in the early EPOCHS Val ACC was slightly low.

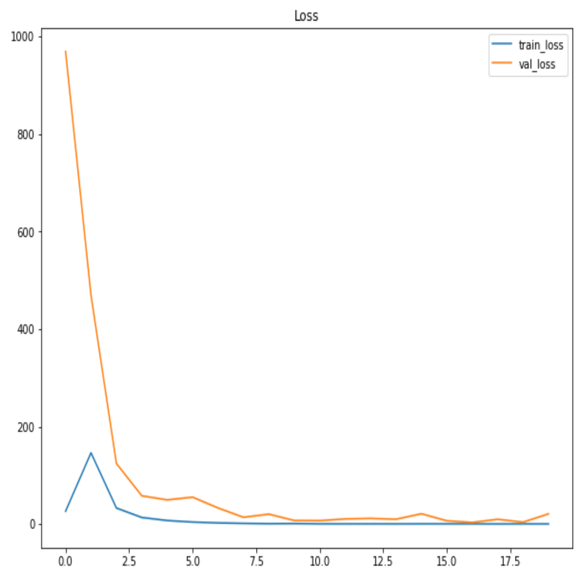

Figure 13.20: Train_loss Vs Val Loss

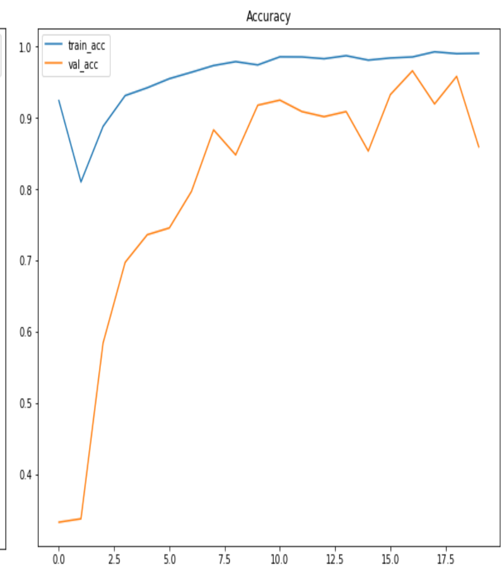

Figure 13.21: Train_acc vs Val acc

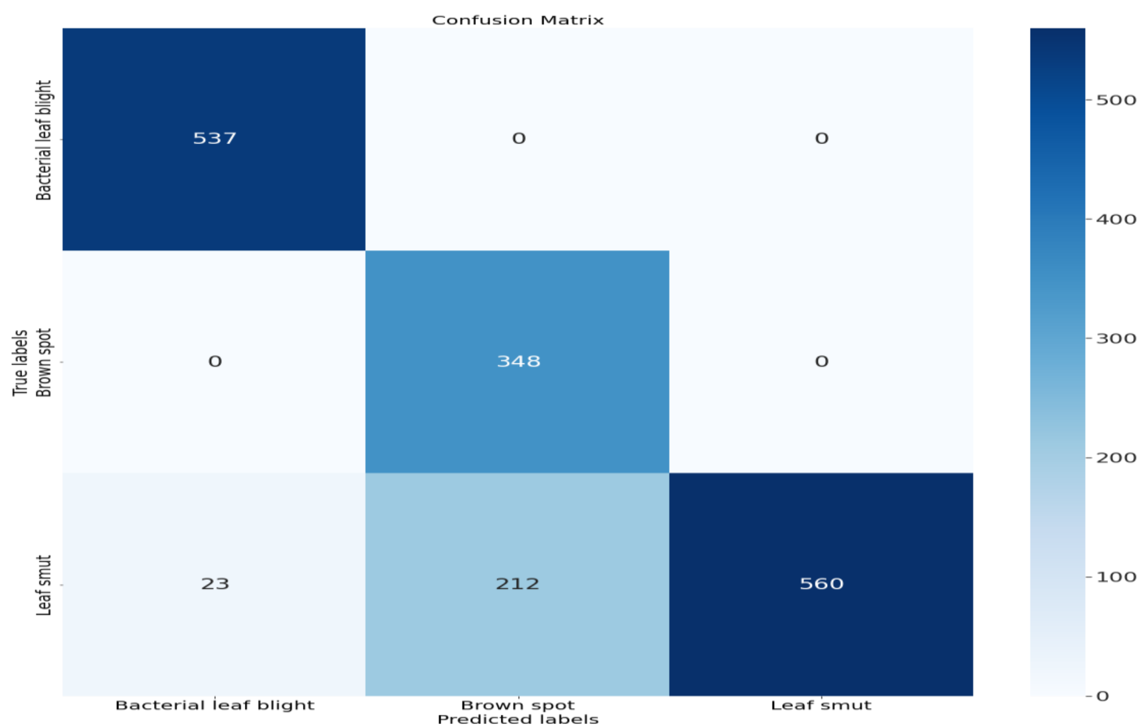

Figure 13.22: Confusion Matrix

In the test dataset, the VGG-16 Confusion Matrix shown in fig-13.22 for Bacterial Leaf Blight fared better than all other diseases and correctly predicted 537 out of 560 images. Additionally, it was effective against the sickness Brown spot out of 560 it correctly predicted 348 out. The prediction accuracy for Leaf Smut was good, although somewhat less than for the Leaf smut predict accurate 560 out of 560.

In the below curve for Inceptionv3 shown in fig-13.23, the trainings and validation loss curve is seen to stay almost near to each other indicating a good fit of the dataset. While the training and validation accuracy also shown in fig-13.24 similar properties by increasing over the time maintaining a symmetry over all of the epochs.

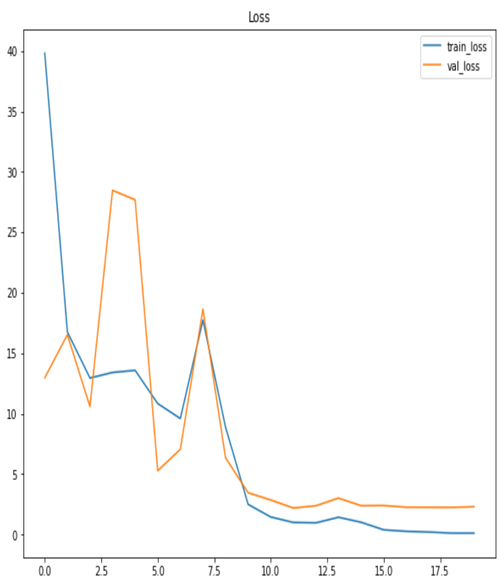

Figure 13.23: Train_loss Vs Val Loss

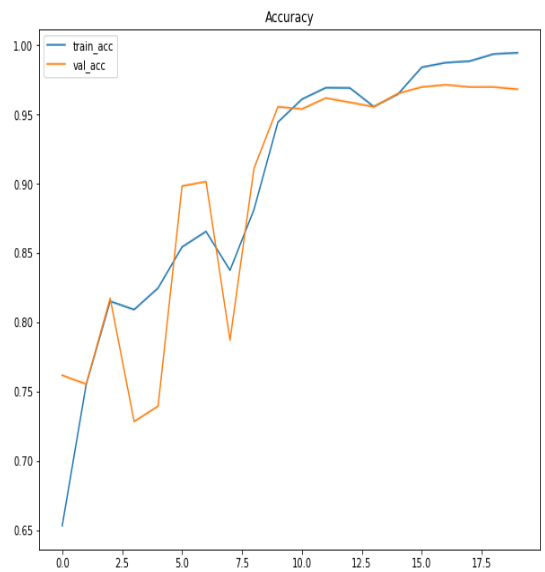

Figure 13.24: Train_acc vs Val acc

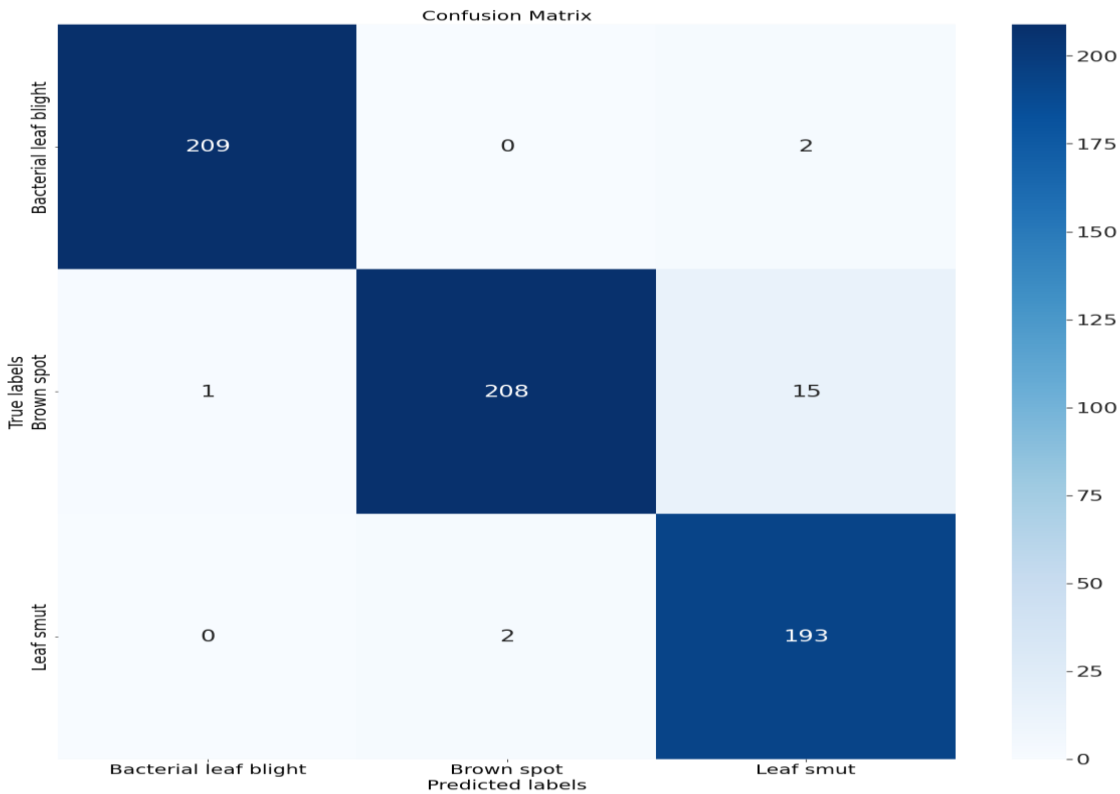

Figure 13.25: Confusion Matrix

In the test dataset, the Inceptionv3 Confusion Matrix shown in fig-13.25 for Bacterial Leaf Blight fared better than all other diseases and correctly predicted 209 out of 210 images. Additionally, it was effective against the sickness Brown spot out of 210 it correctly predicted 208 . The prediction accuracy for Leaf Smut was good, although somewhat less than for the Leaf smut predict accurate 193 out of 210

Performances Indices For Tomato Model

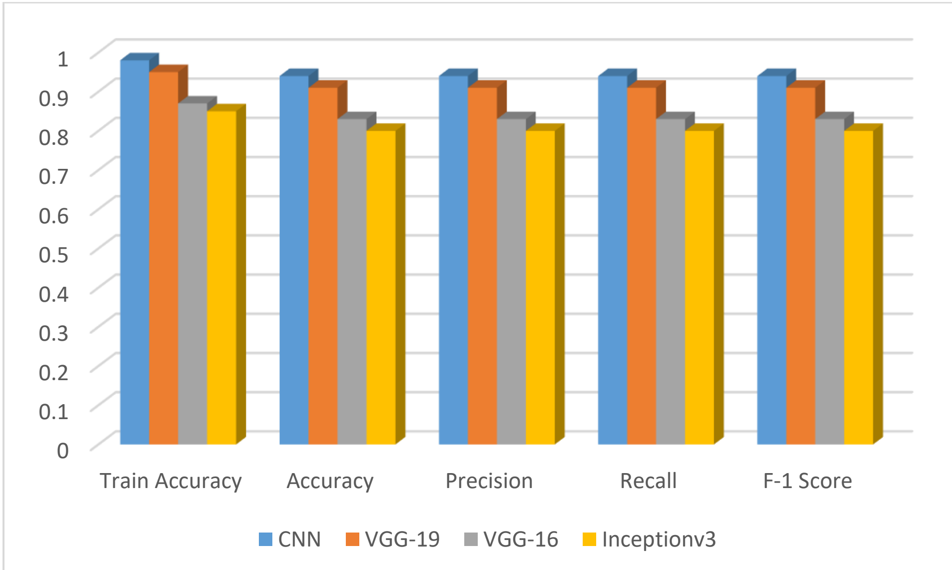

Figure 13.26: Comparing DL Model's Performance for Tomato

Here above fig-13.26 shows us the train accuracy precision Recall F-1 score for implemented DL Model. For train accuracy, CNN gives the highest 0.98 and Inceptionv3 gives the lowest of 0.85. For Precision CNN has the highest value 0.94 and Inceptionv3 shows the lowest value 0.80. In Recall CNN have the highest value 0.94 and Inceptionv3 shows the lowest value as it before. For F-1 Score shows the highest value for CNN again and for Imceptionv3 shows the lowest again. And Finally, CNN and VGG-19 gives us the best accuracy 0.94 and 0.91, second and third position takes VGG-16 and Inceptionv3, 0.83 and 0.80.

In the below curve shown in fig-13.27 for CNN, the trainings and validation loss curve is seen to stay almost near to each other indicating a good fit of the dataset. So, we can take this for build our main model. While the training and validation accuracy shown in fig-13.28 also shows similar properties by increasing over the time maintaining a symmetry over all of the epochs.

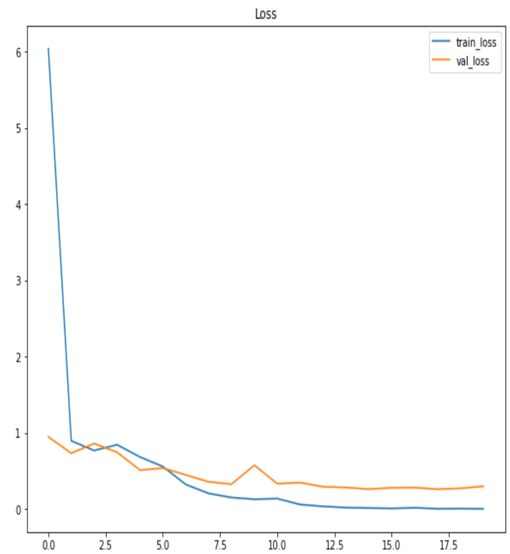

Figure 13.27: Train_loss Vs Val Loss

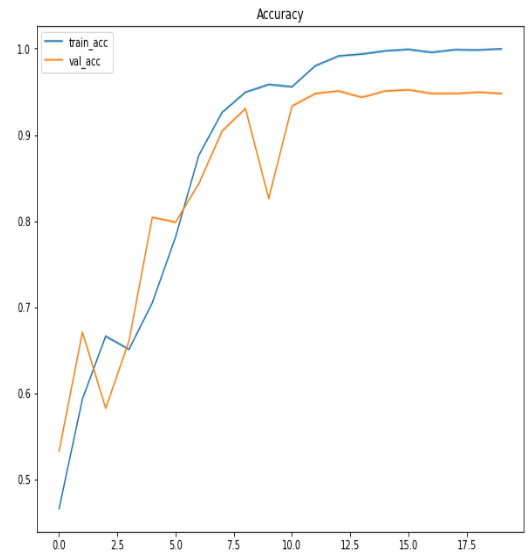

Figure 13.28: Train_acc vs Val acc

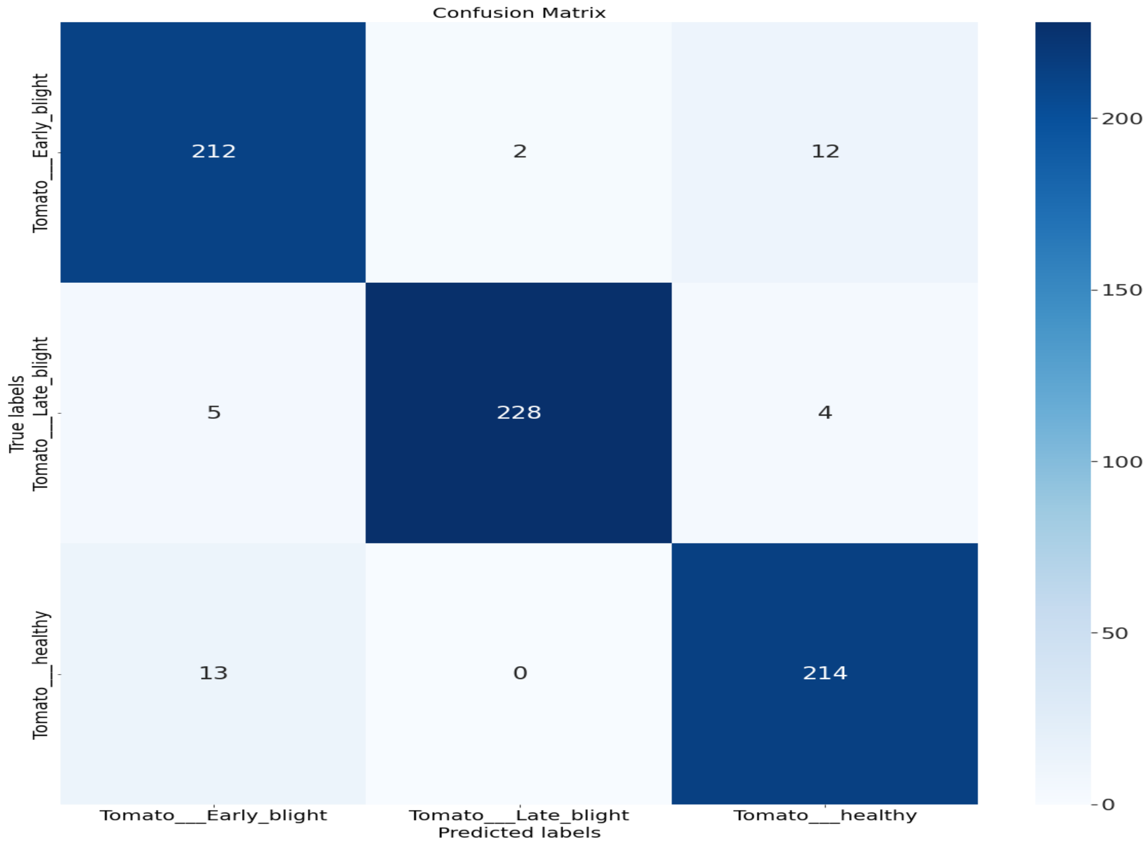

Figure 13.29: Confusion Matrix

In the test dataset, the CNN Confusion Matrix shown in fig-13.29 for Bacterial Leaf Blight fared better than all other diseases and correctly predicted 215 out of 230 images. Additionally, it was effective against the sickness Brown spot out of 230 it accurately predicted 228 images. The prediction accuracy for Leaf Smut was bad, although somewhat less than for the Leaf Blight predict accurately 214 out of 218.

In the below curve for VGG-16 shown in fig-13.30, the trainings and validation loss curve is seen to stay almost near to each other indicating a good fit of the dataset. While the training and validation shown in fig-13.31 accuracy also shows similar properties by increasing over the time maintaining a symmetry over all of the epochs.

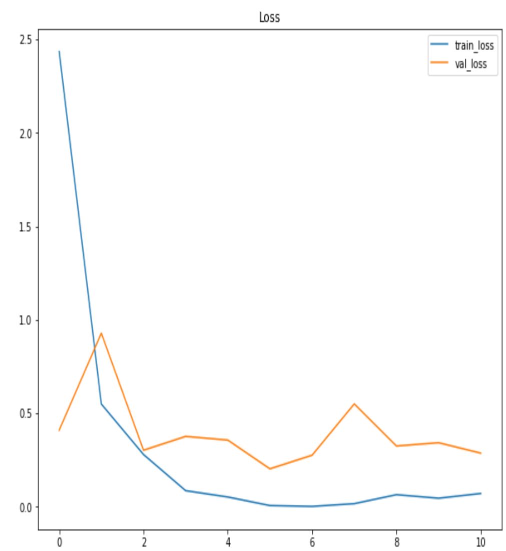

Figure 13.30: Train_loss Vs Val Loss

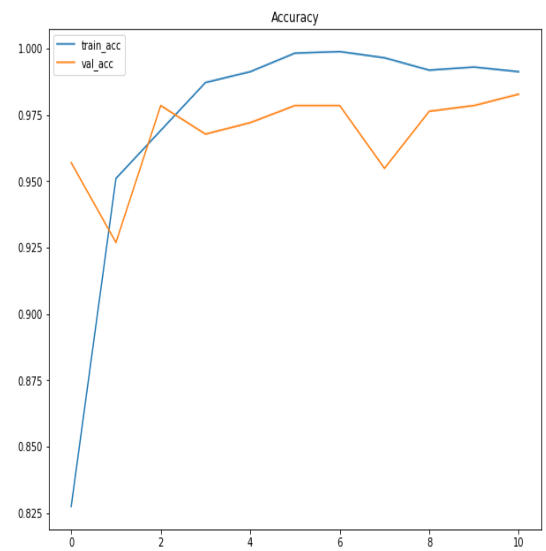

Figure 13.31: Train_acc vs Val acc

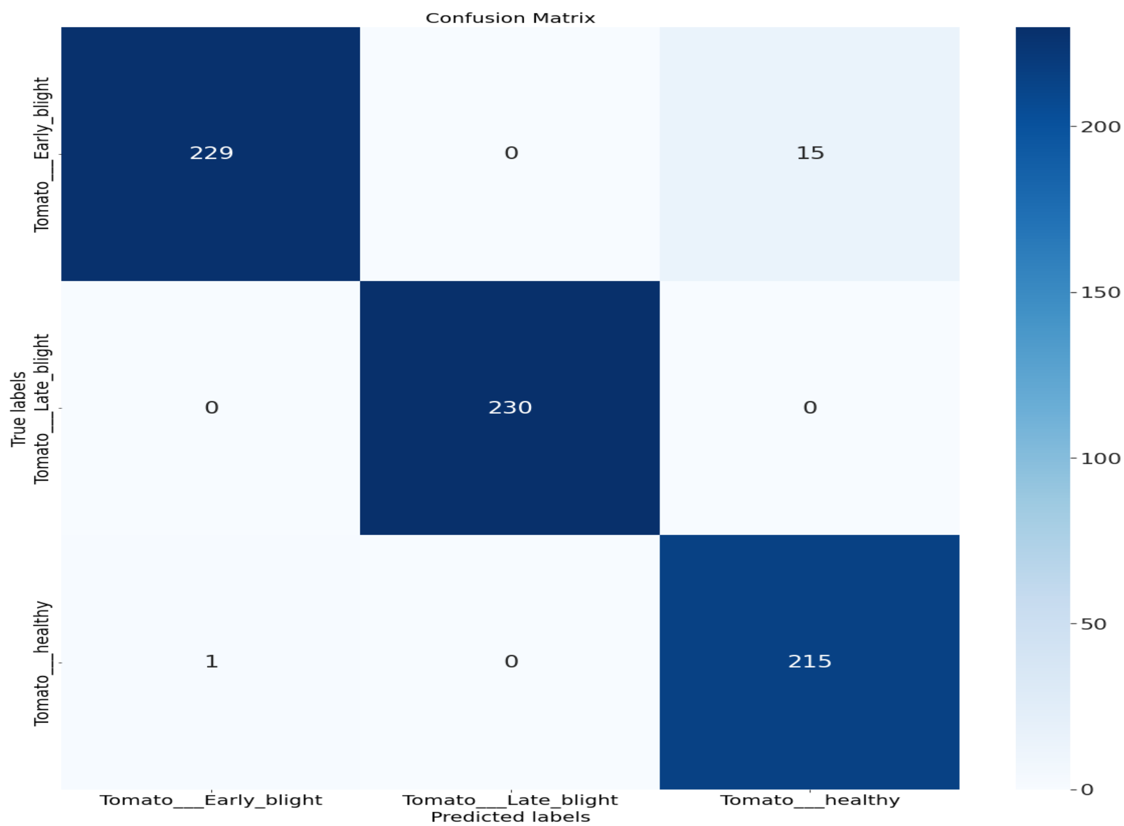

Figure 13.32: Confusion Matrix

In the test dataset, the VGG- 16 Confusion Matrix shown in fig-13.32 for Bacterial Leaf Blight fared better than all other diseases and correctly predicted 229 out of 230 images. Additionally, it was effective against the sickness Brown spot out of 230 it accurately predicted 230 images. The prediction accuracy for Leaf Smut was bad, although somewhat less than for the Leaf Blight predict accurately 215 out of 230.

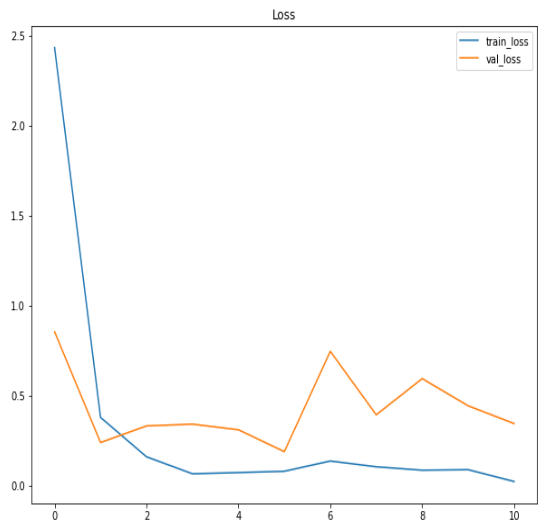

Figure 13.33: Train_loss Vs Val Loss

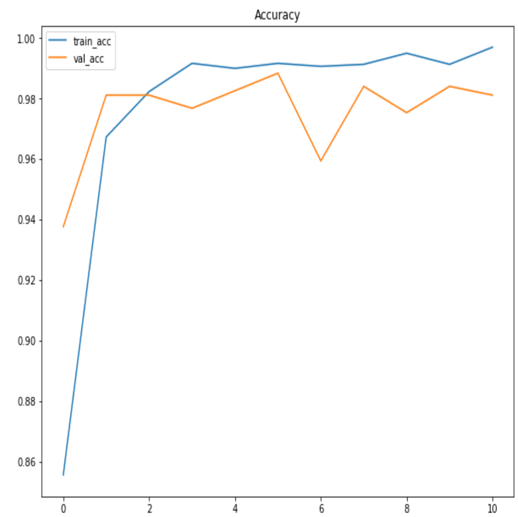

Figure 13.34: Train_acc vs Val acc

In the Above curve shown in fig-13.33 for VGG-19, the trainings and validation loss curve is seen to stay almost near to each other indicating a good fit of the dataset. While the training and validation accuracy shown in fig-13.34 also shows similar properties by increasing over the time maintaining a symmetry over all of the epochs. But in the early EPOCHS Val ACC was slightly low.

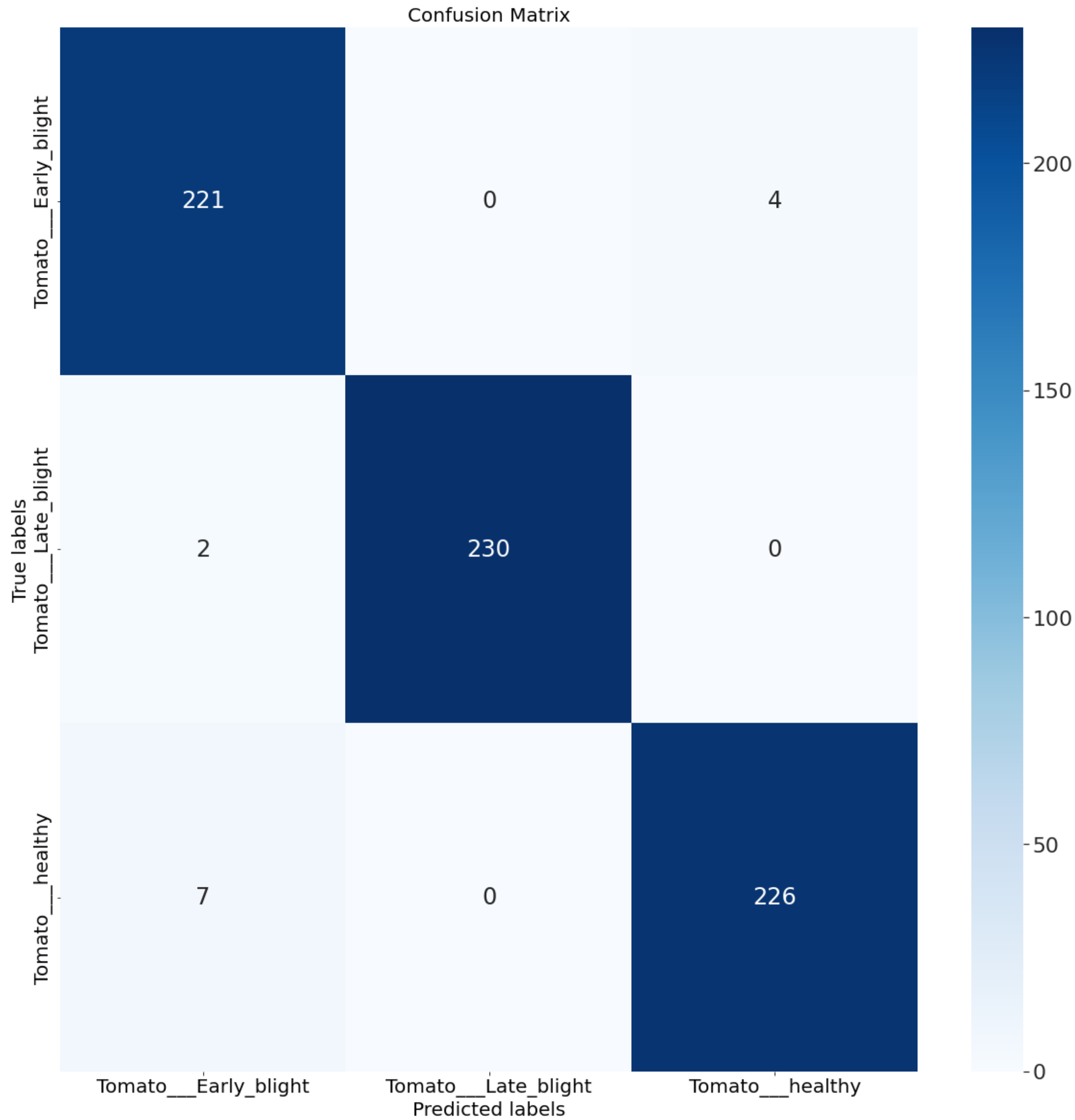

Figure 13.35: Confusion Matrix

In the test dataset, the VGG-19 Confusion Matrix shown in fig-13.35 for VGG-19 Bacterial Leaf Blight fared better than all other diseases and correctly predicted 221 out of 230 images. Additionally, it was effective against the sickness Brown spot out of 230 it accurately predicted 230 images. The prediction accuracy for Leaf Smut was bad, although somewhat less than for the Leaf Blight predict accurately 226 out of 230.

In the below curve shown in fig-13.36 for Inceptionv3, the trainings and validation loss curve is seen that not staying near to each other indicating a over fit of the dataset. But the validation loss curve slightly high. While the training and validation shown in fig-13.37 accuracy shows dissimilar properties by increasing over the time maintaining a symmetry over all of the epochs. So it shows the dataset over fit.

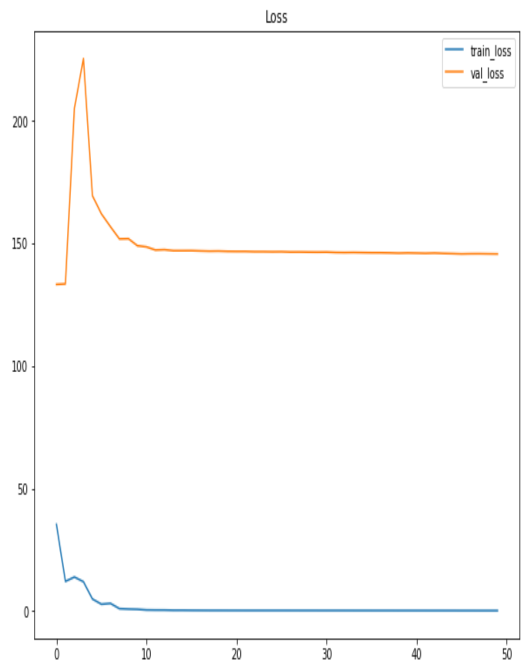

Figure 13.36: Train_loss Vs Val Loss

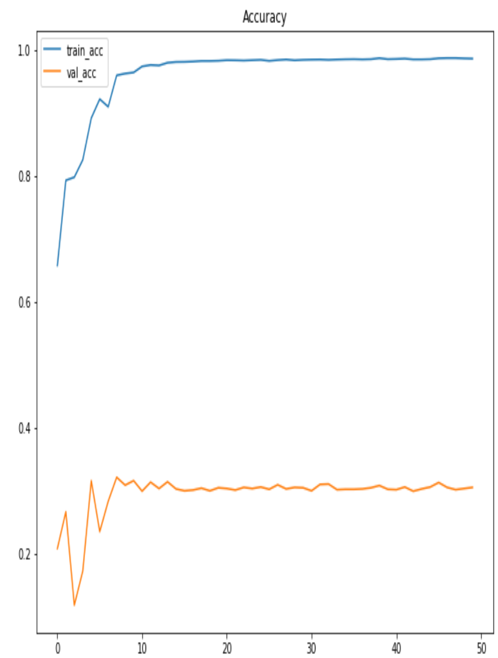

Figure 13.37: Train_acc vs Val acc

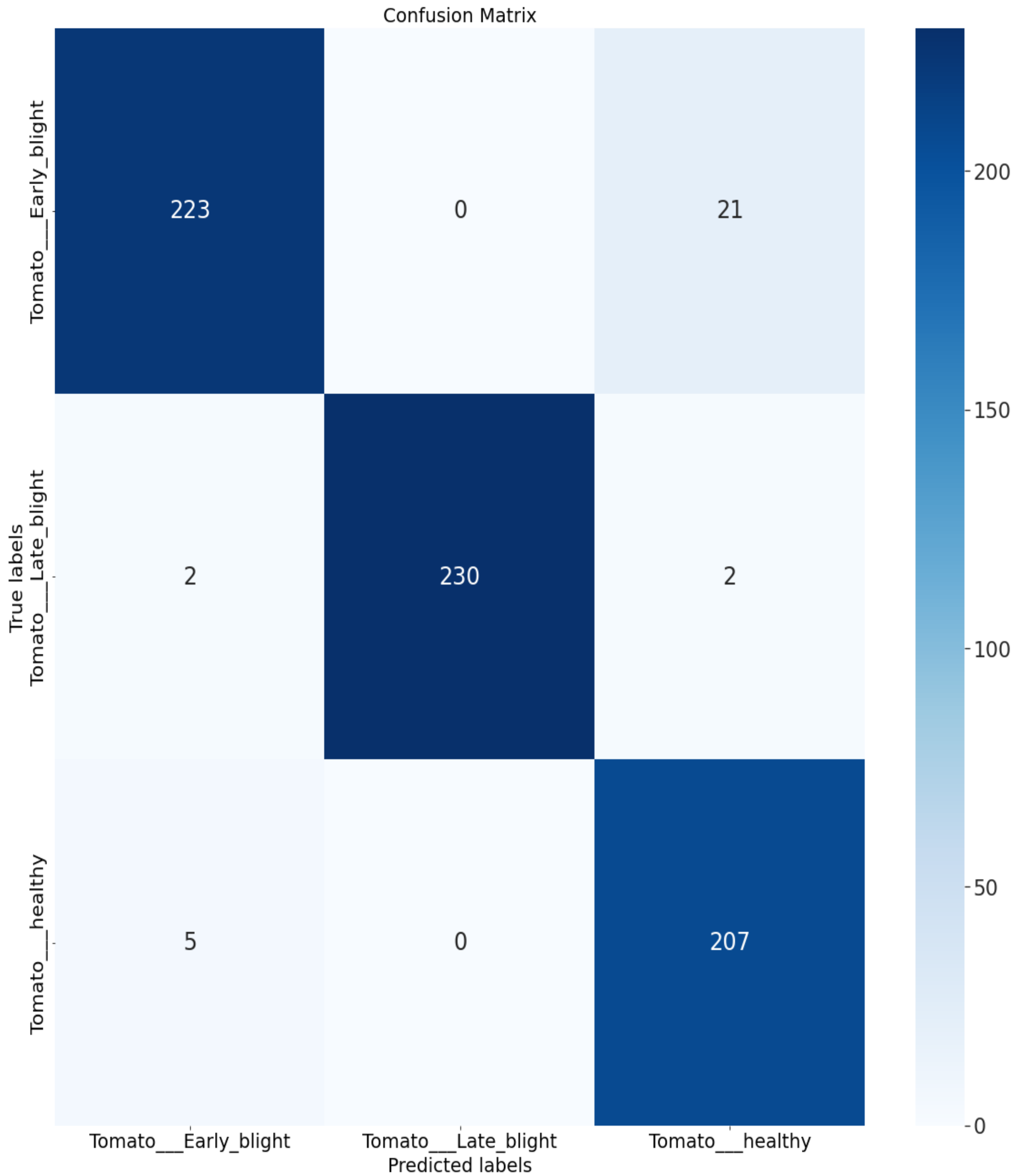

Figure 13.38: Confusion Matrix

In the test dataset shown in fig-13.38, the Inceptionv3 Confusion Matrix for Bacterial Leaf Blight fared better than all other diseases and correctly predicted 223 out of 230 images. Additionally, it was effective against the sickness Brown spot out of 230 it accurately predicted 230 images. The prediction accuracy for Leaf Smut was bad, although somewhat less than for the Leaf Blight predict accurately 207 out of 230.

4.3 Discussion

For each plant type in our categorization dataset, we ran four algorithms. We receive various kinds of accuracy, precision, recall, and F-1 score for this four algorithm. Both the training loss vs. validation loss graph and the validation loss vs. train loss graph were observed. This kind of graph provides us with clear information about our dataset. The confusion matrix for each crop and algorithm was then examined, and by doing so, we were able to determine how well our model would predict. Next, we decide which algorithm will be used for each crop and create our final prediction model. The accuracy of the suggested system, which is based on Python, is about 90% up. We constructed the 98% accurate potato model using the CNN model. To construct the tomato model, we used the 99% accurate VGG-19 model. Once more, the accuracy of the rice model that we built using the CNN model is 93%.

CHAPTER 5
IMPACT ON SOCIETY, ENVIRONENT AND SUSTAINABILITY

5.1 Impact on Society

Plant disease is an alteration to a plant's normal condition that impairs or changes its essential functioning. All plant species, both wild and domesticated, are susceptible to illness. Despite the fact that each species is prone to certain diseases, these diseases are always relatively uncommon. Identify the existence of the pathogen, the surrounding conditions, the crops, and kinds farmed, and the incidence and intensity of plant diseases change from December through February. While some plant kinds are more susceptible to disease outbreaks than others, others are. Our goal is to make it workable for farmers to operate more effectively and economically, safeguard their way of life, and minimize risk. By providing a photo, our website or app helps farmers identify plant illnesses, diseases, and pests. Farmers are not always aware of present plant disease reasons and medicines. They always can't know about the upcoming new medicines. They need a mentor for growing plants in an economic way. All over our country farmers aren't connected to each other. Sometimes it needs to share farmers' knowledge and own experience. It will help others farmers. On this platform farmers, general people, and new farmers can connect with each other. We always see that any disease spreads quickly, but it knew others place people when the news came to any newspaper or television. But if we connect the target people in a platform, we always share any knowledge or suggestion quickly and short time. Sometimes we see many farmers face a big problem that they need a mentor. On this platform, we can suggest them and get information from their local agriculture department employee. We also get their local medicine or fertilizer shop and where they can get the medicine. It means that farmers also can contact the shop owner and buy medicine online or offline. In this app/website farmers can chat live with us and send a query. We can provide offices in every district. In every office, we will appoint some employees. Also, have some field employees. They will work with farmers in the field to help them predict disease and grow their farms. On the platform, farmers also can post and other users can help his/her by throwing comments. We all know how powerful social media is. So, we want to build it to help their quickie. On the out platform, farmers can search by using a filter and get any upazila or district, or division-level employee information. This platform helps any kind of people that haven't any plant or plant disease-related knowledge. We using here plant disease prediction and also suggest medicines. It helps our society to grow up our farmers' working procedures and lifestyle.

5.2 Impact on Environment

The tens of millions of live plants and animals are maintained in balance with each other by several ecological processes, including plant diseases, which are a typical component of nature. To improve their defenses against viruses, animals, and pests, plant cells have unique signal transduction. One illustration is a plant hormone called jasmonate (jasmonic acid). Jasmonate controls crop growth, pollen generation, and other functions when no adverse stimuli are present by binding to unique proteins known as JAZ proteins. Jasmonate, however, changes its transcription factors when damaging stimuli are present and begins to control procedures that enhance plant protection. Jasmonate and JAZ protein-producing genes could be used as genetic engineering targets to create plant variants with higher disease tolerance. Illness control procedures may be a waste of resources and time and therefore can result in additional plant damage if somehow the disease and its cause are not correctly identified. Therefore, accurate illness diagnosis is essential. Plant pathologists frequently have to concentrate on symptoms and illness to determine the presence of a disease. More diagnoses or conserving and protecting times may result from early disease detection. This possibility has prompted public health initiatives that advise communities to undergo routine screening exams with the purpose of identifying particular chronic diseases.

5.3 Ethical Aspects

It is hard to always predict the correct disease for a plant. But I very much possible to do it. We also see some country also build a system that can help them. But all the platforms predict the disease but do not get local support. Framers need to gather some different knowledge. Farmers need to know some plant/crop growing reports and the present situation. We know, farmers have very much knowledge about their previous work. So we think it needs to share the experience with other farmers and also the new farmers. At this point, we plan to build a platform that can help them and also help their crop growth. It will help all users to play a great role.

5.4 Sustainability Plan

People have suffered significant losses due to plant or crop diseases in a number of ways. The Irish famine brought about by the late blight of the potato resulted in starvation and the dispersal of families. With the almost complete eradication of the American chestnut from chestnut blight, a priceless resource was lost. And significant economic damage, as the estimated $1 billion in damages suffered by American maize growers in a single year as a result of southern wheat leaf rust. Each year, numerous plant diseases around the world result in less severe losses for farmers but can also diminish the intrinsic appearance of vegetable crops and landscaping plants. Reducing the financial and aesthetically damaging effects of plant diseases is the aim of plant protection. Plant disease control has historically been used to describe this, but modern social and ecological norms view "control" as an absolute as well as the term as being overly restrictive. However, this mentality change has led to the development of more comprehensive and integrated illness management strategies. Single, frequently harsh measures like applying pesticides, fumigating the land, or destroying are no more frequently used. Furthermore, rather than using a schedule or a script, illness management practices are frequently chosen based on disease prediction or clinical diagnostics. Collecting local infected crop or plant photos. Analyze the reason and learn about the model about it. It improves the prediction quality. The various disease management plan techniques, tactics, and strategies can be categorized under one or even more very general principles of action. It can be difficult to distinguish these principles from one another. Always try to update the dataset and model. Always try to ensure the quality of services.

CHAPTER 6
SUMMARY, CONCLUSION, RECOMMENDATION AND IMPLICATION FOR FUTURE RESEARCH

6.1 Summary of the Study

Plant diseases must be studied carefully since they can harm both plants and their yield. The numerous losses can happen on the farm, in storage, or at any point between planting and harvesting. Direct financial loss and productivity losses are directly attributable to the disorders. Early disease identification and loss reduction have been made feasible by the use of precision farming by making the best judgments possible based on the results of ML approaches. Recent advances in ML provide solutions with incredibly accurate results, and the technology currently available enables rapid processing. However, the decision-making process might be improved. When tested against actual data, the currently available models perform badly. In order to overcome the major barriers to practical implementation, the author developed a new that is based on method for recognizing plant illnesses. A label dataset was offered in this study that contains images of leaves in real situations that were taken from different perspectives and labeled both for classification and detection tasks. The dataset is expanded as a result, improving the classification accuracy and practical usefulness of the model.

6.2 Conclusions

The advantages to farmers and the agriculture industry were taken into consideration when developing the suggested method. The created system is capable of identifying plant diseases and offering a treatment for them. It is possible to improve the health of the plant by having a proper understanding of the disease and its treatment. The proposed system's accuracy, which is based on Python, is around 90% up. We used the CNN model to build the potato model where accuracy is 98%. We used the VGG-19 model with the accuracy 99% to build the tomato model. Again, we used the CNN model to build the rice model and the accuracy is 93%. Buy For many years, plant infections have been a significant problem in agriculture. Through the use of precision farming, early disease detection, and loss minimization have been made possible by making the best decisions possible depending on the outcomes of ML techniques. Recent developments in ML offer solutions with extremely precise findings, and the technology that is currently accessible permits quick processing. The decision-making procedure, though, may be enhanced. The models that are now available perform poorly when evaluated under actual circumstances. This led to the development of a novel based on a technique for identifying plant diseases the author's prior research in order to get beyond the key obstacles to practical application. In this study, a label dataset was presented that includes pictures of leaves in actual environments, shot from various angles and labeled for both classification and detection tasks. By doing this, the dataset is extended, which raises the model's classification precision and practical applicability.

6.3 Implication for Further Study

The utilization of Google's GPU for processing can boost speed and accuracy. The technology can be installed to drones so that agriculture fields can be monitored from above. Future research should concentrate on identifying disease stages and locations throughout the plant. The created model could be a component of a system that supports decision-making and, as such, offers favorable circumstances for making the best choices. By just snapping a snapshot of the plant leaf, it may also be included into a smartphone application and offer an affordable method for identifying plant illnesses.

As mentioned in the sections above, the bulk of research used the effectiveness using the PlantVillage dataset and the performance related architectures. Despite that this is true collection encloses several images of different plant animals with ailments, the background is clear and uncomplicated. But for a realistic situation, the actual surroundings must be considered. A new technique called multispectral and multispectral imaging has been used in many different scientific domains. Therefore, it should be used in conjunction with effective ML designs to identify plant illnesses even before they manifest obvious symptoms. A more effective means of identifying diseased plant areas should be developed since it will prevent the needless use of fungicides, pesticides, and herbicides, which will save expenses. Since the intensity Since the prevalence DL models should be upgraded or changed to reflect changes in plant disease patterns over time for the detection and classification various illnesses over the course of their whole cycles of occurrence. The DL architecture needs to be effective under a variety of lighting circumstances, therefore datasets shouldn't be only reflect the actual additionally to the environment pictures taken under different fields conditions. To comprehend the variables affecting the identification of plant illnesses, such as the classes and quantity of datasets, learning rate and lighting, and similar aspects, a thorough study is necessary.

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IMPLEMENTATION OF AN IMPROVED CNN MODEL FOR DETECTION AND PREVENTION OF PLANT DISEASES USING MACHINE LEARNING IN AGRICULTURE BY MD MAHFUZUR RAHMAN (ID: 191-15-12378), MD ZAHIRUL ISLAM MEHADI (ID: 191-

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