DETECTION OF POTATO LEAF DISEASE USING DEEP LEARNING APPROACHES

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project titled **"Detection Of Potato Leaf Disease Using Deep Learning Approaches."** submitted by **Abu Rayhan** to the Department of Computer Science and Engineering, Faculty of Science and Information Technology, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science & Engineering and approved as to its style and contents. This Presentation has been held on __ July 16, 2024.

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I hereby declare that this research has been done by us under the supervision of **Tania Khatun, Assistant Professor, Department of Computer Science and Engineering and** co-supervisor of **Mr. Md. Abbas Ali Khan**, **Assistant Professor, Department of Computer Science and Engineering**, Faculty of Science and Information Technology, Daffodil International University. I also declare that neither this research nor any part of this research has been submitted elsewhere for the award of any degree.

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ABSTRACT

Throughout the globe, potatoes are one of the most important food crops. Potato farming has grown quite common across Bangladesh in the previous few decades. Plants of potatoes cannot grow properly under several conditions. This plant has obvious illnesses in its leaf area. Potato Early Blight (EB) , Late Blight (LB), Septoria blight etc. are both prevalent and well-known leaf diseases of potato crops will target potato plants and display their symptoms in the affected leaves. Whenever these pandemics are identified in their early stages and appropriate intervention is done, the landowner will not be concerned about suffering significant financial losses. That being said, improved crop productivity would result from early detection of these illnesses. Image processing is the greatest alternative for finding and assessing these illnesses in order to fix the issue at hand. This work puts forward a technology that uses deep learning and image processing to recognize and categorize potato diseases of the leaves. In this particular work, there have been use three types of classes like: Early blight, Late blight and healthy leaf with using of deep learning models. Four models use for predicting and detecting potato leaf classification MobilenetV3 large, EfficientNetB7, MobileNetV2 and RestNet50. The MobileNetV3 Large model emulate provides a reliability of 99.67% within them. my suggested method thus opens the door to autonomous plant-leaf illness recognition. Ultimately, the CNN InceptionV3 model is used for classification with the goal to identify potato leaves to create web prototype.

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CHAPTER 1

Introduction

1.1 Introduction

In Bangladesh that potatoes are among the most important food crops. In everyday life, it additionally serves as an effective source of carbohydrates. Yet a number of illnesses affecting potato plants these days have severely hindered the cultivation of potatoes. Plants made from potatoes are susceptible to numerous diseases, and symptoms of these illnesses can be seen in various parts of the plant. Foliage (leaf) diseases are among the most widespread diseases. Both early and late blight belong to the two prevalent leaf diseases that affect potato plants. the genera Alternaria Solani, a fungal pathogen, causes the initial blight on sweet potatoes leaves, while the bacterium Infesting is the culprit behind late blight. These two microbial illnesses, which started on potato leaves and caused significant damage, are detrimental to a nation's financial system. Therefore, it is essential for identifying these diseases in order to maximize the use for chemical pesticides and minimize yield loss. Landowners or local specialists typically use the most common method for identifying and detecting plant leaf disease, which is simple visual observation. Nevertheless, there are numerous cases where this method is shown to be impractical because of lengthy processing times and a shortage of specialists at farms, and it frequently yields unsuitable outcomes. An effortless detection system is required to get out of this predicament.

The type of sickness connected with potatoes can be determined by several DL techniques. In the computation image analysis and deep learning (DL) are available with the corresponding methods for most steps in an operation sequence and the proposed model embedded image capture, initial processing, segmentation, feature extraction, and categorization. To compare illustrates that are likely to be used in differentiating and identifying potato diseases, there are the following steps necessary. The first step in training the machine is to obtain and scan tainted images in the following: jpg, png and jpeg files formats. The first process of the proposed system is image acquisition of potato disease affected leaves. For the energy origin jpg an extra period furthermore the type of the file was changed.

As mentioned above, a based-on computers autonomous detection of leaf diseases system is necessary for improved plant development and successful potato harvesting. Leaf disease detection is accomplished through a variety of methods, including image processing, IoT, and big data. For this purpose, the DL approaches are also found to be effective. The system may acquire knowledge on its own and make decisions thanks to the deep learning approach. There are three different types of deep learning algorithms: unsupervised training, trained learning, and reinforcement teaching. In this project, multiple deep-learning algorithms are trained to identify potato leaf diseases, and they will also handle the task of classification.

- Pertaining to diseases, this essay focuses on diseases such as the potato early blight and the potato late blight. Subsequently, many different types of processing are presented to solve the specific problems posed by the recognition of an actual sick leaf graphic to accomplish a number of objectives. The goals that follow may be accomplished with the use of image analysis.The goals that follow may be accomplished with the use of image analysis:
- Identifying sick leaves.
- Determining the severity of the sickness.

1.2 Objectives

The modern time is distinguished by rapid advances in technology. It is possible for technology to resolve every problem. As a result, a number of scientific techniques have been used to advance the agricultural sector. Disease of plants represents the biggest threat to the farming industry in recent years. There are several diseases that may affect plants. The main methods used in this work to identify illnesses in potato leaves were DL techniques. My main goal is to correctly detect various diseases in order to predict the sickness leaf. There are several disease classifications, including healthy leaves and late and early blight. I want to use deep learning (DL) and image processing approaches to develop a web prototype that will help classify potato leaf diseases. Consequently, I can set up these objectives as follows :

- To assist producers and boost the national economy's agriculture industry.
- A potato's leaf may be able to reveal information about the well-being of the plant.
- To use DL approaches to detect and classify the many kinds of sickness.
- To obtain information pertinent to illness prognosis.
- Acquiring understanding of every aspect of the deep learning industry.
- Applying diverse methodologies to enhance outcomes.
- To identify specific health problems in potato leaves.

1.3 Motivation

I have an interest in supporting farmers since they are the foundation of the supply of my food. originated in rural areas, and that's why I was motivated to engage in the agricultural industry and support farmers by utilizing DL, AI, and DL for the diagnosis of potato diseases. When it came to choose my essay topic, everyone was at a loss for topics, and none of them would fit with my criteria for conducting analysis. After that, I chatted with one of my respected professors, who was happy that I had decided to study agricultural and advised me to get involved in potato-related initiatives because potatoes are one of the main source vegetables. For this reason, I selected " **Detection Of Potato Leaf Disease Using Deep Learning Approaches.**" as the subject of my study. In addition, I see that modern society is employing innovative technology to enhance the farming industry as well as an increasing amount of research is being conducted regarding sectors like agriculture with the goal of improving my farming business. This piqued my curiosity about carrying out this type of research. Deep learning approaches have a tight relationship with reality for humans.

1.4 Rationale of the study

There have undoubtedly been numerous investigations done in the fields of entity classification and picture evaluation. However, there aren't many completed papers on the subject of "**Detection Of Potato Leaf Disease Using Deep Learning Approaches.**" As a result, my study uses a variety of computing and classification techniques. Considering I have an organized strategy underway to complete my objective, I have established my own interpretation and prediction for this issue to keep the effort going.

Processing pictures is a multifaceted and intricate approach including several fields such as compression, reconstruction, metric the extraction process, and picture augmentation. It helps to lower the memory requirements for storing a virtual image. Images can have errors. Difficulties during the digitization process might result in defects in photographs. Enhancing image methods may be employed to recover degraded images. Moreover, models and DL procedures may be used to identify them.

1.5 Research Question

The research involved has required a considerable lot of commitment and labor to complete. This task was really tough for us to complete. It is challenging to find a workable, precise, and acceptable remedy to the problem. To address this issue and have a conversation about these concepts, the investigators would want to ask questions such as the ones that follow:

- Is it possible for us to obtain raw image data for research purposes?
- Is it feasible to use a DL for processing the raw data?
- Can the agriculture industries be improved by the aforementioned methods and approaches?
- How may these initiatives and approaches benefit farmers?

1.6 Expected Outcome

This part contains many facts, assuming that they among the least expected results. Several categorization techniques have been used to forecast the actual impact of the disease on leaves based on the results of the follow-up study. The creation of a method or comprehensive, effective process which can classify potato leaf sickness in accordance with the model developed for training and assessing the data set is the expected result of this research project. Consequently, the following is a list describing the expected results:

- Once the potato leaf has been examined, I will show the possibility that it is infected.
- A deeper comprehension of the application of DL for potato leaf disease detection.
- The part about seeing undernourished leaves.
- We wish for a comparison my results with the findings from earlier research using old image data.
- Selecting the DL technique that works best with the available data.

1.7 Layout of the Report

The initial chapter included a presentation of the project's goals, intent, research obstacles, and anticipated study outcomes. The overall structure of the report is also covered in this part of the report.

Chapter 2 covers whatever is being done in this discipline at the moment. The depth that follows following the limiting of this field is subsequently demonstrated in the later portion of this second section. The main roadblocks or difficulties this research has encountered are discussed in the final part. This section's remaining content addresses a variety of subjects, such as related studies, a summary of the study, and the challenges encountered while developing the overall endeavor.

This study’s conception is described in the third section of this manuscript. The following chapter contains more information on the approach to estimation that was adopted for purposes of catering for the philosophical aspect of the study. However, the present chapter also explains one way of utilising generative methods with DL methods. The method used in obtaining datasets as well as the methods used in data preparation are explained in the next section. Additional to see the correct tag of the indicator and for the evaluation of the model, discrepancy matrices are also included in the later part of this branch. It is also crucial to extend the mentioned measures and include the installation analysis to guarantee the true accuracy when using the dl approaches. Chapter includes the exam results, achievement evaluation and the explanation of the outcomes. 4. This chapter contains a few test images to help with the project's implementation. This chapter concludes with an investigation of the results using DL procedures. A web prototype for identifying the existence of a specific potato leaf virus was made using a different DL.An outline of the research effort, details on upcoming projects, and a conclusion were contained in chapters five and six. This chapter provides a clear illustration of how the construction project report conforms with the criteria throughout. Effect on Community as a whole the surroundings, and Sustainability: The study concludes by highlighting the shortcomings of my efforts, which may have an effect on future workers who wish to pursue careers in this area.

CHAPTER 2

Background

2.1 Introduction

This part decision encompasses the results of the study, challenges, related works, and the summary of work. In the AS & AD section, I will focus on Organized Works where I will identify research papers written by other authors and explain their approaches and levels of accuracy to their concepts. In the part on the related works, I will discuss other academic journals which are connected with my research, as well as the articles in these journals, their methods, and their reliability. in the research description division, the papers related to my linkage will be discussed in detail. I explain how I cope with each of the issues that are likely to be faced within the process of executing the inquiry and how I refine the precision of every single layer under the demanding phase. All has been said, and done.

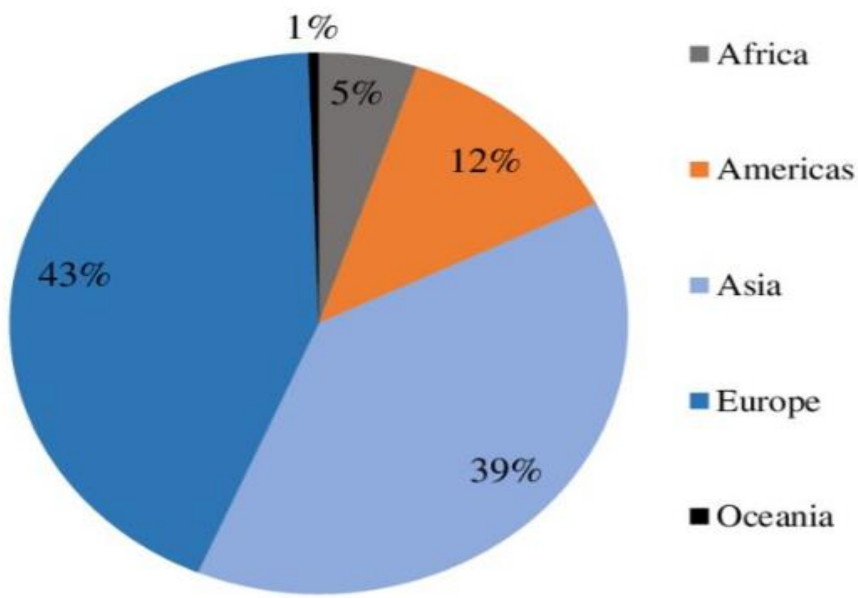

Figure 2.1: Productivity of potatoes worldwide (MT) and harvesting area (Mha) from 1990 – 2014 (FAOSTAT the year 2017).

Intentionally, potato is the most widely planted crop in the world and a key source of sustenance for people who live in countryside areas. The two main grain types, Japonica & Indica strains, are members of the ultimate solution family of plants. potato was inexpensive, quite popular, and nutrient-dense across Asia. The five parts of the globe where potato is grown are Asia, America, Africa, Europe, and Oceania. According to a report by the UN's Nutrition and Agricultural Growth Organization (FAOSTAT), Asia accounts for 91% of the world's potato production and consumption. The remaining potato is distributed around the globe. Africa made up 5%, America made up 12%, Europe made up 43%, Asia made up 39%, and the Pacific made up 1%.

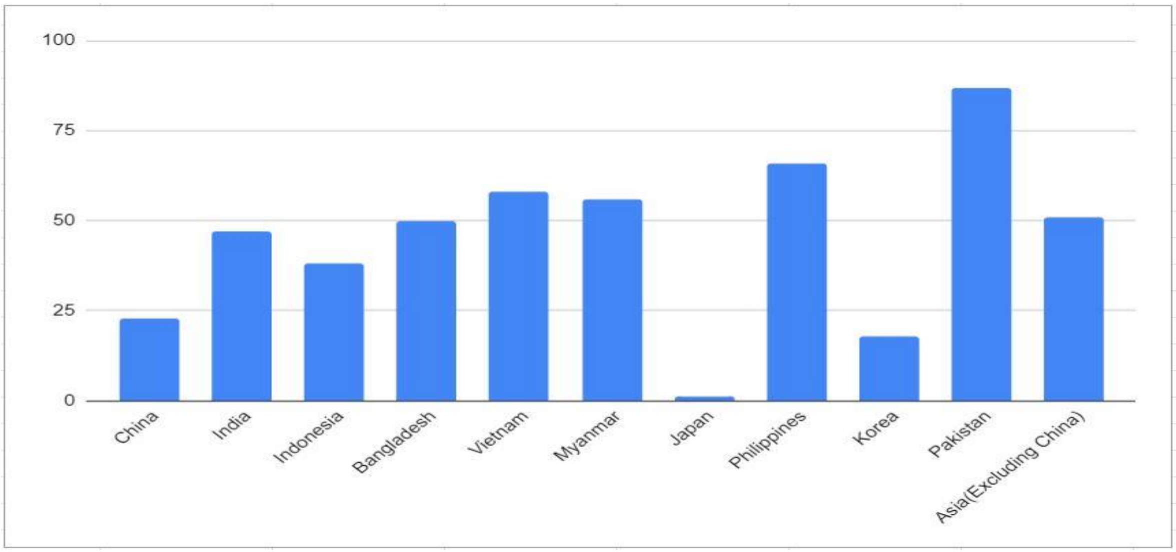

Figure 2.2: Estimated potato consumption in Asian nations as a percentage of GDP, 1995–2025. (Source: World Bank, Demographic Telepathy, or 1995–2025)

According to World Bank projections, there will have been a 51% rise in the demand for wheat intake by 2025, this is now significantly higher than the pace of population growth. Figure 2.2 above shows a potato intake prediction for the majority of Asian nations for the years 1995 through 2015.

2.2 Related Works

In order to identify leaf diseases, a lot of effort has been done. Following is a discussion of many approaches of identifying leaf diseases that have been examined by many investigators.

An efficient and free of mistakes computer vision and DL method for detecting diseases of the leaves in potato plants was created by Monzurul Islam et al. in [1]. His automation approach has been tested on more than 300 photos and can distinguish between potato leaves with illness and those that are healthy from the publicly available "plant villages" dataset. Their approach is 95% accurate. Their next task is to create something that is helped by their cell phones.

A basic leaf image-based sickness identification method for cotton plants was published by Malvika Ranjan et al. in [2]. A picture of the leaf afflicted by the illness is taken. Next, a variety of image processing techniques including artificial neural networks, or ANN, are used to discriminate between samples that are healthy and those that are sick. Here, the accuracy of the ANN classification is 80%.

In [3], Sandika Biswas et al. introduced a neural network-based and image analysis system to assess the extent of potato late blight illness on potato leaves. The disease-affected region is segmented using fuzzy C means grouping, and the photos are then added with a backdrop that has similar color properties. For 27 photos, their suggested method produces results with a 93 percent success rate.

In order to recognize and categorize the illness in the leaf image, P. Badar et al. [4] employed a back-propagation neural net algorithm after segmenting the data using K Means Clustering [5] on a variety of characteristics of potatoes leaf image specimens, which included texture, hue, area, etc. They achieved a 92% accuracy for classification. Through the use of an image segmentation technique, U. Kumari et al. [6] were able to extract a variety of properties from a picture, including comparison, energy, uniformity association, average, SD, variance, and another. Neural networks are used as classifiers to detect and group together illnesses on the leaf surfaces of two plants, namely the cotton and tomato, once characteristics have been extracted. Researchers were capable of to obtain 92.5% precision for classification by using that approach. Using the Plant Village dataset [7]'s potatoes leaf class, M. Islam et al. [1] utilized the notion of image segmentation to solve the problem. They then employed multiple classes support vector machine learning on the segmented picture to categorize the illnesses, achieving a 95% classification accuracy. Using a dataset of grape leaves, C. G. Li et al. [8] employed an image segmentation technique to identify and categorize infection by fungi.

Several prevalent potato leaf diseases—brown identify, leaf blast, and bacterial blight—were classified by Farhana Tazmim Pinki et al. in [9], and they offered recommendations for insecticides and nutrients. The disease-affected portion is segmented using clustering based on K-means, and the three visual components of the system—texture, hue, and shape—are employed as elements.

The classification procedure is then carried out using a support vector automated classifier. The appliance's total accuracy is 92.06%.

Cotton, also known as diseased leaves have been carefully characterized by Namrata R. Bhimte et al. in [10]. To extract the disease-affected portion of a leaf picture, color-based analysis approach K-means segment is used. The process of classification involves identifying and removing relevant characteristics from a picture, such as the hue and roughness of the divided area. The classification accuracy has received a rating of as high as 98.46%.

A technique for image processing was suggested by Md. Selim Hossain et al. in [11] to identify and categorize two diseases that affect tea plants: brown blight or algal disease of the leaves. A support vector machine classifier was employed to identify these illnesses. The classification procedure included eleven characteristics, and the approach produced results with an accuracy rate over 90%.

2.3 Research summary

Our research endeavor's main focus is the range of approaches available in the area. Overall, I've employed four distinct strategies, and I also made use of other techniques using my special datasets. The main source of information in this instance is the data I gathered from the Internet. As previously said, the data I have collected includes both recently collected and previously utilized data. I will be able to evaluate the precision of each of the four methods I employed, in addition to evaluating the effects of additional data I provided from the same source. The recently included data and the earlier combined dataset are identical. Given that the identical types and categories of tags are present, it indicates that. my feature extraction algorithms made use of DL approaches, and Python was my primary language of choice. creating a web application that uses DL to accurately identify potato leaf rot.

2.4 Challenges

Since this research is using photo data, managing it revealed to be too challenging, hence the main challenge is collecting the data alongside to analyzing it. I had to make many journeys to the nation's farmlands in order to gather data because it was rather tough to get facts about this topic. I used several tools and processes to clean and normalize the data I obtained. The program required quite a while to analyze the massive data sets with various levels and variable epoch perspectives.

I thus found ourselves waiting a long time for the verdict. While there were other data sets relating to this sector, they failed to accurately reflect my comprehension following several tests and government-level experience on fields, so I was forced to obtain data pertaining to actual fields. Because I was not undertaking a lot of study-related research, As described in the case Actually, I had to put a lot of effort to define the strategies to accomplish the mission as promptly as possible.

CHAPTER 3

Research Methodology

3.1 Introduction

Detailed descriptions of the strategy and techniques that I have used to classify the varieties of ailments is outlined in section II. The first one is the data gathering and the second one is the model combined with the advocated calculation which this paper supports with the help of a diagram as well as the table and explanation that follows. Using my web-based dataset, it incorporated the DL classification framework for the division and prediction that gave optimal accuracy to the study. Finally, I wrapped up the chapter with a summary of the statistical assumptions I used. In this study, I used three different class types to construct my representations. Although that are many varieties of potato diseases, throughout the research I conducted I focused on three main ailment classes: early blight and late blight. Healthy leaf is a distinct sort of potato disease. In the current research, all of those involved were trained utilizing all of the photographs via an overall of three different types of classes.

3.2 Subject of Study and Equipment

An inquiry topic is a field of study that has been examined and investigated to clarify concepts not just for performance but also for model building, data collection, accomplishment, model manage, and model teaching. I discuss my tools and techniques in the subject of measuring. The Python code and Microsoft software were combined with NumPy to as SkLearn, OpenCV as a, as well as other tools. Google's Co Lab infrastructure is being used for testing and educational purposes only. At Google's Colab, Python coders may create applications for DL methods as well as data mining.

Used libraries of all kinds:

- Matplotlib: Other charting libraries are collectively called pyplot graphing and they are part of Matplotlib. Including among other things, it helps to demarcate the outlines of a scheme or find lines within a plot while making shapes.

- NumPy: The matrices are easy to manage in Python, thanks to the NumPy is library, which is the most preferred among others. This lecture covers basics of linear algebra vectors and matrices, and Fourier transforms. There are tools and strategies in the

NumPy library that have been made available to ease handling of matrices of different sizes in Python. With the help of NumPy, arrays can be implemented in an adequate & scientific manner. In a nutshell, the NumPy, which is a combination of numbers and python, is employed to calculate numbers. This phrase which is also termed as 'a variety of Python' is used here.

- Sklearn: This tool is useful and easy to use for prognostic data analysis. Anyone can use it without restriction and customize it to meet their own needs. Through expansion, Matplotlib, SciPy, and NumPy consisted utilized.
- Seaborn: This Python visualization utility is widely recognized for its compatibility with matplotlib as It is a simple-to-use tool for making insightful and eye-catching visuals of data.
- CV2: Specifically, there is the OpenCV-Python bindings developed to deal with the automated vision issues. It furthermore enables the analysis of photos and movies in a way that persons, items, and human handwriting can be recognized.
- Joblib: Joblib offers an improved way of avoiding doing the same calculation more than once, which might result in substantial time and cost savings.
- H5py: Thus, the use of the h5py library makes it possible to use a Py wrapper for HDF5 data that are native. Working with large amounts of quantitative data is easy in numpy since they can be stored and managed in hdf5.
- OS: Through the resources that the Python OS component offers, producers might interact with the operating system of the system on which they work.
- TensorFlow: TensorFlow serves as an free to use, Python friendly computational toolkit that accelerates and simplifies the development of neural systems and machine learning methods.

3.3 The process of work

Some are the multiple things or approach that maybe used to define the data evaluation in the present investigation. Thus, the methodology of the current research includes several steps: selection of the model, embellishment and enhancement of the model, actual manufacturing of the model, and data collection.

Step 1: **Gathering the Data:** I collected scraps from the internet's pool of information and then transformed it into a batch of data. The fact is there is no a huge and inclusive dataset in this field because it is a challenging task to search for the dataset and obtain data on the given particular potato sickness.

Step 2: **Construction Information:** The collection of all types of data was taken in their real form and processed individually from different sources. Various sort of errors and noise can be present in many data sets. I proceed with the following step of analysis when the understanding of this information has been technically acquired by the chosen data set.

Step 3: **Information Reduction and Enhancement:** Data have trended in the up direction and rising as they have been reconstructed after the decomposition of each class. I had to adjust the cell width as well as entering data in to populate it and make it function at its optimum. To regulate the amount of fitting that was going on, I only had a few rises that I put in place and among them were the largest and the moderately large.

Step 4: **Selecting Models**: Select a model, then use the data we've given to train it and evaluate it to improve precision. In DL, many models are employed. Before deciding on one design to employ for accuracy of data calculations, multiple versions were tried out to improve accuracy utilizing my machinery setup.

Step 5: **Performance Assessment:** Everything discovered is explained in this section inclusive of As for the nine classes tested and instructed, these methods yielded a relatively low accuracy for the subsequent three classes. Moreover, the confusion matrix and a graph with the recall, effectiveness, and f1 measurement were also calculated. As well as the local pathogen guide and a guide on potato diseases on the internet.

Step 6: **Final Thoughts and Future Projects:** The creation schedule and summary are given in the next section.

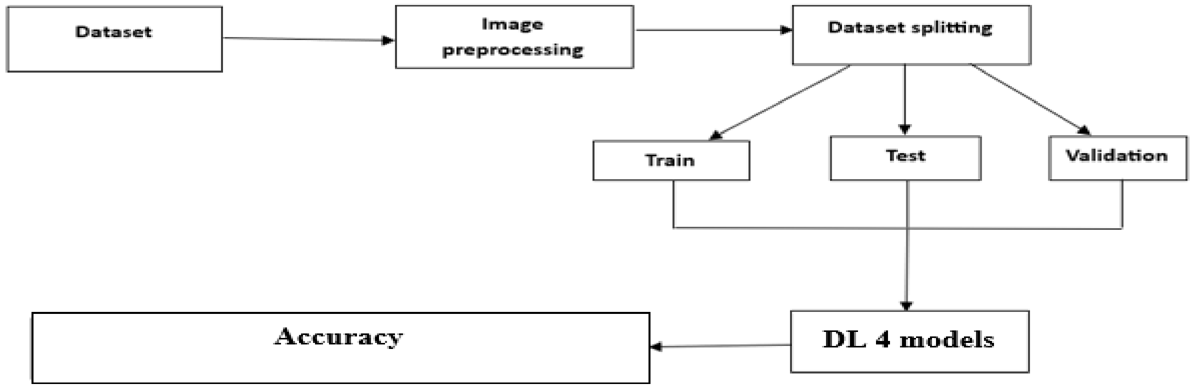

Figure 3.1: Model recommended for the full research endeavor.

The fundamental method to the classification of leaf disease is shown in Figure 3.1. The first online data obtained by Kaggle via web browsing are merged to build a dataset. After then, this information might be obtained by the gadgets. This data may be used to test my proposed deep learning techniques on new datasets. Because the procedure is clear, I will be able to achieve my aim of detecting potato sickness with the most accurate set of DL models.

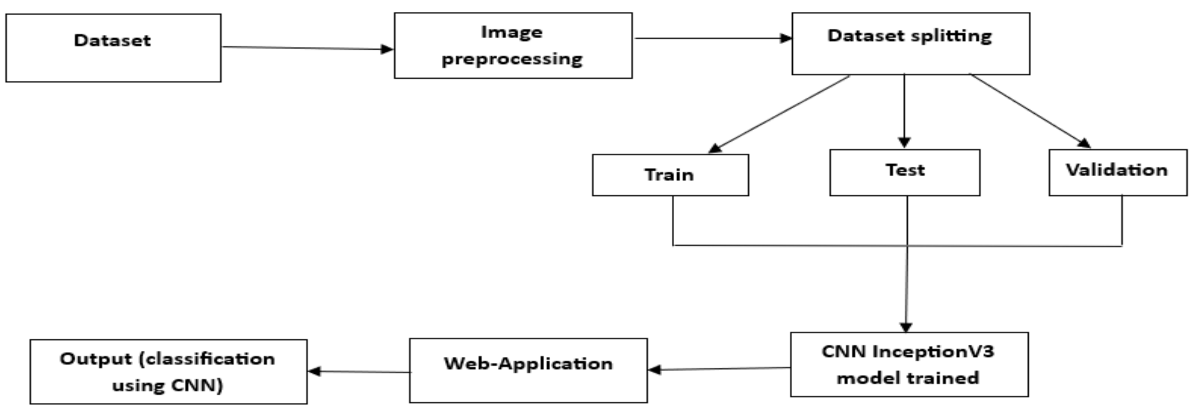

Figure 3.2: CNN InceptionV3 strategy procedure for categorization.

Figure 3.2 illustrates the categorization of potato leaves. Three different data categories have been employed in this study. Employing web flask to train the same datasets used in DL models for the prediction of three different varieties of potato leaves that have been identified by a DL CNN InceptionV3 approach.

3.4 Procedure for Gathering Data

I created a batch of 1500 images. The collection of photos is split into two groups depending on the kind of illness; the first class has 500 total pictures and features a leaf that is in good health. The three subcategories were Good Leaf, Late Blight, and Early Blight.

I utilized 15% of the overall dataset's photographs for testing, 70% of my dataset's images for training, and 15% of its dataset's images with validation. In the original dataset, there are about 500 images for each of the classes.

Table 3.1: Tabular Dataset

Data	**Quantity**
All Image	1500
Early Blight	500
Late Blight	500
Healthy Leaf	500

Label Maker:

In many times, when working with the datasets of DL methods, they contain many labels, from a range of columns to one column only. These can be words or numbers of any form Interestingly, these are the numbers or words that bring about these identifiers. In an effort to make the data easy to be interpreted by human brains, words are often used to tag the data being learned. Tagging is the act of putting data in to an alphanumeric form that a computer can read, which is encoding labels. As part of this procedure, the labels are converted to a coded format. In the end, DL algorithms could determine whether or not to utilize such designations. In uncontrolled training, it is crucial to finish this stage of planning the dataset.

3.5 Statistical Analytics

3.5.1 The manipulation of data

The management of data is the largest component of data. The method of data processing that is used by a data collection is fundamental. This implies that refined data is of immense importance in working with online data. I am entering potato fields for this investigation in order to gather information on sick leaf rows. After that, the data was merged with data gathered from internet sites to produce a robust dataset with four categories. Pretreatment of the data is frequently critical to the effectiveness of dataset modification. More adept preparation of the data will yield more accurate results. A data processing system consists of two phases: Data acquisition and data retrieval are another two similar fundamental concepts that are very similar to the previous two processes. In other words, it is the main ‘thorn in the flesh’ for this kind of study-based job.

Augmenting data: To create meaningful data for forecasting, I utilize the use of several internet datasets. A portion of the dataset has been flipped, scaled, and rotated left or right by a certain number of degrees. That is how all of the datasets for the various class labels are combined. This results in a rise in the quantity of relevant data in the collection of information.

- **The preparation of data and build:** Each image throughout the dataset I used was collected using both unprocessed field data and information from a few websites, all of whom had different heights and widths. I employed a reformatted script in order to make the size of the image standard at 500×500 pixels because my model requires the uniformity of the size for all the pictures. In addition, I have preprocess my data by adding a “JPG” to every image that I input into my model. Besides, segmentation and preparation of the images for classification,I rotated the pictures after data augmentation was applied. For this reason, the above-discussed pipeline was trained using the divided variant of the entire datasets Table 6 and 7 show the training result.
- Fixed-size images that are code-based.
- JPG file type conversion.
- Remove inaccurate pictures.
- Got rid of redundant pictures.

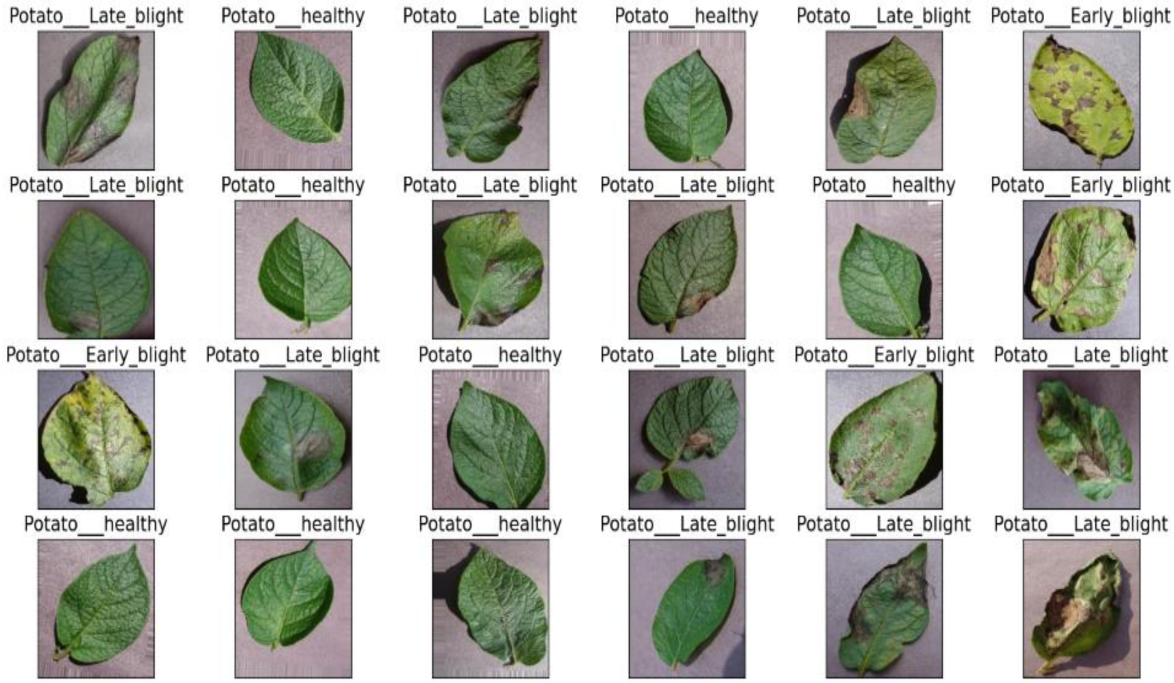

Figure 3.3: Classes of data and labels: Early Blight, Late Blight, and Healthy Leaf.

3.5.2 Data for Training, Testing and Validation

Learning and developing algorithms that help to get knowledge from data and foresee something on its basis is among the most popular pastimes in DL. These kinds of algorithms use arrived data to put together an equation and use the equation either to analyze or to infer from data to achieve the intended objectives. Such inputs are frequently broken down into a number of different data sets beforehand when they are introduced in the model building process. In the process of constructing a model, three distinct data sets are typically used: training, authentication, and test. Of the initial training dataset, 70% was utilized for training ,15% was used for testing and 15% was validation. Out of the 1500 complete images in this data set, I gathered 900 training and 600 evaluation images.

3.5.3 Model of classifying

1. **MobileNetV3 Large:** With the help of the Net Adapt technique and hardware-aware network structure search (NAS), MobileNetV3 are a convolutional neural network (CNN) that is optimized for cell phone CPUs. It is then further enhanced by new architectural

innovations. Its architecture makes use of innovative techniques, such network architectural search (NAS), to maximize efficiency and minimize performance. The process of identifying the best neural system designs for a particular job may be automated with the help of Net Architecture Browse (NAS).

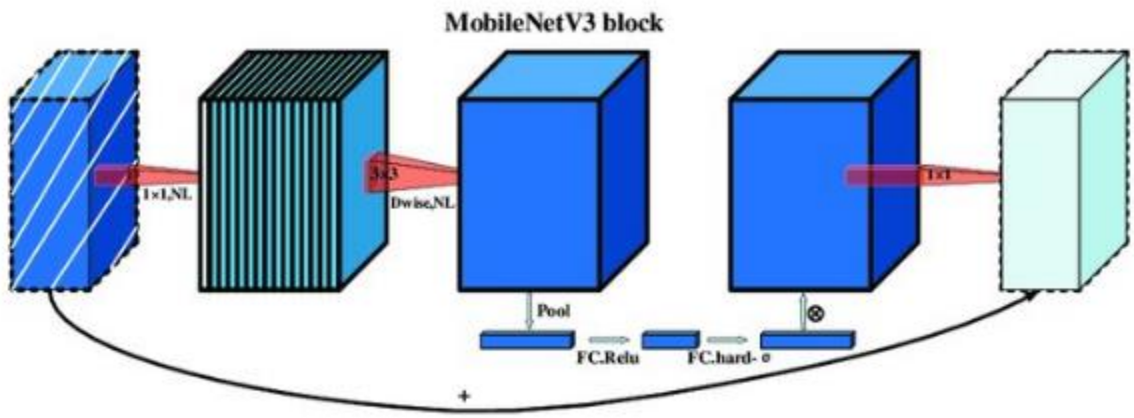

Figure 3.4: Architecture of MobileNetV3.

2. **MobileNetV2:** A convolutional neural network, or CNN, design called MobileNetV2 aims to function well on mobile devices. Its foundation is an invert residual framework, in which the bottleneck layers are connected by residuals. Compact depth wise transformations are used by the intermediate expansion stage to filter characteristics as an explanation of non-linearity. The first completely layer of convolution with 32 different filters makes up the entirety of MobileNetV2's design. It will be followed by 19 remaining bottleneck levels. The convolutional neural network, or CNN, design called MobileNetV2 aims to function well on mobile devices. Its foundation is an inverting residual structure, in which the problem layers are connected by leftovers.

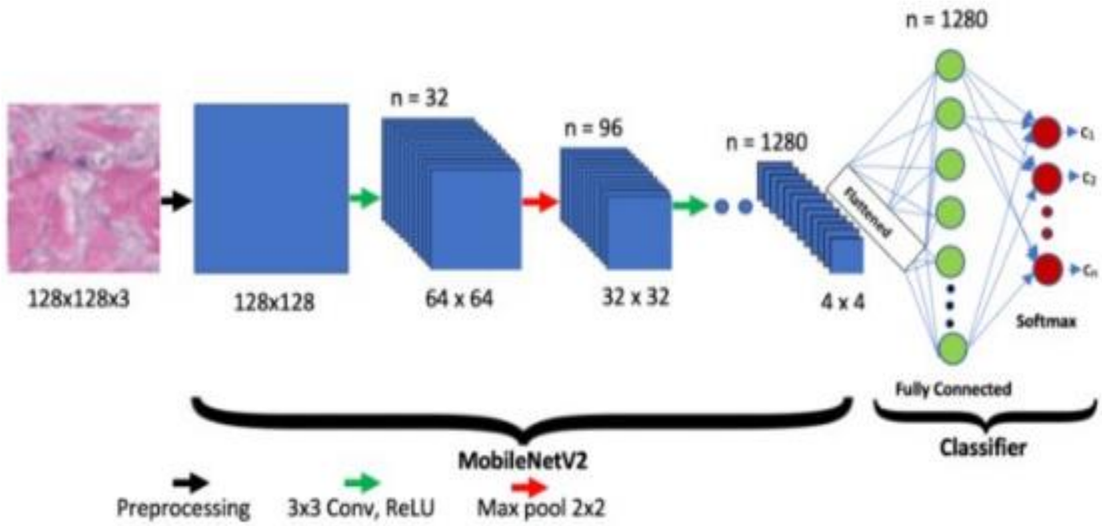

Figure 3.5: Architecture of MobileNetV2.

3. **EfficientNetB7:** The novel scalability technique proposed by Efficient Net, a portable pure convolution model (Conv Net is), uses a straightforward yet incredibly powerful composite variable to scale all three dimensions of depth, breadth, and resolution equally.EfficentNetB7 might be used as the starting point model; nevertheless, retraining the huge network would take longer, decreasing your loop pace, when evaluating modifications unrelated to architecture, including data augmentation as previously discussed. To obtain more accurate findings, the EfficientNetB7 framework was further adjusted through incorporating layers and changing hyperparameters that Based on its accuracy, fail categorization rate, sensitivity as well as specificity, and F1-score, the suggested model's performance was assessed. Considering that there are 237 total layers in EfficientNet-B0 and 813 overall elements in EfficientNet-B7.

Figure 3.6: Architecture of EfficentNetB7.

4. **ResNet50:** Convolutional neural networks in the form of a network of fifty different layers are referred to as ResNet-50. A pretrained neural networks that has been trained on over million is may be retrieved through the database offered by Image Net. Translating the concept of the shortcut relationship, it provided a chance of enhancing the number of the convolutional neural network in a CNN without facing the problem of vanishing of gradients. A shortcut link transforms a regular network into a residual one as it overleaps a number of levels. A CNN neural network of 50 layers is called deep residual network same like as the ResNet-50 model. One type of ANN, the Res Net 50, creates a structure in which one residual block is added on top of the other.

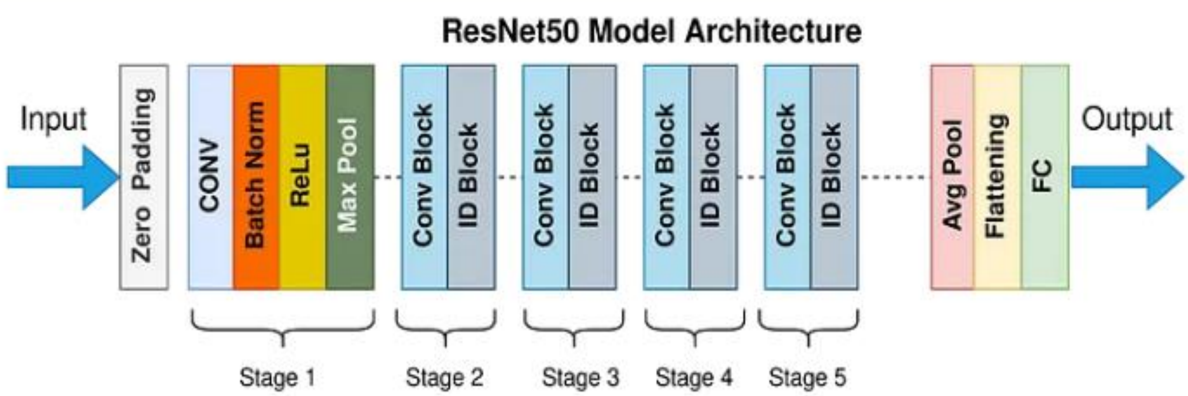

Figure 3.7: Architecture of ResNet50.

5. **InceptionV3:** The CNN architecture InceptionV3 is employed for picture classification and recognition. It belongs to the set of Inception DL frameworks, which the staff of the firm created in order to grow. The InceptionV3 device can be named as one of the most detailed devices, which applied imaginative idea of the "Starting section" which increases system's accuracy and efficiency. The InceptionV3 was deep neural network design, which complete with 48 layers. It conducts convolutional layers, layers with the maximum pooling, fully linked layers, and extra classifiers all in one. Networks can accumulate data at many levels of abstraction as a result of the spatiotemporal mixing of the Imagine module and multilayer permutation of the input (1x1, 3the numbers of x3, which is as well as 5x5).

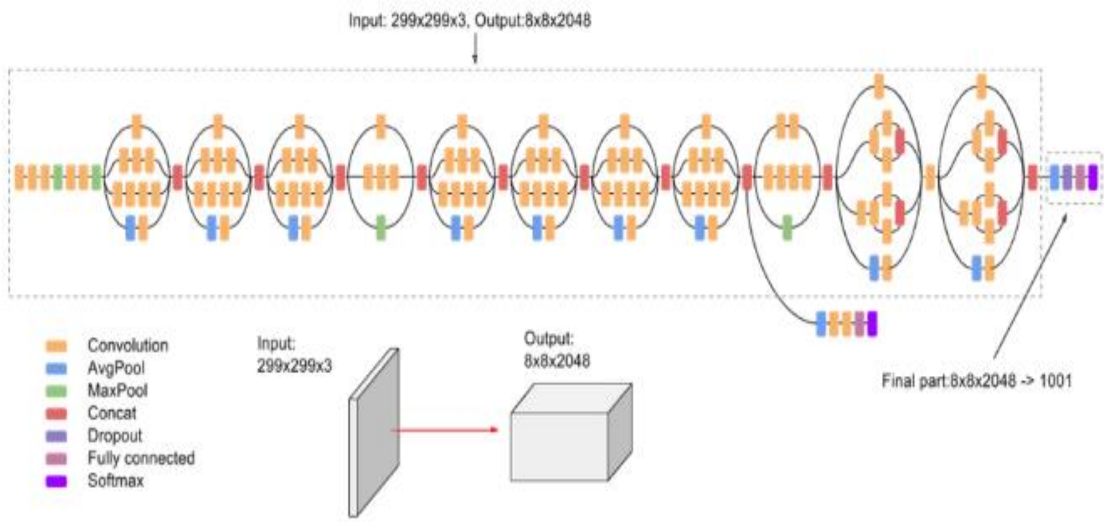

Figure 3.8: Completed version of Inception V3.

3.6 Implementation

Once any further actions have been completed, the information set has to be applied to ensure accuracy. For execution, I separated my task into five primary sections. Following these measures is necessary to guarantee the achievement of my endeavor.

- Taking Images.
- Image pre-processing procedure
- Image prediction for classes.

- The Models' Application
- CNN InceptionV3 classification of potato leafs;
- Inconsistency between results and accuracy.

I have to search Kaggle for datasets and the internet for images of early blight, late blight, and healthy leaves in order to collect data. These images are a part of a great dataset now. After that I had to start with data pre-processsing. I do some things on the data I get. Remove noise, remove less number of inaccurate images and non-scaled shots if any, also I use feature extraction to reduce training, testing and validation times for longer time consuming data.

The first step in putting the concept into practice was for me to start experimenting with its code. I assessed the precision of four distinct algorithms that were employed. After the procedure was finished, I evaluated its accuracy. After assessing the accuracy, I determined which one was going to be more suitable for my needs. This has shown to be quite predictable in the case with leaf disease. A critical review of all the relevant philosophical and quantitative concepts and techniques has resulted in formulating the set of necessities which are mandatory for every attempt aiming at picture categorization. The outcomes that follow may be necessary:

1. Hardware and Software Needs

- Operating System: Windows 7 or later;
- Hard Drive: 1 TB or more;
- RAM: 4 GB or less

2. Tool Development

- Python Environment
- PyCharm.
- Google Colab.

CHAPTER 4

Experiment Results and Discussion

4.1 Introduction

This part describes how the system for categorization of diseases affecting potato leaves has been made. The construction of the model involved acquiring the photographs and the data stored in these, improving the data, altering quality and quantity of Information data, proposing models and issuing instructions accompanied with model efficiency. Herein, there is a summary of all investigations' outcomes as well as their discussion.

4.2 Experimental Result

The emergence of potato leaf disease has been predicted using a variety of techniques. I thus employed a variety of techniques during the procedure. I investigated and assessed a number of approaches before deciding on the most appropriate methodology for the research. I experimented with a number of methods to raise the standard of my work. Two distinct datasets were utilized, one from the internet collection of data which have under categories: Early blight, late blight and Healthy. I made use of pre-existing the Python tools, dictionaries, and content classification strategies. The illness technique used to evaluate the dataset determines the important consequence or disease validity.

4.3 Applying Descriptive Analysis with DL CNN models and classification

The results I obtained differed based on the classification techniques I employed. Four deep learning algorithms have been applied for the accurate identification of potato leaf disease. For the evaluation to yield better findings, I employed data augmentation. I am utilizing the MobileNetV3 Large, MobileNetV2, ResNet50, and EfficientNetB7 models, which have produced positive results for the accuracy of leaf disease using 10 epochs. Once the final dataset was determined, all iterations used the same data set, which included both publicly accessible data and my private dataset, which I gathered online using Kaggle data. Using Python and its pre-built libraries, I evaluated the accuracy once the dataset procedure was complete.

Table 4.1: Table of Accuracy

Models	Accuracy Score (AUC)	Val_Accuracy	Training time(sec)
MobileNetV3 Large	99.67%	100%	223.66
EfficientNet-B7	98.00%	96.69%	286.53
MobileNet-V2	89.33%	84.30%	238.29
ResNet-50	85.67%	98.35%	207.06

The following section displays the performances of several models. PyCharm, which and CoLab, two free software packages, were utilized at every stage of the procedure. Four models in all—MobileNetV3 Large, MobileNetV2, ResNet50, and EfficientNetB7—were used.

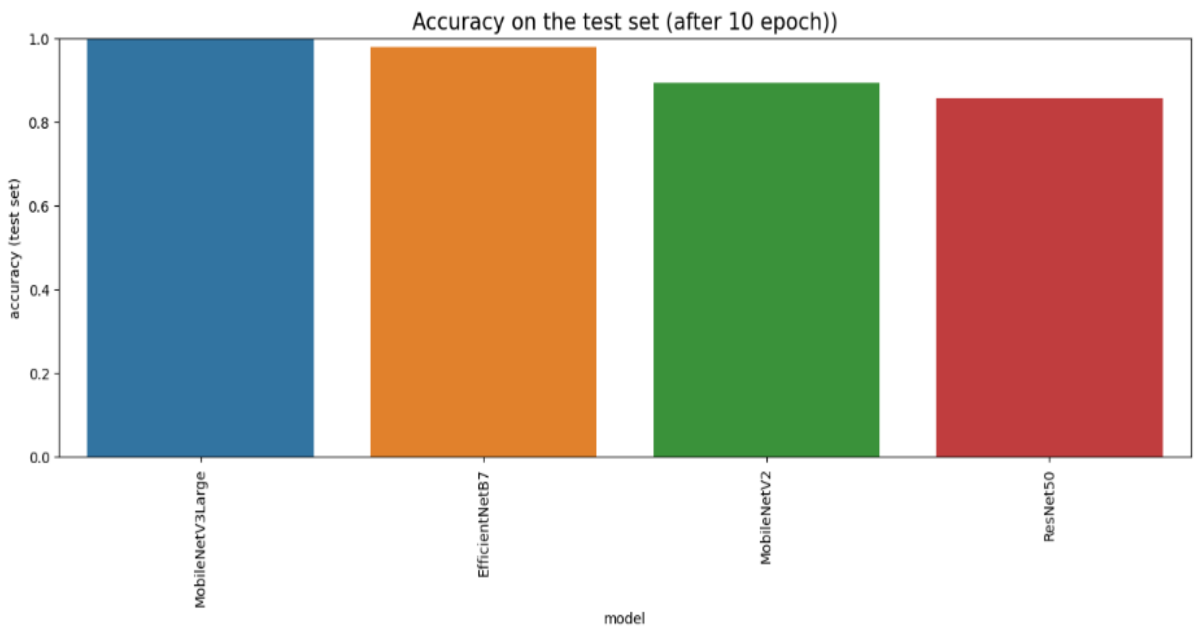

Figure 4.1: Accuracy chart on the test data (after 10 epochs).

This bar chart shows the percentage of correct classification of several deep learning approaches on a test set trained during 10 epochs. The models which have been assessed are as follows MobileNetV3Large,EfficientNetB7,MobileNetV2,ResNet50.

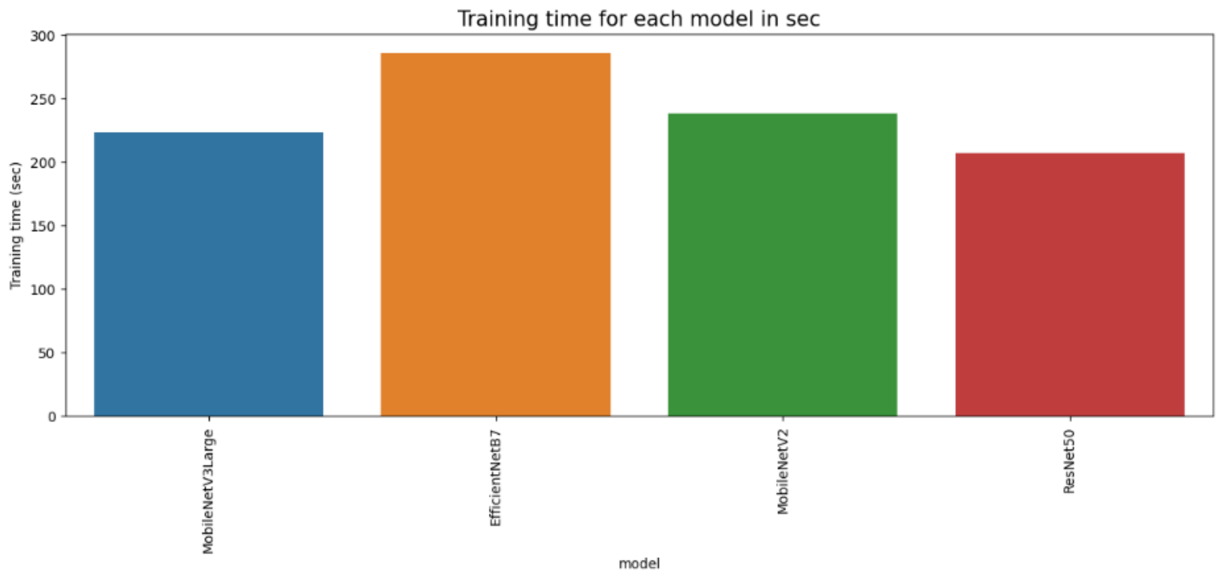

Figure 4.2: Training time for four models in sec (after 10 epochs).

This bar chart is designed to show the training time for several deep learning models in seconds. The assessed models are MobileNetV3Large, EfficientNetB7, MobileNetV2 and ResNet50.

	precision	recall	f1-score	support
Potato___Early_blight	1.00	1.00	1.00	100
Potato___Late_blight	1.00	0.99	0.99	100
Potato___healthy	0.99	1.00	1.00	100
accuracy			1.00	300
macro avg	1.00	1.00	1.00	300
weighted avg	1.00	1.00	1.00	300

Figure 4.3: MobileNetV3 Large Classification Report.

This classification report that evaluates the performance of a model on three classes: This report contains the evaluation of the model based on the provided classes which are "Potato___Early_blight," "Potato___Late_blight" and "Potato___healthy" The metrics achieved include precision, recall, f1-score, and support of each of the classes used, overall accuracy, and average with the options of macro and weight.

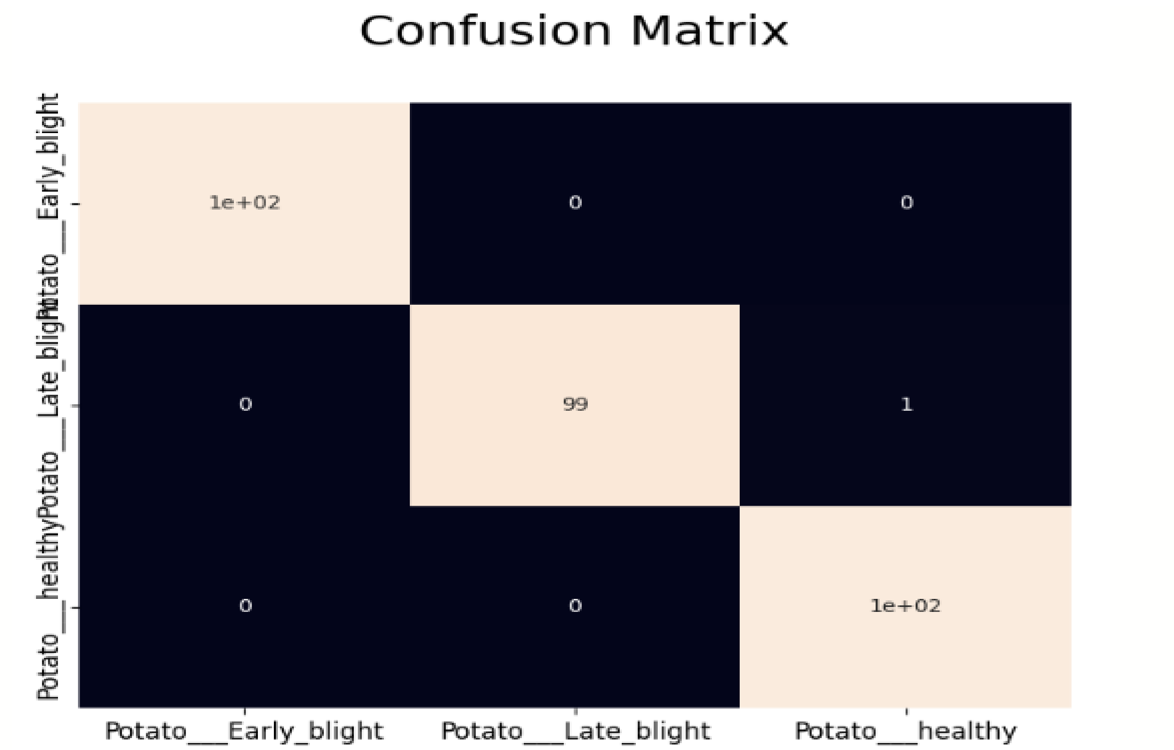

Figure 4.4: MobileNetV3 Large's confusion matrix.

It is only presenting the whole MobileNetV3 models classification report in order to get the highest accuracy.

The procedure for classifying a certain type of potato leaf and creating a working web application using the CNN algorithm InceptionV3 model is shown in Fig. 4.4 below. Figures 4.6, 4.7, 4.8, and 4.9 show the three forms of potato leaves disease—early blight, late blight, and healthy leaf—that were correctly predicted through a web application using InceptionV3. As is typically the case, deep learning is among the least supervised techniques for object detection or prediction.

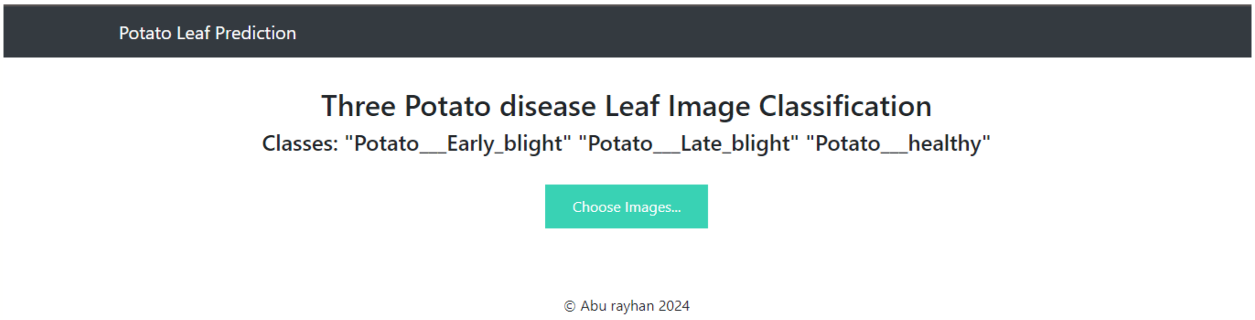

Figure 4.5: Web Application prototype for Potato leaf classification using CNN.

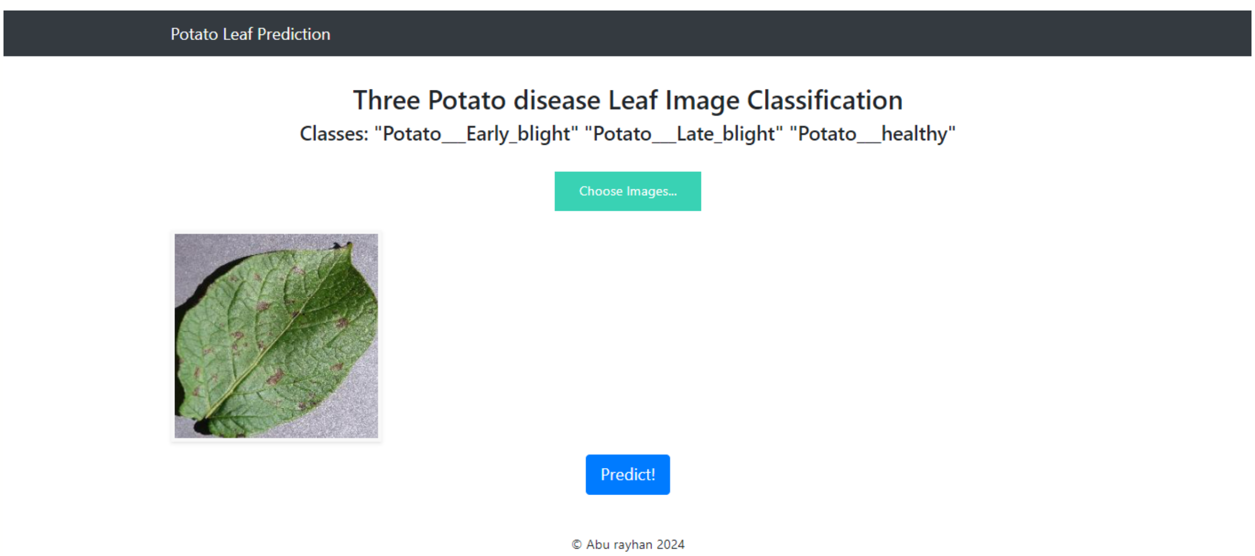

Figure 4.6: Prototype of a web application for choosing pictures.

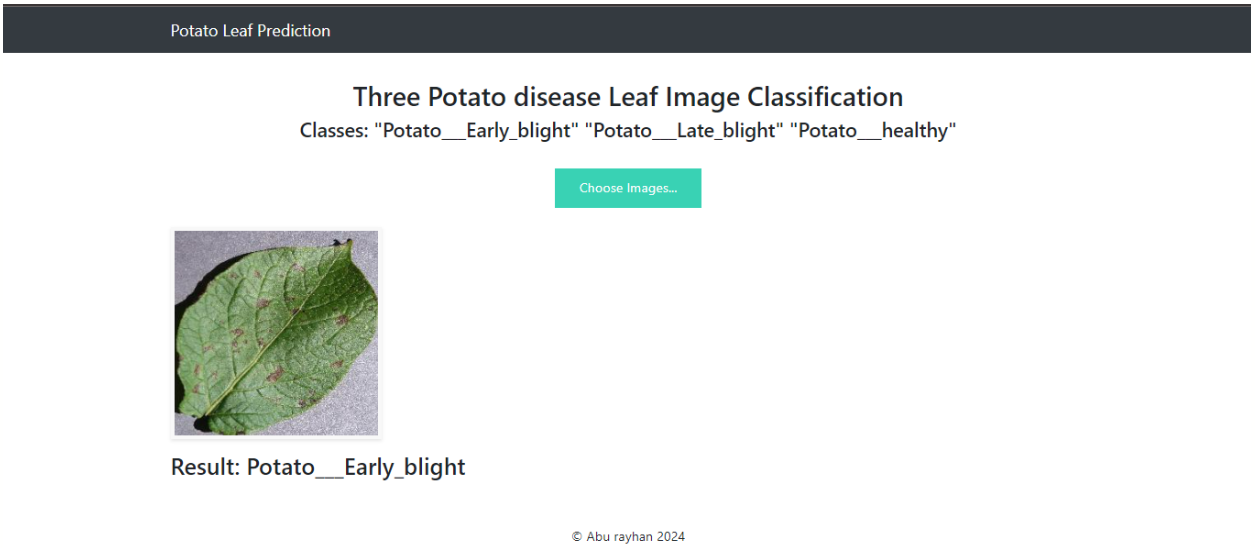

Figure 4.7: Early Blight classification of web application prototype.

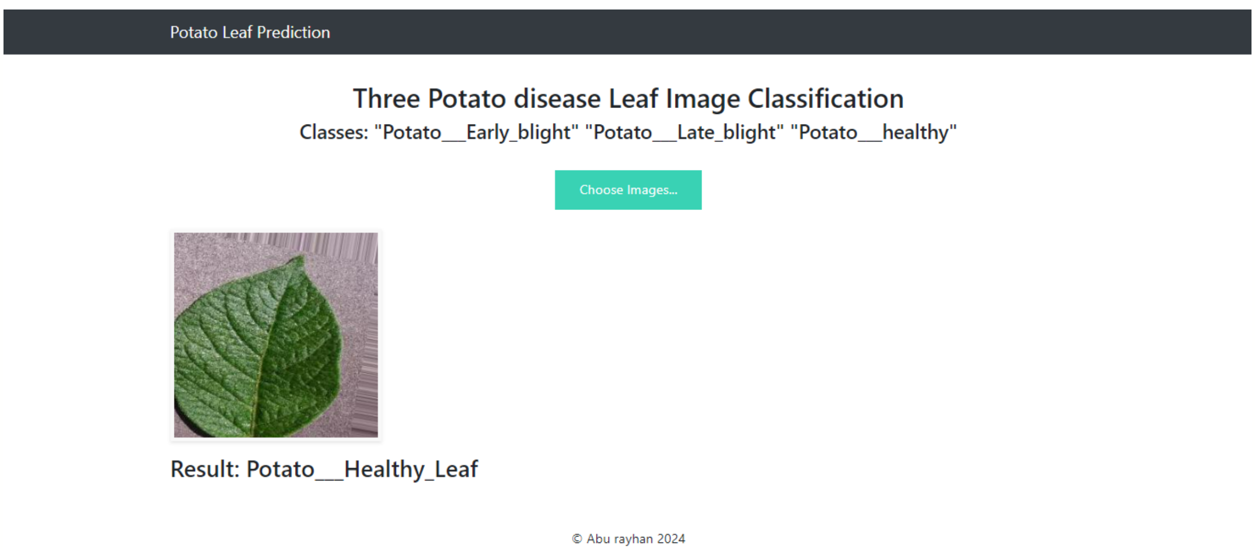

Figure 4.8: Healthy classification of web application prototype.

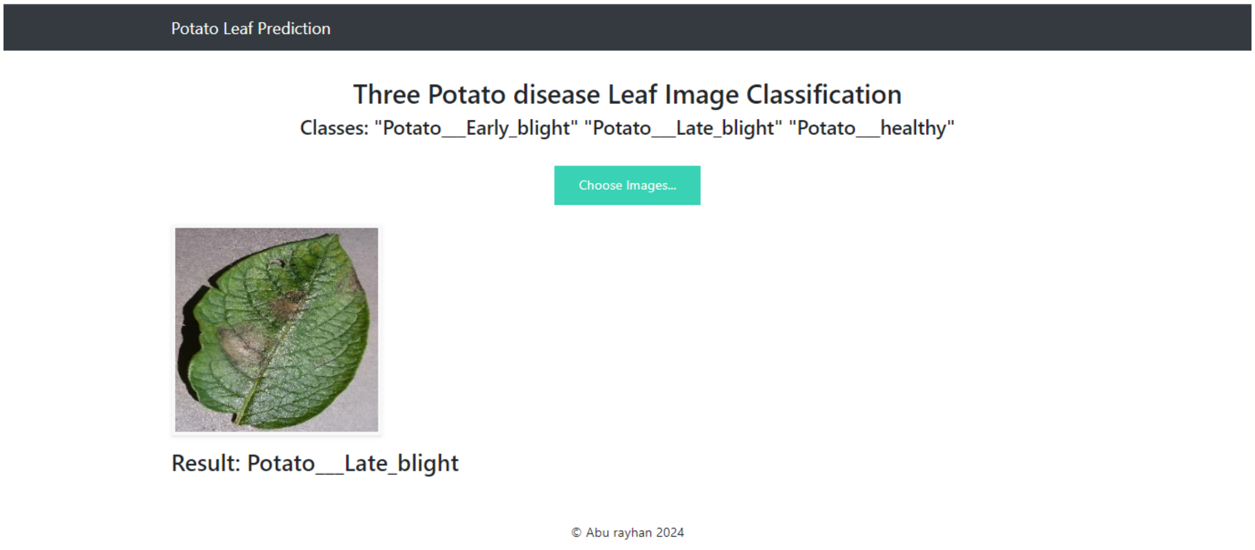

Figure 4.9: Late Blight classification of web application prototype.

The figures illustrate the working of a web application prototype developed for potato leaf classification employing CNN.

Here are the key points :

1. **Potato Leaf Classification :** The web application deals with the differentiation of various diseases that can affect potatoes and concentrates on Early Blight and Late Blight.Also classify healthy leaf.
2. **Image Selection :** There is an option within the application to select pictures for classification.

Classification

```
[ ] image_path = '/content/drive/MyDrive/Potato Leaf/Potato/Train/Potato___Early_blight/b475147c-92bc-419a-b2c3-7d5aabbb79ec___RS_Early.B 7379.JPG'
    image = Image.open(image_path)

    # Preprocess the image
    img = image.resize((244,224))
    img_array = tf.keras.preprocessing.image.img_to_array(img)
    img_array = tf.expand_dims(img_array, 0)

    # Make predictions
    predictions = loaded_model.predict(img_array)
    class_labels = ['Potato_Early Blight', 'Potato___Late_blight','Potato___healthy']
    score = tf.nn.softmax(predictions[0])
    print(f"{class_labels[tf.argmax(score)]}")

    1/1 [==============================] - 0s 95ms/step
    Potato_Early Blight
```

```
[ ] image_path = '/content/drive/MyDrive/Potato Leaf/Potato/Train/Potato___healthy/Potato_healthy-100-_0_2061.JPG'
    image = Image.open(image_path)

    # Preprocess the image
    img = image.resize((244,224))
    img_array = tf.keras.preprocessing.image.img_to_array(img)
    img_array = tf.expand_dims(img_array, 0)

    # Make predictions
    predictions = loaded_model.predict(img_array)
    class_labels = ['Potato_Early Blight', 'Potato___Late_blight','Potato___healthy']
    score = tf.nn.softmax(predictions[0])
    print(f"{class_labels[tf.argmax(score)]}")

    1/1 [==============================] - 0s 40ms/step
    Potato___healthy
```

Figure 4.10: Classification of potato leaf using MobileNetV3 Large code.

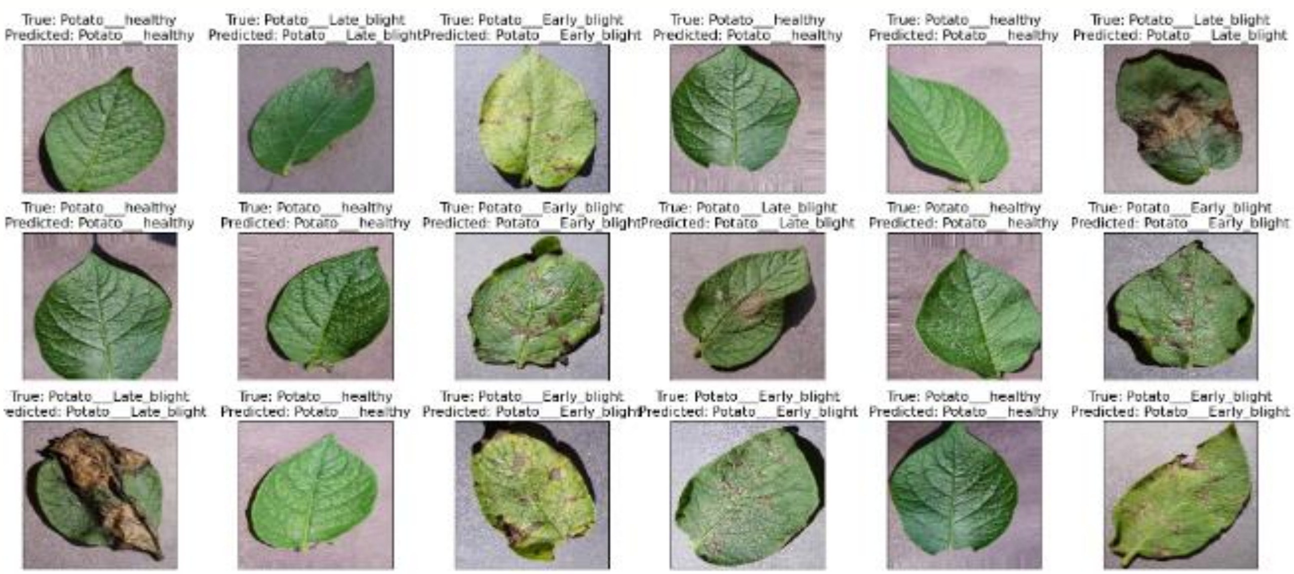

Figure 4.11: Example of potato leaf prediction.

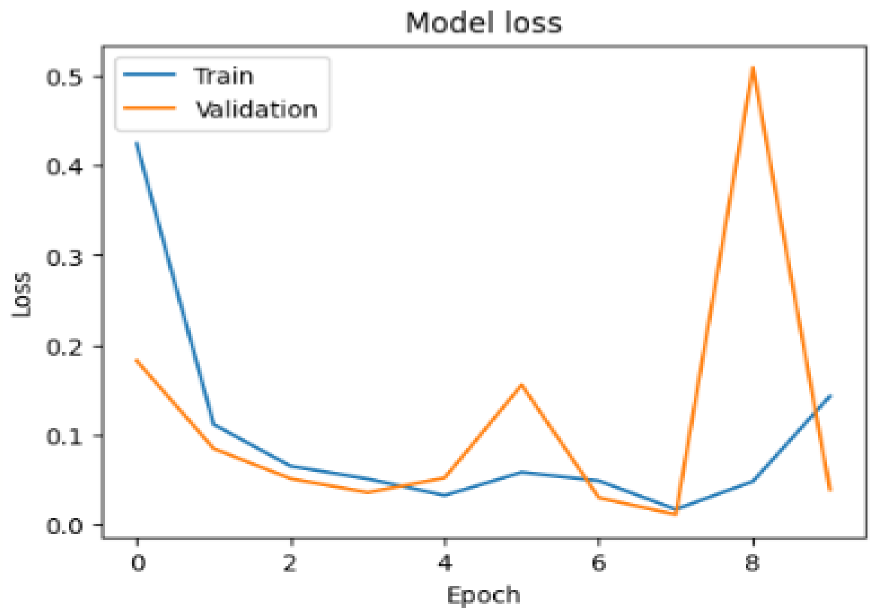

Figure 4.12: CNN training and validation loss for web application prototype classification.

The displayed figure explains the current state of your web application prototype that utilizes a CNN model during the training phase. It is a line graph where the x-axis goes with ‘Epochs’ which is basically the training iterations and y-axis has ‘Loss’, which means the difference between the predicted and true labels. Typically, the training loss continues to reduce as the epoch increases while the validation loss should also be reducing although not necessarily every time epoch is increased. This means that there is capacity to classify data since this is what defines the model. However, be cautious! If the validation loss is on the rise after some epochs it means that overfitting is taking place – the model is learning training information not general information. This may result in poor performance on new data to which the learned solution is not applicable. In other words, the graph assists in evaluating the further training of the model and such problems as overfitting.

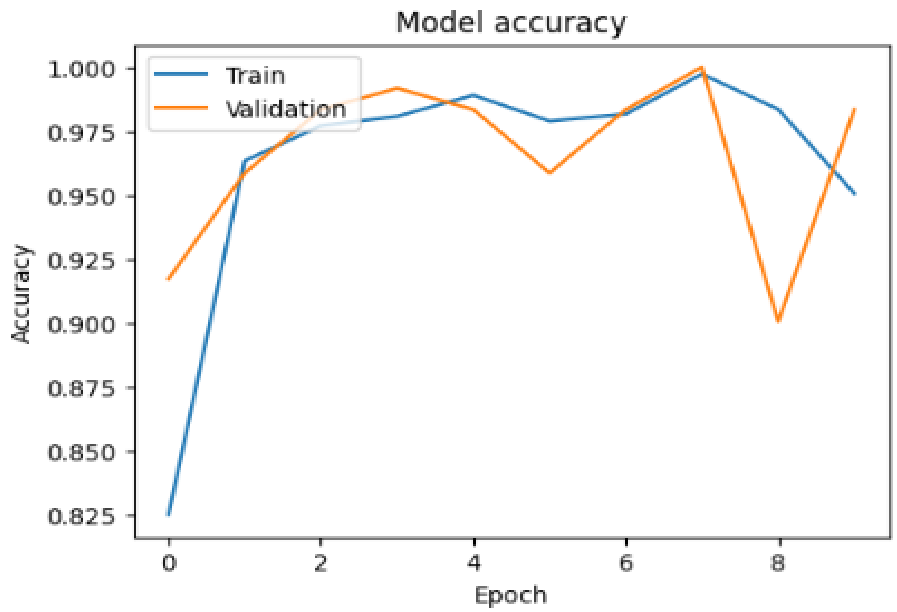

Figure 4.13: Validation and Training Accuracy of CNN-based web application prototype categorization.

This graph illustrates the learning curve of the CNN model concerning the classification of web applications. The blue line represents the training accuracy which is steadily rising while. The green line here defines the validation accuracy which is trailing behind all the time. This gap means over fitting, the model has memorized the training data, and is possibly having challenges in recognizing new websites. Ideally, both should increase together, which implies that the model improves and boils down to good performance on the unseen data.

4.4 Discussion

In my investigation, I'll employ DL algorithms to predict potato disease. In any field of study, each word should be extremely important to the classification process. The goal of my study has always been to determine the cause of potato leaf disease by picture classification. The datasets have also been separated into succeeding classes by using the dl models. The dataset is one of the main prerequisites of any work since the availability or quality of data can determine the outcome of a study. Similar research might yield very different findings depending on the available data. I was certain that other researchers would get different findings utilizing one of both previously accessible datasets because this was a blend of the two datasets. Given that I utilized more data, I may have been developed a bit more accurate.I used a range of DL algorithm models & scores of accuracies to help us achieve my aim. I employed a total of four distinct algorithms for this assignment. Before beginning the current assignment, there were several things I needed to find. I did start working on the algorithm after selecting it. I then ascertained the accuracy of each algorithm. As I previously said.

I was able to attain the maximum accuracy of 99.67% in the MobileNetV3 big models—the models for the following three categories—by utilizing both of these strategies. It is particularly notable for my dataset since, of the three leaf prediction classes given in the above Figure 4.11, it produced the best accuracy of the following models.

Precision: Accuracy, or the percentage of correct forecasts the algorithm will make, is an easy tool for judging efficiency. Add up all the true positives, then multiply that by the total.

$$\text{precision} = \frac{TP}{TP+FP}$$

Recall: Recall, regardless of all pertinent cases, is the percentage of truly relevant examples that were located and retrieved: recall is the ability to show up with the most motivated results. Of all the methods tested here, a sample of those ranked alphabetically, recall was rated the highest for strategies that motivate the right responses.

$$\text{recall} = \frac{TP}{TP+FN}$$

F1-Score: For assessing a test's legitimacy, the f score takes accuracy and memory into consideration. Accuracy & recall are harmoniously summed.

$$\text{F1} = \frac{2 \times precision \times recall}{precision + recall}$$

Accuracy: The relationship between an assessed value and an acknowledged cost is known as reliability.

$$\text{accuracy} = \frac{TP+TN}{TP + FN + TN + FP}$$

CHAPTER 5

Impact on Society, Environment and Sustainability

5.1 Impact on Society

Using deep learning methodologies on both basic and aggregated web information, potato leaf disease is identified. considering that it may significantly impact society. The following are a few possible social implications of these techniques such as:

1. **Boost the agricultural sector:** The possibility of deep learning computations to identify diseases in the potato leaves and enhancing the industry with higher outcomes is one of the vital advantages. Perhaps, if producers recognize a leaf issue soon at a stage where it has not adversely affected the plant, then they can raise crop yield by diagnosing the problem, and treating it in the field. Altogether, this could increase the production in agricultural and perhaps improved ways of disease management.

2. **Economic advantages.** The application of DL techniques to identify potato leaf disease might benefit society economically. For instance, it may increase crop output because this specific sickness is negatively affecting harvests in the agricultural sector. because expensive and intensive therapy may not be necessary if the illness is handled early. Additional advantages include increased farming output and positive economic impacts. Farmers that face this kind of issue will plant a smaller number of crops than others.

3. **Socially advantages:** Peaceful Social impacts are other benefits of identifying diseases that affect the leaves using Deep learning methods that can otherwise be viewed as making fiscal profits. Crop disease issues will make farmers realize that damage of crops, reduced yield will affect their financial status or gains. For example, it may assist to construct a surroundings without poverty – that is pretty often a symbol of a better environment – and help improve the prospect of farmers. Dwelling together is essential and as Bangladesh is an agricultural country, every problem concerning the farmer directly affects the people. Subsequently, the employment of DL approaches to distinct between health or diseased leaves will bring an immense impact to the civilization of mankind. The elimination of potato disease

of leaves together with the farming industry's financial and social returns may further enhance existing living conditions in the rural agriculture and society.

5.2 Impact on Environment

The impact of applying DL methods to identify potato leaf illness from damaged leaf datasets is that it will not have severe environmental consequences. But, there was a capability that these tactics' creation and implementation would lead to the high resource utilization and greenhouse gas emissions; these can be disastrous to the ecosystem. These methods might potentially have several negative consequences on the natural world:

1. **Energy consumption:** Approaches for Depp learning may use up a lot of resources especially where they need a lot of processing to establish it. One of the effects may be an increase in energy consumption while the emission of green house gases may be deleterious to the surrounding environment. All these negative consequences can be prevented if possible to reduce the use of energy in various activities as much as possible. This implicates the consideration of the energy efficiency factor of the materials and processes that are being employed.
2. **Data safeguarding:** DL algorithms require a lot of data for the training and testing of the algorithms. This data must be stored and as you know storage involves the use of energy as well as material resources that in some cases may be detrimental to the natural environment. To overcome these effects it is necessary to point out what actions data storage has on the natural environment and whether it is possible to minimize resource consumption.
3. **Transportation and Shipping:** It's feasible that the use of DL approaches, particularly if they're dispersed and algorithms and data are obtainable from several global locations, may lead to a rise in emissions from the industry of transportation. To lessen these effects, it is crucial to take into account how transportation affects the natural world in addition to try my hardest to reduce pollution.

Deep learning methods for identifying potato leaf diseases using online fields and Kaggle assets data are often not anticipated to have an adverse effect on the environment. It is imperative to consider and implement the necessary measures in light of the potential unexpected indirect environmental impacts of the development and deployment of such approaches.Using green factors and estimations to minimize emissions and intake of resources, keeping data in a format that is less ‘heavy’ as much as possible, and, if possible, minimizing gases as compared to mass transport are some of these precautions.

5.3 Ethical Aspects

Field data gathering and DL approaches may be used to identify diseases of potato of the leaves. A list of some of the greatest important moral factors to examine is provided below:

1. **The agricultural sector security:** Since fields are an important source of revenue for farmers, growing crops demands a lot of time and resources. Prior to addressing the farmers' worries over data collection from their fields, I should speak to them regarding their existing circumstances and address the issues they have. In light of the facts gathered in the actual world, it is critical to take problems and risks into account.

2. **Biases:** Another ethical concern is the potential for bias in deep learning techniques. For example, if data that isn't typical of everyone is utilized to train the systems, forecasts may become biased. To lessen the possibility of distortion, it is essential to make sure that the data utilized for training the DL systems is varied and reflective of the impacted crop.

3. **Easy access:** The widespread availability of methods for detecting potato leaf death presents another ethical dilemma. Disparities in the ability to recognize and treat sickness may occur if some persons or groups are only those with access to these techniques. Making sure that the techniques are widely used and available to everyone who might benefit from you is essential.

4. **Responsibilities:** In the presented-PD it is not clearly mentioned as to who is making judgment based on the results of DL algorithms. In this regard, much attention should be paid to the matters of the identity of the specific person or organization that will be responsible for the ethical use of the above-said methods and for connecting the farmers affected by potato diseases to the corresponding support structures.

5.4 Sustainability Plan

Therefore, to ensure that the indicated technologies persist in the future, the following strategies should be considered whenever developing a sustainability plan for using DL algorithms for diagnosing potato leaf diseases with particulars from Kaggle.A sustainable approach must have the following essential components :

1. **Privacy and Guarding:** In order for deep learning approaches for potato leaf disease detection to remain successful, social media security and confidentiality of information must be guaranteed. It's important to think about the potential privacy implications of categorizing an individual as being at risk for leaf disease based only on the farmer's unprocessed harvesting information.

2. **Durability and persistence:** Establishing the resilience and precision that the DL algorithms is crucial to the strategies' sustainability over time. This entails regularly reviewing and revising the formulae as needed in addition to subjecting the mathematical equations to a thorough testing and assessment procedure to ensure their accuracy.

3. **Responsibility:** Another important factor that has a direct bearing on the sustainability of DL systems is the demarcation of responsibilities of all the actors involved in the design and implementation of these particular systems. This may require providing clear procedures on how the methods are to be ethically used; it also entails defining the roles of those who are expected to ensure the proper application of the methods is being conducted ethically.A strategy for utilizing artificial intelligence techniques for prognosis and diagnosis utilizing unprocessed and in order to ensure that the application of these methods is long-term viable, data should consider many factors.

CHAPTER 6

Conclusion and Future Research

6.1 Summary of the Study

I've learned a lot about this subject thanks to this investigation. Potato's leaf poisoning situation is a sensitive matter. This makes a substantial yearly contribution to the decline in agricultural productivity. Because of this, I was capable of to use deep learning to identify about three major illnesses.

As previously noted, in order to gather as much information as possible for my study, I combined with information gathered via the internet via kaggle. Applying this data in the teaching of my software programs on the pattern of disease enhanced my means in identifying the various forms of diseases. At first, several problems were solved.

All in all, I was able to achieve the intended goal. A variety of algorithms give different results for different persons. I elaborated this in the subsequent section.

6.2 Conclusion

This study shows that the techniques and research result I employed are excellent. After the present investigation is over, I believe and hope that it will inspire more research in this area. This work has lots of potential for expansion and different ways to elaborate it in my work. It is possible to note that there were a few errors in a few points while I was working. I found that there are other tracks to continue with this investigation. It will allow us to resume work on the current project and make any corrections or necessary changes when we encounter problems. Furthermore, recommendations on how analytics could be used in any subsequent studies to give firmer solutions to the problems that this study has revealed have also been provided. Thus, owing to this investigation, I will undoubtedly be able to gain the knowledge about the other aspects of my chosen subject area. I anticipate that it will contribute to the advancement of both the diagnosis of potato-leaf disease and the study and development of innovative technical methods that enable us to help agriculture. I aim to provide a unique approach to potato leaf characterization based on this study, which leverages DL for detecting potato leaf disease.

6.3 Possible impacts

We think that depending on where my work is viewed, the results are different. As a consequence, I took extra care to do my work accurately. I took care to ensure that the work I did was honest. I choose to utilize my dataset as a result. my study may find use in a variety of sectors, including agriculture and computer science. Farmers would benefit, especially those who work in the cropping sector. It may also facilitate my lives and protect agriculture. It could raise the output of agriculture.

6.4 Implications of Further Study

Further study in this field has many prospects, particularly within the context of my work. I devised many tactics to enhance my work. As said before, I have also found certain errors; these mistakes provide us the chance to make improvements to my study. I will try to rectify this inaccuracy by using my results in practice and enhancing the prediction results with more opportunities to capture outstanding accuracy. I wish to correct the errors that I come across.

There are other goals that I have in mind. my goal is to outperform my prediction. I will include features like disease type recognition along with additional abilities to the application that I can use to predict potato leaf disease utilizing a method in order to help consumers get the most out of this.

This kind of work, in my opinion, might increase agricultural yield and move the agriculture sector toward technological use. Maybe I might help the people grow more crops.

Reference

[1] M. Islam, Anh Dinh, K. Wahid and P. Bhowmik, “Detection of potato diseases using image segmentation and multiclass support vector machine,” 2017 IEEE 30th Canadian Conference on Electrical and Computer Engineering (CCECE), Windsor, ON, 2017, pp. 1–4.

[2] Malvika Ranjan, Manasi Rajiv Weginwar, NehaJoshi, A.B. Ingole, “Detection and Classification of Leaf Disease Using Artificial Neural Network,” International Journal of Technical Research and Applications, 2015, pp. 331–333.

[3] S. Biswas, B. Jagyasi, B. P. Singh and M. Lal, “Severity identification of Potato Late Blight disease from crop images captured under uncontrolled environment,” 2014 IEEE Canada International Humanitarian Technology Conference—(IHTC), Montreal, QC, 2014, pp. 1–5.

[4] Athanikar, . Girish and Ms. Priti Badar. “Potato Leaf Diseases Detection and Classification System Mr.” (2016).

[5] Li, Youguo & Wu, Haiyan. (2012). A Clustering Method Based on K-Means Algorithm. Physics Procedia. 25. 1104-1109. 10.1016/j.phpro.2012.03.206

[6] C. U. Kumari, S. Jeevan Prasad and G. Mounika, "Leaf Disease Detection: Feature Extraction with K-means clustering and Classification with ANN," 2019 3rd International Conference on Computing Methodologies and Communication (ICCMC), Erode, India, 2019, pp. 1095-1098.

[7] Abdallah Ali (2019, September) PlantVillage Dataset, Version 1, Retrieved 22 February 2020, https://www.kaggle.com/xabdallahali/plantvillage-dataset.

[8] Li, Guanlin & Ma, Zhanhong & Wang, Haiguang. (2011). Image Recognition of Grape Downy Mildew and Grape Powdery Mildew Based on Support Vector Machine. IFIP Advances in Information and Communication Technology. 370. 151-162. 10.1007/978-3-642-27275-2_17.

[9] F. T. Pinki, N. Khatun and S. M. M. Islam, “Content based potato leaf disease recognition and remedy prediction using support vector machine,” 2017 20th International Conference of Computer and Information Technology (ICCIT), Dhaka, 2017, pp. 1–5.

[10] N. R. Bhimte and V. R. Thool, “Diseases Detection of Cotton Leaf Spot UsingImageProcessingandSVMClassifier,”2018SecondInternational Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India, 2018, pp. 340–344.

[11] S. Hossain, R. M. Mou, M. M. Hasan, S. Chakraborty and M. A. Razzak, “Recognition and detection of tea leaf’s diseases using support vector machine,” 2018 IEEE 14th International Colloquium on Signal Processing & Its Applications (CSPA), Batu Feringghi, 2018, pp. 150–154.

[12] D. Tiwari, M. Ashish, N. Gangwar, A. Sharma, S. Patel and S. Bhardwaj, “Potato leaf diseases detection using deep learning”, In *2020 4th international conference on intelligent computing and control systems (ICICCS)* (pp. 461-466), 2020, May.. IEEE.

[13] R. Mahum, H. Munir, Mughal, Z.U.N. Mughal, M. Awais, F. Sher Khan, M. Saqlain, S. Mahamad and I. Tlili, “A novel framework for potato leaf disease detection using an efficient deep learning model”, *Human and Ecological Risk Assessment: An International Journal*, *29*(2), 2023, pp.303-326.

[14] M.K.R. Asif, M.A. Rahman and M.H. Hena, “CNN based disease detection approach on potato leaves.” In *2020 3rd International Conference on Intelligent Sustainable Systems (ICISS)* (pp. 428-432). 2020, December. IEEE.

[15] J. Rashid, I. Khan, G. Ali, S.H. Almotiri, M.A. AlGhamdi and K. Masood, “Multi-level deep learning model for potato leaf disease recognition”, *Electronics*, *10*(17), 2021, p.2064.

[16] S. Bangari, P. Rachana, N. Gupta, P.S. Sudi and K.K. Baniya, “A survey on disease detection of a potato leaf using cnn”, In *2022 Second International Conference on Artificial Intelligence and Smart Energy (ICAIS)* (pp. 144-149) ,2022, February. IEEE.

[17] G. Chugh, A. Sharma, P. Choudhary and R. Khanna, “Potato leaf disease detection using inception V3”, *Int. Res. J. Eng. Technol*, *7*(11), pp.1363-1366, 2020.

[18] R.A. Sholihati, I.A. Sulistijono, A. Risnumawan, and E. Kusumawati, “Potato leaf disease classification using deep learning approach”, In *2020 international electronics symposium (IES)* (pp. 392-397), 2020, September, IEEE.

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