Image-Based Potato Leaf Disease Detection and Classification Using Deep Learning Approach

By

Shakhir Ahmed	ID:19202103390
Mumtahina Aimon	ID:19202103391
Md Salahin	ID:19202103479
Soheba Akter	ID:19202103484
Md Pollab	ID:19202103520

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Declaration

We do hereby declare that the research works presented in this thesis entitled, "Image-Based Potato Leaf Disease Detection and Classification Using Deep Learning Approach" are the results of our own works. We further declare that the thesis has been compiled and written by us and no part of this thesis has been submitted elsewhere for the requirements of any degree, award or diploma or any other purposes except for publications. The materials that are obtained from other sources are duly acknowledged in this thesis.

Shakhir Ahmed ID: 19202103390	__________________ Signature
Mumtahina Aimon ID: 19202103391	__________________ Signature
Md Salahin ID: 19202103479	__________________ Signature
Soheba Akter ID: 19202103484	__________________ Signature
Md Pollab ID: 19202103520	__________________ Signature

Approval

This report **"Image-Based Potato Leaf Disease Detection and Classification Using Deep Learning Approach"** submitted by **Shakhir Ahmed, Mumtahina Aimon, Md Salahin, Soheba Akter and Md Pollab. ID no: 19202103390, 19202103391, 19202103479, 19202103484 and 19202103520** Department of Computer Science and Engineering (CSE), Bangladesh University of Business and Technology (BUBT) under the supervision of **Md. Raisul Alam, Assistant Professor**, Department of Computer Science and Engineering (CSE) has been accepted as appeasement for the partial fruition of the requirement for the degree of Bachelor of Science (B.Sc.) in Computer Science and Engineering and endorsed as to its contents.

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Supervisor:
Md. Raisul Alam
Assistant Professor
Department of Computer Science and Engineering (CSE)
Bangladesh University of Business and Technology (BUBT)
Mirpur-2, Dhaka-1216.

Md. Saifur Rahman
Assistant Professor and Chairman
Department of Computer Science and Engineering (CSE)
Bangladesh University of Business and Technology (BUBT)
Mirpur-2, Dhaka-1216.

Dedication

We would like to dedicate this study to our devoted parents. We can never express how much we appreciate their love, encouragement, and support during our academic career. Because of their unwavering faith in us, we are powerful. As a token of our appreciation and affection, we dedicate this thesis to them. We appreciate their unwavering love and support, their constant presence in our lives, and the lessons have taught us about the value of perseverance, dedication, and hard work. We would want to pay tribute to them and express our gratitude for everything that they have done for us.

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Abstract

Potato is one of the most cultivated plants in the world, and many farmers earn their livelihood by cultivating potatoes. Inappropriate classification and late detection of disease types can lead to worsened plant conditions. Different types of diseases can cause lower production of healthy potatoes. So a simple disease detection model is needed to quickly detect potato leaf diseases.The main objective of our thesis is to suggest an innovative deep learning method for identifying and categorizing potato leaf diseases using image-based analysis. The model must be trained using image datasets from both healthy and diseased potato plants, such as early blight, late blight etc. In this analysis, a dataset of more than 2000 pictures of healthy and unhealthy potato's leaf is used to train the customized VGG19, ResNet50 and Inception V3 model. After applying these models, VGG19 achieves a higher accuracy(98.10%) than InceptionV3 model(75.06%) and ResNet50 model(97.36%).

Keywords- CNN, leaf disease, VGG19, Inception V3, ResNet50, classification, detectiion, ReLU, SoftMax

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Introduction

1.1 Introduction

Many different professions are available in this world that secure people's livelihoods. Approximately, 60 percent of South Asian population is involved in agriculture. In Bangladesh, the contribution of agriculture to the GDP in FY 2021-22 is about 11.50 percent. Potatoes are one of the most important crops grown worldwide and are the main source of nutrition for many people. After rice and wheat, potatoes are one of the principal food crops in Bangladesh. Bangladesh is the world's seventh-largest producer of potatoes.Around 11 million tons of potatoes were produced in Bangladesh in 2020 according to the Department of Agricultural Extension of Bangladesh. Although potato production has greatly expanded over the past few decades, domestic consumption has remained constant. For instance, 4 million tons of potatoes were actually excess because the yearly internal demand for potatoes is about 7 million tons.It lowers blood cholesterol and is a great source of vitamins and potassium in potatoes. Now-a-days, potato production in Bangladesh has increased, but the industry has challenges in practically every step, including various diseases, late detection of disease, high-quality seeds, harvesting, and even processing, which prevent it from reaching its full potential[1].

Late and early blight of potato, fusarium and brown rot, leaf roll virus, common scab, black heart, and root knot are among the diseases that frequently strike potato farmers and producers. The majority of bacteria and fungi that cause disease in potato leaves.The plant's leaf can also develop spots from time to time. Certain diseases manifest as tiny, oval, circular, and a variety of different shapes, including brown spots, early blight, and late blight. All portions of affected plants exhibit the signs of bacterial wilt. The gray center and dark rim on leaves are signs of septoria leaf spot. Early and late blight is a typical disease of potatoes. The majority of the early blight symptoms are small, black lesions, while the late blight symptoms can appear blistered[2]. A decrease in the quality and quantity of agricultural products could occur from the presence of certain diseases during the growing phase. These issues mainly come through inaccurate disease diagnosis and delayed disease detection in potato plants.

It is critical to detect potato leaf diseases as soon as possible and as accurately as possible in order to successfully limit their impact. Agronomists' manual, subjective, and time-consuming visual inspection is an everyday aspect of traditional methods of disease identification. With the speed at which technology is developing, particularly in the areas of machine learning and computer vision, there is a chance of completely changing how these diseases are identified and treated[3].

Our goal is to develop a reliable, effective system that can identify diseases early through the use of image analysis and machine learning algorithms.Here, we'll go through the broader effects of implementing such technology in the agriculture industry. It will cover the potential advantages, difficulties, and factors involved in putting automated disease detection systems into practice. We imagine a time when farmers can make prompt decisions based on accurate information because of the inclusion of modern technology into potato cultivation processes. This will result in better crop health, higher yields, and more sustainable potato production.

1.2 Problem Statement

The challenge is to create a disease detection model for potato crops so that the farmers can easily detect the diseases and can take immediate action. The aim is to develop an automated system that uses image processing and CNN to identify disease symptoms with a high accuracy rate. Here rapid processing is must for the large number of images. The model should be effective under different types of potato diseases. The success of the model will be judged by the model's ability to detect potato leaf diseases accurately.

1.3 Problem Background

Potato cultivation is vital for global food production and security, but its susceptibility to leaf diseases poses a threat to its stability. These diseases can cause yield losses and impact farmers livelihoods and market availability. Detecting and managing potato leaf diseases requires accurate diagnosis and timely treatment. Traditional methods, such as manual visual inspections, have limitations due to human subjectivity, expertise variations, and overlooking early-stage symptoms. Technology-driven approaches, such as image processing, computer vision, and machine learning, offer opportunities to revolutionize disease detection in agriculture[4]. However, developing an automated system for potato leaf disease detection requires a diverse dataset, machine learning models to recognize visual cues, and ensuring system reliability across different agricultural contexts.

1.4 Research Objectives

The objectives of our research work are as follows:

- Identify and classify the diseases of potato leaves using image processing.
- Utilize a variety of machine learning techniques to train a dataset and determine the accuracy of each approach.
- Offer a model with the best accuracy for detecting potato diseases.

1.5 Motivations

The potato is the fourth most important and crucial non-cereal crop, only after rice, Corn, and wheat, which comprise the world's main food supply. As a vital food source for many countries, many farmers earn their livelihood by cultivating potatoes. Various types of diseases can significantly impact potatoes' production rate and quality. The identification of potato diseases mainly depends on visual inspection by human experts. As this process depends on human beings, many errors are made in identifying the diseases, and it's also time-consuming. It is getting more difficult for humans to distinguish between different potato leaf diseases as new varieties and subtypes arise. Therefore, potato leaf disease detection is so important to identify and classify diseases so easily. It enables farmers to protect their crops from devastating diseases and minimize yield losses. This not only helps in minimizing crop losses but also ensures the production of high-quality potatoes, which directly impacts the livelihoods of farmers and the availability of nutritious food for consumers. So, we feel that doing this research will help the farmers to detect potato diseases more quickly and will play a vital role in the growing agricultural economy.

1.6 Flow of the Research

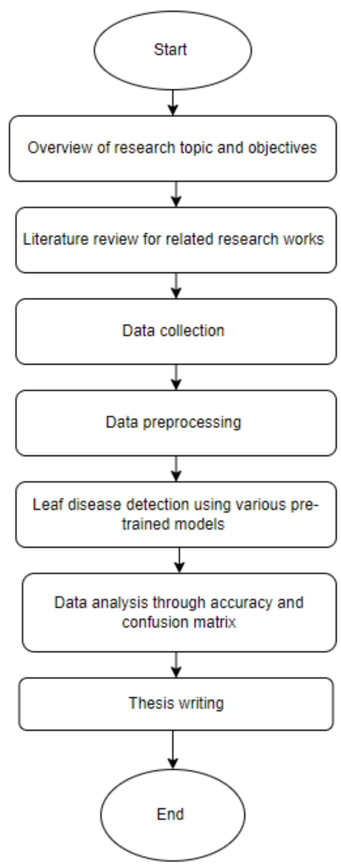

Figure 1.1. The figure illustrates the flow of the thesis work.

1.7 Research Contribution

The overall contribution of the research work are:

- The main contribution of this research is to detect and classify the potato leaf disease
- This system will help the farmers to detect the disease at early age.
- It will reduce the cost for potato production.

1.8 Summary

This chapter provides a comprehensive overview of the problem that our study aim to solve, as well as an explanation of how we accomplished our goals. It also shows the general steps in which we executed our investigation.

Literature Review

2.1 Introduction

In this section, We describe all the topic of existing model of leaf disease detection model which will help us to to complete our research accurately

2.2 Literature Review

Belal Ashqar et al. [5] paper aims at clarifying the feasibility of utilizing deep convolutional neural networks for the detection of plant diseases and they tried to develop a model that could be used by developers in creating smartphone applications for the detection of plant diseases. They wanted to develop a model that can be used by developers to create smartphone applications but they didn't mention the way of using this model in the smartphone application. The model consisting of 4 convolutional layers, each followed by a Max Pooling layer. The second part contained two dense layers for both approaches. In the full-color model, it had 256 hidden units, while the grayscale approach had 128 hidden units. The size of gray-scale network was reduced for use in the Softmax and Output layer.

Divyansh Tiwari et al.[3] wanted to create a Deep Learning method that was used to present a pre-trained model VGG19 model. They used multiple classifiers to extract relevant features to detect Potato Leaf diseases. Various pretrained models were used here as a training model such as inception V3, VGG16 and VGG19. As VGG19 gave highest accuracy rate, several classifiers named KNN, Neural Network, SVM and Logistic Regression were used with the VGG19 model. Here, the combination of VGG19 pre-trained model and Logistic Regression Classifier comes out with the highest accuracy of 97.8 percent.

Rizqi Amaliatus Sholihati et al.[2] suggested a classification and identification model using VGG16 and VGG19 architecture. VGG16 achieved a slightly higher accuracy compared to VGG19. In VGG16, each epoch took an average of 245 seconds, where each epoch took an average of 305 seconds per epoch in VGG19. Experiment shows that the proposed method achieved an average accuracy of 91 percent for both VGG16 and VGG19 models. Peng Jiang et al.[6] proposed model named INAR-SSD is used for real time detection of leaf diseases.the GoogLeNet Inception modules were used in place of the VGGNet conv4-1 and conv4-2 modules, and the rainbow concatenation method was also applied.All cases are taken into consideration while performing simultaneous pooling and deconvolution while performing detection.The stochastic gradient descent (SGD) algorithm is used to discover the neural network's weights and biases that minimize the loss function. The proposed model INAR-SSD gained a performance of 78.8 percent mAP on the dataset and the detection speed was 23.13 FPS.

Lucas G. Nachtigall et al. [7] aims to develop a reliable and accurate system that can identify diseases, nutritional deficiencies, and herbicide damage in apple tree leaves based on Convolutional Neural Network (CNN).The design can be tested by evaluating its performance using predefined metrics and a separate test data set, comparing the predictions with ground truth labels, and analyzing the results to identify strengths and weaknesses. AlexNet architecture, Multilayer Perceptron and different shallow networks used to determine its performance.

In a pioneering study by G. Valarmathi et al. [8], cutting-edge Convolutional Neural Networks were employed to accurately classify plants in agricultural settings. This study went beyond conventional methods by categorizing plants based on criteria such as toxicity, medicinal uses, and edibility. The use of lightweight 3D laser sensors, such as Nippon Signal's FX6, played a pivotal role in creating robust distinctions among various plant species. The results showcased the superiority of this innovative approach over traditional vision-based techniques, offering immense promise for the advancement of agriculture.

Y Zhong's research [9] harnessed the potential of DenseNet-121, a deep learning architecture, to tackle the challenge of recognizing apple leaf diseases. This study introduced three novel methodologies: regression, multi-label classification, and the focus loss function. These innovations significantly improved disease recognition accuracy, achieving impressive rates of up to 93.71% on a challenging and unbalanced dataset. The findings hint at the broader applicability of these methods, particularly in addressing data imbalance issues in plant disease identification.

In the quest for practical solutions in agriculture, Ahmed Abdelmoamen Ahmed et al. [10] introduced a mobile-based system for automated plant leaf disease diagnosis. By harnessing the capabilities of Convolutional Neural Networks and deep learning, this system achieved a remarkable classification accuracy of 94% across 38 disease categories in 14 crop species. This innovation represents a significant step forward in addressing the critical challenge of disease management in agriculture. Farmers can now promptly identify and manage diseases, ultimately enhancing crop production and profitability. The study's robust experimental evaluation further underscores the potential of this system for real-time disease detection in practical agricultural settings.

Another critical area of concern in agriculture is the detection of diseases that affect staple crops, such as potatoes. Md. Khalid Rayhan Asif's study [11] focused on the development of a CNN-based model for potato disease detection, specifically targeting diseases like early and late blight. The results were promising, offering a potential solution for real-time disease recognition in potato crops.

Tomato crops, a valuable agricultural commodity, are also under threat from various diseases. Dr. Madan Lal Saini's research [12] explored the classification of tomato leaf diseases using various CNN architectures. By utilizing the PlantVillage dataset, the study evaluated models such as AlexNet, VGG16, GoogleNet, DenseNet-121, and ResNet-101. Notably, the AlexNet model demonstrated exceptional accuracy and efficiency, achieving a validation accuracy of 97.87%. These findings underscore the transformative potential of deep learning in enhancing disease detection within the agricultural sector.

Adem Tuncer et al.'s study [13] also proposed a robust method for detecting and classifying tomato leaf diseases, employing a combination of Convolutional Neural Networks (CNNs) and the Learning Vector Quantization (LVQ) algorithm. Leveraging a dataset of 500 tomato leaf images, the approach involved intricate feature extraction through convolutional layers and subsequent LVQ-based classification. Despite the inherent challenge of disease similarity, the method demonstrated commendable accuracy in identifying four distinct tomato leaf diseases. Future research avenues may explore further optimizing convolutional parameters to enhance classification outcomes.

In the study by Prajwala TM et al. [14], a convolutional neural network model named LeNet is proposed for the detection and classification of illnesses in tomato leaves. The results show an average accuracy of 94–95 percent, highlighting the effectiveness of neural networks even in challenging conditions.

The primary objective of the research presented in [15] is to employ digital image processing techniques for the early identification and classification of diseases in rose plants. By identifying and treating diseases at an early stage, this study aims to reduce losses in yield and enhance the overall productivity of rose plants.

In [16], the authors focus on the development of a convolutional neural network implementation and an image processing technique for the early detection of tomato plant leaf diseases. The study not only offers a means for early disease identification but also provides practical remedies for curing Tomato Plant Leaf Disease.

Dr. Kamal Sarkar et al. [17] utilize the VGG-16 model to demonstrate a deep learning approach based on a Convolutional Neural Network (CNN) with Transfer Learning. Their model successfully classifies rice leaf diseases with an accuracy of 92.46 percent, aiding farmers in accurately identifying and treating these diseases.

Bin Liu et al.[18] suggested a CNN-based model using the deep learning framework Caffe on Ubuntu 16.04.2 LTS (64-bit).The experimental results show that the proposed CNN-based model achieves an accuracy of 97.62 percent on the hold-out test set. They used Convolution Layer, Max-Pooling Layer, Softmax Regression, ReLU Activation Function, GoogLeNet's Inception and Nesterov's Accelerated Gradient (NAG).

Shivani K. Tichkule et al.[19] uses K-means and neural network approach for detection of plant leaf/stem diseases. Using the segmentation technique, they used to identify infected areas by illness . For the purpose of detecting plant leaf/stem diseases, a K-means and neural network technique has been put forth. After using clustering, a feature extraction technique known as the Color Co-Occurrence Method has also been used to identify various disease symptoms, such as early scorch, cottony mold etc. Color conversion, segmentation, counting of whiteflies and RDI algorithm has been used.

Monzurul Islam et al.[20] analyzed 300 images of of potato leaves, which have several labels as 1) Late blight affected potato leaf. 2)Early blight affected potato leaf. 3)Healthy or Non-diseased potato leaf. They used Support Vector Machine (SVM) to classify the diseases though they doesn't explicitly mention any methodological obstacles faced in those studies.

Junde Chen et al. [21] proposed an approach is generally composed of two parts: the first part is the pre-trained module, the other is an auxiliary structure that utilizes multi-scale feature maps for detection. The pre-trained VGGNet is modified by replacing its last layers with an additional convolutional layer. Then, the convolutional layer is followed by two Inception modules, and the fully connected layers are replaced by a global pooling layer to conduct the dimension reduction of feature maps. Finally, the fully-connected Softmax layer was added as the top layer for the classification. The proposed model achieved an accuracy of 84.25 percent.

MA Jasim al.[22] presents a system that is used to classify and detect plant leaf diseases using deep learning techniques. After Image pre-processing CNN structure was designed that had input, convolution, nonlinear, pooling, normalization, fully connected and lastly softmax function layer. To prevent having to redo the training procedure, the author trained the network and stored the trained network. The accuracy of the proposed system was reported as 98.029 percent.

Junde Chen et al.[23]The research underlines the need to adopt deep learning, namely CNNs, for automatically recognizing plant diseases in agriculture. The authors offer a transfer learning strategy that makes use of pre-trained models such as VGGNet and Inception from ImageNet. This results in considerable performance improvements over previous approaches. Even in the presence of complicated backgrounds, their system obtains over 91.83% validation accuracy and 92.00% average accuracy for rice plant disease classification. The work emphasizes the usefulness of CNNs in plant disease identification, highlighting issues in feature determination and picture segmentation. Prior research demonstrates the promise of deep learning, particularly transfer learning, to overcome these difficulties.

Tahmina Tashrif Mim et al.[24] This study focuses on the use of image processing and artificial intelligence, namely CNN, to identify tomato leaf diseases. The purpose is to solve the issue of crop loss due to disease in Bangladeshi tomato crops. The method classified six forms of tomato leaf illnesses, including healthy leaves, with an accuracy of more than 96.55%. Farmers may use this simple technique to anticipate illnesses by uploading photographs of diseased leaves. The study achieves its objectives by presenting a feasible approach for the effective detection of tomato leaf diseases using Artificial Intelligence and computer science algorithms.

H. Al-Hiary et al.[25]This work proposes an improved technique, which builds on a previous method [1], for faster and more exact diagnosis and categorization of plant leaf diseases. For successful clustering and illness classification, the approach combines K-means clustering with Neural Networks (NNs). The research describes a four-step technique that includes color transformation, K-means-based segmentation, and the detection of mostly green pixels. The newly suggested method achieves illness detection and classification accuracy ranging from 83% to 94%, representing a 20% improvement over the previous technique. The research emphasizes the need for correctly identifying and classifying disorders, particularly those with slight differences that are invisible to the human eye. It uses the findings of K-means clustering for segmentation, allocating separate groups to diseased and undamaged components of the leaves.

Sachin D. Khirade et al.[26]The literature study in the research dives into several image-processing approaches for plant disease identification. It investigates the use of RGB pictures, k-means clustering, and Otsu's approach to identify green pixels and calculate threshold values. The color co-occurrence approach is used for feature extraction, and RGB pictures are converted to the HSI colorspace. The analysis also highlights an important advancement in integrating FPGA and DSP systems for monitoring and managing plant diseases. This includes FPGA-captured plant pictures or video data that has been processed and encoded by the DSP TMS320DM642. Another work featured in the review uses pattern recognition and the HIS model to segment diseased rice plant photos. The following phases entail boundary and spot detection, which allow the identification of diseased parts of the leaf .

Muhammad Hammad Saleem et al.[27]The research provides a comprehensive examination of deep learning (DL) models used to visualize various plant diseases while identifying gaps in early disease identification prior to obvious symptom development. The authors underline the need for construct DL models for hyperspectral image classification in plant disease diagnosis, especially when different real-world backdrops and lighting conditions are taken into account.

DL architectures have been used in a variety of agricultural applications, including leaf classification, fruit counting, crop type categorization, and plant recognition. Diverse deep learning models, such as CNN, Random Forest, VGG 16, and LSTM, were used and evaluated using different performance criteria.

The report examines the growth of DL designs from 1943 to the present, including milestones like AlexNet, a field standard. The following designs have improved picture recognition capabilities, surpassing previous constraints. The research division focuses on well-known deep learning architectures, such as AlexNet, for plant disease identification utilizing datasets such as PlantVillage, which contains photos of various crops infected with diseases. This synthesis of concepts and applications aids in the comprehension of cutting-edge advances in plant disease detection.

2.3 Summary

The literature review highlights the importance of potato disease detection and the growing use of technology-driven solutions. Researchers are utilizing image processing, computer vision, and machine learning to improve accuracy. Despite challenges like variations in disease manifestation and environmental conditions, innovative strategies like data augmentation, model optimization, and real-time analysis have been employed. The review identifies gaps and opportunities for further advancement in potato disease detection, aiming to contribute to developing accurate, efficient, and scalable solutions for detecting potato leaf diseases.

Proposed Methodology

3.1 Introduction

In order to classify potato leaf disease, we followed a work flow diagram.(Figure 3.1). For the classification of potato leaf disease, we used three models named VGG19, ResNet50 and InceptionV3 model with the pretrained model. We added some more customized convolutional layers. The proposed procedure consists of several phases. Initially dataset was collected and then we used some proprocessing steps to preprocess the dataset. Then this dataset was used as input for the customize models.

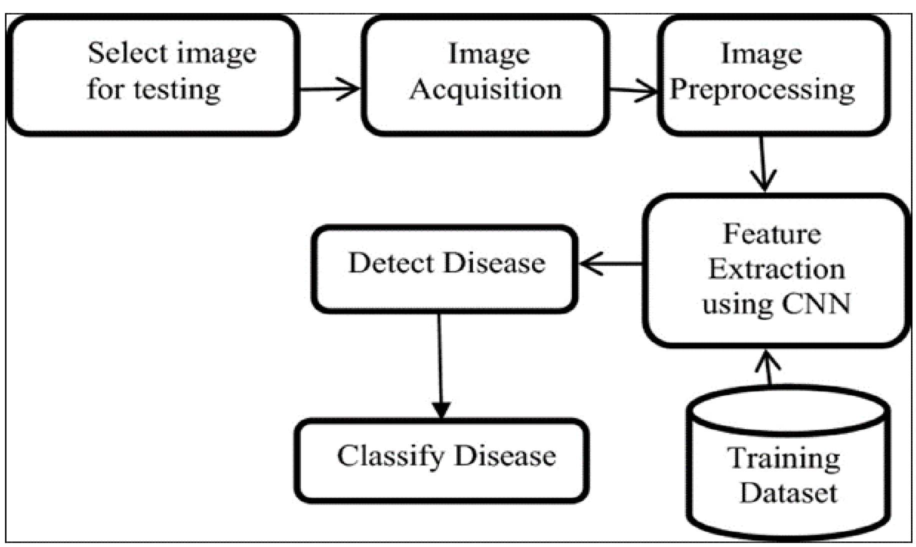

Figure 3.1. Work flow diagram of research

3.2 Feasibility Analysis

Potato cultivation faces challenges due to various diseases affecting leaf health. Implementing advanced technologies, such as deep learning models like VGG19, InceptionV3, and ResNet50, for disease detection can enhance crop management. The feasibility analysis aims to assess the practicality, effectiveness, and economic viability of deploying these models for potato leaf disease detection.

- **Technical Feasibility:** The technical feasibility of implementing potato leaf disease detection involves assessing the suitability of these deep learning models for potato leaf disease detection. This includes evaluating the machine learning model architectures, capabilities in image classification tasks, and the availability and compatibility of necessary hardware and software components.

- **Data Feasibility:** Data feasibility focuses on the availability and quality of the dataset required for training and testing the models. It involves preparing the dataset by addressing issues such as data cleaning, augmentation, and normalization. Additionally, considerations for data privacy and security are essential, especially if the dataset contains sensitive information.

- **Model Training and Evaluation:** This aspect examines the feasibility of the model training process, including the time and computational resources required for training VGG19, InceptionV3, and ResNet50. Model evaluation metrics, such as accuracy, precision, and recall, are crucial for assessing the effectiveness of the trained models.

- **Constraints on Hardware and Resources:** The feasibility study determines if the hardware and resources necessary for training and deploying the model are available within the organization's infrastructure. It takes into account things like processing power, memory, storage, and the availability of specialized hardware for quicker model training.

- **Implementation:** Implementation feasibility considers the integration of the models into existing agricultural systems and the user-friendliness of the interface for end-users, such as farmers and agricultural experts. It involves evaluating the compatibility and ease of incorporating these models into practical applications.

- **Economic Feasibility:** Economic feasibility involves estimating the costs associated with hardware, software, dataset acquisition, and model development. Additionally, it analyzes the potential return on investment, considering economic benefits such as increased crop yield and reduced disease-related losses.

- **Risks and Mitigation:** This aspect identifies potential risks and challenges related to technical issues, data limitations, and uncertainties in model performance. Mitigation strategies are proposed to address these risks and uncertainties, ensuring a smooth implementation process.

The conclusion summarizes the findings from the feasibility analysis, highlighting key aspects related to technical, data, and economic feasibility. It provides recommendations for decision-makers to guide the next steps in deploying VGG19, InceptionV3, and ResNet50 for potato leaf disease detection.

3.3 Requirement Analysis

The Potato Leaf Disease Detection System aims to address the growing need for efficient crop management in potato cultivation. The primary objective is to develop a system that can accurately identify and classify various potato leaf diseases through the integration of advanced deep learning models, including VGG19, InceptionV3, and ResNet50.

- **Functional Requirements:** The system must seamlessly accept input images of potato leaves, integrate multiple deep learning models for classification, process images in real-time for timely disease identification, and offer an intuitive user interface with user-friendly controls for enhanced interaction.

- **Data Requirements:** A diverse and comprehensive dataset of potato leaf images representing various diseases and healthy states is essential. Additionally, the system requires robust data preprocessing capabilities, including cleaning, augmentation, and normalization to enhance model training.

- **User Requirements:** The system should be accessible to farmers and agricultural experts without demanding extensive technical knowledge. It should also include a feedback mechanism allowing users to provide input on system predictions, thereby contributing to continuous improvement.

- **Economic Considerations:** An in-depth cost analysis covering hardware, software, dataset acquisition, and ongoing maintenance is required. Additionally, there should be an examination of potential economic benefits, such as increased crop yield and reduced losses due to diseases.

- **Legal and Ethical Considerations:** Implementation of measures to protect user data, ensuring compliance with privacy regulations, and establishing guidelines for the ethical use of the system aligning with agricultural and environmental practices are vital.

The requirement analysis emphasizes meeting user needs, ensuring system performance, and aligning with ethical and legal considerations. The successful implementation of these requirements will contribute to the effectiveness of the Potato Leaf Disease Detection System.

3.4 Dataset

We used PlantVillage dataset to collect the dataset for potato disease classification. PlantVillage is a dataset from kaggle which is an authentic source for the datasets.

3.5 Data Analysis and Pre-processing

The PlantVillage dataset from kaggle contains various types of plant leaf disease datasets. We used potato leaf disease dataset that has total 2152 files belonging to 3 classes. The three classes are Healthy, Late Blight and Early Blight. For traditional machine learning classifiers, dividing the dataset into 70,15 ratio between training and testing images.

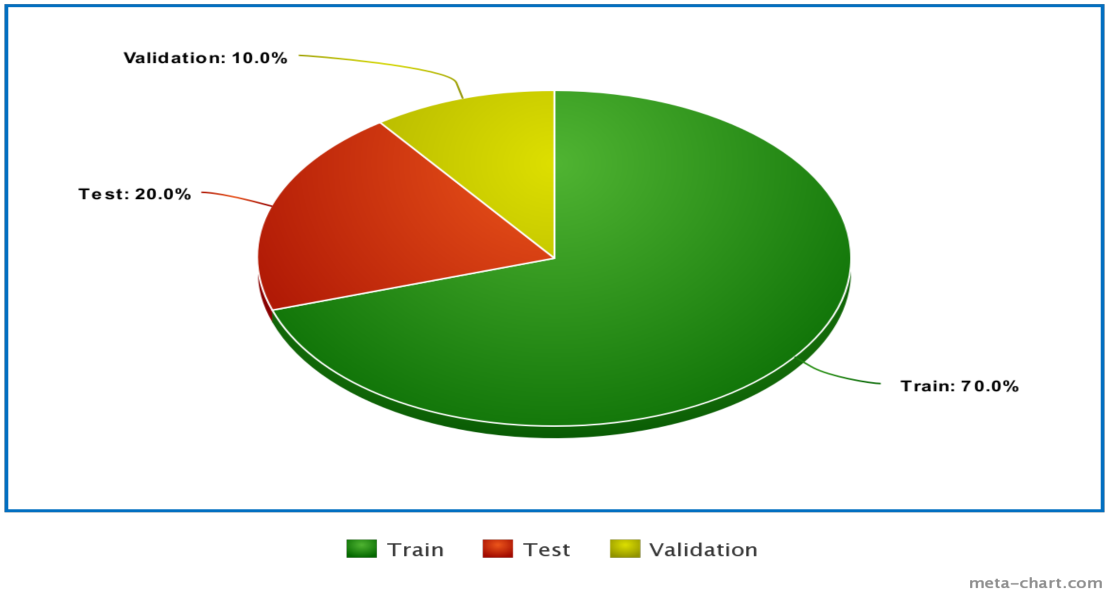

Figure 3.2. Distribution of dataset splitting

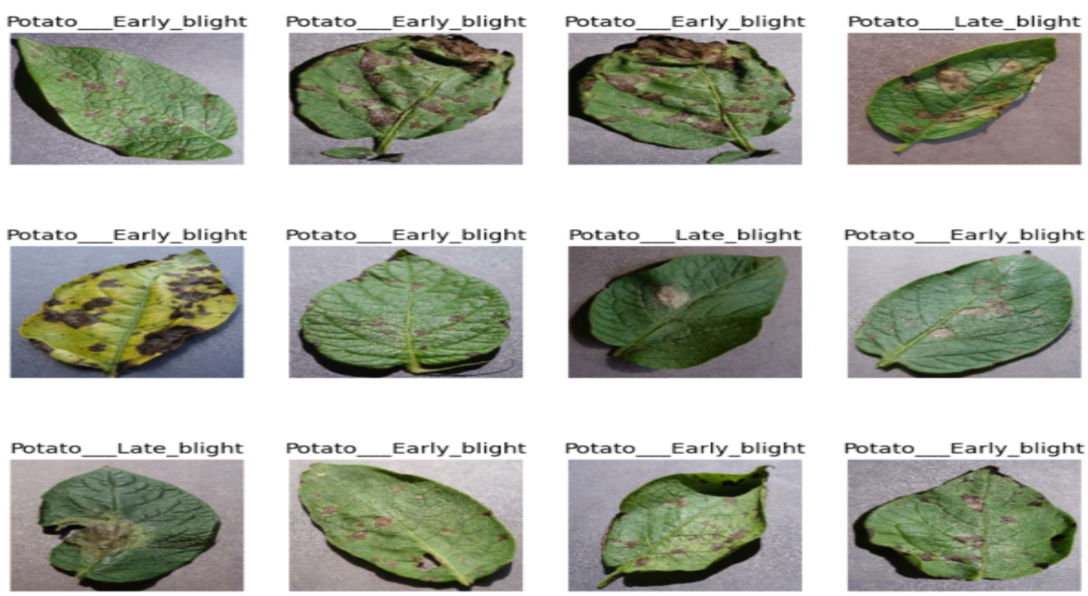

Figure 3.3. Sample dataset of potato leaf

3.5.1 Data Augmentation

In data pre-processing, we used data augmentation to increase robustness,generalization and mitigation of overfitting. We applied random horizontal and vertical flips on the input data. It helps the model become more robust by exposing it to variations in the orientation of the objects in the images. The parameter 0.2 represents the maximum rotation angle in radians. In this case, it allows random rotations up to 0.2 radians. We fixed the image size 224*224 and batch size is 32.

3.6 Model Development

A Convolutional Neural Network (CNN) is a type of deep learning model specifically designed for tasks involving images and visual data. CNNs have proven to be highly effective in tasks such as image classification, object detection, and image segmentation. They are widely used in computer vision applications.

Here are the key components and concepts of a typical CNN model:

- Convolutional Layers: These layers apply convolutional operations to the input data. Convolutional operations involve sliding a small filter over the input image to extract features. The convolutional layers are responsible for capturing local patterns and features.

- Activation Function: Common activation functions used in CNNs include Rectified Linear Unit (ReLU) to introduce non-linearity into the model.

- Pooling Layers: Pooling layers are used to reduce the spatial dimensions of the input volume, leading to a decrease in computational complexity and the number of parameters. Max pooling is a commonly used pooling technique.

- Fully Connected Layers: These layers connect every neuron in one layer to every neuron in the next layer. They are often used in the final layers of a CNN for tasks like classification.

- Dropout: Dropout is a regularization technique where randomly selected neurons are ignored during training. This helps prevent overfitting.

- Batch Normalization: Batch normalization is used to normalize the input of each layer, helping with the convergence and training stability.

- Output Layer: The output layer produces the final prediction of the model. The activation function used in the output layer depends on the task, such as softmax for multi-class classification.

VGG19 Model

VGG stands for Visual Geometry Group; it is a standard deep Convolutional Neural Network (CNN) architecture with multiple layers. The "deep" refers to the number of layers with VGG-16 or VGG-19 consisting of 16 and 19 convolutional layers. The VGG architecture is the basis of ground-breaking object recognition models. Developed as a deep neural network, the VGGNet also surpasses baselines on many tasks and datasets beyond ImageNet. Moreover, it is now still one of the most popular image recognition architectures.

The VGG network is constructed with very small convolutional filters. The VGG-16 consists of 13 convolutional layers and three fully connected layers. Let's take a brief look at the architecture of VGG Input. The VGGNet takes in an image input size of 224×224. For the ImageNet competition, the creators of the model cropped out the center 224×224 patch in each image to keep the input size of the image consistent. Convolutional Layers: VGG's convolutional layers leverage a minimal receptive field, i.e., 3×3, the smallest possible size that still captures up/down and left/right. Moreover, there are also 1×1 convolution filters acting as a linear transformation of the input. This is followed by a ReLU unit, which is a huge innovation from AlexNet that reduces training time. ReLU stands for rectified linear unit activation function; it is a piecewise linear function that will output the input if positive; otherwise, the output is zero. The convolution stride is fixed at 1 pixel to keep the spatial resolution preserved after convolution (stride is the number of pixel shifts over the input matrix). Hidden Layers: All the hidden layers in the VGG network use ReLU. VGG does not usually leverage Local Response Normalization (LRN) as it increases memory consumption and training time. Moreover, it makes no improvements to overall accuracy. Fully-Connected Layers: The VGGNet has three fully connected layers. Out of the three layers, the first two have 4096 channels each, and the third has 1000 channels, 1 for each class. We added 4 dense layers and a maxpooling layer to our potato leaf disease classification model.

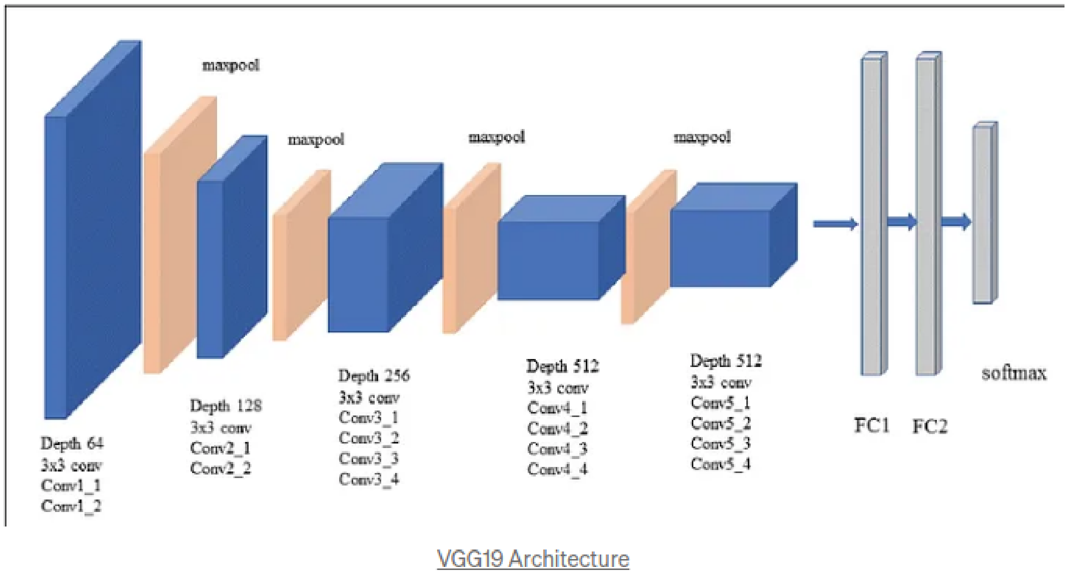

Figure 3.4. VGG 19 model architecture

Inception V3 model

The Inception v3 model is a deep convolutional neural network architecture that was developed by Google as part of the Inception project. It is designed for image classification and recognition tasks. The architecture is known for its use of "Inception modules," which incorporate multiple convolutional filters of different sizes within the same layer. This allows the network to capture features at different scales.

- Input Layer: The standard input size for Inception v3 is 299x299x3, where 3 represents the RGB channels of the input image.
- Stem Network: The initial part of the network, called the "stem," includes a combination of convolutional and pooling layers to process the input image.
- Inception Modules: The core building blocks of Inception v3 are the Inception modules. Each module consists of multiple parallel

convolutional branches of different filter sizes.These branches typically include 1x1, 3x3, and 5x5 convolutions, as well as a 3x3 max pooling operation. The idea is to capture features at different scales and improve the network's ability to recognize patterns of varying sizes. Batch normalization and ReLU activation function are used after each convolution operation.

- Reduction Blocks: Interspersed between Inception modules are reduction blocks. These blocks include a combination of 1x1 convolutions, 3x3 convolutions, and max pooling to reduce the spatial dimensions of the feature maps.

- Auxiliary Classifiers: Inception v3 includes auxiliary classifiers, which are additional classifier heads inserted at intermediate layers of the network. These auxiliary classifiers are used during training to provide additional gradients and help with the training process. They are usually discarded during inference.

- Final Fully Connected Layer: The final layers of the network consist of fully connected layers with softmax activation for the final classification.

InceptionV3 is built upon the Inception modules. They incorporate different sized convolutional filters to extract different kinds of information from the input image. As a result, the network can learn increasingly intricate pixel associations.Even while InceptionV3 is effective at classifying images, it may also be used for a number of other tasks, such as facial recognition, object identification, and even medical image analysis. Innovative features like inception modules, which use parallel convolutional layers with varied filter sizes to capture a variety of features at different scales, are incorporated

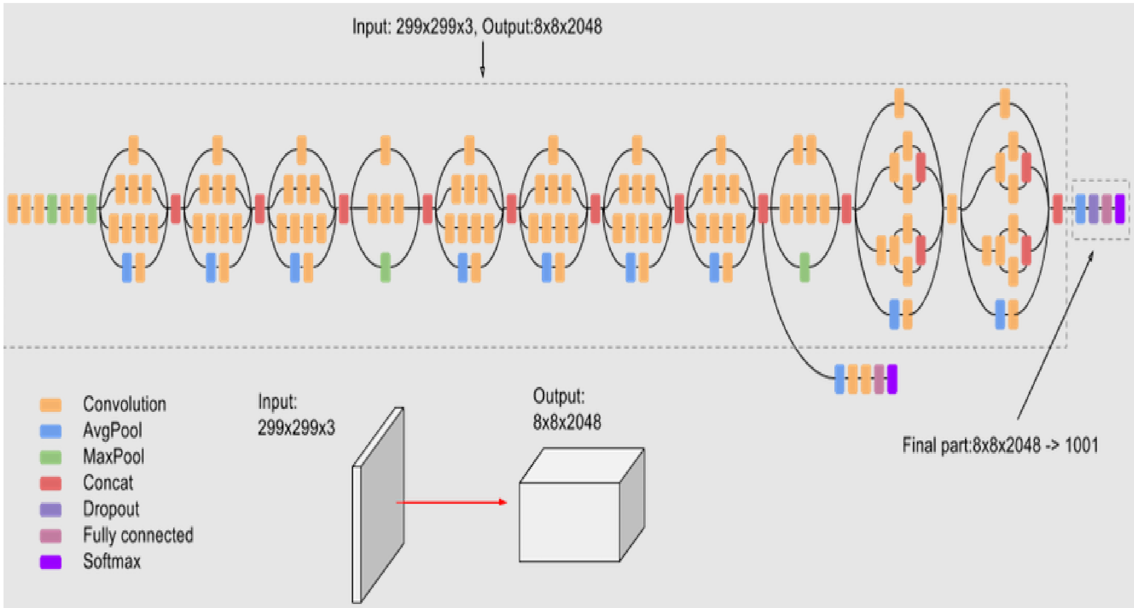

Figure 3.5. Inception V3 model architecture

into Inception v3. The network can efficiently learn hierarchical representations of images with this method. Its use of factorised convolutions, batch normalisation for faster convergence, and auxiliary classifiers for stability during training are noteworthy design features.

ResNet50 Model

ResNet, an acronym for residual network, describes the remaining building components that comprise the network's design. Deep residual learning is the foundation of ResNet-50, which enables the training of extremely deep networks with hundreds of layers. Microsoft unveiled ResNet50 in 2015, a groundbreaking neural network architecture that transforms deep learning by tackling the difficulties of training extraordinarily deep networks. Remaining blocks, each with several convolutional layers, make up its core. The clever usage of skip connections by ResNet50 distinguishes it from other networks by enabling the network to learn residual mappings and solve the vanishing gradient issue. These shortcuts allow information to flow directly during forward and backward passes, which makes training 50-layer networks more efficient.For computational stability and efficiency, the architecture includes batch normalisation and bottleneck structures, respectively. Global average pooling, which reduces model complexity in place of conventional fully connected layers, is a notable feature. With its transfer learning capabilities and extensive training on massive datasets such as ImageNet, ResNet50 is a very effective solution for image classification problems and can be applied to a wide range of computer vision applications.

The standard input size for ResNet-50 is 224x224x3, where 3 represents the RGB channels of the input image. The initial layers include standard convolutional and pooling operations to process the input image. The core building blocks of ResNet are residual blocks. These blocks contain two convolutional layers and a shortcut connection that adds the original input to the output of the two convolutions. Batch normalization and ReLU activations are applied after each convolution operation. In addition to the residual blocks, ResNet-50 has identity blocks with a shortcut connection that doesn't involve any convolution. These blocks are used to maintain the spatial resolution of the input. The final convolutional layer is followed by a global average pooling layer, which reduces the spatial dimensions to a single value per feature map. The output of the global average pooling layer is connected to a fully connected layer with softmax activation for classification.

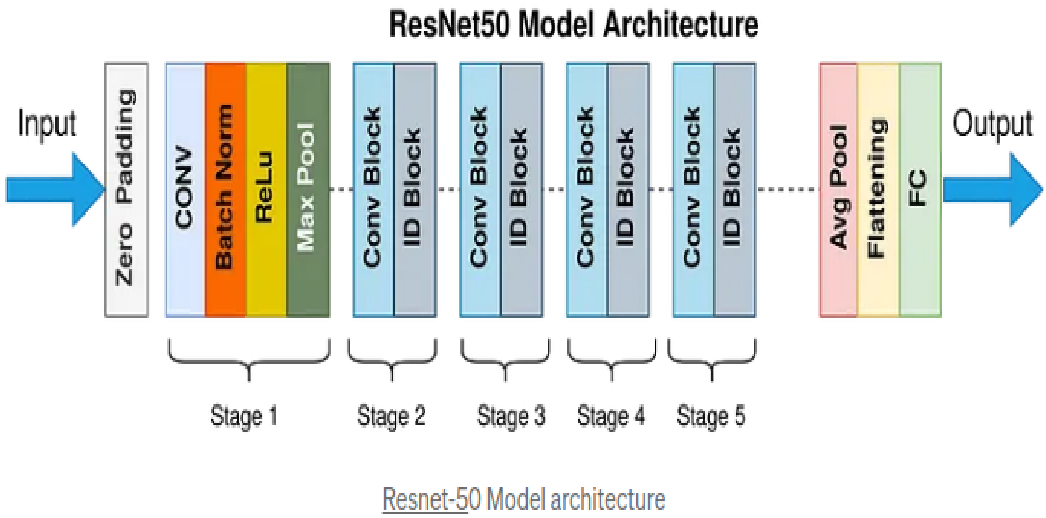

Figure 3.6. ResNet50 model architecture

3.7 Summary

The detailed operations of the proposed model, which we employed for leaf disease detection, are covered in this chapter. The overall architecture also makes use of the features related to machine learning and ensemble learning.

Implementation and Testing

4.1 Introduction

In this section, we will provide an overview of the system and efficiency of our proposed classification model for potato leaf diseases.

4.2 Performance Evaluation

In this phase, we identify potato diseases based on their features using machine learning algorithms, comparing the model result and choose the approach that performs most effectively among them. We used VGG19 and inceptionV3 pre-trained model and then added some more convolutional layers. The entire experiment was conducted by utilizing Google Colab. We used the training datasets to train each algorithm and the test datasets to evaluate the model. The accuracy percentage we obtained with VGG19 is 98.10% . Given the skewness of the dataset, we went beyond simple classification accuracy to assess model performance by using other metrics, such as precision, sensitivity, recall, and F1-score.

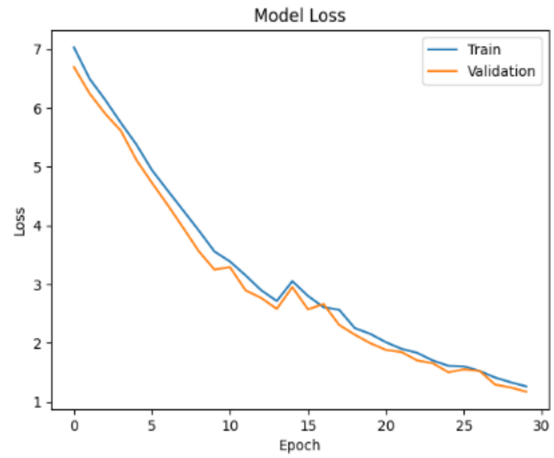

Figure 4.1. VGG19 model loss

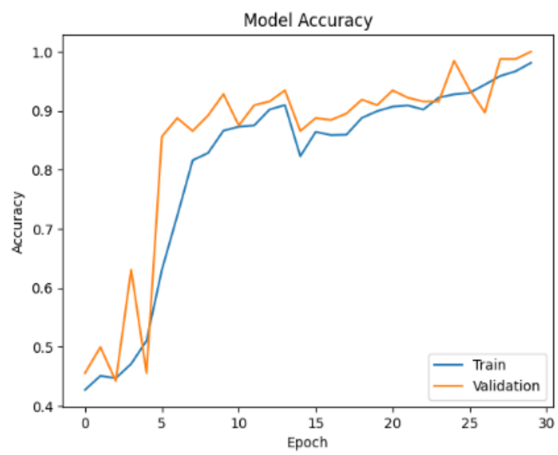

Figure 4.2. VGG19 model accuracy

Inception v3 is a convolutional neural network for assisting in image analysis and object detection, and got its start as a module for GoogLeNet. It is the third edition of Google's Inception Convolutional Neural Network, originally introduced during the ImageNet Recognition Challenge.The Inception V3 is a deep learning model based on Convolutional Neural Networks, which is used for image classification. The inception V3 is a superior version of the basic model Inception V1 which was introduced as GoogLeNet in 2014. As the name suggests it was developed by a team at Google. Customized Inception v3 model is used also for the classification model. We added some extra dense layer to the inception v3 model. Then our inception v3 model achieves an accuracy of 75.05% which is lower than VGG19 model.Inceptionv3 is a pre-trained model, which implies that it has previously been trained on a big picture dataset. This makes it ideal for tasks such as picture categorization and object detection.It's also been successfully used for Object detection, Image Segmentation , Facial Recognition.

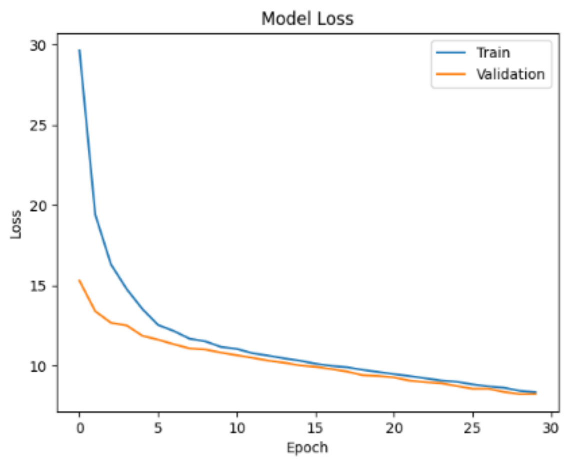

Figure 4.3. Inception model loss

Figure 4.4. Inception model accuracy

ResNet-50 is a 50-layer convolutional neural network (48 convolutional layers, one MaxPool layer, and one average pool layer). Its pre-trained weights are easily adaptable to different positions, saving time and enhancing performance.ResNet-50's standard version is pre-trained on an extensive dataset of more than 14 million photos, which enables it to perform exceptionally well on a range of image identification tasks. The ResNet architecture follows two basic design rules. First, the number of filters in each layer is the same depending on the size of the output feature map. Second, if the feature map's size is halved, it has double the number of filters to maintain the time complexity of each layer. Here we used ResNet50 pretrained model and added some more dense layer to the pretrained to enhance the accuracy. We obtained a accuracy of 98% by using this customized model in Potato leaf disease dataset. The graph of model loss and model accuracy is given below

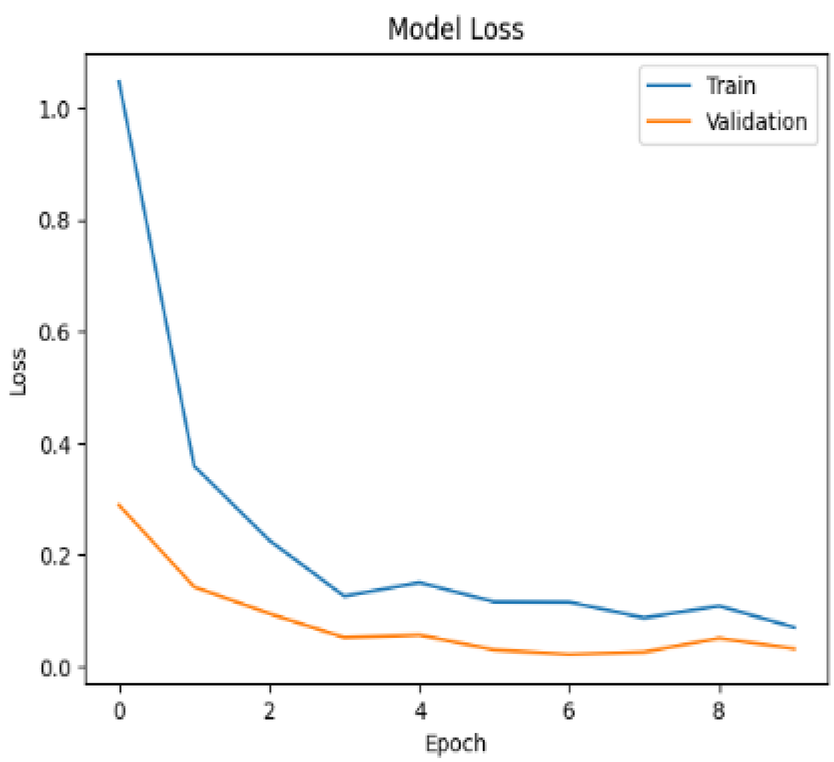

Figure 4.5. ResNet50 model loss

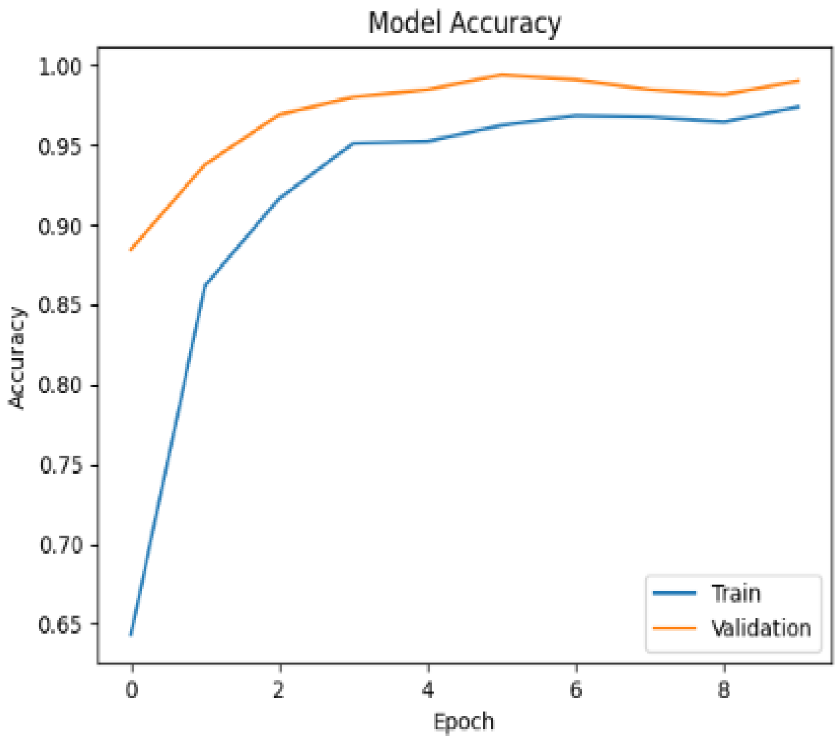

Figure 4.6. ResNet50 model accuracy

Model	**Accuracy**
VGG19	98.10%
Inception V3	75.06%
ResNet50	97.36%

Table 4.1. Accuracy of used models

Testing

Here is an example where we predict an image that results us by giving the name of the disease.

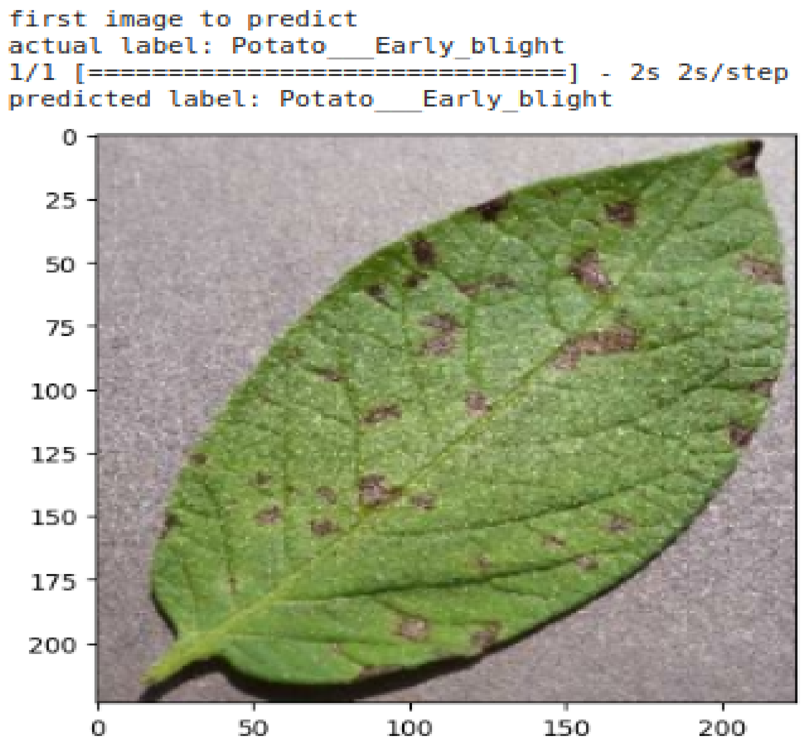

Figure 4.7. Image prediction

4.3 Result and Discussion

Our customized VGG19 model achieved an accuracy of 98.10% for the potato leaf disease image dataset. With pretrained VGG19 model we added 4 extra dense layers and a single Maxpooling layer to achieve this accuracy. We implemented another customized model named Inception V3 model. In Inception V3 model, the accuracy was 75.06% which is much lower than the VGG19 model and We also use ResNet50 model, the accuracy of 97.36% for the potato leaf disease image dataset.So after comparing this three models, we can say that in this potato leaf disease dataset,VGG19 model works more accurately than Inception V3 model and ResNet50.

Standards, Impacts, Ethics, Challenges and Timeline

This part highlights the thesis work's Standards, Impacts, Ethics, and Challenges. The Constraints and the timeline are displayed.

5.1 Impacts on Society

The creation and application of a system for detecting potato leaf disease can greatly benefit society, especially in the agriculture industry. The following are some ways that a system like this can help society:

Crop Yield Improvement:

When potato leaf diseases are discovered early, growers can act quickly by removing afflicted plants or providing targeted remedies. This may result in a notable decrease in crop losses and an increase in production overall.

Food Security:

The detection technology adds to food security by reducing the impact of illnesses on potato harvests. A secure food supply can be ensured by improving the production of potatoes, which are a staple diet for many people worldwide.

Economic Stability for Farmers:

Crop diseases frequently result in financial losses for farmers. The detection system supports the financial stability of farming communities by assisting farmers in making well-informed decisions and averting losses.

Reduced Environmental Impact:

An excessive amount of pesticide use can be avoided by using early disease identification to enable precise and targeted treatment application. Consequently, this reduces the negative effects of chemical inputs on the ecosystem.

Technology Adoption and Skill Enhancement:

Modern farming methods are encouraged to spread by introducing technology-driven solutions in agriculture. Utilising these kinds of technologies, farmers can also learn new technological skills that improve their overall capabilities.

Time and Resource Efficiency:

Farmers save time with automated disease detection technologies that deliver precise and timely findings. This effectiveness is essential for prompt responses, stopping the spread of illnesses, and making the most use of available resources.

Empowerment of Smallholder Farmers:

Automatic disease identification can be very helpful for smallholder farmers, who frequently lack the means for thorough monitoring. They may now compete more successfully in the market and make well-informed judgements thanks to this technology.

Global Agricultural Sustainability:

The adoption of disease detection technologies is consistent with the larger objectives of sustainable agriculture. Reducing crop loss makes global agricultural methods more sustainable overall.

5.2 Ethics

There are several applications and significant implications for potato leaf disease diagnosis, depending on the dataset utilised for model training. It is essential that the system be implemented in a way that considers people's concerns in order to guarantee that it is not utilised for any purpose that might useful for social, national, or worldwide security. Accountability and transparency are given top priority under a strict code of morals and ethics that governs the collection of the dataset. Upholding moral standards for data collection ensures that technology is utilised responsibly and with a commitment to the welfare of individuals and communities.In this paper,We used the kaggle dataset.This is a popular platform for working with various types of dataset and save dataset in it. This module's success relies on its capacity to analyze the vast amounts of data.It is critical that we address the ethical aspects of our activity. The ethical ramifications of using AI in agriculture are covered in this section, with particular reference to the detection of potato leaf disease. A number of factors are carefully considered, including data protection, possible socioeconomic effects on farmers, and ethical technology deployment. Work together with farmers, key stakeholders, and the local government. Assemble the community's advantages from the project and make sure the technology enhances the regional agricultural ecology. The development and application of the potato leaf disease detection solution are guided by our dedication to moral behaviour.

5.3 Challenges

It can be challenging to correctly detect potato leaf disease based on CNN.People without access to social media or mobile phones may find it challenging to benefit from these advancements in agricultural output. The objective of our research is to use deep learning to classify and detect potato leaf disease.Also we faced many problem to choose the model for Potato leaf disease.
Limited training data: CNNs require a large amount of labelled training data in order to learn and generalise efficiently. Obtaining a comprehensive and extensive collection of facial expressions accompanied by accurate emotion labelling can be challenging, especially when dealing with uncommon or culturally specific emotions. Overfitting or inadequate model generalisation to new data might result from a lack of training data.

5.4 Constraints

This section covers a variety of restrictions, including those related to design, resources. An overall framework based on the picture collection is offered. Our model won't function effectively unless we have a strong CPU that can manage a lot of photographs. These components are used in our model's training

- Google Colab
- Minimum processor requirement: Intel i3
- Minimum memory requirement: 4GB

5.5 Timeline

The timetable has led to the division of the thesis work into two separate parts. Work plans and thesis evaluations are part of the two-semester work process during the first semester, after consulting with our supervisor. We present a report outlining the general architecture's outcomes, as well as the entire implementation and testing procedure, in the second semester. Prototype analysis and collaborative creation are components of the work process.

5.6 Gantt Chart

This diagram shows the workflow for the thesis work. Over two semesters, the thesis project was finished in its entirety.

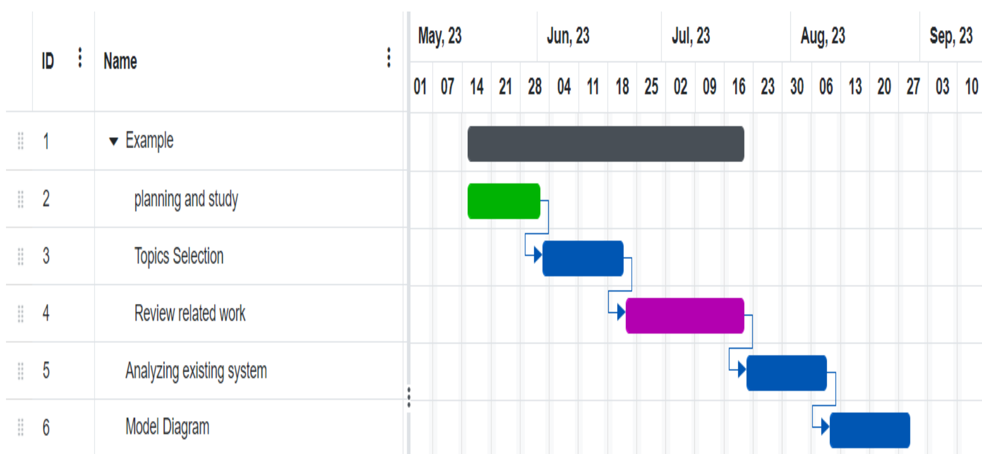

Figure 5.1. Semester 1

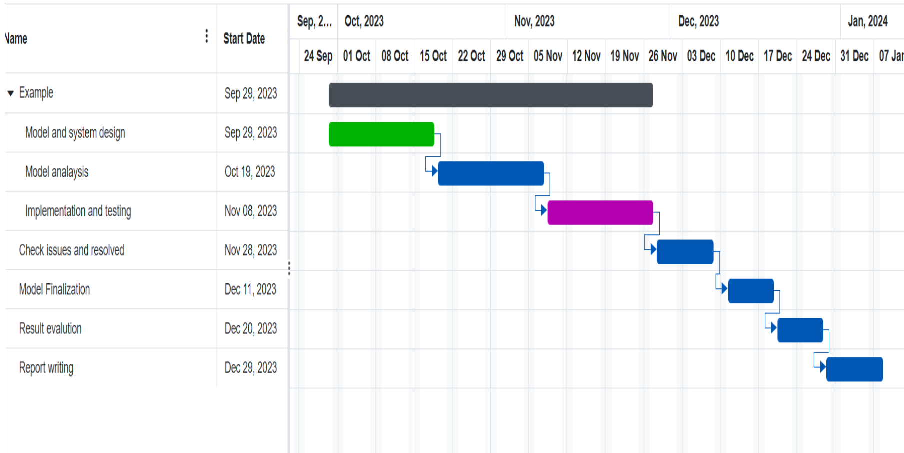

Figure 5.2. Semester 2

5.7 Summary

This chapter provides a thorough overview of our research and development programmer's related to potato leaf disease detection. By addressing standards, consequences, ethics, difficulties, and solutions, we work to get through the complicated environment in agriculture safely and successfully. This road plan lays the groundwork for a fruitful and significant addition to the field of detecting potato leaf disease. Schedules, tasks, and standards The complete thesis work has been separated according to the timeline. We go over how much time we spent on this project in this chapter, including our objectives, tasks, and deadlines.

Conclusion and Future Works

The implementation of Convolutional Neural Networks for potato leaf disease detection shows great potential in revolutionizing the way farmers monitor and manage crop health. The system's accuracy and efficiency make it a valuable tool for early disease identification, contributing to improved crop yield and agricultural sustainability.In this project, with the help of deep learning techniques and convolution neural network classification based approach is proposed to detect the late blight, early blight and healthy leaf images of potato plant. We compared two customized CNN model VGG19 and Inception V3 where VGG19 performs well with an accuracy of 91 percent. Most of the farmers of the village in Bangladesh are not literate and they don't know about the disease properly. We think that, this work can change the situation of the potato grower in Bangladesh. The experiments have been carried out on healthy and diseased leaf images to perform classification. It is concluded that the proposed method effectively recognizes three different types of potato leaf diseases.

6.1 Future Works

In future, we aim to create an android application that can detect the disease of every types of crop and can provide the proper solution for those diseases of the crop. And also, by increasing our database, we will able to get better accuracy. By building an android app we will continue the development process. And we will create a system where the farmers of Bangladesh can easily get instant service and advice on their problem by detecting the disease. The whole project can be put up on the internet and user can simply sit at home and use the system to detect the disease and spray the required disinfectant. The interface will be connected with the internet and then to the database. Also, we will try that these types of proposed method will be applied in various applications such as another leaf plant recognition.

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