Deep Learning Based Approach To Detect Potato Leaf Disease

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CERTIFICATE

This is to certify that the work entitled '***Deep Learning Based Approach To Detect Potato Leaf Disease*** ' authored by Md Masum Rana, Hasi Rani Roy and Mostakim Ara Jaba, has been carried out under our supervision. To the best of our knowledge, this work is original and has not been submitted elsewhere for any diploma or degree.

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DECLARATION

The work entitled '***Deep Learning Based Approach To Detect Potato Leaf Disease***' which has been carried out in the Department of Computer Science and Engineering at Hajee Mohammad Danesh Science and Technology University, is original and conforms to the regulations of this University.

We understand the University's policy on plagiarism and declare that no part of this thesis has been copied from other sources or previously submitted elsewhere for any degree or diploma.

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Dedication

To my family, whose unwavering support and endless encouragement have been my anchor throughout this academic journey. To my friends, who provided both inspiration and moments of respite. And to all the mentors, teachers, and scholars whose guidance and wisdom illuminated the path to this achievement. This thesis is dedicated to you with heartfelt gratitude.

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Abstract

Potato leaf diseases, such as early blight and late blight, pose significant challenges to agricultural productivity. Timely and accurate identification of these diseases is crucial for effective crop management. This thesis investigates the application of deep learning models, including CNN, VGG19, EfficientNetB0, and ResNet50, for the classification of potato leaf diseases using a dataset consisting of 1000 early blight, 1000 late blight, and 152 healthy leaf images. The dataset was split into 80% training, 10% validation, and 10% testing, with data augmentation techniques applied to address class imbalance. The performance of the models was evaluated based on accuracy, precision, recall, and F1-score. Among the models, EfficientNetB0 demonstrated the highest accuracy of 100%, outperforming the others, while CNN and ResNet50 showed comparable results. VGG19, while effective, exhibited the lowest performance among the models. Despite strong results, the study faced challenges due to the limited number of healthy leaf samples, which impacted the classification performance for this class. This study highlights the potential of deep learning models, particularly EfficientNetB0, in enhancing automatic potato leaf disease detection. The findings underscore the importance of addressing class imbalance and optimizing model architectures for real-world agricultural applications.

Keywords: Potato Leaf Disease Detection, Early Blight, Late Blight, Deep Learning, Data Augmentation.

Chapter 1

Introduction

1.1 Introduction

There are many different types of occupations in the world, but agriculture is the most common and Bangladesh economy is heavily reliant on agriculture. Among the various crops grown in Bangladesh, potato is the most in-demand crop. But potato production is being hampered due to some diseases which are increasing the cost of farmers in potato production. So we can't export potatoes to our expectations in the other countries. Among them early blight, late blight are the most terrible diseases of potato leaf at present in Bangladesh. Early blight is caused by a fungus and late blight is caused by a specific microorganism.

In our country, the major area's farmers face many hampers on this disease every year. The farmers and businessmen of our country are facing many problems with those diseases particularly in the case of export to other countries such as Russia, Indonesia, Malaysia, Sri Lanka, Thailand, Hong Kong, Turkey, Vietnam, Maldives etc. Even a decade ago, production was below half a million tons. Now it is moving towards billions of tons [1]. This success has brought Bangladesh the fourth largest potato producing country within Asia and ranks among the top 15 globally. The recognition was given by the Food and Agriculture Organization of the United Nations. According to a report of this organization, an average of one crore metric tons of potatoes are being produced in the country in the last few years. Not only is this a wonderful achievement in production, potato is now one of the most profitable crops in the country. It has also become a means of earning foreign currency. Recent data from the National Board of Revenue (NBR) reveals that Bangladesh imported 98,731 tons of potatoes at a cost of 15.7 million US dollars during the 2023-24 fiscal year, while exporting only 12,352 tons, generating 3.8 million US dollars [From Google]. We believe that, if we detect the disease of potato properly and provide the proper treatment, the production growth will increase to our expectation.

The popular way of identification of these diseases through the utilization of the human eye for decades. But this methodology arises with certain infeasibilities such as overtime will be taken for processing and shortage of experts at fields in remote locations [1]. Therefore, the image analysis turned out to be an efficient methodology that will play a vital role in monitoring as well as the identification of the plant disease conditions effectively.

We have taken the help of image processing to diagnose potato leaf disease. Here we have used CNN, VGG19, EfficientNetB0, ResNet50 model architecture to diagnose the disease which can be identified by looking at the characteristics of the disease and the type of disease. Accuracy is very good with training data in the project and accuracy with sample data is above 99%. So our project will be able to accurately diagnose potato leaf disease.

1.2 Motivation & Inspiration

The motivation for using deep learning in our thesis to detect potato leaf disease is driven by the pressing need to optimize agricultural practices, reduce crop losses, and ensure food security. The motivation and inspiration for our thesis work can stem from several factors:

- **Potato as a Staple Crop**: Potatoes are one of the most important crops globally, including in countries like Bangladesh, India, and several African and South American nations. Disease outbreaks can severely impact crop yields, leading to food shortages and economic losses.
- **Minimizing Losses**: Potato leaf diseases, such as late blight, early blight can cause devastating losses to farmers. Early and accurate detection of these diseases can prevent crop destruction, improve yield, and save costs for farmers.
- **Manual Inspection Limitations**: Traditional methods of disease detection rely heavily on manual inspection by experts, which is time-consuming, labor-intensive, and prone to human error, especially in large farms.
- **Short Disease Lifecycle**: Some potato diseases progress rapidly, and manual identification often comes too late to prevent large-scale losses. Quick and accurate detection is critical to mitigating the effects.
- **Global Food Security**: Deep Learning Based Approach To Detect Potato Leaf Disease using deep learning can contribute to global food security by helping to reduce crop losses and ensuring more stable food supplies, particularly in developing countries.

1.3 Objective

The objectives of using deep learning for Deep Learning Based Approach To Detect Potato Leaf Disease are multifaceted, aiming to address both practical agricultural challenges and advance technological applications in farming. The key goals of the project include:

- To accurately identify and classify various potato leaf diseases (e.g., late blight, early blight) at an early stage using deep learning models. Early detection can help farmers take timely action, preventing the spread of disease and reducing potential crop losses.
- Develop a system that can autonomously detect diseases from images of potato leaves, reducing reliance on manual inspections and human expertise.

1.4 Problem Statement

The core problem is the necessity for accurate and prompt prediction of potato leaf diseases, especially early blight and late blight, based on climate conditions. For this, difficulty in detecting diseases across different environments, lighting conditions, and plant growth stages. Different diseases often display similar visual symptoms, making it hard to differentiate between them. The study aims to fill this gap by proposing a modified dataset and utilizing various models to enhance accuracy, providing a more reliable tool for farmers and agricultural stakeholders. However, these studies have also highlighted the need for further research to improve the accuracy and reliability of existing algorithms. Detecting potato leaf disease through image data is challenging but can be improved with more accurate algorithms and approaches. Keeping this in mind, the following questions need to be addressed:

• What are the challenges in implementing image-based potato disease detection?
• Which Feature Extraction methods are more effective for detecting disease?
• What is the most efficient deep learning algorithm for detecting disease?

1.5 Contribution

In this paper, we consider different deep learning algorithms to detect Potato Leaf Disease. Our contributions are delineated as follows:

- Applying CNNs, transfer learning architecture for accurate classification.
- We have employed data augmentation techniques, such as rotating, and scaling images, to artificially increase the size of training datasets. This helps reduce overfitting and improves model robustness. Preprocessing techniques, such as image normalization and color space transformations, have also been used to enhance model performance.
- Open research problems and future research directions are discussed to enhance food security by using deep learning methods.
- A comprehensive comparison of deep learning techniques and concepts that help understand deep learning's role in our thesis is provided.

1.6 Boundary of the Work

The analysis primarily focuses on detecting potato leaf disease using deep learning techniques applied to a specific dataset. The working boundary of our thesis using deep learning includes the model's design, the nature of input data, the deployment environment, environmental variability, and disease similarity. The goal is to deliver a practical, scalable, and reliable solution that accurately identifies potato diseases, enabling farmers to act swiftly and minimize crop loss. However, the system must be continuously adapted and improved based on new data, environmental conditions, and technological advancements.

1.7 Thesis Organization

This thesis is structured into five chapters, each with a specific focus. A brief summary of these chapters is presented below :

Chapter 1 serves as an introduction to this thesis, highlighting its main objective, motivation and inspiration, boundary of the works. Chapter 2 provides an overview of the existing research on the topic, highlighting key themes, trends, and gaps in the literature. Chapter 3 outlines the complete methodology proposed in this thesis. It covers various aspects such as dataset description, preprocessing techniques, feature encoding and selection methods, performance measures, and the models employed. Chapter 4 delves into the conducted experiments and presents detailed findings. It critically evaluates and discusses the outcomes of these experiments. Chapter 5 concludes the work presented in this thesis and outlines potential directions for future research.

Chapter 2

Literature Review

2.1 Introduction

Deep Learning Based Approach To Detect Potato Leaf Disease using deep learning models aims to provide a comprehensive overview of the current state of research in this area. If one can able to identify these diseases in time, then the crop can be protected using appropriate fertilizers. If this process of identification and classification of diseases is able to digitize which would be helpful for the agriculturists. It will decrease the time for the identification of disease and precision in classifying the diseases. The research will explore existing literature that utilizes detecting tactics and techniques to identify potato leaf disease. It will examine different methods and approaches employed in detecting potato leaf disease, including deep learning algorithms, feature extraction methods etc. The discussion will encompass the accuracy, reliability, and validity of Deep Learning Based Approach To Detect Potato Leaf Disease. Deep Learning techniques have gained significant popularity in the detection of potato leaf disease due to their efficiency and scalability. This literature overview will highlight recent publications that utilize Deep Learning approach to detect potato leaf disease.

2.2 Related Work

Detecting diseases in plants in early stages is one of the major concerns in the Agriculture field. So, there are many researchers who are already working on the issue of detecting plant diseases and diagnosing them some of the results of the research done in detecting plant diseases are as follows:

Aditi Singh, Harjeet Kaur [1] in their research has tried to use the process of image segmentation, the K-means methodology to detect and classification of tomato leaf diseases. For the feature extraction purpose, the gray level co-occurrence matrix concept was utilized, and for the classification purpose, the multi-class support vector machine methodology was utilized and the accuracy of the proposed model was about 95.99%. Yet, this accuracy needs to be improved. The existing work further can be extended by using artificial neural networks, particularly, convolutional neural networks. Deep Kothari et al. [2] used deep learning to classify two types of diseases in potato plants based on leaf conditions, using the GoogleNet, ResNet50, and the VGG16 convolutional neural network architecture model to create an accurate classification system. They used only 900 images to train our model and 300 images for validation and this experiment achieved 97% accuracy for the first 40 CNN epochs. The data augmentation process helps the model to be more robust. Our technique can help farmers in detecting diseases in their early stages and in enhancing their crop yields. Divyansh Tiwari et al. [3] in their research used pre-trained models like VGG19 for fine-tuning(transfer learning) to extract the relevant features from the dataset. Then, with the help of multiple classifiers results were perceived among which logistic regression outperformed others by a substantial margin of classification accuracy obtaining 97.8% over the test dataset. In [4] this work, they have made a CNN model with the help of Inception V3 architecture and Adam Optimizer to diagnose and classify disease of potato plants such as early and late blight where we achieved an accuracy of 90% over the test dataset in classification. This paper [5] offers a proposed method that uses a pre-trained CNN model, which is fine-tuned on a dataset of potato leaf images. The proposed approach achieves 97.4% accuracy in the classification of potato leaf diseases such as early blight potato leaf disease and late blight potato leaf disease, and can be used as an effective tool for early detection and management of these diseases in potato crops. Md Moshiur Rahman et al. [6] in their research has tried to perform disease detection with the help of two architectures which are Random Forest and Decision Tree classifiers, which properly categorize the disease with an accuracy of over 95%. Md. Marjanul Islam Tarik et al. [7], in this thesis mainly focuses on disease detection of potatoes from any surface by using machine learning (CNN). They found that CNN is the best way to perform this type of detection object and gains 99% of validation accuracy. Simonyan and Zisserman [9] introduced VGG16 and VGG19, deep convolutional networks using small 3x3 filters for large-scale image recognition. The models achieved state-of-the-art performance on the ImageNet dataset, with VGG16 achieving 71.5% accuracy and VGG19 achieving 71.9% accuracy. Mohanty and Dutta [10] used a fine-tuned AlexNet model for image-based plant disease detection, achieving over 99% accuracy in classifying 38 different plant diseases. The model demonstrated effective transfer learning by leveraging pre-trained weights from ImageNet. Rabbia Mahum et al. [11] proposed a deep learning-based framework using CNN for potato leaf disease detection, achieving high accuracy with efficient model performance. The approach showed promise for accurate and scalable plant disease identification. Islam et al. [12] developed a potato disease detection method using image segmentation and a multiclass support vector machine (SVM), achieving accurate classification of multiple potato diseases. The approach effectively combined image processing techniques with machine learning for disease identification. Hritwik Ghosh et al.[13] utilized convolutional neural networks (CNNs) for potato leaf disease recognition and prediction, achieving high accuracy in identifying various leaf diseases. The model demonstrated effective performance for real-time disease detection. Adluri, Vijaya et al. [14]. Potato Leaf Disease Detection and Classification Using VGG16. The study implemented the VGG16 architecture for detecting and classifying potato leaf diseases, achieving an accuracy of 95.2%. The results demonstrated the model's effectiveness in enhancing disease detection for agricultural practices. Nishad, Md Ashiqur Rahaman et al.[15] Predicting and Classifying Potato Leaf Disease using K-means Segmentation Techniques and Deep Learning Networks. The study combined K-means segmentation with deep learning networks for potato leaf disease prediction and classification, achieving an accuracy of 92.5%. This approach effectively enhanced disease detection and classification in agricultural applications. Sikder, Md & Islam, Md. [16] A Deep Learning Approach (CNN) to Classify the Potato Leaf Disease. The study implemented a deep learning model to classify potato leaf diseases, achieving an accuracy of 94.3%. This approach demonstrated strong potential for effective disease identification in agricultural practices.

The above-discussed literature review indicating the importance of agriculture and the detection of disease at the right time will not affect the very essential yield. The detection and classification of diseases in various plants will be followed with various phases such as data acquisition in the form of images, pre-processing of the obtained images using image processing methodologies, image segmentation for the identification of the region of interest, extraction of features, and finally, depending on the obtained patterns classifying the images. The methodologies are mainly discussed based on machine learning and image processing methodologies as the proposed framework is also based on those methodologies only. Table 2.1 gives a tabular summary of the literature review.

Research Paper	**Algorithm Approach**	**Dataset Size**	**Classifier with Accuracy**	**Limitations**
[4]	CNN, VGG16, ResNet50	1000	98%	Use small size of dataset
[6]	CNN, InceptionV3	2152	90%	Low accuracy
[10]	CNN, VGG19	2152	98.2%	Imbalance dataset
[11]	DenseNet, CNN	3852	97.8%	Using large dataset but less accuracy
[12]	SVM	2000	95%	segmentation techniques may not capture all relevant features
[14]	VGG16	1200	95%	Comparatively less accuracy

Table 2.1: Related work for the potato leaves disease detection.

2.3 Conclusion

In our study of related studies, we looked at how other people have dealt with the same issue of how to classify potato leaf disease detection. We learned that old ways of doing things that are slow and might not always be right. The other work we looked at in this area gave us a good place to start. We've seen what other people have done and learned from it. Now we're ready to take their ideas and make something that will help people.

Chapter 3

Methodology

3.1 Introduction

The methodology part of this report on Deep Learning Based Approach To Detect Potato Leaf Disease describes the data sources, tools, techniques, and procedures used to collect, process, and analyze image-based data of potato leaves for detecting late blight, early blight & healthy potato leaves using several deep learning techniques.

3.2 Proposed Methodology

In this study, a robust framework for the recognition of diseases in potato leaves is proposed. The deep and high dimensional features play a major role in the detection and characterization of disease in plants leaf. Deep learning models are famous for the mining of key features that distinguish the images and classify them in various classes. The approach suggested in this research comprises five phases: data collection, data preprocessing, data augmentation, training and image categorization, particularly concentrating on the utilization of CNN algorithms, EfficientNetB0, VGG19, and ResNet50.

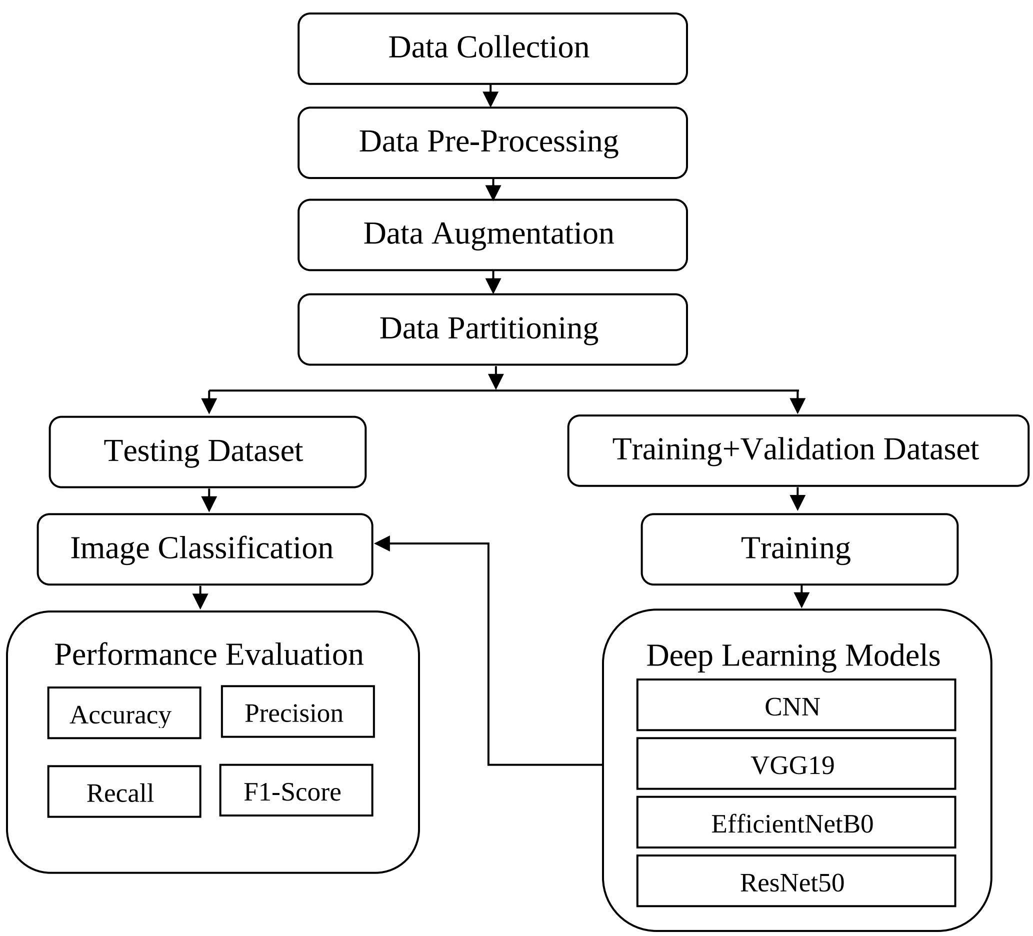


Fig. 3.1 Block Diagram of System Architecture

3.3 Data Collection

In the initial stage, the potato leaves images have been collected from kaggle. It is an open source repository that provides Plant Village Dataset for research purposes that contains a total of 2,152 images for Potato Leaves diseases among which 1000 of “Late Blight”, 1000 of “Early Blight” and 152 of “Healthy Plants” are included. Dataset has images belonging to classes like Early blight, Late blight and Healthy have shown below :

Label	Category	Number
0	Early Blight	1000
1	Late Blight	1000
2	Healthy Blight	152
Total		2152

Table 3.1 Number of samples

Fig. 3.2 Dataset Images

3.4 Data Pre-Processing

After collecting the dataset, the images undergo preprocessing to prepare them for analysis. Pre-processing steps may involve resizing images for uniformity, converting them to grayscale or enhancing color channels, normalizing pixel values, and applying noise reduction techniques to improve image quality. These steps ensure a consistent dataset suitable for effective feature extraction and classification.

- **Image Preprocessing:** In the context of the potato leaf dataset, the image preprocessing stage is tailored specifically to address the unique features and challenges associated with potato leaf images. The primary goal is to optimize the images for the classification models, ensuring accurate and efficient disease detection. The following steps are undertaken during the image preprocessing phase for potato leaves.

- **Resizing:** To maintain consistency across the dataset, all potato leaf images are resized to a standard dimension, such as 256x256 pixels. This uniformity ensures that the CNN models, such as VGG19, EfficientNetB0, and ResNet50 can efficiently process and analyze the images.
- **Normalization:** Pixel values in the potato leaf images are normalized to a range between 0 and 1 by dividing by 256. This step ensures uniformity in the input data, making it easier for the classification models to identify patterns and generalize across the dataset.
- **Noise Reduction:** Potato leaf images may contain noise from various sources, such as camera artifacts or environmental factors. Noise reduction techniques, like Gaussian blur or median filtering, are applied to minimize the impact of noise on the classification models' performance.

3. 5 Data Augmentation

As our dataset is imbalance We firstly augment the data to simply increase the quantity of data. Data Augmentation is a process that generates several realistic variants of each training sample, to artificially expand the size of the training dataset. This aids in the reduction of overfitting. In data augmentation, we will slightly shift, rotate, and resize each image in the training set by different percentages, and then add all of the resulting photos to the training set. This allows the model to be more forgiving of changes in the object's orientation, position, and size in the image. The contrast and lighting settings of the photographs can be changed. The images can be flipped horizontally and vertically. We may expand the size of our training set by merging all of the modifications. We then create batches of size 32 images each,3 channels and 50 epochs.

3. 6 Data Partitioning

Dataset has divided into 3 subsets, namely:

- Training: Dataset to be used while training. 80% data has used for training.
- Validation: Dataset to be tested against while training. 10% data has used for validation.
- Test: Dataset to be tested against after we trained a model. 10% data has used for testing

3.7 Training

We have used 80% data to train the proposed models for the potato leaves disease detection, an adaptive optimization algorithm for learning rate is employed. It is known as Adam, used for the modification of the weights for potato leaves samples. To analyze the efficiency of the proposed model’s classification, cross-entropy (CE) loss is computed. Its probability value ranges between 0 and 1. When the predicted class has a difference from the real class label, loss rises. As we have employed multiple classifications for that we used categorical loss function.

3.8 Image Classification

The potato leaves are classified into three classes such as early blight, late blight, and healthy. The final classification layer consists of the fully connected layer with the softmax function. In this layer, the number of neurons is constant conferring to the classes in the dataset. Therefore, the softmax function has been employed here for the multi-class cataloguing. With the pre-processed and enhanced dataset, the selected CNN algorithms, VGG19, EfficientNetB0 and ResNet50 are employed to classify the potato leaf images into their respective categories. These DL models are trained and optimized on the dataset, leveraging their unique architectural strengths for effective classification. By implementing this proposed methodology with a focus on VGG19, EfficientNetB0, ResNet50 and CNN algorithms, an efficient and accurate system for detecting and classifying potato leaf diseases can be developed. This system can contribute to better crop management practices and increased potato yields.

3.9 Feature extraction

The feature extraction process is fundamental to the success of the potato leaf disease detection model. It begins with image preprocessing, including resizing, normalization, and data augmentation to increase variability in the dataset. Using convolutional neural networks (CNNs), key features are automatically extracted from the input images through multiple convolutional layers. These layers identify patterns such as edges, textures, and shapes that differentiate healthy leaves from diseased ones.

Transfer learning techniques were employed, leveraging pre-trained models like VGG19 and EfficientNetB0 to extract high-level features. The feature maps generated from these models provide a rich representation of the leaf images. Subsequently, these features are flattened and passed to fully connected layers for classification. The overall approach enhances the accuracy and robustness of disease detection, allowing the model to generalize well to unseen data. Finally, the extracted features are evaluated to determine their relevance in distinguishing between healthy and diseased potato leaves.

3.10 Model Architectures

Now, we use various CNN architectures, VGG19, ResNet50, and EfficientNetB0 over the above data and compute accuracy and their performance to find out the best neural network that can be used to predict the disease type of potato disease based on input image fed.

3.10.1 Convolution Neural Network (CNN)

CNN Architecture forms the backbone of this thesis on potato leaf disease detection, enabling automatic feature extraction and classification of images into healthy, early blight, or late blight categories. CNNs, or Convolutional Neural Networks, are a class of deep learning models specifically designed for image data, and they are highly effective at recognizing patterns and spatial hierarchies in visual data.

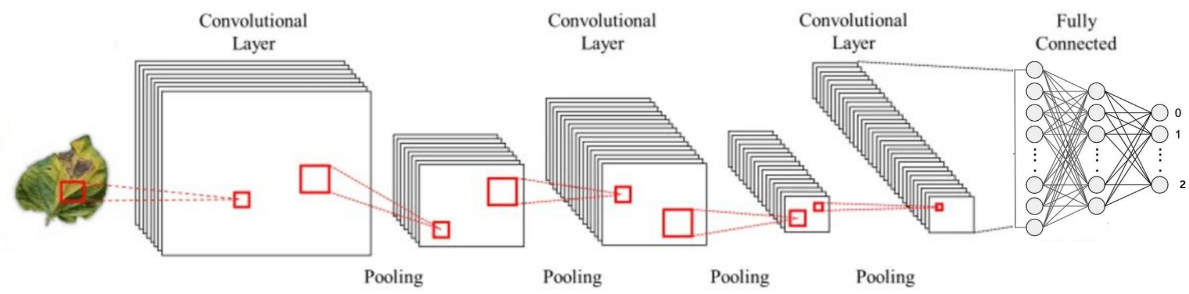


Figure-3.3: Pictorial Representation of Convolution Neural Network (CNN)

Components of CNN Architecture:

- **Input Layer:** The input layer takes raw pixel values of the potato leaf images, typically resized to a fixed dimension. Each pixel in the image is represented by its RGB (Red, Green, Blue) values, which serve as the input data for the model.

- **Convolutional Layers:** Convolutional layers are the core of CNNs. These layers apply a series of filters (or kernels) to the input image to extract different features. Each filter detects specific patterns like edges, textures, or shapes in the image. The filter slides over the image and generates feature maps, highlighting the presence of particular patterns such as spots or lesions, which are critical for distinguishing diseased from healthy leaves. Mathematically, the convolution operation multiplies the pixel values in the image by the filter values, producing feature maps that reveal crucial visual details.

- **Activation Function (ReLU):** After the convolution operation, the Rectified Linear Unit (ReLU) is typically applied to introduce non-linearity into the model. This allows the CNN to learn complex patterns and relationships within the image, ensuring the network can represent intricate features.

- **Pooling (Downsampling) Layers:** Pooling layers reduce the spatial dimensions of the feature maps, keeping only the most important information while discarding redundant data. This helps reduce computational complexity and prevents overfitting. The most common type is Max Pooling, which selects the maximum value from a defined region of the feature map, preserving the strongest activations.

- **Flattening:** After the last pooling layer, the 2D feature maps are "flattened" into a 1D vector, preparing the data for the fully connected layers. Flattening converts the spatial feature maps into a format suitable for classification.

- **Fully Connected Layers (Dense Layers):** The fully connected layers take the flattened feature vector and learn to classify the input image. Each node in these layers is connected to all activations from the previous layer, enabling the model to combine features and make predictions. The last fully connected layer uses a softmax or sigmoid activation function to output probabilities for each class (healthy, early blight, late blight).

- **Output Layer:** The final output layer provides a classification for the input image. For this thesis, the output could be a three-class classification corresponding to healthy, early blight, or late blight. The output is typically a softmax function that assigns a probability to each class, with the highest probability indicating the predicted class.

3.10.2 Transfer Learning

Transfer learning in the context of Convolutional Neural Networks (CNNs) is a technique that leverages pre-trained neural networks to solve new, related tasks. CNNs are widely used for image recognition, and transfer learning has proven to be a powerful approach to making the most of large, labeled datasets and deep neural networks. Here’s an overall description of transfer learning with CNNs:

(I) **Pre-trained Models:** Transfer learning begins with a pre-trained CNN model. These models are typically trained on massive datasets (e.g., ImageNet) to learn a broad range of features from images. Popular pre-trained models include VGG, ResNet, Inception, and MobileNet.

(II) **Feature Extraction:** The initial layers of a CNN learn to detect low-level features like edges, textures, and simple shapes. In transfer learning, you can use these pre trained layers as a feature extractor. By removing the fully connected layers, you retain the convolutional layers and their learned features.

(III) **Fine-tuning:** To adapt the pre-trained model to a new task, you add your own layers on top of the pre-trained layers. These new layers are typically fully connected layers that are specific to the new task. You can train these layers on your smaller, task-specific dataset, which is often less resource-intensive than training the entire model from scratch.

(IV) **Transfer of Knowledge:** The knowledge learned by the pre-trained model (low level features, textures, object shapes, etc.) is transferred to your new task. The lower layers of the network capture general, low-level features that are useful for various computer vision tasks. By fine-tuning the higher layers, you adapt the model to recognize specific features or patterns relevant to your task

Benefits of Transfer Learning:

• **Faster Training:** Transfer learning typically requires fewer iterations to converge compared to training from scratch because the model has already learned valuable features.

• **Improved Performance:** Leveraging a pre-trained model often results in higher accuracy on the target task, especially when you have limited data.

• **Reduced Data Requirements:** Transfer learning can work well with smaller datasets because it starts with a model that has learned general features.

(V) **Applications:** Transfer learning with CNNs is widely used in various computer vision applications, including object recognition, image classification, object detection, image segmentation, and more. It has also been applied to medical imaging, autonomous driving, and other domains.

(VI) **Model Selection:** The choice of a pre-trained model and the architecture of the new layers depends on the specifics of your problem. Some models might be better suited for certain tasks or have a trade-off between model size and performance.

In summary, transfer learning with CNNs is a valuable approach for leveraging pre trained models and adapting them to solve specific image-related tasks. It accelerates training, improves performance, and is widely used in practical applications where labeled data is limited or computational resources are constrained.

3.10.3 VGG19

VGG19 is a CNN based approach proposed by K.Simonyan and A.Zisserman [9]. It is widely recognized for its simplicity and effectiveness in image classification tasks. VGG19, a variation of the VGG family, is a deeper version with 19 layers that help extract more detailed and complex features from images. In this thesis, VGG19 is used to classify potato leaf diseases (healthy, early blight, and late blight), capitalizing on its deep architecture for accurate detection.

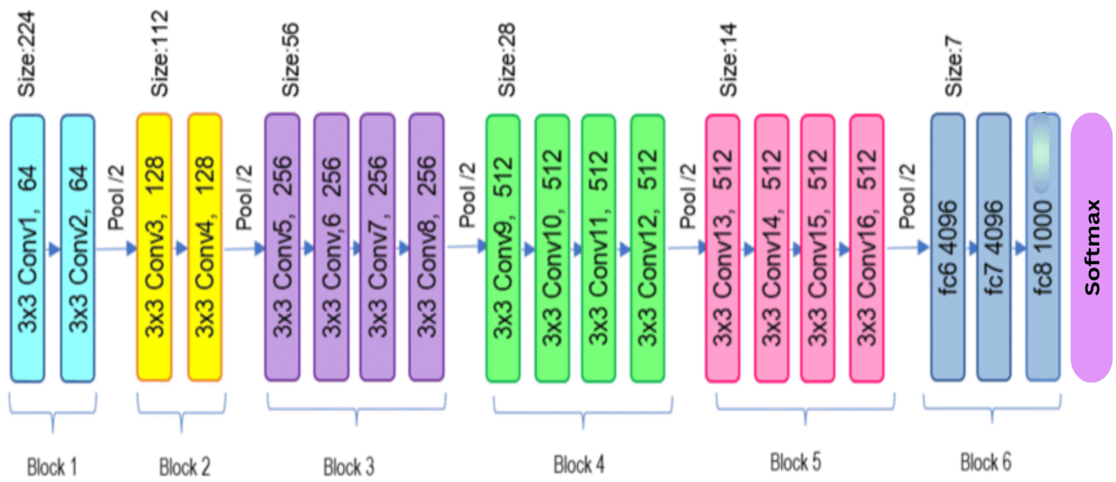


Figure-3.4: Pictorial Representation of VGG19 [From Google].

The VGG19 model consists of:

- 16 Convolutional Layers
- 3 Fully Connected Layers
- Max Pooling Layers
- Softmax Classifier

What sets VGG19 apart from earlier CNNs is its simplicity in design, using very small (3x3) convolution filters throughout the network and stacking them deeper.

Components of VGG19:

- **Input Layer**: The input to VGG19 is typically an image with dimensions 224x224x3 (RGB image). If used in potato leaf disease detection, the input images of diseased and healthy leaves are resized to this standard size before being fed into the network.

- **Convolutional Layers**: VGG19 has 16 convolutional layers grouped into blocks. Each convolutional layer applies a set of filters to the input image, detecting various patterns and features like edges, textures, and shapes. These filters are all 3x3, which is a key characteristic of VGG models.

  The convolutional layers are divided into five blocks, with each block containing two or more convolutional layers. Each convolutional layer in a block is followed by a non-linear ReLU (Rectified Linear Unit) activation function. ReLU introduces non-linearity into the model, allowing it to learn more complex features.

  The structure of the convolutional blocks is as follows:

  - **Block 1**: 2 convolutional layers (64 filters) + Max Pooling

- **Block 2**: 2 convolutional layers (128 filters) + Max Pooling
- **Block 3**: 4 convolutional layers (256 filters) + Max Pooling
- **Block 4**: 4 convolutional layers (512 filters) + Max Pooling
- **Block 5**: 4 convolutional layers (512 filters) + Max Pooling

Each convolutional layer applies 64, 128, 256, or 512 filters depending on the depth of the block. As the network progresses to deeper layers, the number of filters increases, allowing the model to capture more complex features.

- **Max Pooling Layers**: After each convolutional block, there is a Max Pooling layer with a 2x2 window and stride of 2. Pooling reduces the spatial dimensions of the feature maps, essentially "downsampling" the image data to reduce the computational complexity of the network. It keeps only the most prominent features, like key edges or disease spots in leaf images, while discarding less important information.

  Max Pooling helps control overfitting by reducing the number of parameters and computation in the network, all while retaining the most significant features.

- **Fully Connected Layers**: After the last pooling layer, the output is flattened into a 1D vector and passed through three fully connected layers**:**

  - **FC1**: 4096 neurons
  - **FC2**: 4096 neurons
  - **FC3 (Output Layer)**: The number of neurons here corresponds to the number of output classes, which in this thesis would be 3 (healthy, early blight, late blight).

  These fully connected layers are responsible for making final predictions based on the features extracted by the convolutional and pooling layers. The first two fully connected layers contain 4096 neurons each, and they apply the ReLU activation function to introduce non-linearity, while the third layer is the output layer with a softmax activation function for classification.

- **Softmax Output**: The softmax function is used in the final layer to normalize the output into probability distributions across the classes. For instance, if an image of a diseased potato leaf is inputted, the softmax function would assign a high probability to either early blight or late blight, while assigning a lower probability to the healthy class.

3.10.4 EfficientNetB0

EfficientNetB0 is a state-of-the-art deep learning model that is designed for image classification tasks. It is part of the EfficientNet family of models, which aim to achieve a balance between accuracy and efficiency by scaling neural networks in a more effective way. EfficientNetB0 is the baseline model, and it uses a unique scaling method that adjusts the network's depth (number of layers), width (number of neurons in each layer), and resolution (input image size) to create a more optimized architecture.

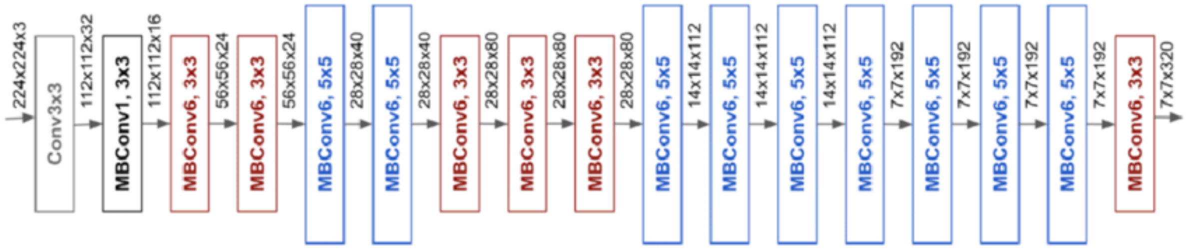


Figure-3.5: Pictorial Representation of EfficientNetB0 [From Google].

- **Input Layer**: The input size for EfficientNetB0 is typically 224x224 pixels. The input image is resized to this fixed size, and the pixel values are normalized. For potato leaf disease detection, the leaf images (healthy, early blight, and late blight) would be resized to this dimension before being fed into the model.

- **Stem (Initial Convolution)**: The first layer is a convolutional layer with 32 filters and a kernel size of 3x3, followed by a Swish activation. This layer acts as a feature extractor, capturing basic patterns like edges and colors from the input image.

- **MBConv Blocks**: The core of the EfficientNetB0 model consists of several Mobile Inverted Bottleneck Convolution (MBConv) blocks. Each MBConv block contains:
  - **Expansion Layer**: Expands the input features to a higher-dimensional space (using 1x1 convolutions).
  - **Depthwise Convolution**: A lightweight convolution applied separately on each input channel, which reduces the computational cost.
  - **Pointwise Convolution**: A 1x1 convolution that projects the expanded features back to a lower-dimensional space, producing the output of the block.
  - **SE (Squeeze-and-Excitation) Block**: These blocks are added to recalibrate the feature maps by weighting the importance of each channel, helping the model focus on the most important parts of the image.
  - **Stride** defines how much the input is downsampled, with a stride of 2 meaning that the spatial dimensions of the feature map are halved.

- **Squeeze-and-Excitation (SE) Layers**: The SE layers inside the MBConv blocks play a critical role in feature recalibration. They "squeeze" the global spatial information into a small representation, then "excite" the channels by reweighting them according to their importance. This enables the model to focus on disease-related features in the potato leaves, such as lesions, spots, and discolorations.

- **Global Average Pooling**: After passing through the MBConv blocks, the output feature map is reduced to a single value per feature channel through global average pooling. This reduces the feature map size without losing essential information, creating a more compact and computationally efficient representation.

- **Fully Connected Layer**: The pooled features are passed through a fully connected (dense) layer, which is responsible for final classification. In the case of potato leaf disease detection, this layer would output three probabilities corresponding to the three classes: healthy, early blight, and late blight.

- **Output Layer**: The output of EfficientNetB0 is a softmax layer that assigns probabilities to each of the classes (e.g., healthy, early blight, late blight). The class with the highest probability is the model's prediction for the input image.

3.10.5 Residual Networks (ResNet50)

ResNet50, or Residual Networks, is a 50-layer deep convolutional neural network (CNN) that has revolutionized image classification tasks by introducing residual learning. ResNet50 is part of the larger ResNet family, which is known for its ability to train deep networks by mitigating the vanishing gradient problem. It uses skip connections (also known as residual connections) to allow gradients to flow more easily through the network, making it possible to train very deep networks without degradation in performance. In this thesis, ResNet50 is applied to classify potato leaves as healthy or affected by early or late blight. Here's a detailed explanation of its architecture.

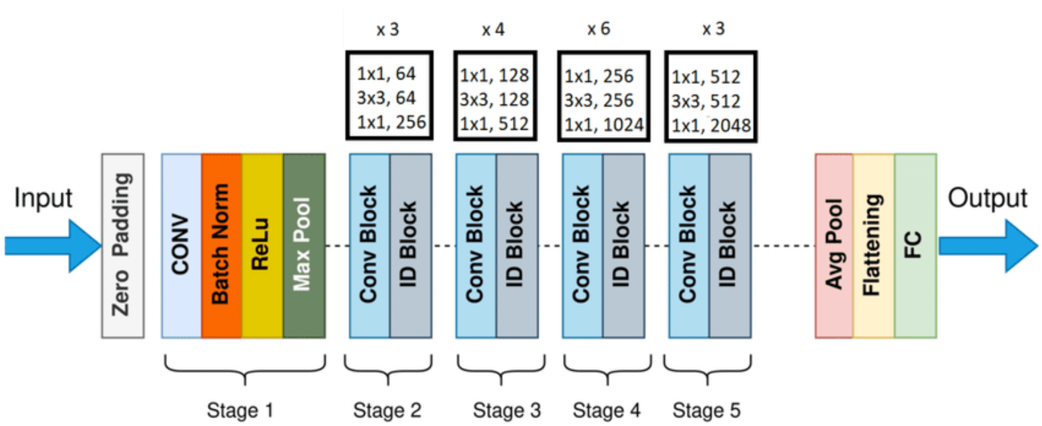


Figure-3.6: Pictorial Representation of ResNet50 [From Google].

a. Input Layer: The input to ResNet50 is typically a 224x224 RGB image (3 channels). The potato leaf images used for disease detection (healthy, early blight, late blight) are resized to this fixed dimension before feeding them into the model.

b. Initial Convolutional Layer:

- 7x7 convolution with 64 filters and a stride of 2. This layer is followed by batch normalization and ReLU activation**.**
- This layer extracts basic features like edges and textures.
- Output feature map size is reduced using a 3x3 max pooling layer with a stride of 2.

c. Residual Blocks (Conv2_x, Conv3_x, Conv4_x, Conv5_x): The main body of ResNet50 is composed of **four stages of residual blocks**, which are responsible for extracting increasingly complex features. Each stage has multiple blocks, and within each block, skip connections are used to pass the input directly to deeper layers.

The residual blocks contain both identity blocks and convolutional blocks:

- **Identity Block**: Contains layers where the input and output dimensions are the same, so the skip connection directly adds the input to the output.
- **Convolutional Block**: Used when the input and output dimensions differ (e.g., due to downsampling), the skip connection involves a 1x1 convolution to match the dimensions.

These blocks are stacked multiple times, and the number of filters increases as we move deeper into the network.

- **Stage 2 (Conv2_x)**: 3 residual blocks, each block includes 1x1, 3x3, and 1x1 convolutions with 64, 64, and 256 filters respectively.
- **Stage 3 (Conv3_x)**: 4 residual blocks, each block includes 1x1, 3x3, and 1x1 convolutions with 128, 128, and 512 filters respectively.
- **Stage 4 (Conv4_x)**: 6 residual blocks, each block includes 1x1, 3x3, and 1x1 convolutions with 256, 256, and 1024 filters respectively.
- **Stage 5 (Conv5_x)**: 3 residual blocks, each block includes 1x1, 3x3, and 1x1 convolutions with 512, 512, and 2048 filters respectively.

d. Batch Normalization and ReLU Activation:

- Each convolutional layer is followed by batch normalization, which normalizes the output to stabilize and accelerate training.
- ReLU activation is applied after each batch normalization step, adding non-linearity to the network.

e. Average Pooling:

- After the final stage of residual blocks (Conv5_x), the feature map is passed through global average pooling. This reduces the spatial dimensions (height and width) to 1x1, producing a compact representation of the image without losing important information.
- Global average pooling replaces fully connected layers in modern architectures, reducing overfitting by removing large numbers of parameters.

f. Fully Connected Layer:

- The output from the global average pooling layer is fed into a fully connected layer with a softmax activation function is used to map the learned features to the required number of output classes (early blight, late blight, healthy) for multi-class classification..

- The final output is passed through a softmax activation function to provide a probability distribution over the classes.

3.11 Performance metrics

Performance metrics are used to evaluate the accuracy and effectiveness of machine learning models. In this section, we describe several commonly used performance metrics.

3.11.1 Accuracy

In machine learning, accuracy refers to the degree to which a model can predict the correct outcome. This measure is determined by dividing the total number of correct predictions by the total number of predictions made by the model. The formula for accuracy is,

$$\text{accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{True Positives} + \text{False Positives} + \text{True Negatives} + \text{False Negatives}} \tag{3.1}$$

Where, True Positive are the correctly predicted positive cases True Negatives are the correctly predicted negative cases, False Positives are the incorrectly predicted positive cases, and False Negative are the incorrectly predicted negative cases.

3.11.2 Precision

Precision is a performance metric that evaluates the accuracy of positive predictions made by a model. In other words, it measures the proportion of true positives out of all predicted positives. To compute precision, we divide the number of true positive cases by the total number of positive predictions. A higher precision score indicates that the model is more precise and makes fewer false positive predictions. The formula for precision is:

$$\text{precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \tag{3.2}$$

3.11.3 Recall

Recall is a statistical measure that evaluates a model's ability to identify all relevant cases in a dataset. In other words, recall measures how well the model can "recall" or correctly identify all positive cases in a dataset. It is calculated by dividing the number of true positive cases by the total number of actual positive cases. A high recall score indicates that the model is effective at identifying positive cases, while a low score suggests that the model is missing many positive cases. The formula for recall is:

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \tag{3.3}$$

3.11.4 F1-Score

The F1-Score is a metric that determines the trade-off between precision and recall. It calculates the harmonic mean of precision and recall, with a range of values from 0 to 1. A higher F1-Score indicates a better balance between precision and recall, while a lower score indicates an imbalance between the two metrics. The formula for F1-Score is:

$$\text{F1} = 2\,.\,\frac{\text{precision}\,.\,\text{recall}}{\text{precision} + \text{recall}} \tag{3.4}$$

3.12 Experimental Setup

Python and its libraries are used for data collection, dataset construction, and model implementation and evaluation. The most popular and commonly used Python libraries for data manipulation were used in this work. The following is a list of the used libraries and what they are used for:

a) TensorFlow - used for building and training deep learning models due to its powerful tools and GPU acceleration.
b) Matplotlib - Data visualization.
c) NumPy - Data collection, dataset construction.
d) Scikit-learn - Model evaluation, dataset splitting.

The computations for the model training and evaluation are done on the jupyter notebook.

3.13 Summary

In brief, we have discussed several deep learning methodologies such as CNN, VGG19, EfficientNetB0 and ResNet50 along with the evaluation metrics accuracy, precision, recall, and F1-score. CNN is a general architecture for processing image data, VGG19 features a deep network with 19 layers for detailed feature extraction, EfficientNetB0 optimizes efficiency and accuracy with a scalable architecture, and ResNet50 uses residual connections to enable very deep networks without vanishing gradients. Evaluation metrics such as accuracy, precision, recall, and F1-score are important for measuring the performance of these models. Overall, deep learning provides effective algorithms for prediction modeling, and evaluation metrics help measure their performance.

Chapter 4

Result and Discussion

4.1 Introduction

In this section, we present the outcomes of our analysis and examine the implications of these discoveries for the creation of more precise and efficient leaf disease detection model. We also discuss the difficulties we faced during the analysis and the techniques we employed to overcome them. Our discoveries offer useful insights into the application of deep learning algorithms for leaf disease detection and may have significant consequences for the development of more effective strategies in the future.

4.2 Performance Analysis

This study assessed the effectiveness of various deep learning approaches for detecting leaf disease using datasets. Their average performance scores were calculated.
The performance of the four models sheds light on their respective advantages and limitations in identifying potato leaf diseases, as well as their ability to adapt to previously unencountered data. To gain a comprehensive understanding of each model's capabilities, it is crucial to evaluate their performance on both the training and validation datasets. The comparative analysis of these models illustrates their effectiveness in classifying potato leaf diseases and provides a deeper understanding of how successfully they can manage new data samples.

The dataset was split into 80% for training, 10% for validation, and 10% for testing.. We have used 50 epochs to allow the model sufficient time to learn and optimize its parameters.

4.2.1 CNN

The CNN model demonstrated a strong performance on the training dataset, with a loss of 0.0070 and an accuracy of 0.9971 at 45th epoch. However, its performance on the validation dataset, with a loss of 0.0219 and an accuracy of 1.0000 at 33th epoch.

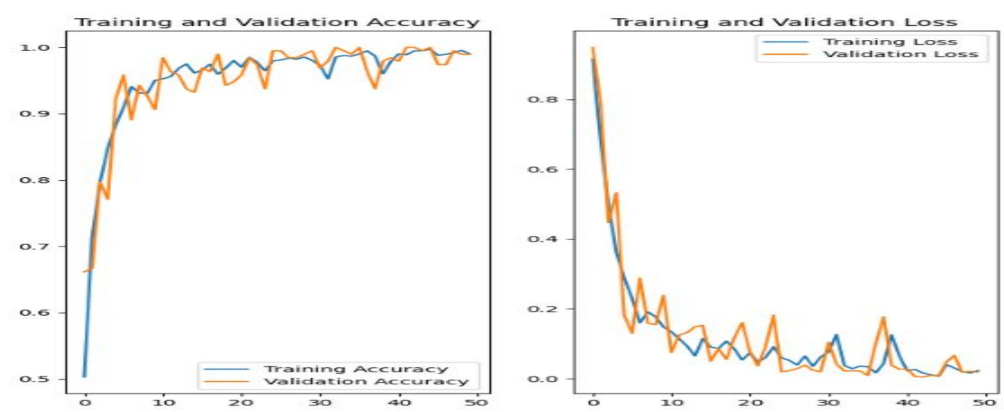


Figure 4.1 The Plot Diagram of Training and Validation Accuracy, Training and Validation Loss using CNN

The classification report shows the CNN performance in detecting Potato Early Blight, Potato Late Blight and Healthy Leaves with precision**,** recall**,** f1-score.

Category Name	Precision	Recall	F1-Score
Potato_Early_Blight(0)	0.56	0.56	0.56
Potato_Late_Blight (1)	0.65	0.66	0.65
Potato_Healthy (2)	0.41	0.39	0.40

Table 4.1 Evaluation Metrics of CNN

The CNN model achieved a test accuracy of 0.9961 in detecting and classifying potato leaf diseases.

4.2.2 VGG19

The VGG19 model demonstrated a strong performance on the training dataset, with a loss of 0.0476 and an accuracy of 0.9983 at 46^{th} epoch. However, its performance on the validation dataset, with a loss of 0.0012 and an accuracy of 1.0000 at 10^{th} epoch.

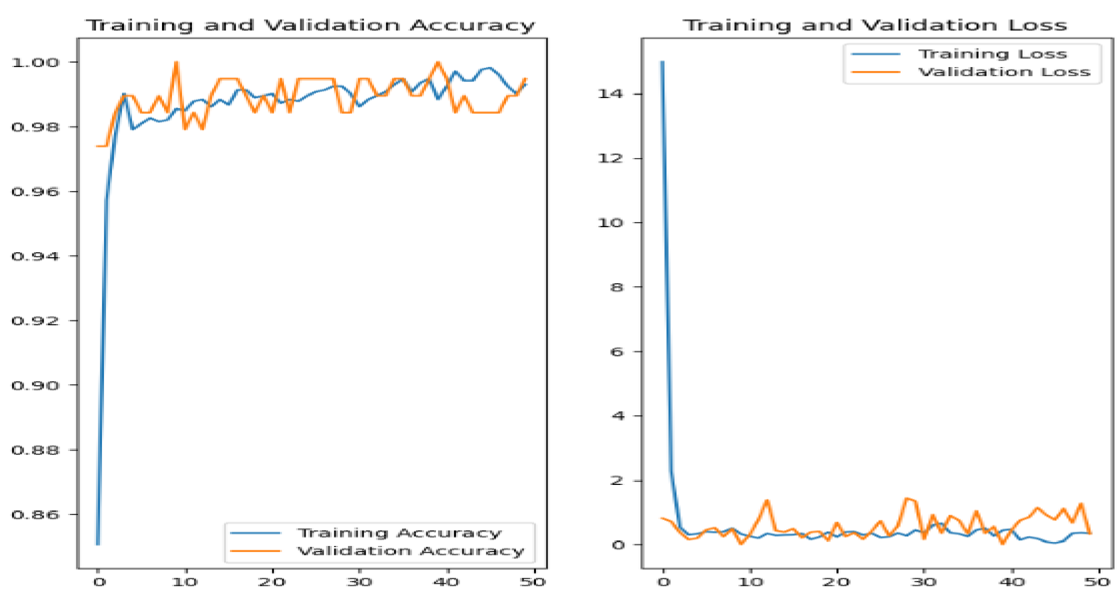


Figure 4.2 The Plot Diagram of Training and Validation Accuracy, Training and Validation Loss using VGG19

The classification report shows the VGG19 performance in detecting Potato Early Blight, Potato Late Blight and Healthy Leaves with precision, recall, f1-score.

Category Name	Precision	Recall	F1-Score
Potato_Early_Blight (0)	0.44	0.45	0.44
Potato_Late_Blight (1)	0.56	0.55	0.55
Potato_Healthy (2)	0.17	0.17	0.17

Table 4.2 Evaluation Metrics of VGG19

The VGG19 model achieved a test accuracy of 0.9922 in detecting and classifying potato leaf diseases.

4.2.3 EfficientNetB0

The EfficientNetB0 model demonstrated a strong performance on the training dataset, with a loss of 0.0013 and an accuracy of 1.00 at 48^{th} epoch. However, its performance on the validation dataset, with a loss of 0.0296 and an accuracy of 1.00 at 2^{th} epoch.

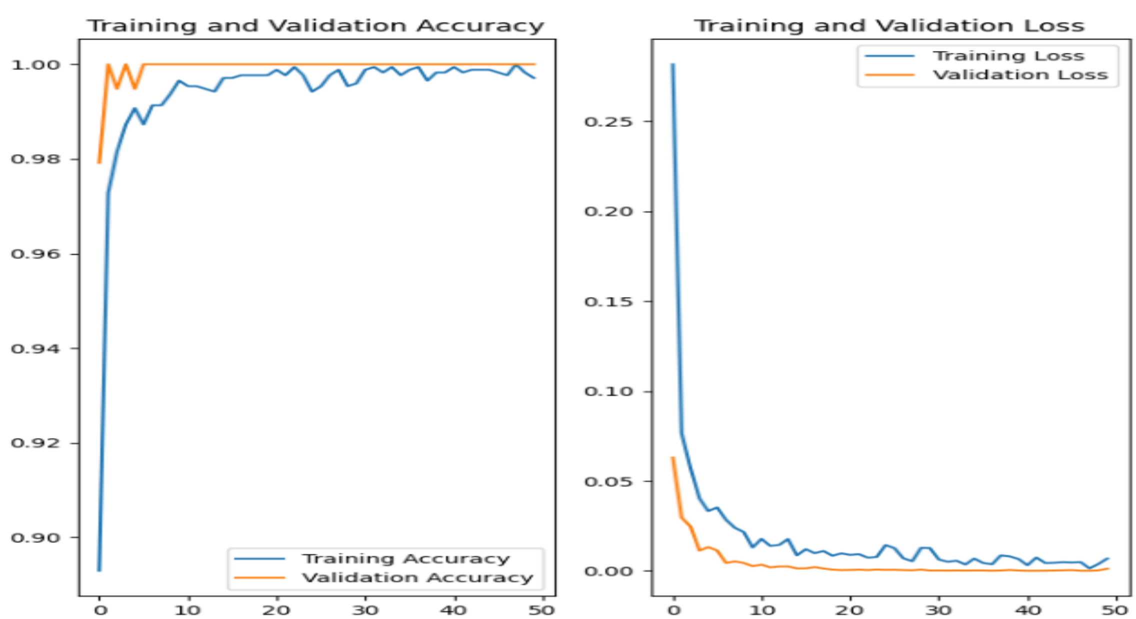


Figure 4.3 The Plot Diagram of Training and Validation Accuracy, Training and Validation Loss using EfficientNetB0

The classification report shows the EfficientNetB0 performance in detecting Potato Early Blight, Potato Late Blight and Healthy Leaves with precision, recall, f1-score.

Category Name	Precision	Recall	F1-Score
Potato_Early_Blight (0)	0.46	0.46	0.46
Potato_Late_Blight (1)	0.52	0.52	0.52
Potato_Healthy (2)	0.28	0.28	0.28

Table 4.3 Evaluation Metrics of EfficientNetB0

The EfficientNetB0 model achieved a test accuracy of 1.00 in detecting and classifying potato leaf diseases.

4.2.4 ResNet50

The ResNet50 model demonstrated a strong performance on the training dataset, with a loss of 0.0537 and an accuracy of 1.00 at 8^{th} epoch. However, its performance on the validation dataset was slightly lower, with a loss of 0.0008 and an accuracy of 0.9983 at 38^{th} epoch.

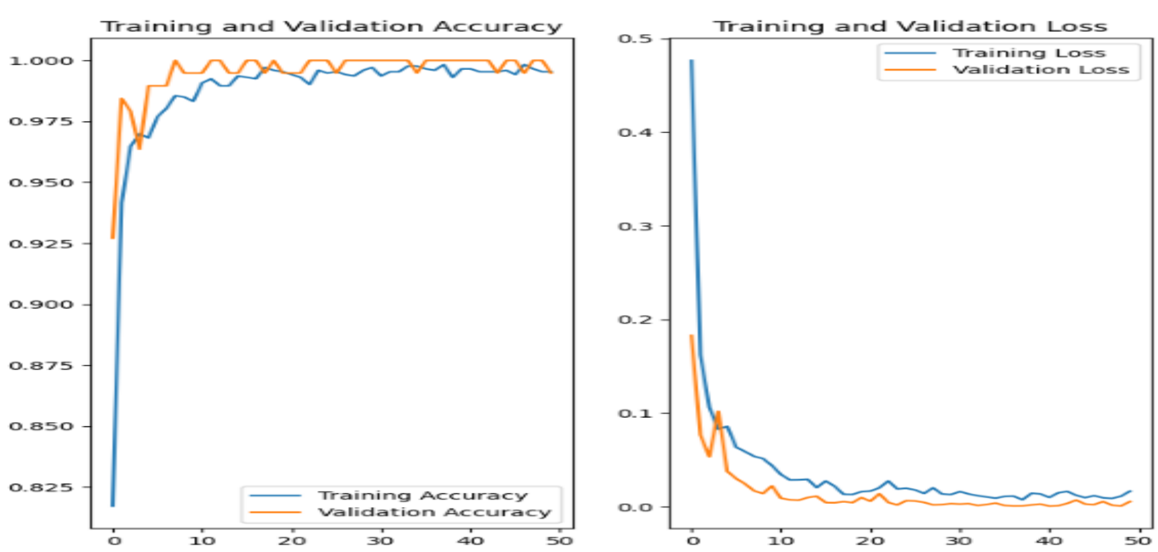


Figure 4.4 The Plot Diagram of Training and Validation Accuracy, Training and Validation Loss using ResNet50

The classification report shows the ResNet50 performance in detecting Potato Early Blight, Potato Late Blight and Healthy Leaves with precision, recall, f1-score.

Category Name	Precision	Recall	F1-Score
Potato_Early_Blight (0)	0.44	0.44	0.44
Potato_Late_Blight (1)	0.50	0.51	0.51
Potato_Healthy (2)	0.12	0.12	0.12

Table 4.4 Evaluation Metrics of ResNet50

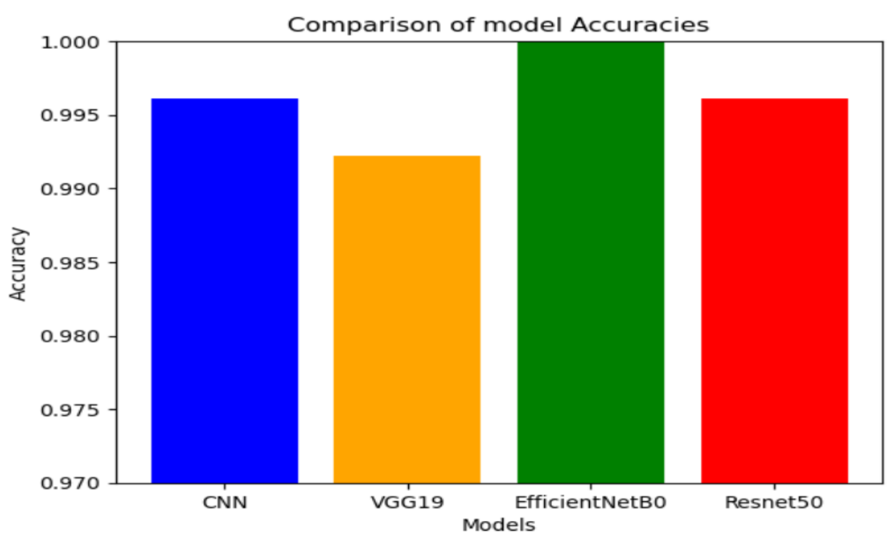
The ResNet50 model achieved a test accuracy of 0.9961 in detecting and classifying potato leaf diseases

4.3 Overall Result Analysis and Discussion

We summarize the performance result of the four deep learning models in term of accuracy.

Performance Metrics	CNN	VGG19	EfficientNetB0	ResNet50
Accuracy	0.9961	0.9922	1.0000	0.9961

Table 4.5 The results of each model in terms of accuracy



The performance metrics table provides a comparison of four models — CNN, VGG19, EfficientNetB0, and ResNet50 — for potato leaf disease detection. Among these models, EfficientNetB0 emerges as the best-performing model, achieving the highest scores accuracy 1.00. Other models like CNN accuracy are 0.9961,VGG19 0.9922 and Resnet50 0.9823.
Gunjan Chugh [6] working on the same dataset using CNN and getting 90% accuracy, they don’t balance the dataset. Rabbia Mahum [11] working on the same dataset using CNN, DenseNet and getting 97.2% accuracy using 40 epochs. We have got more accuracy. As we use data augmentation techniques, 50 epochs and more algorithms to acquire more accuracy.

Overall, EfficientNetB0 stands out as the most robust model, while CNN andVGG19 are similarly strong, and ResNet50, though slightly behind, remains a reliable option.

Chapter 5

Conclusion and Future Work

5.1 Conclusion

This thesis explored the application of advanced deep learning architectures — CNN, VGG19, EfficientNetB0, and ResNet50 — to classify potato leaf diseases, focusing on early blight, late blight, and healthy leaves. Among these models, EfficientNetB0 emerged as the best-performing, achieving the highest accuracy, making it the most reliable model for disease detection in this study. CNN and ResNet50 also performed well, showing nearly identical metrics but falling slightly short of EfficientNetB0. VGG19, while still effective, displayed the lowest performance metrics, indicating that it may not handle the specific complexities of this dataset as well as the other models.
A significant challenge in the study was the class imbalance, particularly the small number of healthy leaf samples, which impacted the model's ability to generalize well to this class. Although data augmentation helped mitigate this issue, increasing the number of healthy samples and using more sophisticated augmentation techniques would likely improve the model's performance. In future work, exploring additional architectures or hybrid models could further enhance accuracy and generalization. Overall, this research demonstrates that deep learning models, especially VGG19, are highly effective tools for automatic potato leaf disease detection, offering a promising solution for precision agriculture, early disease diagnosis, and improved crop management strategies.

5.2 Challenges Faced and Solutions

The study encountered several challenges such as model selection, feature extracting but we successfully tackled them by analyzing and optimizing deep learning algorithms, preprocessing image carefully, and utilizing computational resources efficiently. One of the challenges faced during this study was the imbalance in the dataset, particularly the limited number of healthy leaf images. Although data augmentation techniques were applied, a more balanced dataset could further improve model performance. By overcoming these challenges, the study has provided significant insights into the use of deep learning algorithms for leaf disease detection, which can potentially lead to the development of more accurate and efficient detection strategies in the future. Overall, we have demonstrated how we faced the challenges and showcased the potential of deep learning algorithms in detecting diseases, paving the way for further research in this area.

5.3 Future work

There are several avenues for future work that could enhance the results and extend the findings of this thesis. First, addressing the class imbalance by increasing the dataset size, especially for the healthy leaf class, would likely improve model performance. Collecting more diverse data under various environmental conditions or generating synthetic data using techniques like GANs

(Generative Adversarial Networks) could help in achieving a more balanced dataset and better generalization across different conditions.

Another promising direction is to explore hybrid models that combine the strengths of different architectures. For instance, integrating features from VGG19 with EfficientNetB0 could potentially yield a model that balances accuracy with computational efficiency. Transfer learning can also be explored further, particularly leveraging pre-trained models on larger, more general datasets to improve the performance of potato disease classification with smaller datasets.

Finally, exploring more lightweight models suitable for edge computing or mobile platforms would make real-time, in-field disease detection more practical. This would allow the deployment of models on low-power devices, enhancing accessibility and scalability of these solutions for use in remote agricultural areas.

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