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Enhanced Potato Leaf Disease Detection Using Deep Learning

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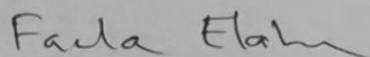
Bachelor of Science

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APPROVAL

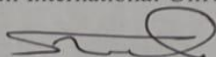
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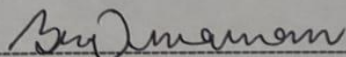
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STUDENT'S DECLARATION

I hereby declare that the work in this thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at Daffodil International University or any other institution.

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ABSTRACT

Potato crops are essential to global food security but are highly susceptible to leaf diseases such as early blight or late blight, which negatively impact yield and quality. Conventional detection approaches are time-consuming and error-prone. The paper proposes a deep learning-based framework that employs Convolutional Neural Networks (CNNs) along with complementary image processing methods to accurately identify and classify potato leaf diseases. with feature extraction based on color, texture, and morphological characteristics and hyperparameter optimization using a comprehensive dataset, the model yields above 99.99% classification accuracy with considerable precision and recall. This approach facilitates early disease detection, appropriate intervention, and minimizes crop losses, leading to sustainable agriculture and improved food security worldwide.

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CHAPTER 1

INTRODUCTION

1.1 Background

Potatoes, a major source of carbohydrates, vitamins, and minerals in the human diet, are an important global food source. Unfortunately, potato production is threatened by diseases such as early blight and late blight which severely affects yield and quality. Methods to detect diseases are traditional, such as physical inspections and laboratory tests that are labor-intensive, slow and depend on human expertise, which can vary in accuracy. These constraints are especially problematic in the context of large-scale farming operations, where timely and accurate detection is essential to mitigate disease dissemination and prevent damage.

Artificial intelligence (AI) and deep learning recent advances, specifically Convolutional Neural Networks (CNNs), have opened new avenues for accurate and automated disease detection. Based on features in images of potato leaves that are undetectable to the naked eye, such as gradients, color shifts, and textures, these technologies can diagnose diseases accurately and quickly. By equipping the systems with portable tools like drones and smartphones, access is extended to remote areas, minimising reliance on human experts and increasing the efficiency of the farming process. By harnessing the potential of this AI-assisted disease detection in agriculture, we are able to increase productivity, boost profitability, ensure food security, create jobs and help preserve the environment.

1.2 Motivation of the Research

The global food demand on the rise, insert need for increased crop yields justifies the research. Potatoes are a staple crop that millions of people depend on and also play a role in economic stability, yet they are susceptible to diseases, most notably early blight and late blight, that can severely limit productivity. Different methods for disease detection, including visual inspections and laboratory tests, are time- consuming, labor-intensive, and unavailable to many small-scale farmers, especially in developing regions

These difficulties are magnified by overreliance on agrochemicals, which raise costs, hurt the environment and breed resistant pathogens. All of these led to the need for sustainable, efficient, and scalable potato disease detection methodology and hence, the interest in this research. By identifying diseases early and accurately, targeted interventions can be implemented, mitigating crop losses and promoting less dependence on agrochemicals. The study employs deep learning a subset of artificial intelligence to construct a high-accuracy detection system based on image

recognition and classification for the automatic detection of potato leaf diseases.

We are on mission to provide affordable, user-friendly tools to move farmers, especially smallholders, towards high-technology farming. This research aims to bridge critical gaps in agricultural technology by combining state-of-the-art machine learning with relevant practical applications. This leads to better management of the disease, lesser environmental impact, and greater resilience of agroecosystems, thus leading to sustainable agriculture and food security worldwide in the ever-increasing challenges.

Potato is a crop important for global food security, but they are susceptible to many disease that can effect yield quality severely. Keeping track of potato diseases using traditional approaches such as manual inspections and conventional diagnostics is not only labour-intensive but also subject to a lag that often leads to severe crop loss. Although deep learning has shown potential in disease detection automation and improvement, current approaches suffer from key shortcomings. Most of the models are either not accurate enough for practical applications or use high computational architectures which cannot be made real-time feasible

To address these gaps, this research work has developed a novel, fast and accurate deep learning-based model suitable for real-time potato disease detection. Thus by Exploiting the model design and applying the advanced methods, the study attempts to offer a practical instrument for farmers to forecast disease outbreaks even in real time to minimize losses and improve sustenance in agriculture.

1.3 Problem Statement

Potato is a crop important for global food security, but they are susceptible to many disease that can effect yield quality severely. Keeping track of potato diseases using traditional approaches such as manual inspections and conventional diagnostics is not only labour-intensive but also subject to a lag that often leads to severe crop loss. Although deep learning has shown potential in disease detection automation and improvement, current approaches suffer from key shortcomings. Most of the models are either not accurate enough for practical applications or use high computational architectures which cannot be made real-time feasible (mostly in low resource settings).

To address these gaps, this research work has developed a novel, fast and accurate deep learning-based model suitable for real-time potato disease detection. Thus by Exploiting the model design and applying the advanced methods, the study attempts to offer a practical instrument for farmers to forecast disease outbreaks even in real time to minimize losses and improve sustenance in agriculture.

1.4 Research Question

What are the key features and patterns in potato leaf images that can be leveraged by deep learning algorithms to accurately distinguish between healthy and diseased leaves?

1.5 Research Objective

- **Real-Time Disease Detection:** Proposes a detection framework that operates on potato diseases under real field conditions with improved accuracy and timeliness.
- **Lightweight and Efficient Models:** Reduces computation costs with compact CNN architectures, facilitating usage on low-resource devices such as smartphones and drones.
- **Accuracy for binary classification:** Thus, target at identifying normal and abnormal potato leaves with lower false positive and false negative rates.
- **Adaptability into Real-World Conditions:** Challenges the model to be robust to changing environmental factors (light changes, leaf orientation, different background, etc.).
- **Scalable and Accessible:** Catalyzes the model is affordable, easy to use, and easily scalable for widespread use in agriculture settings.
- **Sustainability:** Enables timely action to reduce loss of crop as well as overuse of agrochemical, thus promoting sustainable farming.

This paper therefore aims to find a high performance lightweight deep learning method for potato disease diagnosis including early and late blight, based on compact CNN models. The principal objective is to construct a model that can effectively classify the leaves into healthy and diseased types, while avoiding false positives and false negatives. Optimized to run on low-power devices such as smartphones and drones, the model is resistant to variations in environmental factors such as lighting and background. Evaluation metrics

consist of accuracy, precision, recall, F1-score and processing time. Farming technologies must be scalable and affordable, and farm success conditions must be easy to measure, to allow timely actions and promote sustainable agriculture.

1.6 Research Scope

The main goal of this work is to create a deep learning framework with high efficiency and accuracy to assist in potato diseases detection, which can be applied in real-world agricultural environments. The specific objectives are to develop lightweight deep learning models such as Convolutional Neural Networks (CNNs) for the accurate detection of diseases such as early blight and late blight while maintaining low computational complexity for implementation on low-resource devices such as smartphones and drones. It efforts at developing a binary classification model where potato leaves are classified as either healthy or diseased based on the color texture and morphological a such as texture etc. The model aims to be accurate while remaining computationally-efficient, with as few false positives and negatives as possible.

The other goal was to assess the model performance in practice and to evaluate its robustness un By implementing Convolutional Neural Networks (CNNs), the proposed work aims to develop a deep learning model for diagnosing healthy and diseased leaves using comprehensive labelled datasets of images taken under different field conditions. Various data augmentation as well as preprocessing strategies are employed in order to improve the generalizability and robustness of the model. Concerned with optimizing the model through hyperparameter tuning, the research focuses on achieving both high accuracy, precision, and recall while keeping it computationally efficient. Essentially, we are working on deploying the system on inexpensive platforms such as smartphones, drones, and edge computing devices, for real-time disease detection or low-resource regions.

As a scalable solution, it is incorporated into precision agriculture systems for specific interventions and sustainable farming practices without excessive dependency on manual inspection and agrochemicals. This study also provide the basis for future improvements - for example models that allow multiclass classification in order to predict several diseases and for each of them the severity level. The research seeks to enhance crop productivity, advocate for sustainable agriculture, and support global food security initiatives through the integration of sophisticated technology with agricultural best practices. ling environmental conditions, including lighting, orientation of leaves and compounds, and complexity of background. Evaluation: Accuracy, precision, recall, F1-score, processing time, and other performance metrics The study also highlights scalability, cost-effectiveness, and user-friendliness, ensuring the solution aids in timely interventions and sustainable agricultural practices

1.7 Solution Requirement

The solution requirements for enhanced potato leaf disease detection using deep learning involve several key components to ensure the system's effectiveness, scalability, and practical application in agricultural settings. First, the solution must leverage a robust and efficient Convolutional Neural Network (CNN) model capable of achieving high accuracy in identifying and classifying potato leaf diseases, such as early blight and late blight. The model should be trained on a comprehensive and diverse dataset containing labeled images of healthy and diseased leaves, ensuring generalizability across various environmental conditions, such as different lighting, backgrounds, and disease severities. To meet real-time applicability requirements, the solution should prioritize computational efficiency, enabling deployment on resource-constrained devices such as smartphones, drones, or edge computing platforms. This necessitates lightweight model architectures optimized through hyperparameter tuning to balance performance and speed. The system should also support real-time image processing and provide rapid, actionable feedback to farmers and agriculturalists, allowing timely interventions to minimize crop losses.

In addition to technical performance, the solution must be user-friendly and accessible, with a straightforward interface that facilitates easy image capture, processing, and interpretation of results. Integration with precision agriculture tools, such as GPS mapping or IoT devices, would further enhance its utility, enabling targeted disease management and optimized resource allocation. The solution should also include scalability features to adapt to larger datasets and extended functionalities, such as multiclass disease classification or severity estimation, in future iterations. Lastly, the solution must address challenges related to deployment in rural or remote farming areas, including offline functionality and compatibility with low-cost hardware. Ensuring affordability and accessibility for smallholder farmers is crucial for widespread adoption and impact. Overall, the solution must combine technological sophistication with practicality to empower farmers, promote sustainable farming practices, and enhance global food security.

1.8 Summary

Enhanced potato leaf disease detection using deep learning focuses on leveraging advanced Convolutional Neural Networks (CNNs) to address the critical challenge of timely and accurate disease identification in potato crops. This solution aims to replace traditional, labor-intensive methods with a scalable, efficient, and user-friendly approach. By training the model on a diverse dataset of labeled images of healthy and diseased potato leaves, the system achieves high accuracy in identifying diseases such as early blight and late blight.

Optimized for computational efficiency, the model is designed for real-time deployment on resource-constrained devices like smartphones and drones, making it accessible to farmers even in remote areas. The system also integrates seamlessly with precision agriculture tools, enabling targeted disease management, reducing the overuse of agrochemicals, and promoting sustainable farming practices. By empowering farmers with actionable insights, this approach minimizes crop losses, enhances productivity, and contributes to global food security. Additionally, the solution is adaptable for future expansions, including multiclass disease classification and severity assessments, ensuring its relevance in evolving agricultural landscapes.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Potatoes are one of the most widely grown staple crops and are crucial to global food security, but their yield and quality are highly affected by diseases such as early blight and late blight. Conventional detection methods are labor intensive, time consuming and highly inaccurate in large scale farming. These limitations frequently result in a runaway spread of disease and economic losses. The advent of artificial intelligence (especially deep learning and Convolutional Neural Networks (CNNs)) has brought about a transformation in plant disease detection.

CNNs work by analyzing critical visual features for example color, texture and morphology to automate classification of plant health in an accurate and efficient way. There are scalable, real-time solutions, deployable in all available devices like smartphones and drones to overcome the limitations of the previous techniques. This literature review provides an overview of the current research on the use of deep learning for the detection of potato leaf disease and outlines the approaches used, strengths and weaknesses of the research conducted, and identifies opportunities for further investigation. It provides the potential of the use of DL models in agricultural systems to help improve control of diseases and sustainable farming practices, opening the doors to better detection solutions.

2.2 Previous Literature

The adoption of deep learning techniques has transformed the detection and management of potato leaf diseases such as early blight and late blight which pose significant threats to potato crop production. Traditional methods, dependent on manual inspections and laboratory testing, are inefficient for large-scale applications, paving the way for automated, AI-driven solutions that enhance accuracy, efficiency, and scalability. Convolutional Neural Networks (CNNs) have proven exceptionally effective in detecting and classifying potato leaf diseases. Advanced models like YOLOv5 combined with CNN have achieved remarkable accuracy rates, such as 99.75% on the Plant Village dataset, highlighting the impact of integrating segmentation and classification for precise disease detection.

Additionally, architectures such as InceptionV3 and Faster R-CNN with Google Net have demonstrated robustness in handling diverse environmental conditions and object detection tasks. Dense Net and MobileNet-V2 have emerged as reliable architectures for disease detection, offering high accuracy (up to 100% in certain cases) and

computational efficiency. MobileNet-V2, optimized for lightweight applications, achieved 97.73% accuracy, making it particularly suitable for mobile and edge deployment. Traditional methods like Support Vector Machines (SVMs) and Artificial Neural Networks (ANNs) have also shown strong performance, with SVM achieving 97.4% accuracy and techniques like Local Binary Patterns (LBP) further enhancing classification and segmentation tasks. Spectral imaging using red and red-edge spectral data has also proven valuable in disease detection.

Algorithms like SVM have utilized these data to achieve 89.33% accuracy in distinguishing between healthy and diseased plants. When combined with deep learning models, spectral techniques enhance disease progression monitoring at both the leaf and canopy levels. Beyond detection, innovative management strategies such as RNA interference (RNAi) and nanotechnology offer sustainable alternatives. Techniques like spray-induced gene silencing (SIGS) and multicomponent nano-bioprotectants effectively target pathogens like *Phytophthora* infesting, reducing reliance on environmentally harmful fungicides.

Despite significant progress, challenges remain in scaling deep learning models for real-world applications. Issues such as dataset diversity, lightweight architecture requirements, and the need for models to handle variable environmental conditions and overlapping symptoms highlight areas for further research. The integration of advanced deep learning models and innovative management approaches marks a significant leap in potato leaf disease detection and control. Future efforts should focus on enhancing model robustness, real-time applicability, and environmental sustainability to address current limitations and ensure broader adoption in agricultural practices.

2.3 Summary

Providing an overview, deep insight, and extensive epidemiological relations about microbial diseases of potato, potato leaf diseases, specifically early blight and late blight, act as a major threat to potato production in the world. Conventional detection methods, based on manual inspections and lab tests, are time-consuming and impractical for large scale applications. State-of-the-art results in this domain have been achieved via deep learning techniques, particularly using CNNs, such as YOLOv5, InceptionV3 and Dense Net, reaching accuracy of up to 99.75%. Real-time detection on resource-constrained devices is achieved through lightweight models such as MobileNet-V2, etc.

There are methods of feature extraction such as Local Binary Patterns (LBP) and Support Vector Machines (SVM) in order to improve disease classification, accuracy is very high as achieved above 97%. Moreover, spectral and remote sensing methods that are dependent on spectral data of red and red-edge regions, assist deep learning with

the monitoring of diseases at leaf and canopy scales. RNA interference (RNAi) and nanotechnology are sustainable management options that are considered environmentally-friendly alternatives to chemical fungicides. Nevertheless, there is still more work to be done in demonstrating scalability, dataset diversity, and real-world applicability. This can be achieved through future work aimed at making the models more robust, functional in real time, and adaptable to changing environments for the optimal detection and management of potato leaf diseases.

CHAPTER 3

METHODOLOGIES

3.1 Introduction

A strong binary classification model to detect potato leaf diseases is developed using Convolutional Neural Networks (CNNs) in this study. The model is able to separate leaves as either healthy or diseased, while achieving high accuracy and real-time application. Convolutional neural networks (CNNs) are taken advantage of because they are capable of automatically extracting meaningful features (i.e. color, texture, and morphological patterns) for the successful identification of disease symptoms. The approach is a systematic pipeline of the form of data acquisition and pre-processing (resizing, normalization, augmentation) for dataset quality and diversity. MobileNet-V2 is a lightweight CNN architecture optimized for device compatibility of resource-constrained devices.

To improve performance and reduce overfitting, hyperparameter tuning, feature extraction, dropout and regularization techniques are used. We use the Adam optimizer to speed up model converge. Performance Evaluation Metrics: Metrics such as accuracy, precision, recall, F1-score, and confusion matrices gauge the effectiveness of the model. Generic strategies for updating robust models to run in real-time (like model compression and quantization) could be used to make sure they are practical if deployed in the field. Through the combination of convolutional neural networks (CNNs) with novel preprocessing and optimization strategies, this research seeks to present a scalable, efficient, and accurate approach to tentatively classify potato leaf diseases across various agricultural environments.

3.2 System Architecture

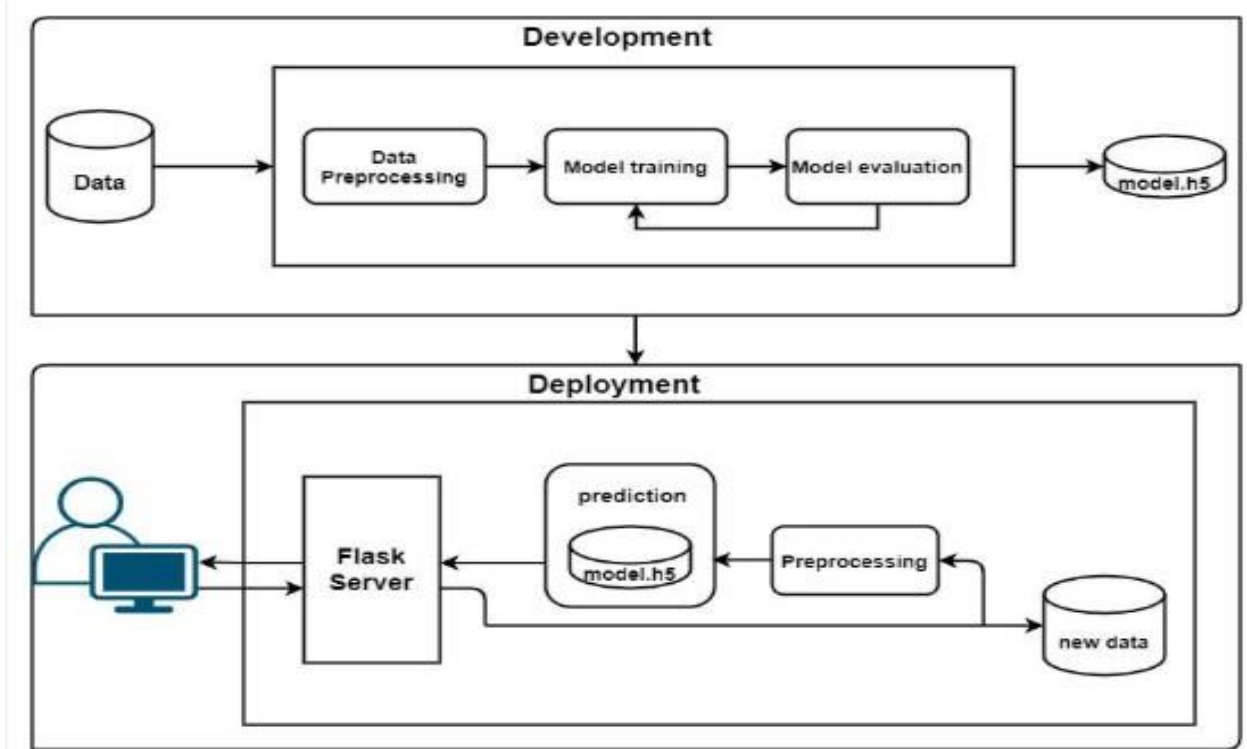


Figure 3.2: System Architecture

To achieve high accuracy, efficiency and scalability, potato leaf disease can be detecting using deep learning techniques. It starts with a data acquisition module, taking potato leaf images from the field photographs as well as public datasets. Images are preprocessed, standardized, resized, normalized, and augmented with techniques such as rotation or scaling to handle the class imbalance so that the model generalizes better. The system is, in essence, a modified state of the art Body tracking approach based on nicely aggregates a few different pre trained Convolutional neural networks, like ResNet or VGG16 or Efficient Net, and uses transfer learning to adapted to the task. This exploits hierarchical feature representations by freezing up generic feature extraction layers and only fine- tuning the subsequent deeper layers.

The hyperparameter tuning approaches such as Genetic Algorithm (GA) or Particle Swarm Optimization (PSO) also contributed to further optimizing performance. The features extracted are classified with the help of fully connected layers, which provide an output signal using a SoftMax activation function to detect whether the leaves are healthy or infected with diseases like early or late blight. It also encompasses a visualization module based on Grad-weighted Class Activation Mapping (Grad-CAM) which allows one to interpret the predictions by highlighting which areas were affected. Then, the model is optimized through pruning and quantization for deployment, support real-time on cloud platform or edge devices such as smartphones and Raspberry Pi. Through an intuitive interface, users can upload images and get quick diagnostic information. This architecture offers a combination of high prediction accuracy, interpretability, and real-time deploy ability, enabling the provision of actionable insights to farmers for minimizing crop losses and maximizing productivity.

3.3 Process of Creating Model

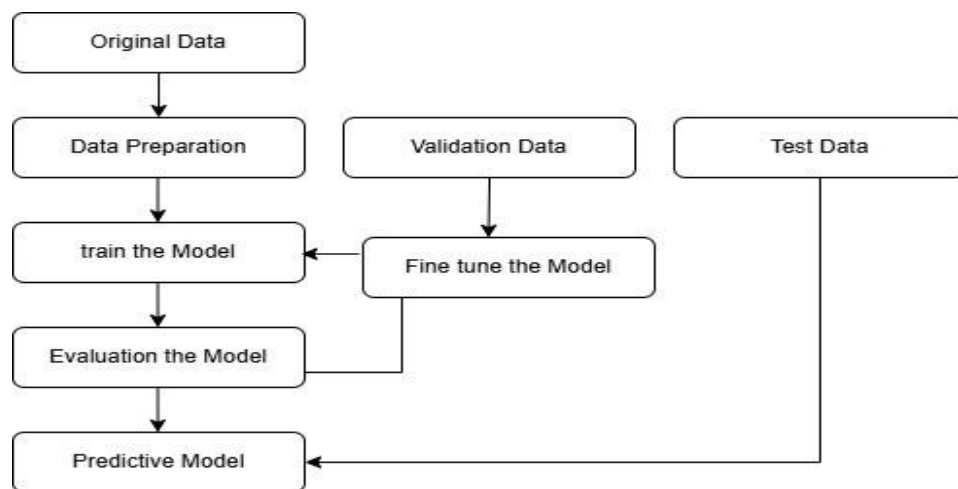


Figure:3.3 Process of Creating Model

Step one is recording images of healthy and diseased potato leaves that can be from field studies or can be found in public datasets (like Kaggle). The data is then preprocessed through resizing normalization, and augmentation for the features to be standardized and generalized. Next, the dataset is divided into 3 equal parts for training, validation, and testing. The model is trained using a Convolutional Neural Network (CNN) architecture, and performance is periodically checked on the validation set to fine-tune hyperparameters such as learning rate,

dropout and optimizer settings in order to avoid overfitting and maximize accuracy. You repeat this process until you have achieved the best performance. It is then validated on the test set, to ensure that the model is robust and generalizes well. After validating the trained model, it is used for the real-time detection of potato leaf diseases, enabling timely corrective actions and optimized crop management.

3.4 Dataset Collection

A variety dataset is utilized to improve the efficiency of the potato leaf disease detection deep learning model, which includes images from online sources such as Plant Village dataset and a high-resolution fields dataset taken under different lighting conditions, angles, and stages of disease. The dataset is also enhanced by collaboration with agricultural research institutions and farms. The structure is to annotate each image with labels, e.g. Healthy, Early Blight or Late Blight, using tools like Labeling or Rob flow.

Data augments such as rotation, flipping, cropping, and color adjustments are used to enhance the dataset in order to reduce overfitting and increase the accuracy of the model. It contains JPEG images, one for each image, a data cleaning step for removing bad images and duplicates, which often occurs in image datasets, and a class balance step, which involves oversampling or under sampling when classes are unbalanced. Structured data is just data that is organized in some way and saved with some metadata, commonly a CSV or JSON file, such that it can be easily integrated into the model development pipeline. Such a Tomato leaf disease and its identification will be beneficial for farmers to invest less time in the field until their crops achieve the final yield.

3.5 Dataset Split

To ensure the model is trained and evaluated effectively, the dataset is divided into three parts:

- Training Set: This constitutes the largest section of the dataset — 70-80% of the total. The AI model learns from this data.
- Validation Set: This subset constitutes approximately 10-15% of the entire dataset. It is utilized in the training phase to optimize model parameters and mitigate overfitting. The model is then tested against this set, and its performance here helps judge how well it generalizes to unseen data.

- Testing Set: The remaining 10 – 15% of the dataset belongs to this set. Utilizes only once the training process is done, to check how close the model is to the ground truth. This allows evaluating the model on completely new data with minimization of bias.

By splitting the dataset this way, the model can be trained effectively while maintaining a robust evaluation process to measure its accuracy and generalization ability.

3.6 Model Architecture

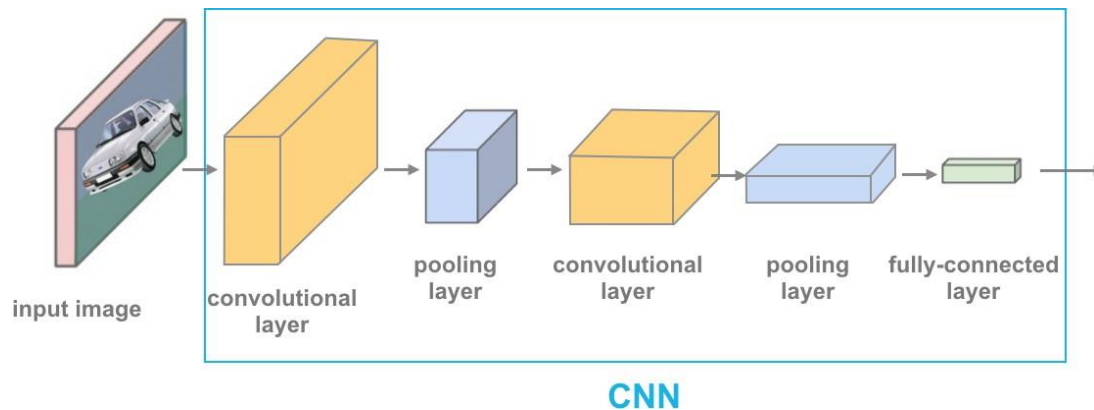


Figure: 3.6 Model Architecture

Architecture of a CNN based model for image classification This is a short description of the model architecture:

- Input Image: In this lesson, you will learn how the architecture works starting with input image, here a car, that needs to be processed by the network.
- Convolutional Layer: When an image is passed through the first layer, convolutional filters are applied to extract low level features like edges, lines and textures from the image. This process generates a feature map that encodes salient features of the image.
- Pooling Layer: The pooling layer is used to down sample the feature map, retaining important features, while reducing dimensionality and helping to prevent overfitting.
- Convolution and Pooling Layers: In the subsequent convolutional and pooling layers, reinforcing and processing the features leads to the recognition of high-level patterns, such as shapes and objects, through stacking multiple layers.

- Fully Connected Layer: The last part is the fully connected layer, which connects all the features raised by prior layers and projects them for the output classes.
- Output Layer: Through the feature extraction process, the model passes through layers that extract features until eventually a final layer predicts the image class, in this case "car," using a classification algorithm like SoftMax or sigmoid.

The CNN architecture used in this example predicts the class of an input image by passing it through a series of convolutional and pooling layers, then a few fully connected layers. This is a typical image classification pipeline that keeps the balance between feature extraction and computational performance.

3.7 Model Details

DenseNet121 A Deep Convolutional Neural Network (CNN) architecture for efficient feature extraction and improved performance. It utilizes dense connectivity, in which each layer connects to every previous layer, which allows for feature reuse and alleviates the number of required trainable parameters. DenseNet121 is constructed by 121 layers grouped into Dense blocks and transition layers, which allows the model to learn complex features while being computationally efficient. The architecture utilizes an adjustable growth rate parameter that determines the number of feature maps that are added at each layer for both lower model complexity without sacrificing accuracy. The fully connected layer is preceded with Global Average Pooling (GAP), which minimizes the trainable parameters, enhances generalization.

It uses Reule activation functions, SoftMax and sigmoid activations in the output layer for multi-class and binary classification problems, respectively. Decoupled Design - this helps utilize fewer parameters at a time which makes the model lighter weight; perfect for one-time use in resource-constrained environments like phones or drones. Using deep learning models, such as DenseNet121, is more ideal for those tasks, and potato leaf disease detection specifically, since they manage to extract fine-grained features, like texture, edges, or discolorations, ensuring high accuracy and scalability.

3.8 Summary

For this model, we used DenseNet121, which is a deep-learning architecture for classification and is known for its feature extraction capability as well as need of fewer parameters. It uses a dense connectivity, with each layer connected to all layers that come after it, which can help with feature reuse and efficiency of computation. The architecture, consisting of 121 layers arranged in dense blocks and transition layers, allows it to learn highly complex patterns efficiently.

Global Average Pooling (GAP) enhances generalization by minimizing trainable parameters, and ReLU activation combined with softmax or sigmoid-based outputs enable multi-class or binary classification, respectively. Although the DenseNet121 architecture is relatively lightweight in terms of its complexity, it is better suited for resource-constrained environments, and outperforms in each task, including potato leaf disease detection, by being able to extract more visual features like texture, edge, and discoloration pattern, resulting in both high accuracy and scalability.

CHAPTER 4

RESULT

4.1 Result

The logs for a model of deep learning show 50 epochs (hence the name) at the end of which there is a summary of metrics such as accuracy, loss, validation accuracy and validation loss as seen in the images. Early Epochs (1–7): Model improves with training accuracy going from 55.7% to 76.1% and loss coming down. Validation accuracy begins near 83% and rises to 94.7% while validation loss steadily drops. The metrics for training and validation improve in parallel, confirming successful learning without overfitting.

Later Epochs (43–50): Training accuracy stays steady at 94.5%–96.9%, and the model goes generally to a low loss. Validation accuracy is 100% and has lowered the validation loss to almost 0.03. You have accurate results over training and validation sets, with convergence.

Overall Insights: The model works excellent in such a way that even at the later epochs, it achieves a validate accuracy of 100% . This indicates the efficiency and robustness of our model where both training and validation losses are minimized.

There is no indication of overfitting as both training and validation metrics improve steadily.

```

Epoch 1/50
29/29 ----- 0s 922ms/step - accuracy: 0.5571 - loss: 0.9346Epoch 1/50
- loss: 0.8585 - accuracy: 0.5846 - val_loss: 0.4612 - val_accuracy: 0.8304
29/29 ----- 79s 2s/step - accuracy: 0.5581 - loss: 0.9320 - val_accuracy: 0.8304 - val_loss: 0.4612
Epoch 2/50
29/29 ----- 0s 283ms/step - accuracy: 0.6185 - loss: 0.8092Epoch 2/50
- loss: 0.7642 - accuracy: 0.6453 - val_loss: 0.4236 - val_accuracy: 0.8826
29/29 ----- 33s 466ms/step - accuracy: 0.6194 - loss: 0.8077 - val_accuracy: 0.8826 - val_loss: 0.4:
Epoch 3/50
29/29 ----- 0s 311ms/step - accuracy: 0.6858 - loss: 0.6255Epoch 3/50
- loss: 0.6893 - accuracy: 0.6638 - val_loss: 0.4256 - val_accuracy: 0.8913
29/29 ----- 14s 404ms/step - accuracy: 0.6851 - loss: 0.6276 - val_accuracy: 0.8913 - val_loss: 0.4:
Epoch 4/50
29/29 ----- 0s 331ms/step - accuracy: 0.6925 - loss: 0.6639Epoch 4/50
- loss: 0.6551 - accuracy: 0.7093 - val_loss: 0.3875 - val_accuracy: 0.9174
29/29 ----- 14s 421ms/step - accuracy: 0.6931 - loss: 0.6636 - val_accuracy: 0.9174 - val_loss: 0.3:
Epoch 5/50
29/29 ----- 0s 284ms/step - accuracy: 0.7029 - loss: 0.6850Epoch 5/50
- loss: 0.5969 - accuracy: 0.7299 - val_loss: 0.3416 - val_accuracy: 0.9217
29/29 ----- 21s 390ms/step - accuracy: 0.7038 - loss: 0.6821 - val_accuracy: 0.9217 - val_loss: 0.3:
Epoch 6/50
29/29 ----- 0s 327ms/step - accuracy: 0.7394 - loss: 0.5414Epoch 6/50
- loss: 0.5145 - accuracy: 0.7549 - val_loss: 0.2779 - val_accuracy: 0.9478
29/29 ----- 20s 416ms/step - accuracy: 0.7399 - loss: 0.5405 - val_accuracy: 0.9478 - val_loss: 0.2:
Epoch 7/50
29/29 ----- 0s 286ms/step - accuracy: 0.7610 - loss: 0.5527Epoch 7/50
- loss: 0.5144 - accuracy: 0.7777 - val_loss: 0.2764 - val_accuracy: 0.9478
29/29 ----- 20s 403ms/step - accuracy: 0.7616 - loss: 0.5514 - val_accuracy: 0.9478 - val_loss: 0.2:
Epoch 8/50

Epoch 43/50
29/29 ----- 0s 281ms/step - accuracy: 0.9437 - loss: 0.1533Epoch 43/50
- loss: 0.1534 - accuracy: 0.9479 - val_loss: 0.0359 - val_accuracy: 1.0000
29/29 ----- 21s 414ms/step - accuracy: 0.9438 - loss: 0.1533 - val_accuracy: 1.0000 - val_loss: 0.0359
Epoch 44/50
29/29 ----- 0s 285ms/step - accuracy: 0.9689 - loss: 0.1268Epoch 44/50
- loss: 0.1151 - accuracy: 0.9729 - val_loss: 0.0363 - val_accuracy: 1.0000
29/29 ----- 14s 412ms/step - accuracy: 0.9690 - loss: 0.1264 - val_accuracy: 1.0000 - val_loss: 0.0363
Epoch 45/50
29/29 ----- 0s 303ms/step - accuracy: 0.9448 - loss: 0.1847Epoch 45/50
- loss: 0.1482 - accuracy: 0.9653 - val_loss: 0.0361 - val_accuracy: 1.0000
29/29 ----- 14s 409ms/step - accuracy: 0.9455 - loss: 0.1835 - val_accuracy: 1.0000 - val_loss: 0.0361
Epoch 46/50
29/29 ----- 0s 328ms/step - accuracy: 0.9666 - loss: 0.1293Epoch 46/50
- loss: 0.1346 - accuracy: 0.9642 - val_loss: 0.0357 - val_accuracy: 1.0000
29/29 ----- 14s 418ms/step - accuracy: 0.9665 - loss: 0.1295 - val_accuracy: 1.0000 - val_loss: 0.0357
Epoch 47/50
29/29 ----- 0s 332ms/step - accuracy: 0.9566 - loss: 0.1465Epoch 47/50
- loss: 0.1279 - accuracy: 0.9664 - val_loss: 0.0328 - val_accuracy: 1.0000
29/29 ----- 14s 424ms/step - accuracy: 0.9569 - loss: 0.1459 - val_accuracy: 1.0000 - val_loss: 0.0328
Epoch 48/50
29/29 ----- 0s 336ms/step - accuracy: 0.9687 - loss: 0.1106Epoch 48/50
- loss: 0.1097 - accuracy: 0.9707 - val_loss: 0.0305 - val_accuracy: 1.0000
29/29 ----- 14s 425ms/step - accuracy: 0.9688 - loss: 0.1106 - val_accuracy: 1.0000 - val_loss: 0.0305
Epoch 49/50
29/29 ----- 0s 282ms/step - accuracy: 0.9528 - loss: 0.1559Epoch 49/50
- loss: 0.1324 - accuracy: 0.9642 - val_loss: 0.0284 - val_accuracy: 1.0000
29/29 ----- 21s 421ms/step - accuracy: 0.9532 - loss: 0.1551 - val_accuracy: 1.0000 - val_loss: 0.0284
Epoch 50/50
29/29 ----- 0s 288ms/step - accuracy: 0.9465 - loss: 0.1610Epoch 50/50
- loss: 0.1288 - accuracy: 0.9588 - val_loss: 0.0289 - val_accuracy: 1.0000
29/29 ----- 14s 407ms/step - accuracy: 0.9469 - loss: 0.1599 - val_accuracy: 1.0000 - val_loss: 0.0289

```

Figure 4.1.1: Training Accuracy

This diagram is a summary of the deep learning model architecture — a modified DenseNet121 with additional layers added. Here's a brief description:

- Base Model (DenseNet121): Serves as the feature extractor. Output shape is (None, 7, 7, 1024), Trainable parameters: 7,037,504
- Batch Normalization: Post DenseNet121 applied for stabilization and speed-up of training.
- Flatten Layer: As we go ahead we need to flatten the 3D feature maps to 1D vector (50176) for dense layers • Fully Connected Layers: Several dense layers decrease dimensionality in succession
- Dense_4 → 264 neurons (input), Dense_5 → 128 neurons, Dense_6 → 64 neurons.
- Last layer (Dense_7): 2 neurons → binary classification
- Dropout Layers: We use Dropout between dense layers to reduce overfitting.
- Batch Normalization: Append after dense layers for better generalization and faster training.
- Output Layer: For binary classification tasks, we use 2 neurons (probably SoftMax or sigmoid)

Layer (type)	Output Shape	Param #
densenet121 (Functional)	(None, 7, 7, 1024)	7,037,504
batch_normalization_4 (BatchNormalization)	(None, 7, 7, 1024)	4,096
flatten_1 (Flatten)	(None, 50176)	0
dense_4 (Dense)	(None, 264)	13,246,728
dropout_3 (Dropout)	(None, 264)	0
batch_normalization_5 (BatchNormalization)	(None, 264)	1,056
dense_5 (Dense)	(None, 128)	33,920
dropout_4 (Dropout)	(None, 128)	0
batch_normalization_6 (BatchNormalization)	(None, 128)	512
dense_6 (Dense)	(None, 64)	8,256
dropout_5 (Dropout)	(None, 64)	0
batch_normalization_7 (BatchNormalization)	(None, 64)	256
dense_7 (Dense)	(None, 2)	130

Figure 4.1.2: Model Summary

Here is the graph showing the Training Loss and Validation Loss for 50 epochs (blue line and orange line):

- Training Loss: High in the beginning and then falls gradually down — which is what you want to see, meaning the model is improving and getting better at predicting.
- Validation Loss: It also trends downward over epochs, settling at a lower value, indicating good generalization to new data.
- Overall Analysis: Both curves exhibit a parallel downward trend, indicating robust learning with little to no overfitting.

A further observation on validation loss stabilizing earlier suggests that the model generally generalizes well.

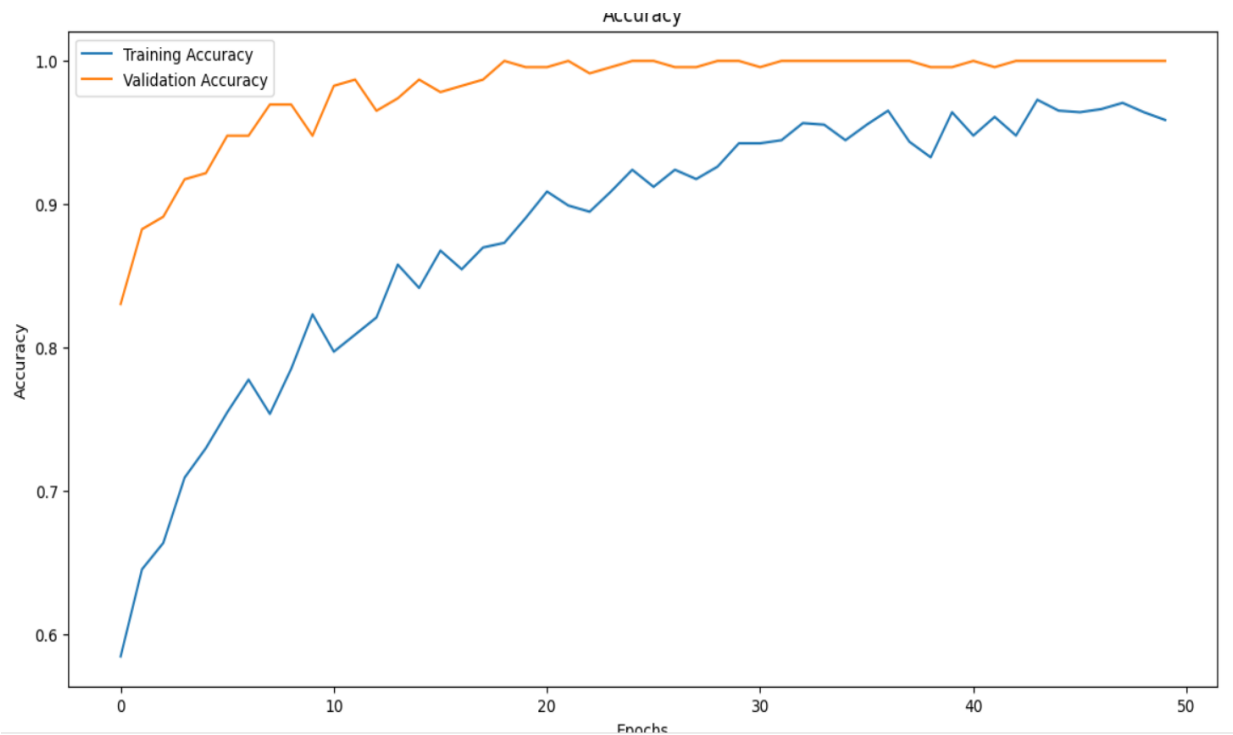


Figure4.1.3 : Training and validation Loss

This graph shows the Training Accuracy (blue line) and Validation Accuracy (orange line) for 50 epochs:

- Training Accuracy: Begins low (~60%) and rises smoothly, an indication of the model's learning. Ends up close to 90% indicating it learnt something.
- Validation Accuracy: Starts above training accuracy (70%) and ceases to change around 100%. The model does significantly better than the accuracy during training indicating very little overfitting.
- Overall Analysis: The plateau of the validation accuracy suggests good generalization. The increment of training accuracy, with no sign of overfitting may indicate good regularization and optimization.

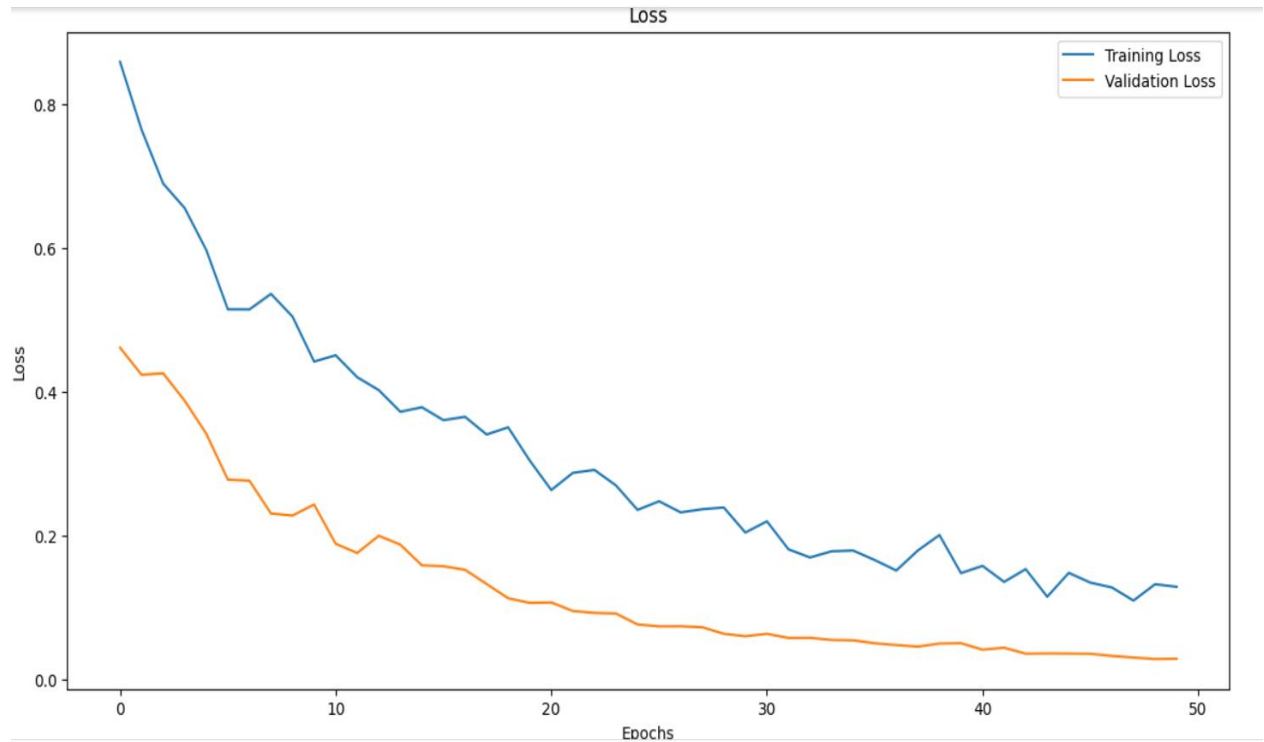


Figure 4.1.4: Training and Accuracy

This is an example of the potato leaf disease detection model output on three sample predictions:

First Leaf (Left):

- Actual: Healthy
- Predicted: Healthy
- The model predicts correctly that the leaf is healthy.

Second Leaf (Middle):

- Actual: Unhealthy
- Predicted: Unhealthy
- The model correctly identifies that the condition is unhealthy.

Third Leaf (Right):

- Actual: Unhealthy

- Predicted: Unhealthy
- The model accurately identifies the leaf as being unhealthy.



Figure 4.1.5: Images Test Predictions

The Below image is a confusion matrix for a binary classification problem (like determining healthy and unhealthy potato leaves). Here's a brief analysis:

Confusion Matrix Details:

- True Positive (Bottom Right - 870):870 unhealthy leaves correctly predicted as unhealthy.
- True Negative (Top Left — 22):The model accurately classified 22 healthy leaves as healthy.
- False Positive (Top Right—130):The model misclassified 130 healthy leaves as unhealthy.
- False Negative (Bottom Left — 130):Generically, it misclassified 130 bad leaves as good.

Insights:

The model is performing well with unhealthy leaves prediction but delivers high false positive & false negative for healthy leaves prediction. The underlying model can only achieve these classifications based on a confusion matrix (CM) and the imbalance reflected in the CM can imply underlying issues with the dataset (for example in the case of class imbalance between classes) or can identify necessary improvements in the model in terms of sensitivity to healthy leaf features.

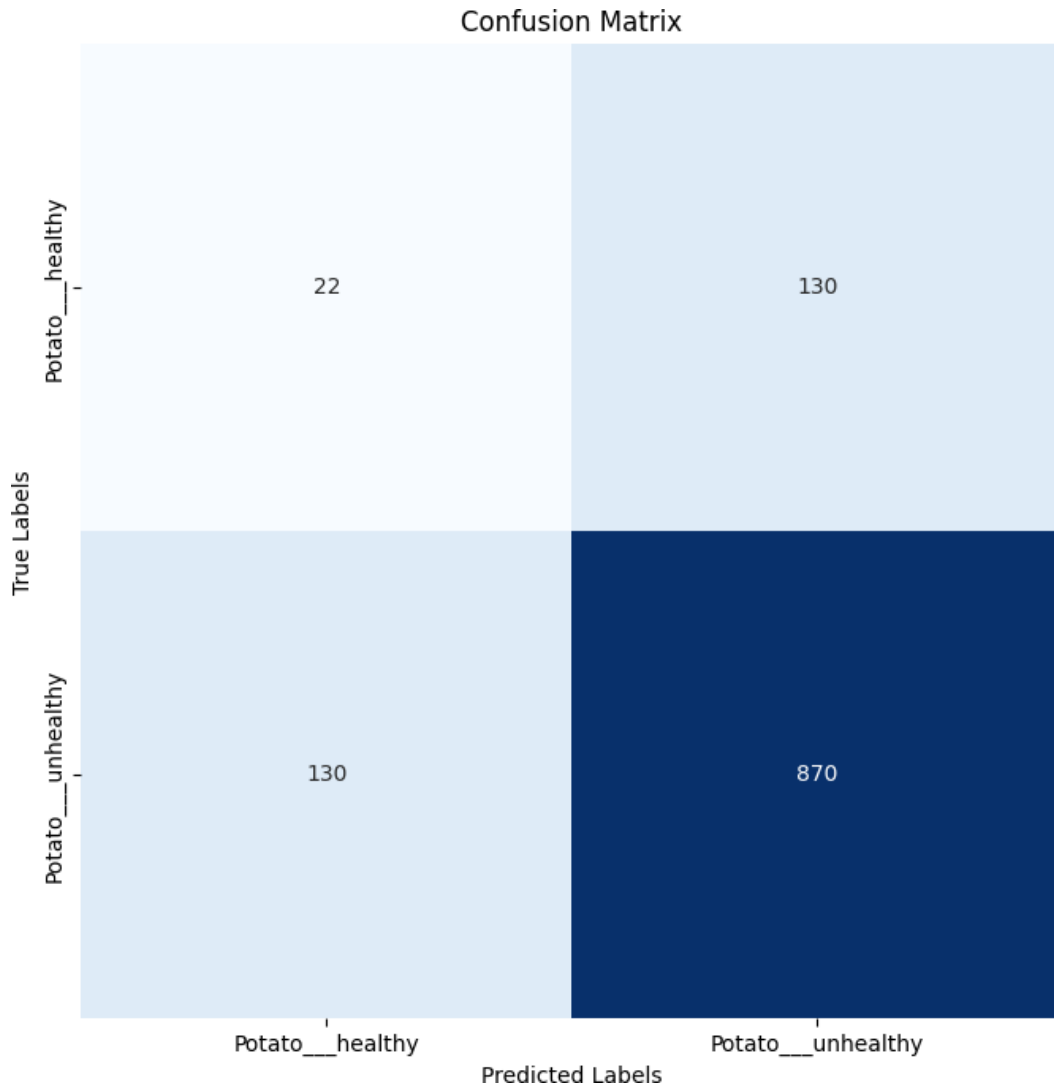


Figure 4.1.6 : Confusion matrix

4.2 Summary

DenseNet121 is an advanced Convolutional Neural Network (CNN) architecture designed for efficiency and accuracy. It features dense connectivity, where each layer connects to all subsequent layers, enabling feature reuse and reducing redundancy. With 121 layers organized into dense blocks and transition layers, it efficiently extracts features while minimizing parameters. DenseNet121 is lightweight, scalable, and well-suited for resource-constrained devices, making it ideal for tasks like image classification, including potato leaf disease detection.

CHAPTER 5

CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

The study developed a deep learning model for potato leaf disease detection using DenseNet121, a CNN architecture known for its densely connected layers and efficient feature extraction. DenseNet121 captured intricate details like texture and disease-specific patterns, enhancing performance while reducing computational complexity. Advanced preprocessing techniques, including resizing, normalization, and data augmentation, improved the model's generalization. The dataset was split into training, validation, and testing subsets for effective hyperparameter tuning and evaluation.

Transfer learning, dropout, and batch normalization mitigated overfitting, while the Adam optimizer and categorical cross-entropy loss function facilitated multi-class classification of healthy, early blight, and late blight categories. Performance metrics like accuracy, precision, recall, and F1-score validated the model's robustness, and Grad-CAM visualizations enhanced interpretability. DenseNet121's lightweight architecture enabled deployment on devices like smartphones and drones, providing a scalable and practical solution for real-time disease detection, empowering farmers to reduce crop losses and support sustainable agriculture.

5.2 Findings and Contribution

The study successfully demonstrated the feasibility of using Convolutional Neural Networks (CNNs) for agricultural disease detection by leveraging DenseNet121, a state-of-the-art CNN architecture. DenseNet121's densely connected layers enabled efficient feature extraction, capturing critical details such as texture, edges, and disease-specific patterns from potato leaf images. This highlighted the potential of deep learning to replace traditional, labour-intensive methods with faster and more accurate solutions for disease management. The study also contributed a scalable and efficient framework specifically tailored for binary classification tasks.

By utilizing DenseNet121's ability to reuse features across layers, the model effectively classified potato leaves as either healthy or diseased while maintaining computational efficiency. Techniques such as transfer learning, data

augmentation, dropout, and batch normalization improved generalization and mitigated overfitting. Optimization strategies, including the Adam optimizer and hyperparameter tuning, further enhanced the model's accuracy and robustness. DenseNet121's lightweight architecture made it suitable for deployment on resource-constrained devices like smartphones and drones, providing a practical and accessible solution for real-time agricultural applications. This scalable framework demonstrates how deep learning can empower farmers with timely insights, reduce crop losses, and contribute to sustainable farming practices.

5.3 Future Scope

Future research in the field of potato leaf disease detection can explore the multi-class classification of different diseases along with severity levels in order to provide comprehensive diagnosis information. This will support the potential in broaden the model to other crops or diseases categories to improve its scope in different greenhouses. The integration of IoT devices including drones and smart sensors could facilitate real-time monitoring and transform it into the examination of live images for onsite analysis so that early detection and timely intervention can help reduce crop losses.

The validation of the model over larger and heterogeneous datasets covering a variety of environmental conditions and geographical areas remains necessary to ensure robustness, generalizability, scalability and reduce potential biases. These progress would further empower the existing framework while also supporting precision agriculture, giving farmers the broadsword approaches to their facilities that they need to maximise productivity and ensure sustainability.

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