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Απο τα Εικονοστοιχεια στη Διαγνωση: Προσεγγισεις Μηχανικης Μαθησης για Ανιχνευση Ασθενειων Φυλλων Ντοματας

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From Pixels to Diagnosis: Machine Learning Approaches for Tomato Leaf Disease Detection

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Ευχαριστίες

Φθάνοντας στη λήξη της φοιτητικής μου ιδιότητας με την περάτωση της παρούσας πτυχιακής εργασίας, θα ήθελα να ευχαριστήσω τον κ.Νικόλαο Τσελίκα για την εμπιστοσύνη που μου έδειξε με την ανάθεση αυτής της πτυχιακής εργασίας, για την καθοδήγηση και τις συμβουλές του κατά τη διάρκεια εκπόνησης αυτής. Τον ευχαριστώ ιδιαίτερα για την υπομονή, την δεκτικότητα και την αμέριστη αρωγή του.

Ακόμα, θα ήθελα να ευχαριστήσω την οικογένειά μου για τη βοήθεια, την υποστήριξη και την ενθάρρυνση τους κατά τη διάρκεια όλων αυτών των ετών.

Περίληψη

Ο γεωργικός τομέας αντιμετωπίζει πολυάριθμες προκλήσεις, μεταξύ των οποίων η ταχεία αναγνώριση και διαχείριση των ασθενειών των φυτών είναι πρωταρχικής σημασίας. Τα φυτά ντομάτας, που αποτελούν βασικό συστατικό πολλών διατροφών παγκοσμίως, είναι ιδιαίτερα ευαίσθητα σε διάφορες ασθένειες που μπορούν να μειώσουν δραστικά την απόδοση και την ποιότητα. Οι παραδοσιακές μέθοδοι ανίχνευσης ασθενειών βασίζονται σε μεγάλο βαθμό στη χειροκίνητη επιθεώρηση, η οποία είναι χρονοβόρα, εντάσεως εργασίας και συχνά μη πρακτική για επιχειρήσεις μεγάλης κλίμακας. Η έλευση της μηχανικής μάθησης (ML) και της τεχνητής νοημοσύνης (AI) προσφέρει πολλά υποσχόμενες προοπτικές για την επανάσταση στη διαχείριση των ασθενειών των φυτών μέσω αυτοματοποιημένων, ακριβών και αποτελεσματικών διαγνωστικών συστημάτων.

Η παρούσα πτυχιακή εργασία διερευνά τις δυνατότητες αξιοποίησης του ML και του AI για την ανάπτυξη ενός ισχυρού μοντέλου για τον εντοπισμό και την ταξινόμηση ασθενειών σε φύλλα ντομάτας. Πρωταρχικός στόχος της παρούσας πτυχιακής εργασίας ήταν η δημιουργία ενός μοντέλου ικανού να μαθαίνει από ένα ολοκληρωμένο σύνολο δεδομένων εικόνων φύλλων ντομάτας, να διακρίνει μεταξύ υγιών και ασθενών φύλλων και να προσδιορίζει περαιτέρω συγκεκριμένους τύπους ασθενειών. Έτσι, στο πλαίσιο της πτυχιακής εργασίας, αρχικά κατασκευάστηκε ένα προσαρμοσμένο νευρωνικό δίκτυο συνελικτικού τύπου (CNN) από το μηδέν και στη συνέχεια εκπαιδεύτηκε σε ένα σχολαστικά επιμελημένο σύνολο δεδομένων.. Το σύνολο δεδομένων περιλάμβανε εικόνες φύλλων ντομάτας που είχαν προσβληθεί από διάφορες ασθένειες, εξασφαλίζοντας ένα ποικιλόμορφο και αντιπροσωπευτικό δείγμα για την εκπαίδευση.

Εκτός από το προσαρμοσμένο μοντέλο, διερευνήθηκαν οι επιδόσεις προ-εκπαιδευμένων μοντέλων όπως τα VGG16 και VGG19, τα οποία έχουν χρησιμοποιηθεί εκτενώς για ερ-

γασίες ταξινόμησης εικόνων. Προσαρμόζοντας λεπτομερώς αυτά τα μοντέλα ώστε να ταιριάζουν στο συγκεκριμένο σύνολο δεδομένων, επιχειρήθηκε η αξιολόγηση του κατά πόσο αυτές οι καθιερωμένες αρχιτεκτονικές θα μπορούσαν να ξεπεράσουν ή να συμπληρώσουν το προσαρμοσμένο CNN. Αυτή η συγκριτική ανάλυση παρείχε πολύτιμες πληροφορίες σχετικά με τα πλεονεκτήματα και τους περιορισμούς των δύο προσεγγίσεων.

Προκειμένου να ενισχυθεί η πρακτική εφαρμογή του μοντέλου, αναπτύχθηκε μια διαδικτυακή εφαρμογή που επιτρέπει στους χρήστες να ανεβάζουν εικόνες φύλλων ντομάτας για τη διάγνωση ασθενειών. Η εφαρμογή αυτή δεν προσδιορίζει μόνο την ασθένεια, αλλά προσφέρει και συστάσεις θεραπείας, παρέχοντας έτσι ένα ολοκληρωμένο εργαλείο για τη διαχείριση της υγείας των φυτών ντομάτας. Αυτή η λειτουργικότητα μετατρέπει το μοντέλο από ένα θεωρητικό πλαίσιο σε μια πρακτική λύση που μπορεί να χρησιμοποιηθεί από αγρότες, γεωπόνους και ερευνητές.

Το σύνολο δεδομένων που χρησιμοποιήθηκε στην παρούσα μελέτη χωρίστηκε σε τρία υποσύνολα: εκπαίδευση, επικύρωση και δοκιμή. Το υποσύνολο εκπαίδευσης, το μεγαλύτερο από τα τρία, χρησιμοποιήθηκε για την εκπαίδευση του μοντέλου. Το υποσύνολο επικύρωσης επέτρεψε την παρακολούθηση της απόδοσης του μοντέλου κατά τη διάρκεια της εκπαίδευσης, ενώ το υποσύνολο δοκιμής περιλάμβανε πραγματικές εικόνες από πολλούς κήπους, παρέχοντας μια αυστηρή δοκιμή της δυνατότητας εφαρμογής του μοντέλου στον πραγματικό κόσμο. Αυτή η συστηματική προσέγγιση εξασφάλισε την αυστηρή αξιολόγηση του μοντέλου και την ικανότητά του να αποδίδει υπό διάφορες συνθήκες.

Επιπλέον, η παρούσα πτυχιακή εργασία εξετάζει μελλοντικές επεκτάσεις, όπως η ανάπτυξη εφαρμογών για κινητά τηλέφωνα και η ενσωμάτωση δυνατοτήτων επεξεργασίας εικόνων σε πραγματικό χρόνο. Αυτές οι βελτιώσεις θα αυξήσουν περαιτέρω την προσβασιμότητα και τη χρησιμότητα του διαγνωστικού εργαλείου, καθιστώντας το ένα ευέλικτο πλεονέκτημα στην καταπολέμηση των ασθενειών των φυτών.

Συνοψίζοντας, η παρούσα εργασία παρουσιάζει μια ολοκληρωμένη διερεύνηση της χρήσης του ML και του AI στην ανίχνευση και ταξινόμηση ασθενειών σε φύλλα ντομάτας. Μέσω της δημιουργίας ενός προσαρμοσμένου CNN, της τελειοποίησης προεκπαιδευμένων μοντέλων και της ανάπτυξης μιας φιλικής προς τον χρήστη διαδικτυακής

εφαρμογής, αποδεικνύονται οι μετασχηματιστικές δυνατότητες αυτών των τεχνολογιών στη διαχείριση γεωργικών ασθενειών. Τα ευρήματα και οι μεθοδολογίες που συζητούνται εδώ θέτουν τις βάσεις για μελλοντικές καινοτομίες και εφαρμογές σε αυτόν τον κρίσιμο τομέα.

Λέξεις κλειδιά: Μηχανική Μάθηση, Ταξινόμηση, Ασθένειες της ντομάτας, Συνελικτικό νευρωνικό δίκτυο, Σύνολο δεδομένων

Abstract

The prevalence of diseases in tomato plants poses a significant challenge to agriculture, necessitating innovative solutions to address this problem. This thesis explores the application of Machine Learning (ML) and Artificial Intelligence (AI), specifically leveraging Computer Vision (a field within AI), to develop a model capable of identifying and classifying diseases in tomato leaves. Our approach involved creating a custom Convolutional Neural Network (CNN) trained on a diverse dataset of tomato leaf images, alongside fine-tuning pre-existing models such as VGG16 and VGG19 for comparative analysis. Additionally, we developed a web application to make our model accessible and practical for real-world use, allowing users to upload images and receive diagnoses and treatment recommendations. This research not only demonstrates the efficacy of ML and AI in agricultural disease management but also provides insights into the potential for extending these applications to real-time and mobile platforms.

Keywords: Machine Learning, Classification, Tomato Diseases, Convolutional Neural Network, Dataset

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Chapter 1

Introduction

1.1 Background and Motivation

The agricultural sector plays a crucial role in ensuring food security and economic stability worldwide. However, the prevalence of diseases in crops, particularly tomato plants, poses a significant challenge to agricultural productivity. Tomato plants are especially vulnerable to a wide range of diseases, which can lead to substantial losses in both yield and quality. Traditional methods for identifying and managing these diseases are often manual, labor-intensive, and time-consuming, making them impractical for large-scale agricultural operations. With the growing global population and the increasing demand for food, there is a pressing need for more efficient and scalable solutions for plant disease management.

Machine Learning (ML) and Artificial Intelligence (AI) have emerged as promising technologies capable of revolutionizing various sectors, including agriculture. By automating and enhancing the accuracy of disease detection, these technologies can play a pivotal role in improving crop health and productivity. This thesis explores the application of ML and AI, specifically in the form of Convolutional Neural Networks (CNNs), to develop a model that can accurately identify and classify diseases in tomato leaves.

1.2 Problem Statement

Tomato plants, being a key component of the global agricultural economy, are highly susceptible to numerous diseases that affect their growth and yield. Current disease detection practices are mainly reliant on visual inspection by experts, which is not only labor-intensive but also prone to human error. This thesis aims to address the need for an automated, accurate, and scalable solution to identify and classify diseases in tomato leaves, leveraging the power of ML and AI.

1.3 Objectives

The primary objectives of this research are as follows:

1. **Develop a Custom Convolutional Neural Network (CNN)**: Create and train a CNN model from scratch using a diverse dataset of tomato leaf images to accurately distinguish between healthy and diseased leaves.

2. **Fine-Tune Pre-Trained Models**: Investigate the performance of established pre-trained models such as VGG16 and VGG19 by fine-tuning them on the tomato leaf dataset and comparing their performance with the custom CNN.

3. **Develop a Web Application**: Implement a user-friendly web application that allows users to upload images of tomato leaves for disease diagnosis and receive treatment recommendations, thereby making the model accessible for practical use.

4. **Evaluate Model Performance**: Systematically evaluate the model using training, validation, and testing datasets to ensure its robustness and applicability in real-world scenarios.

5. **Explore Future Extensions**: Discuss the potential future extensions of this work, including the development of mobile applications and real-time image processing capabilities.

1.4 Research Methodology

This research follows a systematic approach to develop and validate a ML model for tomato leaf disease detection. The process can be broken down into the following key steps:

1. **Data Collection and Preprocessing**: A comprehensive dataset of tomato leaf images was collected, encompassing a wide range of diseases. The data was then preprocessed to ensure it was suitable for training the ML models.

2. **Model Development**: A custom CNN was developed and trained on the dataset. Additionally, pre-trained models VGG16 and VGG19 were fine-tuned to the dataset for comparative analysis.

3. **Model Evaluation**: The models were evaluated using three subsets of the dataset—training, validation, and testing. The performance metrics were analyzed to determine the effectiveness and accuracy of the models.

4. **Web Application Development**: A web application was developed to make the model accessible for real-world use, enabling users to diagnose diseases and receive treatment recommendations.

5. **Future Work**: Potential enhancements, such as the development of mobile applications and real-time image processing capabilities, were explored to extend the utility of the diagnostic tool.

1.5 Thesis Structure

This thesis is structured as follows:

1. **Chapter 2: Background and Technologies** - Provides an overview of the importance of tomato plants and common leaf diseases, along with a detailed introduction to machine learning fundamentals and image classification algorithms, including Convolutional Neural Networks (CNNs) and pre-trained models like VGG16 and VGG19.

2. **Chapter 3, 4 and 5: Tools and Technologies** - Describes the technical environment used in this project, including the role of Graphics Processing Units (GPUs), CUDA toolkit, and cuDNN for deep neural networks. It also covers the installation and configuration of essential software, such as the GNU Compiler Collection (GCC) and Python, highlighting their importance for machine learning tasks.

3. **Chapter 6: Dataset Preparation for Tomato Leaf Disease Classification** - Discusses the source and structure of the dataset used for tomato leaf disease classification, including the process of creating and processing the dataset. It also covers the strategies for splitting the dataset into training, validation, and test sets.

4. **Chapter 7: Machine Learning Models** - Provides an in-depth explanation of the machine learning models used for tomato leaf disease classification, focusing on CNN architecture, transfer learning with pre-trained models (VGG16 and VGG19), and the process of model compilation and training.

5. **Chapter 8: Model Evaluation and Metrics** - Presents the evaluation framework and metrics used to assess model performance, including loss, accuracy, precision, recall, and F1-score. It includes a comparative analysis of the custom CNN, VGG16, and VGG19 models, using classification reports, confusion matrices, and training-validation curves.

6. **Chapter 9: Streamlit Web Application for Disease Detection** - Details the implementation of the web application developed for tomato leaf disease detection using Streamlit. This chapter covers the application's workflow, user interface, and the image diagnosis process.

7. **Chapter 10: Thesis Enhancement: Tomato Leaf Disease Detection** - Discusses the image collection, preprocessing steps, experimental setup, and manual classification methods used to enhance the project's outcomes. This chapter also provides insights into testing and evaluating the final model.

8. **Chapter 11: Potential Improvements and Future Work** - Explores potential future enhancements to the project, such as mobile and real-time processing capabilities, and discusses how these improvements can enhance the model's practical applicability.

1.6 Significance of the Study

The results presented in this study represent the transformative potential of ML and AI in the management of agricultural diseases. This study, by developing an automated, appropriate, and user-friendly diagnostic tool, has laid a foundation on how the management of plant diseases will be done more easily and effectively. Lessons learned from this work set the stage for further development into applications that involve a wide range of crops and real-time diagnostic tools. Additionally, it is recommended to download or browse the thesis repository while reading this document. The repository contains the various implementations that will be discussed and presented, offering a clearer understanding of the results and demonstrating how to interact with the implementations. This includes using the developed website and engaging with the implementations—whether building, customizing, adjusting, or adding extra features. The repository is hosted on GitHub at `https://github.com/ZamirOsmenaj/tomato-leaf-disease-detection-and-classification` [45]. Following the document alongside the code can greatly enhance your comprehension and make it easier to explore or interact with the results and the underlying implementations.

Chapter 2

Background and Technologies

2.1 Importance of Tomato Plants

Tomatoes are one of the most widely cultivated and consumed vegetables globally, serving as a vital component in numerous diets and cuisines. The plant, Solanum lycopersicum, is a member of the nightshade family and is valued for its rich nutritional content, including vitamins A, C, and K, as well as folate and antioxidants like lycopene. Given its economic and nutritional significance, ensuring the health and productivity of tomato plants is crucial for both farmers and consumers.

2.2 Overview of Tomato Leaf Diseases

Tomato plants are susceptible to a variety of diseases that can significantly impact yield and quality. This section provides an overview of the nine tomato leaf diseases addressed in this project, along with the characteristics of healthy leaves. Each disease or condition described is visually represented in Figure 2.1, where the images are numbered to correspond with the list below.

1. **Bacterial Spot**: Bacterial spot is caused by the bacterium Xanthomonas campestris pv. vesicatoria. It manifests as small, water-soaked spots on leaves that eventually turn brown and necrotic. Severe infections can lead to defoliation and reduced fruit quality.

2. **Early Blight**: Early blight, caused by the fungus Alternaria solani, is characterized by concentric rings forming a "bullseye" pattern on older leaves. It often starts as small, dark spots and can lead to significant defoliation, reducing the plant's ability to photosynthesize.

3. **Healthy Leaves**: Healthy tomato leaves are vibrant green with a smooth texture and no visible spots, lesions, or discoloration. They are free of pests and show no signs of wilting or deformities, indicating a well-maintained plant.

4. **Late Blight**: Late blight, caused by the oomycete Phytophthora infestans, is a devastating disease that can affect all parts of the plant. It presents as water-soaked lesions that quickly turn brown and can lead to the plant's collapse under favorable conditions for the pathogen.

5. **Leaf Mold**: Leaf mold, caused by the fungus Passalora fulva, appears as yellow spots on the upper leaf surface and a velvety, olive-green mold on the underside. It thrives in high humidity and can severely reduce photosynthesis.

6. **Septoria Leaf Spot**: Septoria leaf spot, caused by the fungus Septoria lycopersici, is characterized by small, circular spots with dark borders and gray centers. It primarily affects the lower leaves and can cause premature defoliation.

7. **Spider Mites (Two-Spotted Spider Mite)**: The two-spotted spider mite, Tetranychus urticae, causes stippling and bronzing of leaves due to its feeding. Severe infestations can lead to webbing and significant leaf damage, affecting the plant's vigor.

8. **Target Spot**: Target spot, caused by the fungus Corynespora cassiicola, is identified by small, water-soaked spots that enlarge into concentric rings with a light center. It can lead to leaf drop and reduced plant productivity.

9. **Tomato Mosaic Virus**: Tomato mosaic virus (ToMV) causes mottled and mosaic patterns on leaves, along with leaf distortion and reduced fruit quality. The virus spreads through contaminated tools, seeds, and human handling.

10. **Tomato Yellow Leaf Curl Virus**: Tomato yellow leaf curl virus (TYLCV) is transmitted by the whitefly Bemisia tabaci. Infected plants show upward curling and yellowing of leaves, stunted growth, and reduced fruit set, severely impacting yields.

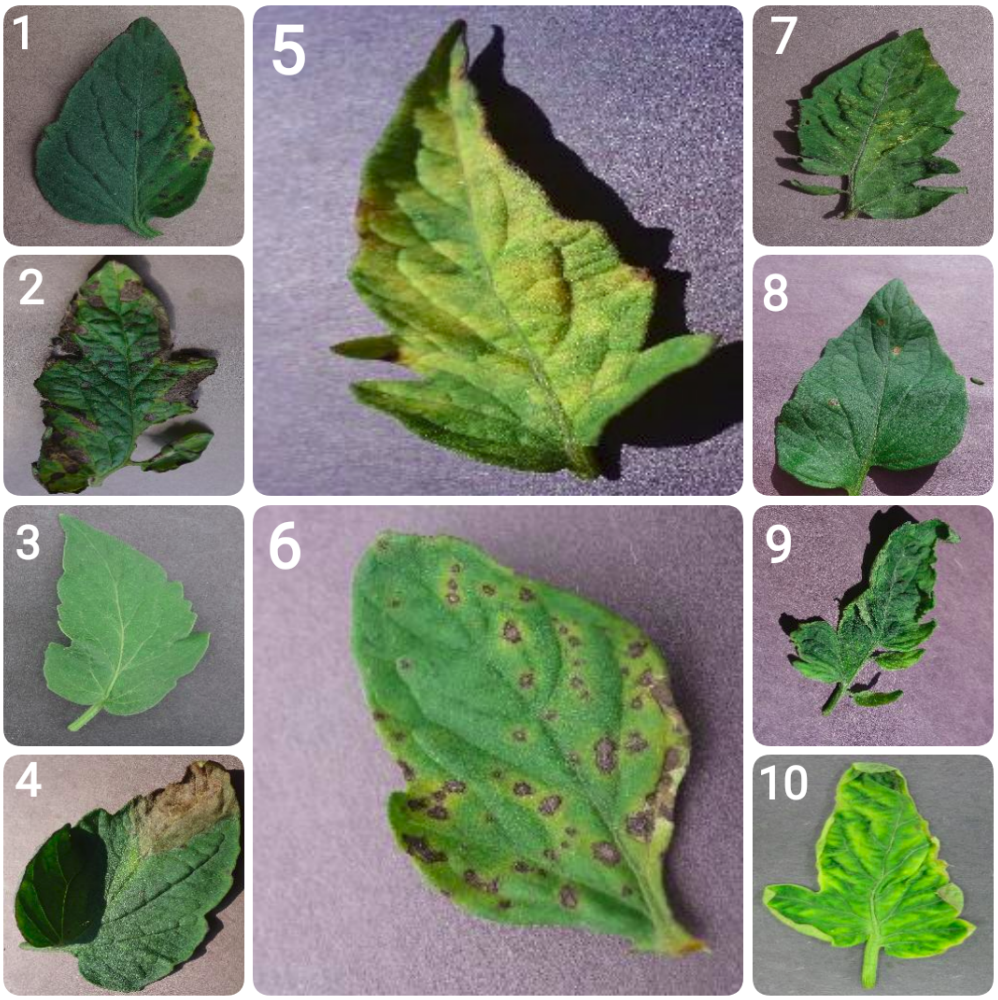

Figure 2.1: Collage of tomato leaf disease symptoms and healthy leaves. The images are numbered 1 through 10, corresponding to the diseases and healthy leaves described in this section.

2.3 Machine Learning Fundamentals

To understand the approach used in this thesis, it is essential to grasp the fundamentals of machine learning, particularly classification and then clustering, and regression.

Core Concepts in Intelligent Systems

- **Artificial Intelligence (AI)**: Refers to the simulation of human intelligence in machines that are capable of performing tasks requiring human-like thinking, such as learning, reasoning, and problem-solving.
- **Machine Learning (ML)**: A subset of AI that enables systems to learn from data, improve from experience, and make predictions or decisions without being explicitly programmed.
- **Deep Learning Algorithms**: A subset of machine learning that uses artificial neural networks with many layers to automatically learn patterns and features from large amounts of data, enabling tasks like image recognition, speech processing, and natural language understanding.

2.3.1 What is Machine Learning?

Machine Learning (ML) is a subset of artificial intelligence (AI) that involves the development of algorithms that allow computers to learn from and make decisions based on data. Unlike traditional programming, where explicit instructions are given for every task, ML systems improve their performance as they are exposed to more data over time.

2.3.2 Applications of Machine Learning in Our Daily Lives

Machine learning has become pervasive in many aspects of our daily lives. Here are some key applications:

- **Healthcare**: Predictive diagnostics, personalized treatment plans, and drug discovery.
- **Finance**: Fraud detection, algorithmic trading, and credit scoring.
- **Retail**: Personalized recommendations, inventory management, and demand forecasting.

- **Transportation**: Route optimization, self-driving cars, and predictive maintenance.
- **Entertainment**: Content recommendation systems used by platforms like Netflix and Spotify.
- **Customer Service**: Chatbots and automated customer support systems.

2.3.3 Recent Surge in Machine Learning Adoption

Several factors contribute to the growing attention and adoption of machine learning:

- **Data Availability**: The proliferation of digital data from various sources, such as social media, IoT devices, and online transactions, provides a rich source of information for training ML models.
- **Computational Power**: Advances in hardware, especially GPUs and cloud computing, have significantly reduced the time and cost required to train complex ML models.
- **Algorithmic Innovations**: Continuous improvements in ML algorithms have enhanced their accuracy, efficiency, and applicability to a broader range of problems.
- **Open-source Tools**: The availability of open-source ML frameworks like TensorFlow, PyTorch, and Scikit-learn has democratized access to powerful ML tools, making it easier for researchers and developers to experiment and innovate.
- **Business Impact**: ML solutions have demonstrated significant ROI (Return on Investment) by improving efficiency, reducing costs, and enabling new business models.

2.3.4 Challenges in the Adoption of Machine Learning

Despite its benefits, adopting machine learning comes with several challenges:

- **Data Quality and Quantity**: ML models require large amounts of high-quality data, which can be difficult to obtain and preprocess.
- **Interpretability**: Many ML models, particularly deep learning models, act as "black boxes," making it challenging to understand and trust their predictions.
- **Scalability**: Deploying ML models at scale and integrating them with existing systems can be complex and resource-intensive.
- **Ethical and Privacy Concerns**: Ensuring that ML systems are fair, transparent, and compliant with privacy regulations is crucial.
- **Skill Gap**: There is a high demand for skilled ML practitioners, which can make it difficult for organizations to find and retain talent.

2.3.5 Understanding Machine Learning Models

A Machine Learning (ML) model is a mathematical or computational representation designed to make predictions or decisions without being explicitly programmed for a specific task. It is created through a process called *training*, where the model learns patterns, relationships, and behaviors from historical data. Once trained, the model can generalize this learning to new, unseen data to perform tasks like classification, regression, or clustering.

2.3.5.1 Key Concepts

- **Training Data**: The data used to train the model, which contains input-output pairs or features and labels.
- **Features**: The input variables or attributes used to make predictions.
- **Labels**: The output or target values the model aims to predict (in supervised learning).

- **Learning Algorithm**: The method or algorithm used to learn from the data and adjust the model. Examples include decision trees, neural networks, and linear regression.
- **Parameters**: The internal configuration of the model, learned during training.
- **Hyperparameters**: Configuration settings specified before training, such as learning rate and number of epochs.
- **Prediction**: After training, the model uses new data (test data) to make predictions or decisions.

2.3.5.2 Types of ML Tasks

- **Classification**: Classification is a supervised learning technique used to assign labels to instances based on input features. It involves training a model on a labeled dataset, where the model learns to predict the category or class of new, unseen instances. In this thesis, classification is used to identify and categorize the type of disease affecting tomato leaves.
- **Clustering**: Clustering is an unsupervised learning technique that groups instances into clusters based on their similarities. Unlike classification, clustering does not require labeled data. Instead, it identifies natural groupings within the data, which can be useful for exploratory data analysis and identifying patterns.
- **Regression**: Regression is a supervised learning technique used to predict continuous outcomes based on input features. It involves training a model to understand the relationship between independent variables and a dependent variable. Common applications of regression include predicting prices, trends, and other numerical values.

2.3.5.3 Types of ML Models

- **Supervised Learning Models**: Trained on labeled data (e.g., classification models like decision trees or regression models like linear regression).

- **Unsupervised Learning Models**: Trained on data without labels to find patterns (e.g., clustering models like k-means).

- **Reinforcement Learning Models**: Learn through interactions with an environment, optimizing for long-term rewards.

In essence, an ML model extracts knowledge from data and applies it to future situations.

2.4 Algorithms for Image Classification

The following section outlines the key algorithms and methodologies employed in this thesis, including the custom Convolutional Neural Network (CNN) and pre-trained models like VGG16 and VGG19.

2.4.1 Introduction to Convolutional Neural Networks (CNN)

CNNs are a class of deep learning models particularly effective for image recognition tasks. They use convolutional layers to extract features from images, followed by fully connected layers to make predictions. In this thesis, a custom CNN was developed and trained on a dataset of tomato leaf images to classify and identify diseases.

2.4.2 Pre-trained Models: VGG16 and VGG19

VGG16 and VGG19 are pre-trained models known for their performance in image classification tasks. They are based on deep convolutional architectures trained on the ImageNet dataset. By fine-tuning these models on our specific dataset, we aimed to leverage their pre-learned features and adapt them to the task of tomato leaf disease classification.

2.5 Summary and Conclusion

The section "Background and Technologies" lays a concrete foundation with which to understand the context and methodologies adopted in this thesis. Elaboration on the importance of tomatoes, diseases that the crop is prone to, and applied concepts of machine learning form a basis on which subsequent analysis and findings rest in the thesis.

Chapter 3

Tools and Technologies

3.1 Role of Graphics Processing Units (GPUs)

3.1.1 Importance of GPUs in Machine Learning

Graphics Processing Units (GPUs) have become an essential component in the field of machine learning, particularly for tasks involving deep learning and large-scale data processing. Unlike Central Processing Units (CPUs), which are designed to handle a wide range of tasks, GPUs are specialized for parallel processing. This makes them exceptionally well-suited for the complex computations required in training machine learning models.

Efficiency and Performance

1. **Parallel Processing**: GPUs contain thousands of smaller cores designed to handle multiple tasks simultaneously. This parallelism allows for significant speedups in processing large datasets and performing the numerous calculations required for tasks such as training neural networks.

2. **High Throughput**: The architecture of GPUs enables high throughput for processing large blocks of data. This is particularly beneficial for operations like matrix multiplications, which are fundamental in neural network training.

3. **Energy Efficiency**: For the same amount of computational work, GPUs tend to be more energy-efficient than CPUs. This is critical in both reducing the operational costs and the environmental impact of running large-scale machine learning tasks.

4. **Optimized Libraries**: Many machine learning libraries, such as TensorFlow and PyTorch, are optimized to leverage GPU capabilities, providing built-in functions that take advantage of GPU acceleration.

3.1.2 Overview of NVIDIA GPUs

NVIDIA has been at the forefront of GPU development, providing robust solutions that are widely adopted in both academic research and industry applications. The CUDA (Compute Unified Device Architecture) platform developed by NVIDIA allows developers to harness the power of NVIDIA GPUs for general-purpose processing, making it a popular choice for machine learning tasks.

3.1.3 GPU Drivers

To effectively utilize NVIDIA GPUs, it is essential to have the correct drivers installed. The drivers ensure that the GPU operates efficiently and that software can communicate with the hardware properly. The following section was an approach followed for this thesis and will guide us through finding, downloading, and installing the appropriate NVIDIA GPU drivers.

3.1.3.1 How to Find the Appropriate Drivers?

1. **Identify the GPU**:

   - To determine the specifications of the GPU, we have to use the command:

   ```
   $ sudo lshw -c video
   ```

   - The output will look like below and it is going to include details about the GPU. Focus on the attributes `product` and `vendor`.

```
*-display
       description: VGA compatible controller
       product: TU117M [GeForce GTX 1650 Ti Mobile]
       vendor: NVIDIA Corporation
       physical id: 0
       bus info: pci@0000:01:00.0
       logical name: /dev/fb0
       version: a1
       width: 64 bits
       clock: 33MHz
       capabilities: pm msi pciexpress vga_controller bus_master
    cap_list rom fb
       configuration: depth=32 driver=nvidia latency=0 mode=1920
    x1080 visual=truecolor xres=1920 yres=1080
       resources: iomemory:f90-f8f iomemory:f90-f8f irq:84 memory
    :d0000000-d0ffffff memory:f980000000-f98fffffff memory:
    f990000000-f991ffffff ioport:3000(size=128) memory:d1080000-
    d10fffff
```

2. **Official NVIDIA Website**:

   - Open a browser and navigate to the Official NVIDIA Drivers [19] page.
   - Fill in the form with details about your GPU, including Product Type, Product Series, Product, Operating System, and Language. In our case the inputs were (based on the results of the previous command):
     - **Product Type**: GeForce
     - **Product Series**: GeForce 16 Series
     - **Product**: GeForce GTX 1660 Ti
     - **Operating System**: Linux 64-bit
     - **Language**: English (US)
   - Click *Search* to find the appropriate driver for your system.

3. **Determine Your Linux Distribution Codename**:

- Run the following command to get the codename of your Linux distribution:

```
$ lsb_release -a
```

- The output will include the codename of your Linux distribution (e.g., focal, jammy, noble):

```
Distributor ID:    Ubuntu
Description:       Ubuntu 24.04 LTS
Release:           24.04
Codename:          noble
```

- Note the codename (e.g., `noble`), as you'll need it to locate the correct GPU driver PPA.

3.1.3.2 How to Download the Appropriate Drivers?

1. **Add the GPU Driver PPA**:

   - Visit the Proprietary GPU Drivers page.
   - Under the *Overview of published packages* section, find and select your distribution codename (e.g., noble) and filter the packages.
   - Add the PPA to your system with the following commands:

```
$ sudo add-apt-repository ppa:graphics-drivers/ppa
$ sudo apt-get update
```

2. **Install the Driver**:

   - Install the driver with the command:

```
$ sudo apt install nvidia-driver-XXX
```

   Replace *XXX* with the driver number from the NVIDIA website that is compatible with your GPU (e.g., `nvidia-driver-535`).

3. **Verify Installation**:

   - After installation, we will need to restart our computer.

- Open the terminal and type:

```
$ nvidia-smi
```

- This command will display the GPU specifications and confirm that the driver is installed correctly. The output will look similar to the Figure 3.1.

4. **NVIDIA X Server Settings**:

   - We can also verify the driver installation through the *NVIDIA X Server Settings* application, which should be installed alongside the driver. This application provides a graphical interface to manage and configure the NVIDIA GPU.

5. **System Settings**:

   - Navigate to your system settings and check the *Graphics* section to confirm that your GPU is listed correctly.
   - If necessary, go to the *Additional Drivers* panel and ensure that the installed driver is selected.

6. **Final Verification**:

   - Restart the system once more and re-run the *nvidia-smi* command to ensure everything is set up properly.

3.1.4 Conclusion

Proper configuration and utilization of the GPU are very much essentials in running machine learning tasks efficiently. This will ensure that the system, with the installation and verification of NVIDIA drivers, is all set to go with the computational demands of training sophisticated models. Thus, this section has provided a comprehensive guide on how to set up your NVIDIA GPU, a critical step in the successful deployment of machine learning projects.

```
Fri Sep 20 12:36:22 2024
+---------------------------------------------------------------------------------------+
| NVIDIA-SMI 535.171.04             Driver Version: 535.171.04   CUDA Version: 12.2     |
|-----------------------------------------+----------------------+----------------------+
| GPU  Name                 Persistence-M | Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp   Perf          Pwr:Usage/Cap |         Memory-Usage | GPU-Util  Compute M. |
|                                         |                      |               MIG M. |
|=========================================+======================+======================|
|   0  NVIDIA GeForce GTX 1650 Ti     Off | 00000000:01:00.0 Off |                  N/A |
| N/A   42C    P8              2W /  35W |      6MiB /  4096MiB |      0%      Default |
|                                         |                      |                  N/A |
+-----------------------------------------+----------------------+----------------------+

+---------------------------------------------------------------------------------------+
| Processes:                                                                            |
|  GPU   GI   CI        PID   Type   Process name                            GPU Memory |
|        ID   ID                                                             Usage      |
|=======================================================================================|
|    0   N/A  N/A      2197      G   /usr/lib/xorg/Xorg                            4MiB |
+---------------------------------------------------------------------------------------+
```

Figure 3.1: GPU Status via nvidia-smi Command

3.2 CUDA Toolkit

The CUDA Toolkit, developed by NVIDIA, is a suite of software development tools and libraries designed to work with NVIDIA GPUs. This toolkit enables developers to harness the power of GPU parallel computing for high-performance applications, including machine learning and deep learning tasks. Here, we will discuss the importance and usage of the CUDA Toolkit, particularly version 11.8.0, along with detailed steps for its installation on a Linux system.

At this point, one might wonder why version 11.8.0 was chosen over other options. The selection of 11.8.0 is not arbitrary; it was specifically picked for its compatibility with the other components we'll be downloading, ensuring seamless integration with the rest of the system. Additionally, it has proven to be one of the most stable versions of the CUDA Toolkit.

3.2.1 What is the CUDA Toolkit?

The CUDA (Compute Unified Device Architecture) Toolkit is a comprehensive software development environment that provides everything needed to develop applications that run on NVIDIA GPUs. It includes:

- **CUDA Libraries**: Optimized libraries for mathematical operations, linear algebra, signal processing, and more.
- **CUDA Compiler (nvcc)**: A compiler for CUDA code, enabling the creation of GPU-accelerated applications.
- **CUDA Debugger and Profiler**: Tools for debugging and optimizing CUDA applications.
- **CUDA Runtime and Driver APIs**: Interfaces to control and manage CUDA devices.

3.2.2 How to Use CUDA Toolkit

The CUDA Toolkit is essential for developers looking to leverage GPU acceleration for various computational tasks, such as:

- **Deep Learning**: Training neural networks efficiently using frameworks like TensorFlow and PyTorch, which integrate with CUDA.
- **Scientific Computing**: Performing complex simulations and data analysis with higher efficiency.
- **Graphics Rendering**: Accelerating rendering processes in graphics applications and games.
- **Parallel Computing**: Executing multiple tasks simultaneously to speed up processing times.

In the context of our thesis, the CUDA Toolkit will be used to train and run machine learning models for the classification and identification of tomato leaf diseases. By utilizing the GPU's parallel processing capabilities, we can significantly reduce the time required to train deep learning models, thereby improving the efficiency and effectiveness of our disease identification system.

3.2.3 Installation Guide for CUDA Toolkit 11.8.0

Here are the detailed steps to download and install CUDA Toolkit 11.8.0 on a Linux system, specifically **Ubuntu 22.04** LTS.

1. **Enter the CUDA Toolkit Archive**:
   - Navigate to the CUDA Toolkit Archive [6]
2. **Select CUDA Toolkit 11.8.0**:
   - Choose CUDA Toolkit 11.8.0 from the list.
3. **Choose the System Combination**:
   - Go to the CUDA 11.8.0 Download Archive and select the appropriate combination for your system. In our case the combination was:
     - **Operating System**: Linux
     - **Architecture**: x86_64
     - **Distribution**: Ubuntu
     - **Version**: 22.04
     - **Installer Type**: deb (local)
4. **Review the CUDA Toolkit Documentation**:
   - Open the CUDA Toolkit Documentation v11.8.0 to understand the system requirements and installation steps.
5. **Refer to the NVIDIA CUDA Installation Guide for Linux**:
   - Follow the steps in the CUDA Installation Guide for Linux

3.2.3.1 Pre-Installation Actions

Before installing the CUDA Toolkit, several pre-installation actions need to be performed to ensure compatibility and proper functioning.

1. **Verify a CUDA-Capable GPU**:

   - Run the command:

```
$ lspci | grep -i nvidia
```

   - Check the output to confirm that the GPU is listed and supported by CUDA. The output will be something like this:

```
01:00.0 VGA compatible controller: NVIDIA Corporation TU117M [
    GeForce GTX 1650 Ti Mobile] (rev a1)
```

2. **Verify Linux Distribution**:

   - Ensure the Linux distribution is supported. Check the system's version with:

```
$ uname -m && cat /etc/*release
```

   - The result for Ubuntu distos should be:

```
x86_64
DISTRIB_ID=Ubuntu
DISTRIB_RELEASE=24.04
DISTRIB_CODENAME=noble
DISTRIB_DESCRIPTION="Ubuntu 24.04 LTS"
PRETTY_NAME="Ubuntu 24.04 LTS"
NAME="Ubuntu"
VERSION_ID="24.04"
VERSION="24.04 LTS (Noble Numbat)"
VERSION_CODENAME=noble
ID=ubuntu
ID_LIKE=debian
HOME_URL="https://www.ubuntu.com/"
SUPPORT_URL="https://help.ubuntu.com/"
BUG_REPORT_URL="https://bugs.launchpad.net/ubuntu/"
PRIVACY_POLICY_URL="https://www.ubuntu.com/legal/terms-and-
    policies/privacy-policy"
UBUNTU_CODENAME=noble
LOGO=ubuntu-logo
```

3. **Verify gcc Installation**:

   - Verify that gcc is installed by running:

```
$ gcc --version
```

   - If not installed, use the package manager to install gcc.

4. **Verify Kernel Headers and Development Packages**:

   - Check your kernel version with:

```
$ uname -r
```

   - Ensure the corresponding kernel headers and development packages are installed. For our system the result was:

```
6.8.0-31-generic
```

3.2.3.2 Installation Steps

Follow these steps to install the CUDA Toolkit:

1. **Download the Installer**:

   - - Download the CUDA Toolkit installer from the CUDA 11.8.0 Download Archive as stated previously on the section: *Downloading and Installing the CUDA Toolkit 11.8.0.*

2. **Run the Installer**:

   - Follow the installation guide for your specific Linux distribution. For Ubuntu, use:

```
$ sudo dpkg -i cuda-repo-<distro>_<version>_amd64.deb
$ sudo apt-key adv --fetch-keys http://developer.download.nvidia
    .com/compute/cuda/repos/<distro>/x86_64/7fa2af80.pub
$ sudo apt-get update
$ sudo apt-get install cuda
```

3.2.3.3 Post-Installation Actions

After installing the CUDA Toolkit, we had to perform these mandatory post-installation actions to set up the environment.

1. **Set Up Environment Variables**:

   - We added the CUDA Toolkit binary path to the PATH variable:

```
export PATH=/usr/local/cuda-11.8/bin${PATH:+:${PATH}}
```

   - For 64-bit systems as ours, we added the library path like:

```
export LD_LIBRARY_PATH=/usr/local/cuda-11.8/lib64${
    LD_LIBRARY_PATH:+:${LD_LIBRARY_PATH}}
```

2. **Update .bashrc File**:

   - Open the *.bashrc* file and add the above environment variables:

```
$ nano ~/.bashrc
```

   - Append the export commands and save the file. Then, source the updated *.bashrc*:

```
$ source ~/.bashrc
```

3. **Verify Installation**:

   - Close the terminal and open a new one. Verify the CUDA Toolkit installation by running:

```
$ nvcc -V
```

   - The output of the above command should look like:

```
nvcc: NVIDIA (R) Cuda compiler driver
Copyright (c) 2005-2022 NVIDIA Corporation
Built on Wed_Sep_21_10:33:58_PDT_2022
Cuda compilation tools, release 11.8, V11.8.89
Build cuda_11.8.r11.8/compiler.31833905_0
```

This will ensure that the installation and configuration of the CUDA Toolkit are correctly done to efficiently utilize the GPU on our machine learning tasks. Setting up the CUDA Toolkit properly is a very important step in using the full potential of NVIDIA-GPU-accelerated computing, which forms the backbone of our thesis in identifying and classifying diseases of tomato leaves.

3.3 CuDNN: An Essential Library for Deep Neural Networks

3.3.1 What is CuDNN?

CuDNN, or the CUDA Deep Neural Network library, is a GPU-accelerated library of primitives for deep neural networks developed by NVIDIA. It provides highly optimized implementations for standard routines such as forward and backward convolution, pooling, normalization, and more. These implementations are crucial for efficiently training and running deep learning models on NVIDIA GPUs.

CuDNN integrates seamlessly with popular deep learning frameworks like TensorFlow, PyTorch, and Caffe, enhancing their performance on NVIDIA hardware by utilizing the GPU's parallel processing capabilities.

For more information, visit the CuDNN overview page.

3.3.2 How to Use CuDNN

CuDNN is primarily used to accelerate the computation of deep neural networks by providing optimized implementations of common neural network operations. This includes:

- **Convolutional Layers**: Efficient computation of convolution operations, which are fundamental in CNNs.

- **Pooling Layers**: Fast execution of pooling operations that reduce spatial dimensions.
- **Normalization Layers**: Optimized batch normalization and other normalization techniques.
- **Recurrent Layers**: Enhanced performance for RNNs and LSTMs.
- **Activation Functions**: Efficient computation of activation functions like ReLU, Sigmoid, and Tanh.

In the context of our thesis, CuDNN will be used to optimize the training and inference processes for our machine learning models, specifically for the classification and identification of tomato leaf diseases. By leveraging CuDNN, we can achieve significant speedups, enabling faster model training and more responsive inference.

3.3.3 Installing CuDNN

To install CuDNN, we need to follow a series of steps to ensure compatibility with our existing CUDA Toolkit. Here's a detailed roadmap for downloading and installing CuDNN 8.x.x, which is compatible with CUDA Toolkit 11.8.0.

3.3.3.1 Step-by-Step Guide

1. **Visit the CuDNN Archive**:
   - Navigate to the CuDNN Archive [7]
2. **Select the Appropriate CuDNN Version**:
   - Choose the version of CuDNN that is compatible with CUDA Toolkit 11.8.0.
3. **Check Compatibility**:
   - Refer to the compatibility matrix in the CuDNN Release Notes to ensure the select the correct version.

4. **Download the CuDNN Library**:

   - We will need to create a free NVIDIA account to download CuDNN.
   - After logging in, download the appropriate CuDNN package for your Linux distribution (Ubuntu 22.04 LTS in our case).

5. **Install CuDNN**: **Tar File Installation**:

   - Navigate to your download directory:

```
$ cd <cudnnpath>
```

   - Extract the CuDNN package:

```
$ tar -xvf cudnn-linux-x86_64-8.x.x.x_cuda11.8-archive.tar.xz
```

   - Copy the CuDNN files to the CUDA Toolkit directory:

```
$ sudo cp cudnn-*-archive/include/cudnn*.h /usr/local/cuda/
    include
$ sudo cp -P cudnn-*-archive/lib/libcudnn* /usr/local/cuda/lib64
$ sudo chmod a+r /usr/local/cuda/include/cudnn*.h /usr/local/
    cuda/lib64/libcudnn*
```

3.3.4 Post-Installation Steps

1. **Verify CuDNN Installation**:

   - To ensure CuDNN is installed correctly, check the version by running:

```
$ cat /usr/local/cuda/include/cudnn_version.h | grep CUDNN_MAJOR
    -A 2
```

2. **Integrate CuDNN with CUDA Toolkit**:

   - Ensure the CUDA Toolkit and CuDNN paths are correctly set in the environment variables. The following lines should appear to the *.bashrc* file as configured previously:

```
export PATH=/usr/local/cuda-11.8/bin${PATH:+:${PATH}}
export LD_LIBRARY_PATH=/usr/local/cuda-11.8/lib64${LD_LIBRARY_PATH
    :+:${LD_LIBRARY_PATH}}
```

With these steps, carefully followed, we will be assured that the installation and configuration of CuDNN have taken place, hence enabling GPU acceleration of deep learning tasks with efficiency. These will be important in our optimum performance and efficiency of the machine learning models used in the identification of tomato leaf diseases.

3.4 The Role of GPU Drivers, CUDA Toolkit, and cuDNN in Accelerating Deep Learning

In deep learning, the ability to leverage GPU acceleration significantly improves the speed and efficiency of training complex models, such as Convolutional Neural Networks (CNNs) or fine-tuning pre-trained models like VGG16 and VGG19. This acceleration is made possible by the **GPU drivers**, **CUDA Toolkit**, and **cuDNN** working in tandem to allow the deep learning framework (such as TensorFlow or PyTorch) to fully utilize the GPU's parallel processing capabilities.

These three components form the critical infrastructure needed to unlock the full computational power of NVIDIA GPUs for machine learning tasks.

1. **GPU Drivers: Enabling Basic Communication with the GPU**:
   The **GPU drivers** act as the foundational layer of communication between the operating system and the GPU hardware. They are essential for detecting and utilizing the GPU. Without the correct drivers, your operating system would be unable to recognize the GPU, and your deep learning framework would be forced to rely solely on the CPU, which is far slower for tasks like training neural networks.

   For machine learning tasks:

- **Drivers provide GPU access**: The GPU drivers ensure that TensorFlow, PyTorch, or any other machine learning framework can detect and communicate with the GPU.
- **Performance and stability**: Updated drivers are crucial to ensuring optimal GPU performance and minimizing system crashes or slowdowns during intensive computational tasks.

2. **CUDA Toolkit: Enabling Parallel Processing on GPUs**:
   The **CUDA Toolkit** is a parallel computing platform and programming model developed by NVIDIA. It enables developers, and deep learning frameworks, to offload complex computations onto the thousands of cores present in a GPU, dramatically accelerating the speed of operations like matrix multiplication, convolutions, and backpropagation.

   When performing deep learning tasks, the CUDA Toolkit plays the following roles:

   - **Parallel computation**: CUDA allows operations such as matrix multiplication (central to neural networks) to be split across the many cores of the GPU. This leads to orders-of-magnitude faster processing times than on CPUs.
   - **Core libraries**: CUDA includes several libraries for high-performance computing. For deep learning, the key libraries are:
     - **cuBLAS**: For fast linear algebra computations (used heavily in neural networks).
     - **cuFFT**: or fast Fourier transforms, sometimes used in signal processing tasks within deep learning.
     - **cuDNN**: Provides highly optimized routines for deep learning operations like convolutions, pooling, activation functions, etc.

   These libraries allow frameworks like TensorFlow and PyTorch to execute matrix operations and other computations much faster than they could on the CPU.

3. **cuDNN (CUDA Deep Neural Network Library): Specialized Deep Learning Optimizations**:

   While CUDA is designed for general parallel computation, the cuDNN library is specifically optimized for deep learning tasks. cuDNN is built on top of CUDA and provides highly efficient implementations of common deep learning operations, making it indispensable for training deep neural networks like CNNs.

   cuDNN is responsible for:

   - **Optimizing deep learning-specific operations**: Operations such as convolutions, pooling, activation functions, and batch normalization, which are critical in CNNs, are optimized by cuDNN for faster execution on the GPU. These operations are the backbone of models like VGG16 and VGG19.
   - **Minimizing memory usage**: cuDNN is designed to optimize memory management during training, which is crucial for handling large datasets and deep network architectures without running out of GPU memory.
   - **Maximizing performance**: cuDNN enhances the speed and efficiency of both the forward and backward pass in neural networks. For instance, it accelerates convolution operations during the forward pass and gradient computations during backpropagation, both of which are computationally intensive.

How They Work Together: A Holistic View

When you run a deep learning task like training or fine-tuning a pre-trained model (e.g., VGG16), these three components—GPU drivers, CUDA Toolkit, and cuDNN—work in concert to accelerate the computations.

1. **GPU Drivers**: The GPU drivers allow the deep learning framework (e.g., TensorFlow or PyTorch) to recognize the available NVIDIA GPU. Without drivers, the framework would not be able to utilize the GPU, limiting computations to the CPU, which would lead to much slower training times.

2. **CUDA Toolkit**: Once the GPU is detected, the **CUDA Toolkit** enables the framework to offload operations from the CPU to the GPU. CUDA handles tasks like matrix multiplication, which are central to deep learning models, and splits them into smaller parallel tasks that can be distributed across the GPU cores. These operations include all forms of linear algebra and matrix manipulations that are central to training and inference in neural networks.

3. **cuDNN**: When the model performs deep learning-specific operations, such as convolutions (in CNNs), pooling, or activation functions, **cuDNN** provides optimized routines that are much faster than what general-purpose CUDA functions would offer. cuDNN is specifically designed for deep learning and ensures that these computations run efficiently and use as little memory as possible.

In a typical workflow:

- During **forward propagation**, when the neural network processes input data (e.g., an image in VGG16), cuDNN accelerates operations such as convolutional layers and activation functions, while CUDA executes parallel matrix multiplications.

- During **backpropagation**, cuDNN and CUDA work together to compute gradients and update model weights efficiently, ensuring fast convergence during training.

Conclusion

In summary, the **GPU drivers**, **CUDA Toolkit**, and **cuDNN** form a cohesive stack that enables deep learning frameworks to utilize the full power of NVIDIA GPUs. The **GPU drivers** handle basic communication and hardware recognition, while the **CUDA Toolkit** provides the general parallel processing framework necessary to accelerate computations. **cuDNN**, built on top of CUDA, offers specialized optimizations for deep learning, ensuring that operations like convolutions and backpropagation are executed as efficiently as possible. Together, these three components enable massive

speedups in training and fine-tuning deep learning models, making tasks like working with VGG16 or other CNN architectures much more efficient.

Chapter 4

GNU Compiler Collection (GCC)

4.1 GCC Overview

The GNU Compiler Collection (GCC) is a compiler system produced by the GNU Project supporting various programming languages. GCC is a key component of the GNU toolchain and is used for compiling C, C++, and other languages. It plays a crucial role in software development on Linux/Unix systems, offering robust optimization features and support for many architectures.

4.1.1 GCC Usage

GCC is essential for compiling and building applications from source code. It's widely used for system and application software development on Unix-like operating systems. In the context of our thesis, GCC is required for:

- **Compiling CUDA Programs**: The CUDA Toolkit relies on GCC for compiling CUDA kernels and applications.

- **Building Dependencies**: Various libraries and dependencies in the machine learning and deep learning stack often need to be compiled using GCC.

4.1.2 Why GCC is Needed for Machine Learning?

1. **CUDA Toolkit**: The CUDA Toolkit requires GCC for compiling CUDA programs. Specifically, CUDA 11.8.0 supports up to GCC 11.

2. **CuDNN**: Although primarily a library, CuDNN relies on the CUDA Toolkit, which in turn requires GCC for compiling CUDA applications.

4.1.3 Verifying Existing GCC Installation

Most Linux/Unix systems come with GCC pre-installed. To check if GCC is already installed and to verify the version, we have to use the following command:

```
$ gcc --version
```

If the output is similar to:

```
gcc (Ubuntu 11.4.0-9ubuntu1) 11.4.0
Copyright (C) 2021 Free Software Foundation, Inc.
This is free software; see the source for copying conditions. There is NO
warranty; not even for MERCHANTABILITY or FITNESS FOR A PARTICULAR
PURPOSE.
```

then GCC 11 is already installed, and no further action is required.

4.2 Installing GCC 11

If GCC 11 is not installed, the following steps will guide us through the installion of it:

1. **Update the Package Lists**:

   ```
   $ sudo apt-get update
   ```

2. **Install GCC 11 and G++ 11**:

   ```
   $ sudo apt-get install gcc-11 g++-11
   ```

3. **Verify Installation**:

   ```
   $ gcc-11 --version
   ```

   The result of this command should match the output we presented earlier.

4.3 Managing Multiple GCC Versions

As previously mentioned, most Linux/Unix distributions come with GCC pre-installed. It's a good practice to retain all existing versions of GCC and select the one we need as required. To manage multiple versions and switch between them, we can use the tool *update-alternatives*. To do that we can follow the steps below.

1. **Install *software-properties-common***:

```
$ sudo apt install software-properties-common
```

2. **Add the GCC PPA**:

```
$ sudo add-apt-repository ppa:ubuntu-toolchain-r/test
$ sudo apt update
```

3. **Install GCC 11 and G++ 11**:

```
$ sudo apt install gcc-11 g++-11
```

4. **Update Alternatives**:

```
$ sudo update-alternatives --install /usr/bin/gcc gcc /usr/bin/gcc
    -11 60
$ sudo update-alternatives --install /usr/bin/g++ g++ /usr/bin/g
    ++-11 60
```

5. **Switch Between GCC Versions**:

```
$ sudo update-alternatives --config gcc
```

This command will prompt us to select the version of GCC we want to use. For example:

```
There are 2 choices for the alternative gcc (providing /usr/bin/gcc)
    .

Selection    Path            Priority   Status
------------------------------------------------------------
* 0            /usr/bin/gcc-11   60        auto mode
```

```
1              /usr/bin/gcc-14    50          manual mode
2              /usr/bin/gcc-11    60          manual mode

Press <enter> to keep the current choice[*], or type selection
    number:
```

4.4 Conclusion

This is where, after the following steps, GCC 11 will be correctly installed and configured on our system to compile CUDA applications using the CUDA 11.8.0 Toolkit. Keeping multiple GCC versions makes it easier for us to be compatible with different software requirements without uninstalling installed versions. This setup is necessary; it will keep the deep learning tasks stable and efficient.

Chapter 5

Python Environment for Machine Learning

5.1 Python Overview

Python in Data Science and Image Classification: A Focus on Agricultural Disease Detection

Python is a high-level, interpreted programming language renowned for its simplicity and readability. First released in 1991 by Guido van Rossum, Python has since become a cornerstone of modern programming due to its emphasis on code readability and significant whitespace. It supports various programming paradigms such as procedural, object-oriented, and functional programming, and its extensive standard library, combined with active community support, makes it a popular choice for developers and researchers alike.

5.1.1 Role of Python in Data Science

Python plays a pivotal role in data science because of the large-scale ecosystems of libraries that make it very easy to manipulate, analyze, visualize, and perform machine learning on data. Contributions it makes include:

- **Data Analysis and Manipulation**: Libraries such as Pandas and NumPy en-

able efficient handling and processing of large datasets, crucial for exploring agricultural datasets.

- **Data Visualization**: Tools like Matplotlib and Seaborn allow for the creation of detailed, informative visualizations that can represent disease spread, crop health, and other agricultural metrics.
- **Machine Learning**: Scikit-learn provides essential tools for building and evaluating machine learning models, streamlining the process of classification and regression tasks.
- **Deep Learning**: TensorFlow and PyTorch are widely used for developing complex neural networks, a necessity for sophisticated image classification models.
- **Automating Data Pipelines**: Tools like Apache Airflow help in scheduling and managing workflows, ensuring efficient data processing and model training.

5.1.2 Image Classification for Agricultural Disease Detection

Image classification is a vital task in computer vision, where models are trained to categorize images into predefined labels. In the agricultural domain, it can be applied to various use cases, such as:

- **Disease Identification**: Detecting diseases in plants, such as tomato leaves, to help farmers address problems early.
- **Crop Monitoring**: Evaluating the health of crops and identifying nutrient deficiencies.
- **Weed Detection**: Differentiating between crops and unwanted plants to optimize farm management practices.

This thesis focuses specifically on the use of image classification to detect and classify diseases in tomato plants, a key problem in agriculture that affects productivity and sustainability.

5.1.3 Python for Tomato Disease Detection

Python simplifies the complex task of image classification through its comprehensive set of tools and libraries, which are particularly suited for the kind of deep learning models used in this project:

- **Image Preprocessing**: Libraries like OpenCV and Pillow (PIL) were instrumental in loading, resizing, and transforming images of tomato leaves, preparing them for model training.
- **Custom Convolutional Neural Network (CNN)**: Python's TensorFlow framework was used to develop a custom CNN architecture tailored for disease classification. This framework provided flexible tools to design, train, and fine-tune neural networks for high accuracy.
- **Transfer Learning**: Pre-trained models like VGG16 and VGG19 were fine-tuned for tomato disease classification. Python's Keras library enabled easy adaptation of these pre-trained models, speeding up the training process while maintaining accuracy.
- **Data Augmentation**: To increase the robustness of the model, libraries such as Albumentations and ImageDataGenerator were used for augmenting the dataset by applying transformations like rotation, scaling, and flipping. This helped improve the generalization of the model by exposing it to diverse image variations.
- **Model Evaluation and Visualization**: After training, libraries like Scikit-learn and Matplotlib were used to evaluate the model's performance. Metrics like accuracy, precision, and recall were plotted, and confusion matrices were generated to visualize how well the model distinguished between different tomato diseases.

5.1.4 Suitability of Python for This Project

Python's ecosystem of machine learning and computer vision libraries made it the ideal choice for this thesis, which focused on the detection of diseases in tomato

plants. The ability to quickly prototype and iterate over models, combined with Python's simplicity, allowed for efficient development of both the custom CNN and the fine-tuned VGG models.

Specifically, Python's suitability in this project was evident in the following areas:

- **Fast Prototyping**: Python's simple syntax and dynamic typing enabled quick experimentation with various model architectures, including our custom CNN and pre-existing models like VGG16 and VGG19.
- **Wide Range of Libraries**: The vast array of specialized libraries available in Python made it easier to handle tasks ranging from image preprocessing (OpenCV) to model training (TensorFlow) and deployment.
- **Web Application Integration**: Python's Streamlit framework was used to develop a web application that allows users to upload images of tomato leaves, receive diagnoses, and access treatment recommendations in real time, showcasing how Python integrates seamlessly into end-to-end applications.
- **Community Support**: Python's active community and the abundance of online resources ensured quick troubleshooting and continuous learning, which was essential during the development of complex models and deployment pipelines.

The ease of integrating all components—from preprocessing and model training to deploying the model via a web app—demonstrates Python's unparalleled flexibility and power in solving real-world problems like agricultural disease detection.

5.1.5 Conclusion

Python is a crucial tool for tackling complex data science challenges, such as image classification for tomato plant disease detection. Its readability, extensive libraries, and strong community support enable the rapid development of sophisticated machine learning models. In this thesis, Python's tools played a central role in developing a

machine learning pipeline that not only achieves high accuracy in disease classification but is also deployable in a real-world web application. With its robust framework for machine learning and deep learning tasks, Python is indispensable for modern agricultural problem-solving.

5.2 Python Version Compatibility with CUDA, CuDNN, and GCC

When setting up a deep learning environment, it's crucial to ensure that the versions of Python, CUDA, CuDNN, GCC and Tensorflow —which we are going to discuss later— are compatible. Mismatched versions can lead to situations where Python cannot locate the other components, or vice versa. This is typically more common with Python failing to recognize the other components.

To determine the appropriate Python version that will work seamlessly with the versions of CUDA, CuDNN, and GCC we have installed, refer to the compatibility table provided by TensorFlow. This table can be accessed via the following link: TensorFlow Tested Build Configurations - Linux. The table specifies which versions of Python are compatible with the versions of CUDA, CuDNN, GCC and Tensorflow we are using and we are going to use.

From this table, it is evident that Python versions 3.9 to 3.11 are compatible with our setup. However, the operating system typically comes pre-installed with a version of Python. In our case, Python 3.12 was pre-installed, which falls outside the acceptable range. Therefore, it was necessary to install a compatible Python version. We chose to install Python 3.10, which is within the acceptable limits and ensures compatibility with the other components.

To maintain flexibility, similar to the approach with the GCC compiler, we decided to keep both versions of Python—3.12 and 3.10—installed on the system. This allows us to switch between them as needed. The process for installing Python 3.10 alongside the pre-installed version is as follows:

5.2.1 Installing Python 3.10 on Linux

1. **Add the PPA repository for alternative Python versions**:

```
$ sudo add-apt-repository ppa:deadsnakes/ppa
```

2. **Update the package list**:

```
$ sudo apt update
```

3. **Verify the availability of Python 3.10**:

```
$ apt list | grep python3.10
```

   - If available, we'll see an output like so:

```
idle-python3.10/noble 3.10.14-1+noble2 all
libpython3.10-dbg/noble 3.10.14-1+noble2 amd64
libpython3.10-dev/noble,now 3.10.14-1+noble2 amd64
libpython3.10-minimal/noble,now 3.10.14-1+noble2 amd64
libpython3.10-stdlib/noble,now 3.10.14-1+noble2 amd64
libpython3.10-testsuite/noble 3.10.14-1+noble2 all
libpython3.10/noble,now 3.10.14-1+noble2 amd64
python3.10-dbg/noble 3.10.14-1+noble2 amd64
python3.10-dev/noble,now 3.10.14-1+noble2 amd64
python3.10-distutils/noble,now 3.10.14-1+noble2 all
python3.10-examples/noble 3.10.14-1+noble2 all
python3.10-full/noble 3.10.14-1+noble2 amd64
python3.10-gdbm-dbg/noble 3.10.14-1+noble2 amd64
python3.10-gdbm/noble 3.10.14-1+noble2 amd64
python3.10-lib2to3/noble,now 3.10.14-1+noble2 all
python3.10-minimal/noble,now 3.10.14-1+noble2 amd64
python3.10-tk-dbg/noble 3.10.14-1+noble2 amd64
python3.10-tk/noble 3.10.14-1+noble2 amd64
python3.10-venv/noble,now 3.10.14-1+noble2 amd64
python3.10/noble,now 3.10.14-1+noble2 amd64
```

4. **Install Python 3.10**:

```
$ sudo apt install python3.10
```

5. **Set up alternatives to manage multiple Python versions**:

   - Add Python 3.12 to the alternatives system:

```
$ update-alternatives --install /usr/bin/python3 python3 /usr/
    bin/python3.12 1
```

   - Add Python 3.10 to the alternatives system:

```
$ update-alternatives --install /usr/bin/python3 python3 /usr/
    bin/python3.10 2
```

6. **List available Python alternatives**:

```
$ update-alternatives --list python3
```

   - The above command should now list the alternative installations of python3 we've installed and added to update-alternatives:

```
/usr/bin/python3.10
/usr/bin/python3.12
```

7. **Configure the default Python version**:

```
$ update-alternatives --config python3
```

   - Entering the above command we should be hit with a prompt like the one below. This will list all the versions of Python the system recognizes. Select the version of Python we'd like to use by providing the "selection" number to the prompt:

```
There are 2 choices for the alternative python3 (providing /usr/
    bin/python3).

  Selection    Path                  Priority   Status
------------------------------------------------------------
* 0            /usr/bin/python3.10    2         auto mode
  1            /usr/bin/python3.10    2         manual mode
  2            /usr/bin/python3.12    1         manual mode
```

```
8
9  Press <enter> to keep the current choice[*], or type selection
     number:
```

8. **Resolve any potential issues with Python package management**:

   - Remove and clean up *python3-apt*:

```
1 $ sudo apt remove --purge python3-apt
2 $ sudo apt autoclean
```

   - Reinstall *python3-apt*:

```
1 $ sudo apt install python3-apt
```

9. **Install additional Python 3.10 components**:

```
1 $ sudo apt-get install python3.10-distutils python3.10-dev python3
    .10-venv
```

10. **Install *pip* for Python 3.10**:

```
1 $ curl -sS https://bootstrap.pypa.io/get-pip.py | python3.10
```

During this process, we can easily install and manage multiple versions of Python, maintain the compatibility of CUDA, CuDNN, GCC, and Tensorflow, and switch between different Python versions with ease.

5.3 Package Management with pip3

5.3.1 Importance of pip3

The package installer for Python 3 is *pip3*, and it comes bundled with Python versions 3.4 and later. It allows users to install and manage additional Python libraries and dependencies that are not included in the standard library. *pip3* is essential for setting up a Python environment tailored to specific project needs.

Using *pip3*, one can easily install packages like TensorFlow, NumPy, Pandas, and many others, ensuring that the development environment has all the necessary tools for efficient coding and execution.

Below are some of the most important commands we used:

1. **Install a Package**: To install a Python package, the following command is used:

```
$ pip3 install package_name
```

   Example:

```
$ pip3 install numpy
```

   This will install the NumPy library.

2. **Upgrade an Installed Package**: To upgrade an already installed package to the latest version:

```
$ pip3 install —upgrade package_name
```

   Example:

```
$ pip3 install —upgrade pandas
```

3. **Install a Specific Version of a Package**: If we need a specific version of a package—like we did and we will see later on— we can specify it:

```
$ pip3 install package_name==version_number
```

   Example:

```
$ pip3 install tensorflow==2.12.0
```

4. **List Installed Packages**: To view all installed Python packages, we use:

```
$ pip3 list
```

5. **Uninstall a Package**: If we need to remove a package from our environment, we can do so with:

```
$ pip3 uninstall package_name
```

Example:

```
$ pip3 uninstall seaborn
```

These examples demonstrate the versatility of *pip3* for managing Python packages and customizing the development environment.

5.3.2 Difference Between *pip* and *pip3*

- ***pip***: This is the Python package manager typically used for managing and installing packages in **Python 2.x** environments (versions prior to Python 3.0). It simplifies the process of downloading and installing external libraries for Python.
- ***pip3***: This is the package manager designed specifically for **Python 3.x** environments. It works similarly to *pip* but ensures compatibility with Python 3, which is critical given the differences between Python 2 and Python 3.
- **Clarification on Usage**: You may notice that, in this thesis, there will be instances where *pip* is used in place of *pip3*. This is because the default Python version on many systems, including the environment used for this research, is **Python 3**. In such cases, using *pip* automatically installs packages compatible with Python 3. However, if **both Python 2 and Python 3** are installed on a system, it is important to distinguish between the two and use *pip3* for Python 3 environments, ensuring no conflicts arise from Python 2 packages. In this thesis, to avoid ambiguity, we will explicitly refer to *pip3* whenever Python 3 packages are required, even when *pip* may suffice.

5.4 Virtual Environment Management with venv

5.4.1 Creating and Using Virtual Environments

Virtual Environment *venv* is a module that provides support for creating lightweight, isolated Python environments. This isolation ensures that dependencies required by

different projects do not interfere with each other, preventing version conflicts and promoting reproducibility.

5.4.2 Installation and Activation

1. **Install venv**:

```
$ sudo apt-get install python3.10-venv
```

2. **Create a Virtual Environment**:

```
$ python3.10 -m venv myenv
```

   This command creates a directory named *myenv* containing a separate Python installation and a copy of the *pip3* installer.

3. **Activate the Virtual Environment**:

```
$ source myenv/bin/activate
```

   After activation, the command prompt changes to indicate the active virtual environment. All Python packages installed via *pip3* will be confined to this environment.

4. **Deactivate the Virtual Environment**:

```
$ deactivate
```

   This command exits the virtual environment, returning to the global Python environment.

5.5 Jupyter Notebooks for Development

5.5.1 Benefits and Features

Jupyter Notebook is an open-source web application that allows us to create and share documents containing live code, equations, visualizations, and narrative text. It is

an interactive computing environment that supports dozens of programming languages.

Benefits:

- **Interactive Coding**: Execute code cells interactively and see immediate results.
- **Rich Media Support**: Include images, videos, and interactive widgets alongside code.
- **Data Visualization**: Integrate plots and charts directly within the notebook.
- **Documentation**: Combine code with markdown for comprehensive explanations and easy-to-follow analysis.

Installation:

- If *pip3* is installed, we can easily install Jupyter Notebook by running the following command in the terminal or command prompt:

```
$ pip3 install notebook
```

Running Jupyter Notebook:

- To start the Jupyter Notebook, use the following command:

```
$ python3 -m notebook
```

  This will launch Jupyter in our default web browser, opening a page on *localhost* usually at *http://localhost:8888/tree*. From there, we can create new or open existing notebook (.ipynb) files. Inside these notebooks, we can write, execute, and instantly view the results of small code snippets.

- To stop the Jupyter Notebook, return to the terminal where it was launched and press *Ctrl+C*.

5.6 Key Libraries and Modules

The following libraries formed the core of the machine learning and data analysis pipeline used in this thesis. They were installed and managed using *pip3* to ensure the environment had all the necessary tools for efficient data handling, visualization, and model development.

5.6.1 NumPy, Pandas, Matplotlib, Seaborn, Scikit-learn

These libraries are integral to Python's data science and machine learning ecosystem and played a pivotal role in the development of the tomato plant disease detection model.

- **NumPy**: NumPy was essential for handling large, multi-dimensional arrays and matrices, which were used extensively during image processing and data augmentation. Its optimized mathematical functions ensured efficient computations during model training and evaluation.

```
$ pip3 install numpy
```

- **Pandas**: Pandas provided powerful data manipulation capabilities for organizing and analyzing the dataset of tomato leaf images. It was used for tasks such as loading and cleaning data, which were critical in preparing the dataset for machine learning tasks.

```
$ pip3 install pandas
```

- **Matplotlib**: This library was used to visualize model performance and data distributions. From plotting learning curves to generating confusion matrices, Matplotlib was instrumental in gaining insights into the effectiveness of the models.

```
$ pip3 install matplotlib
```

- **Seaborn**: Built on top of Matplotlib, Seaborn was employed to create more advanced, aesthetically pleasing statistical plots. It was particularly useful in

visualizing the relationships between different features of the dataset, aiding in exploratory data analysis.

```
$ pip3 install seaborn
```

- **Scikit-learn**: Scikit-learn [20] provided key functionalities for model evaluation and preprocessing tasks. It was used for splitting the dataset into training and testing sets, applying scaling techniques, and evaluating model performance through metrics such as accuracy, precision, and recall.

```
$ pip3 install scikit-learn
```

These libraries were central to the thesis, facilitating everything from data manipulation and visualization to machine learning model development and evaluation. Each of these packages was chosen for its efficiency, ease of use, and compatibility with Python's broader machine learning ecosystem, making them indispensable for both research and development in the project.

5.7 TensorFlow Overview

TensorFlow, developed by Google, is a powerful open-source machine learning framework that offers a wide array of tools, libraries, and resources for building and deploying machine learning models. It is widely used in various machine learning applications, from simple linear models to advanced deep learning architectures like convolutional neural networks (CNNs) and recurrent neural networks (RNNs). TensorFlow supports both research and production environments, making it a versatile choice for developers and researchers alike.

5.7.1 Usage and Purpose

TensorFlow excels in a variety of machine learning tasks, including but not limited to:

- **Deep Learning**: TensorFlow provides efficient tools for building and training deep learning models, including CNNs, which are especially useful for image and speech recognition tasks.

- **Natural Language Processing (NLP)**: TensorFlow is used for text-based tasks like sentiment analysis, language translation, and text generation, utilizing models like transformers.

- **Reinforcement Learning**: TensorFlow supports the development of agents that learn by interacting with their environment through trial and error.

- **Time Series Analysis**: TensorFlow helps in forecasting and modeling time-dependent data using RNNs and other recurrent models.

5.7.2 Appropriateness for Tomato Plant Disease Classification

TensorFlow is particularly well-suited for this project, which involves classifying diseases in tomato plants using images of leaves. Its ability to handle convolutional neural networks (CNNs) makes it an ideal framework for this task, as CNNs are highly effective for image classification problems. In addition to its core features, TensorFlow offers the following advantages:

- **Pre-trained Models**: TensorFlow provides access to a wide range of pre-trained models, such as VGG16 and VGG19, which were fine-tuned for comparative analysis in this project.

- **GPU Support**: TensorFlow supports GPU acceleration, which significantly speeds up the training of deep learning models, particularly for large datasets of images.

- **Extensive Documentation and Community Support**: TensorFlow has comprehensive documentation and an active community, ensuring quick troubleshooting and ease of integration into various projects.

- **Ease of Deployment**: TensorFlow's ecosystem includes tools like TensorFlow Serving, which simplifies the deployment of machine learning models, such as the tomato disease classification model used in this project.

Overall, TensorFlow's flexibility and extensive feature set make it the perfect choice for developing and deploying the disease classification model used in this thesis.

5.7.3 Installation Guide

To ensure compatibility with the project's environment, TensorFlow version 2.12.0 was selected. The installation followed a step-by-step process to set up TensorFlow with GPU support for efficient deep learning model training.

1. **TensorFlow Installation Guide**:
   Start by visiting the official TensorFlow website to follow the installation instructions:

   - TensorFlow Installation Guide [21]

   For this project, refer specifically to the **Build from Source** guide for Linux/macOS systems. This ensures that TensorFlow is correctly compiled and optimized for GPU support.

   - TensorFlow Build from Source - Linux/macOS

2. **Review Tested Build Configurations**:
   To ensure compatibility, review the **Tested Build Configurations** for Linux:

   - Tested Build Configurations - Linux

   This section lists the compatible versions of various tools and libraries required for TensorFlow with GPU support. Key components like CUDA, cuDNN, Python, and GCC must match the recommended versions to avoid issues during installation or runtime.

3. **Identify the Compatible Version**:
   Based on the compatibility matrix provided on the TensorFlow site, version 2.12.0 was selected for this project. This version aligns well with the GPU requirements and other dependencies, ensuring optimal performance during model training and evaluation.

4. **Install TensorFlow 2.12.0 Using *pip3***:

   To install TensorFlow version 2.12.0, run the following command:

```
$ pip3 install tensorflow==2.12.0
```

   This command installs TensorFlow version 2.12.0 along with all necessary dependencies, ensuring the environment is ready for deep learning tasks.

Verifying Installation Overview

Once TensorFlow is installed, it's crucial to verify that the installation is successful and that the system is properly configured to utilize the GPU for accelerated training.

1. **Check TensorFlow Installation Version**:

   To confirm that TensorFlow is installed and functioning, run the following command in our Python environment:

```
import tensorflow as tf
print(tf.__version__)
```

   This will output the installed version of TensorFlow, which should be 2.12.0.

2. **Verify GPU Availability**:

   Next, verify that TensorFlow can detect the GPU, ensuring that the deep learning models can take advantage of GPU acceleration:

```
import tensorflow as tf
print(tf.config.list_physical_devices('GPU'))
```

   If TensorFlow is properly set up to use the GPU, this command will display a list of available GPUs. If no GPUs are detected, we may need to check the CUDA and cuDNN installation to ensure compatibility with TensorFlow.

   A successful output would look like:

```
[PhysicalDevice(name='/physical_device:GPU:0', device_type='GPU')]
```

5.7.4 Conclusion

TensorFlow forms the backbone of development and deployment for machine learning models, especially those dealing with image classification, just as the project would require in terms of tomato plant disease detection. With an excellent ecosystem, pre-trained models, and support for GPUs, it is indeed the perfect tool for the effective training and fine-tuning of neural networks within this scope. Thus, subsequent to all installation and verification above, it would be said that TensorFlow is properly set up to run optimally within the developer environment for speed and completeness of model iteration and deployments.

5.8 Setting Up the Technical Environment

In this section, we outline the approach followed in setting up the technical environment for the tomato leaf disease detection and classification system. We began by selecting the appropriate Python version (*3.10*, as previously discussed) and ensuring that *pip3* was installed, either by default or through manual installation as necessary. We then installed the *venv* module to create a virtual environment. Once the virtual environment was created and activated, all required packages—both those discussed earlier and any to be introduced later—were installed within this isolated environment. This ensured that all dependencies were contained within the virtual environment, avoiding potential conflicts with other system-wide packages.

For future work, the virtual environment must be activated each time to utilize the installed components, as they are encapsulated within this environment and separated from the rest of the system. After we open the notebook and make the necessary implementations. Once work within the environment is completed, it is important to deactivate the virtual environment to ensure the system returns to its normal state and to maintain the isolation of dependencies.

To interact with the .ipynb file, it is essential to first follow the process outlined above, which initializes the necessary components and activates them if they are not

already in place. And as already mentioned, it is recommended to download the thesis repository, which contains the various implementations discussed. These can be utilized by following the appropriate steps. Reviewing this document will provide a clearer understanding of the results and demonstrate how to use the different implementations, including interacting with the website developed. The thesis repository is available at Github and specifically to the https://github.com/ZamirOsmenaj/tomato-leaf-disease-detection-and-classification [45] along with a README file.

Chapter 6

Dataset Preparation for Tomato Leaf Disease Classification

Before delving into the core of our project, which involves training, validating, and testing our machine learning model, it is crucial to establish a robust dataset. This dataset serves as the foundation upon which the model will learn, generalize, and be evaluated. In this section, we will discuss the source of our dataset, the modifications we made to suit our needs, and the rationale behind these changes.

6.1 Source and Structure of the Dataset

We sourced our initial dataset from Kaggle, specifically the **Tomato Leaf Disease dataset** curated by Kaustubh B. The dataset can be accessed from Kaggle: Tomato Leaf Disease Dataset [17]. This dataset comprises images of tomato leaves, categorized into ten different classes, each representing a specific type of disease. The dataset was originally divided into two subsets: training and validation.

6.1.1 Dataset Classes Overview

The dataset includes the following ten classes of tomato leaf diseases:

1. **Bacterial spot**
2. **Early blight**
3. **Healthy**
4. **Late blight**
5. **Leaf Mold**
6. **Septoria leaf spot**
7. **Spider mites (Two-spotted spider mite)**
8. **Target Spot**
9. **Tomato Mosaic Virus**
10. **Tomato Yellow Leaf Curl Virus**

Each class contains images showing the symptoms of the respective disease on tomato leaves. However, this initial setup, while useful, lacked a dedicated testing set, which is crucial for an unbiased evaluation of our model's performance.

6.2 Creating a Comprehensive Dataset

To build a comprehensive dataset that includes training, validation, and testing sets, we performed the following steps:

- **Merging the Initial Subsets**:
  We combined the images from the initial training and validation subsets into a single dataset. This was necessary to ensure that the final splits for training, validation, and testing were balanced and representative of each class.

- **Balancing the Dataset**:
  Ensuring that each class had the same number of images was crucial for balanced learning. An imbalanced dataset could lead to a biased model that performs well on some classes but poorly on others.

- **Splitting the Dataset**:
  We split the merged dataset into three distinct subsets:

  - **Training Set (80%)**: Used to train the model. This set should be large enough to allow the model to learn the underlying patterns in the data.
  - **Validation Set (10%)**: Used to tune the model's hyperparameters and make decisions about changes in the model architecture during training. This set provides an ongoing check against overfitting and underfitting.
  - **Testing Set (10%)**: Used to evaluate the final performance of the model. This set is crucial for assessing how well the model generalizes to new, unseen data. It must be kept separate and only used once the model is fully trained to ensure an unbiased evaluation.

It's common practice to use a split like 80% of the images for training and 20% (splitted equally) for validation and testing to ensure that the model is trained on a diverse set of data and validated on enough examples to be statistically significant. This helps in developing a robust model that performs well on new, unseen images.

Another thing worth noting is that the source of the sets should ideally be as diverse and representative of the real-world application as possible. The goal is to have sets that challenges the model, providing a reliable measure of its predictive capabilities.

On Figure 6.1, all the above steps are visually represented, showcasing the process of merging the initial subsets, balancing the dataset, and splitting it into the training, validation, and testing sets, ensuring a comprehensive and balanced dataset for model development.

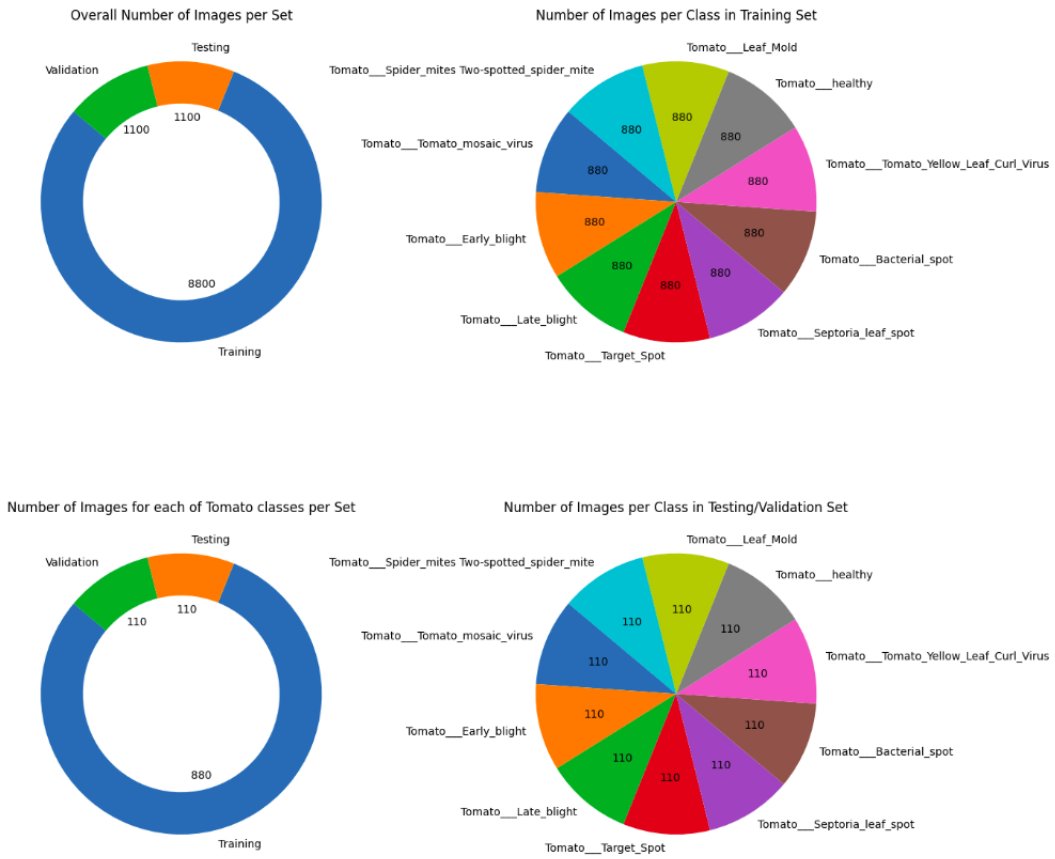

Figure 6.1: Dataset Overview: Splits and Class Distribution

6.3 Roles of Different Datasets

- **Training Set**: This is the primary dataset used to train the model. It consists of a large number of labeled images that the model uses to learn the features and patterns associated with each class. The model's parameters are adjusted based on this data to minimize the error in predictions.

- **Validation Set**: This dataset is used to evaluate the model's performance during the training process. It is separate from the training set and helps prevent overfitting by providing a check on the model's performance on unseen data. The validation set is also used to tune hyperparameters and estimate the model's performance on new data.

- **Test Set**: This dataset is used for the final evaluation of the model after it has been trained and validated. The test set is completely separate from both the training and validation sets and is only used once at the end to provide an unbiased assessment of the model's generalization performance.

Here's a simple breakdown of their roles in the process:

1. **Training Set**: Used during the training phase.

$$\text{Model Training} \rightarrow \text{Training Set}$$

2. **Validation Set**: Used to fine-tune the model and prevent overfitting.

$$\text{Model Fine-Tuning} \rightarrow \text{Validation Set}$$

3. **Test Set**: Used after the model has been trained and validated.

$$\text{Model Evaluation} \rightarrow \text{Test Set}$$

The key is to have a clear separation between these sets to prevent data leakage, which occurs when the model is inadvertently exposed to the test data during training. This separation ensures that the model's performance metrics are reliable and indicative of how it will perform on entirely new data.

Importance of Separate Test Set

It is crucial to keep the validation and test sets separate to avoid biased performance evaluations. Using the validation set as a test set is generally **not recommended** because:

- **Bias in Performance Evaluation**: The validation set is used multiple times during the training process, leading to potentially overly optimistic performance estimates if used as a test set.

- **Overfitting to the Validation Set**: The model may become optimized to perform well on the validation set, which can result in poor generalization to truly unseen data.

Therefore, a proper machine learning workflow involves keeping a separate test set, untouched during the training and validation phases, to ensure an accurate and unbiased evaluation of the model's performance.

6.4 Dataset Processing Script

We created a script, *merge_and_split_dataset.py*, to automate the process of merging and splitting the dataset. The script performs the following actions:

- Combines the images from the training and validation sets into a single dataset.
- Randomly splits the combined dataset into training, validation, and testing sets based on the specified ratios (80%-10%-10%).
- Ensures that each split maintains class balance, preventing any class from being over- or under-represented in any subset.

The script is located in the *ThesisDataset_Creation* directory and can be executed to recreate the dataset splits. The command to execute this file is:

```
$ python3 merge_and_split_dataset.py
```

Below is a small snippet of code of the **merge_and_split_dataset.py**. More details are inside the overall code in the directory we already mentioned.

```
import os
import shutil
import random

# ...

def main(input_base_dir, output_base_dir, train_ratio=0.8, test_ratio
    =0.1):
```

```
    """Main function to orchestrate the split and copying of files into train, validation, and test sets."""
    # Create the directory structure for the output
    create_directory_structure(output_base_dir)

    # Paths to the original subdirectories
    train_data_dir = os.path.join(input_base_dir, 'train')
    val_data_dir = os.path.join(input_base_dir, 'val')

    # List all subcategories (e.g., classes or types of leaves)
    subcategories = [category for category in os.listdir(val_data_dir) if os.path.isdir(os.path.join(val_data_dir, category))]

    for subcategory in subcategories:
        subcategory_train_dir = os.path.join(train_data_dir, subcategory)
        subcategory_val_dir = os.path.join(val_data_dir, subcategory)

        # Combine and shuffle files from both directories
        combined_file_list = combine_and_shuffle_files(subcategory_train_dir, subcategory_val_dir)

        if not combined_file_list:
            print(f"No files found in subdirectories for {subcategory}. Skipping...")
            continue

        # Split files into training, validation, and test sets
        train_files, val_files, test_files = split_files(combined_file_list, train_ratio, test_ratio)

        # Copy the files to the respective output directories
        copy_files_to_subfolder(train_files, os.path.join(output_base_dir, 'train'), subcategory)
        copy_files_to_subfolder(val_files, os.path.join(output_base_dir, 'val'), subcategory)
        copy_files_to_subfolder(test_files, os.path.join(output_base_dir,
```

```
        'test'), subcategory)
37
38      print("Files have been successfully copied and split into train,
        validation, and test sets.")
39
40  if __name__ == "__main__":
41      input_base_dir = 'tomato'
42      output_base_dir = '../Tomato_Leaves_Dataset'
43      main(input_base_dir, output_base_dir)
```

Listing 6.1: Script for merging and splitting datasets into training validation and test sets while maintaining class balance.

6.5 Splitting the Dataset: Rationale and Strategy

The choice of splitting the dataset into 80%-10%-10% is driven by best practices in machine learning:

- **Training Set**: A larger training set helps the model learn better and generalize from more data points.
- **Validation Set**: A sufficiently large validation set helps in fine-tuning the model without overfitting to the training data.
- **Testing Set**: An unbiased testing set is crucial for evaluating the model's performance on unseen data.

Alternative splits like 70%-15%-15% were also considered, but empirical results showed that the 80%-10%-10% split provided better performance in terms of accuracy and generalization.

6.6 Conclusion

Proper preparation of the dataset is a significant step in the machine learning pipeline. If we can manage to split the dataset well and comprehensively, then we will have

probably laid a very good foundation for effective model training and evaluation. After the preparation of the dataset, we should feel free to proceed to the creation of the model that will be involved in designing and training a neural network for accurate classification of tomato leaf diseases.

Chapter 7

Machine Learning Models

7.1 Convolutional Neural Network (CNN) Overview

Convolutional Neural Networks (CNNs) are a class of deep learning models that have proven highly effective for various tasks in computer vision. They are specifically designed to process and classify visual data, such as images and videos, by learning hierarchical features through multiple layers of convolutions and other operations. The key advantage of CNNs over traditional fully connected neural networks is their ability to capture spatial hierarchies and patterns in data, making them particularly well-suited for image classification, object detection, segmentation, and related tasks.

7.1.1 Key Applications of CNNs

CNNs have become the dominant approach for a wide range of image-related tasks, including but not limited to:

- **Image Classification**: Assigning a label to an image based on its contents (e.g., identifying a cat or dog or even more complex identifications as type of diseases affecting a plant).
- **Object Detection**: Locating and classifying objects within an image.

- **Image Segmentation**: Dividing an image into meaningful regions or objects.
- **Face Recognition**: Identifying or verifying individuals based on facial features.
- **Medical Image Analysis**: Assisting in tasks such as detecting abnormalities in X-rays or MRI scans.

7.1.2 Building a CNN for Image Classification

The process of building a CNN for image classification involves several key steps, each contributing to the overall effectiveness of the model:

1. **Data Collection**: The first step in any image classification project is gathering a large dataset of labeled images. Each image in the dataset must be annotated with the correct classification label to serve as ground truth during training.
2. **Preprocessing**: Raw images must be preprocessed to ensure that they can be effectively used by the neural network. This typically includes:
    - **Resizing**: Standardizing the dimensions of all images to a fixed size.
    - **Normalization**: Scaling pixel values to a common range (e.g., 0 to 1) to stabilize the learning process.
    - **Data Augmentation**: Applying random transformations (e.g., rotation, flipping, scaling) to artificially increase the diversity of the dataset and improve model generalization.
3. **Model Design**: The next step is designing the architecture of the neural network. Convolutional Neural Networks (CNNs) are widely adopted for image tasks due to their ability to learn spatial hierarchies from data through the use of:
    - **Convolutional Layers**: These layers apply filters to detect features such as edges, textures, or complex patterns.
    - **Pooling Layers**: Used to reduce the spatial dimensions of feature maps, maintaining important information while reducing computational complexity.

- **Fully Connected Layers**: Layers at the end of the network where the learned features are combined to make predictions.

4. **Training**: During training, the CNN learns to associate image features with their corresponding labels by iteratively adjusting the model's weights. This is achieved through the following:

   - **Backpropagation**: A technique to calculate the gradient of the loss function with respect to each weight, enabling updates.
   - **Optimization Algorithm**: Algorithms like stochastic gradient descent (SGD) or Adam are commonly used to adjust the weights during training based on the computed gradients.

5. **Evaluation**: After training, the model's performance is evaluated on a separate test set that was not used during training. Metrics such as accuracy, precision, recall, and F1-score are often used to assess the classification performance.

6. **Hyperparameter Tuning**: Fine-tuning hyperparameters such as the learning rate, batch size, number of epochs, and the number of filters in each convolutional layer is essential for optimizing model performance. Hyperparameter tuning may involve systematic searches, such as grid search or random search.

7. **Deployment**: Once the CNN model has been trained and validated, it can be deployed into production environments. The deployed model can then classify new, unseen images in real-time applications or batch processes, depending on the system's requirements.

7.1.3 Designing CNN Architectures

Building an effective CNN isn't a matter of blindly trying every possible combination of filters and layers. Instead, we use principles, experience, and some trial-and-error to guide the final design. Here are some strategies and considerations to help us design our CNN architecture more systematically:

- **Understand Your Dataset**:
  - **Size**: Larger datasets can support more complex models. For smaller datasets, simpler models help prevent overfitting.
  - **Complexity**: More diverse and complex data may require deeper models with more filters to capture intricate patterns.
- **Start with Proven Architectures**:
  - Use well-established architectures (like VGG, ResNet, Inception) as starting points. These architectures have been extensively tested and validated on large datasets.
  - Modify these architectures incrementally to suit the specific dataset and problem.
- **Incremental Design and Testing**:
  - Start with a simple model and progressively increase its complexity.
  - Monitor performance metrics (accuracy, loss, etc.) on the validation set to identify overfitting or underfitting.
- **Use Transfer Learning**:
  - Leverage pre-trained models and fine-tune them for your specific task. This can save time and computational resources while often providing excellent results.
  - Transfer learning can be particularly effective when we have limited data.
- **Parameter Tuning Guidelines**:
  - **Initial Filters**: Start with a smaller number of filters (e.g., 32 or 64) in the first convolutional layer.
  - **Filter Increase**: Double the number of filters every few layers (e.g., $32 -> 64 -> 128$) to capture more complex features.

- **Kernel Size**: Stick to smaller kernel sizes (e.g., 3x3) which are effective for most image processing tasks.
- **Pooling Layers**: Use max pooling layers after every few convolutional layers to reduce spatial dimensions and prevent overfitting.

Initial Design:

- Start with 32 filters in the first layer.
- Use 3x3 kernels for convolutions.
- Apply ReLU activation and max pooling after every convolutional block.
- Incremental Complexity: Gradually increase the number of filters to capture more complex patterns.

A typical starting point might look like this:

```
cnn = tf.keras.models.Sequential()

# First Convolutional Block
cnn.add(tf.keras.layers.Conv2D(32, (3,3), activation='relu', input_shape
    =[224, 224, 3]))
cnn.add(tf.keras.layers.MaxPooling2D(pool_size=(2, 2)))

# Second Convolutional Block
cnn.add(tf.keras.layers.Conv2D(64, (3,3), activation='relu'))
cnn.add(tf.keras.layers.MaxPooling2D(pool_size=(2, 2)))

# Third Convolutional Block
cnn.add(tf.keras.layers.Conv2D(128, (3,3), activation='relu'))
cnn.add(tf.keras.layers.MaxPooling2D(pool_size=(2, 2)))

# Fourth Convolutional Block
cnn.add(tf.keras.layers.Conv2D(256, (3,3), activation='relu'))
cnn.add(tf.keras.layers.MaxPooling2D(pool_size=(2, 2)))

```

```
19 # Flatten and Dense Layers
20 cnn.add(tf.keras.layers.Flatten())
21 cnn.add(tf.keras.layers.Dense(256, activation='relu'))
22 cnn.add(tf.keras.layers.Dense(number_of_classes, activation='softmax'))
```

Listing 7.1: Sequential CNN architecture example with multiple convolutional blocks and dense layers.

Here's a general guideline for each type of layer mentioned above:

- **Conv2D**: These are convolutional layers that extract features from the images. Start with a few layers and increase the number if the model isn't learning enough complex features.
- **MaxPool2D**: Pooling layers reduce the spatial dimensions of the output from the previous layers. They help to make the detection of features invariant to scale and orientation changes. Typically, you'll add a pooling layer after one or more convolutional layers.
- **Dropout**: This layer randomly sets a fraction of input units to 0 at each update during training, which helps prevent overfitting. The dropout rate is usually set between 0.2 and 0.5.
- **Flatten**: This layer is used to flatten the input and is usually placed before the fully connected layers after all convolutional and pooling layers.
- **Dense**: These are fully connected layers. A common practice is to increase the number of neurons in early layers and decrease in later ones, leading to the output layer. The last dense layer should have a number of neurons corresponding to the number of classes we're trying to predict.

Evaluation and Adjustment:

- Train the model on your dataset and monitor performance.
- Adjust the architecture based on validation accuracy and loss. If the model overfits, consider adding dropout layers.

7.1.4 Key Parameters and Methods

Another thing to construct an effective CNN model, it is crucial to understand its fundamental components and the preprocessing steps involved.

1. **Parameters**: These are the trainable elements within the model, such as weights and biases, that the network learns during training.

2. **Attributes**: These refer to fixed properties or characteristics of the model, such as input shapes, number of layers, and types of layers.

3. **Methods/Functions**: These are specific functions used to manipulate data and train the model, including methods like *fit*, *compile*, and various preprocessing functions.

7.1.5 Preprocessing: Data Augmentation

Preprocessing is a critical step in preparing the data for model training. The following preprocessing steps were implemented:

1. **Rescaling (rescale=1255.0)**:

    - **Rationale**: Images usually have pixel values ranging from 0 to 255. Rescaling normalizes these values to a range between 0 and 1, which helps improve the performance and convergence speed of neural networks.
    - **Implementation**: This is typically done using a Rescale layer in Keras or by manually dividing the pixel values by 255.

2. **Data Augmentation for Training Data**:

    - **Shear Range (shear_range=0.2**: Applies random shear transformations, distorting images along an axis to make the model more robust to variations.
    - **Zoom Range (zoom_range=0.2**: Randomly zooms into images, helping the model learn to handle objects of different sizes.

- **Horizontal Flip (horizontal_flip=True)**: Randomly flips images horizontally, augmenting the dataset and making the model invariant to horizontal orientation changes.

These preprocessing steps are crucial to increase the diversity of the training data and help the model generalize better to new, unseen data.

7.1.5.1 Data augmentation: Offline vs Online Augmentation

Offline Data Augmentation:

- Offline data augmentation refers to applying transformations to the dataset before training the model. These transformations create new examples by modifying existing ones. Common techniques include rotation, flipping, cropping, and adjusting brightness or contrast.

- Offline augmentation is typically performed once, during the data preprocessing phase. It helps increase the diversity of the training data, which can improve model generalization.

Online Data Augmentation:

- Online data augmentation, on the other hand, occurs during training. Instead of creating augmented copies of the entire dataset upfront, we apply random transformations to each batch of data as it's fed into the model.

- Common online augmentation techniques include random cropping, random rotation, and random flipping. These augmentations introduce variability to the model during training, making it more robust.

- Online augmentation has several advantages:

  – It reduces memory requirements because the is no need to store augmented copies of the entire dataset.

- It allows for dynamic augmentation, meaning different examples in each batch can have different transformations.
- It simulates real-world scenarios where input data can vary.

7.1.5.2 Commonly Used Data Augmentation Strategies

The choice of 20% for most of the augmentation parameters (such as width_shift_range, height_shift_range, shear_range, zoom_range, and flipping) is not arbitrary; it's based on practical considerations and empirical observations. Let's explore why this value is commonly used:

1. **Balancing Variability and Realism**:
   - Augmentation aims to introduce variability to the training data, making the model more robust.
   - Too small a range (e.g., 5% or 10%) might not provide enough diversity, limiting the model's ability to generalize.
   - Too large a range (e.g., 50% or more) could lead to overfitting, where the model memorizes augmented examples rather than learning meaningful features.
   - 20% strikes a balance: It introduces noticeable variations without extreme distortions.
2. **Empirical Observations**:
   - Researchers and practitioners have experimented with different augmentation settings across various datasets and tasks.
   - 20% emerged as a reasonable default value based on these experiments.
   - However, it's essential to fine-tune this value based on specific use case.
3. **Domain-Specific Considerations**:
   - The choice of augmentation parameters depends on the domain and the type of data we're working with.

- For natural images (e.g., photos), 20% provides a good trade-off.
- For medical images or specialized domains, we might need to adjust these values.

4. **Avoiding Extreme Distortions**:
   - Augmentation should simulate realistic variations that occur naturally.
   - Extreme transformations (e.g., rotating an image by 180 degrees or zooming by 80%) can lead to unrealistic examples.
   - Augmentations should maintain semantic integrity (e.g., a cat remains a cat even after rotation).
5. **Experimentation and Validation**:
   - Always validate the impact of augmentation on the model's performance.
   - Use techniques like cross-validation to assess how well the model generalizes.
   - Adjust the parameters based on validation results.

Remember that there's **no one-size-fits-all** solution.

7.1.5.3 FAQ about Augmentation

1. **Are augmentation techniques applied to the already defined images?**
   - Yes, in online augmentation, the defined augmentation techniques (like rotation, zooming, shearing, etc.) are applied **to the existing images in real-time, on the fly, during the training process**. The original images remain unchanged in the dataset, and new variations of these images are created as they are fed into the model. This means that **each time a batch of images is fed to the model, augmentations are applied to those images dynamically**, resulting in slightly different versions of the images being presented during each training epoch.

2. **Do we feed more images to the model because of augmentation?**

    - No, when using online augmentation, you do **not increase the number of images** fed into the model. **The batch size remains the same.** For example, if we have 8800 images and a batch size of 32, each batch will still consist of 32 images. The difference is that these 32 images may be **augmented versions** of the original images, but the total number of images per batch doesn't increase. Essentially, augmentation alters the images in each batch, but **you are manipulating the existing images rather than adding new ones.**

3. **Can augmentation techniques be used in combination, and are they applied to all images or randomly?**

    - Yes, augmentation techniques can be used in combination on the same image. For example, an image can be rotated, zoomed, and sheared all at once, depending on the augmentation pipeline you've defined. Whether **all** techniques are applied to every image or **randomly selected** is up to how the augmentation is configured.

        – In most implementations, augmentations are applied randomly based on a probability you define, meaning some images will be augmented, and others may remain unchanged. For example, you might set it up so that each augmentation technique has a certain chance (like 50%) of being applied, which means not all images will undergo the same transformations, and some might not be augmented at all during a given batch.

7.1.6 Handling Overfitting and Underfitting

- **Overfitting**: Occurs when the model performs well on the training data but poorly on unseen data. It indicates that the model has learned the training data's noise and specific details rather than general patterns.

- **Underfitting**: Happens when the model performs poorly on both training and unseen data. It suggests that the model is too simple to capture the underlying patterns in the data.

In detail description of Overfitting and Underfitting

1. **Overfitting**:
   - **Characteristics of Overfitting**:
     - The model performs exceptionally well on the training data (low training loss).
     - However, it performs poorly on unseen data (validation or test data).
     - The model has high variance, meaning it is too sensitive to small variations in the training data.
     - The decision boundary becomes too complex, fitting the noise rather than the true signal.
   - **Causes of Overfitting**:
     - Having too many model parameters (e.g., too many layers, too many neurons).
     - Using a complex model that can memorize the training data.
     - Lack of regularization (e.g., dropout, weight decay).
     - Insufficient training data.
   - **Remedies for Overfitting**:
     - Use regularization techniques (e.g., dropout, L2 regularization) to penalize large weights.
     - Collect more diverse training data.
     - Simplify the model architecture (reduce complexity).
     - Early stopping during training based on validation performance.

2. **Underfitting**:

   - **Characteristics of Underfitting**:
     - The model performs poorly on both the training data (high training loss) and unseen data (validation or test data).
     - The model has high bias, meaning it oversimplifies the problem.
     - The decision boundary is too rigid and cannot adapt well to the data.
   - **Causes of Underfitting**:
     - Using an overly simple model (e.g., linear regression for a complex problem).
     - Insufficient model capacity (too few layers or neurons).
     - Insufficient training time (not enough epochs).
   - **Remedies for Underfitting**:
     - Increase model complexity (add more layers, neurons, or features).
     - Train for more epochs.
     - Use a more expressive model (e.g., deep neural networks).
     - Ensure proper feature engineering.

In summary:

- **Overfitting** is when the model fits the training data too closely, leading to poor generalization.
- **Underfitting** is when the model is too simple and fails to capture the underlying patterns in the data.

Balancing between these two extremes is crucial for building effective machine learning models.

7.1.7 Example CNN Architecture

Designing a CNN involves several considerations, including understanding the data, reviewing related literature, and designing a robust architecture that matches the data characteristics. Here is a detailed description of the architecture design:

1. **Input Layer**:
    - **Input Shape**: *[224, 224, 3]* for images with 224x224 pixels and 3 color channels.
    - **Purpose**: Specifies the shape of input images to the model.
2. **Convolutional Layers and Max Pooling**:
    - **Conv2D Layers**: Apply convolution operations to extract features.
        - **Filters**: Number of filters increases with each layer (e.g., 32, 64) to capture more complex features.
        - **Kernel Size**: *(3, 3)* for detecting local patterns in images.
        - **Activation Function**: $ReLU$ introduces non-linearity and helps in learning complex patterns.
    - **MaxPooling2D Layers**: Down-sample feature maps, reducing dimensionality and computational load.
        - **Pool Size**: *(2, 2)* reduces each dimension by a factor of 2, helping in spatial invariance.

Example of Layer Functionality on Tomato Leaves Dataset

- **Initial Layers**: Detect simple patterns like edges or textures on leaves.
- **Intermediate Layers**: Recognize more complex features like spots, blights, or mosaic patterns.
- **Final Layers**: Combine these features for a comprehensive understanding, distinguishing between healthy and diseased leaves.

CNN Model Layers on Tomato Leaves Dataset

The following Convolutional Neural Network (CNN) architecture is used to classify various tomato leaf diseases. The CNN consists of multiple layers, with each layer learning progressively more complex features from the input images. The architecture of the CNN is illustrated in Figure 7.1, and each layer is described below.

```
import tensorflow as tf
number_of_classes = 10
cnn = tf.keras.models.Sequential()
```

First Convolutional Layer

The first convolutional layer focuses on extracting basic features like edges, shapes, and boundaries. At this stage, the model might detect edges around the tomato leaf, identifying the basic outline of the leaf, veins, or any color shifts that may indicate disease spots.

```
# First convolutional layer
cnn.add(tf.keras.layers.Conv2D(filters=32, kernel_size=(3, 3), activation
    ='relu', input_shape=[224, 224, 3]))
cnn.add(tf.keras.layers.MaxPooling2D(pool_size=(2, 2)))
```

Second Convolutional Layer

As the model progresses, it starts to identify more complex patterns. The second convolutional layer might now detect specific patterns related to diseases, such as discolored spots, mold growth, or leaf deformation. These features are more subtle and intricate compared to simple edges.

```
# Second convolutional layer
cnn.add(tf.keras.layers.Conv2D(filters=64, kernel_size=(3, 3), activation
    ='relu'))
cnn.add(tf.keras.layers.MaxPooling2D(pool_size=(2, 2)))
```

Third Convolutional Layer

By the third layer, the model becomes capable of differentiating between more specific features, such as small lesions or subtle color differences associated with distinct tomato diseases. It begins to learn specific patterns that help distinguish between different

disease classes.

```
# Third convolutional layer
cnn.add(tf.keras.layers.Conv2D(filters=64, kernel_size=(3, 3), activation
    ='relu'))
cnn.add(tf.keras.layers.MaxPooling2D(pool_size=(2, 2)))
```

Fourth Convolutional Layer

At this stage, the model can recognize textures like fungal growth or bacterial clusters, which are key indicators of certain tomato diseases. The features become increasingly more complex, allowing the model to handle disease-specific patterns effectively.

```
# Fourth convolutional layer
cnn.add(tf.keras.layers.Conv2D(filters=64, kernel_size=(3, 3), activation
    ='relu'))
cnn.add(tf.keras.layers.MaxPooling2D(pool_size=(2, 2)))
```

Fifth Convolutional Layer

The fifth convolutional layer may focus on disease-specific patterns like viral spots, leaf necrosis, or distinct fungal growth. At this point, the model has developed a clear ability to distinguish between different types of damage or disease symptoms in the leaves.

```
# Fifth convolutional layer
cnn.add(tf.keras.layers.Conv2D(filters=64, kernel_size=(3, 3), activation
    ='relu'))
cnn.add(tf.keras.layers.MaxPooling2D(pool_size=(2, 2)))
```

Sixth Convolutional Layer

By the final convolutional layer, the model is fine-tuning its recognition of highly detailed and disease-specific features, such as the exact shape, color variation of lesions, or the spread of fungal infections. It is now prepared to make precise and accurate classifications between the various diseases.

```
# Sixth convolutional layer
cnn.add(tf.keras.layers.Conv2D(filters=64, kernel_size=(3, 3), activation
    ='relu'))
cnn.add(tf.keras.layers.MaxPooling2D(pool_size=(2, 2)))
```

Flattening and Dense Layers

After extracting features through convolutional layers, the model flattens the output and passes it to dense (fully connected) layers. The dense layers allow the model to make sense of the extracted features and classify the images into their respective categories.

```
# Flattening and dense layers
cnn.add(tf.keras.layers.Flatten())
cnn.add(tf.keras.layers.Dense(units=64, activation='relu'))

# Output layer
cnn.add(tf.keras.layers.Dense(units=number_of_classes, activation='
    softmax'))
```

The dense layers, especially the final output layer, allow the model to classify the tomato leaves into 10 different classes, each representing a specific disease or condition. The architecture of the CNN, as shown in Figure 7.1, plays a vital role in processing the visual patterns and making accurate predictions for tomato leaf disease classification.

7.1.8 Key Takeaways

7.1.8.1 Explanation of Filter Usage in CNN Architecture

The choice of filters in each layer of a CNN architecture is critical to the model's performance. We confidently examined two scenarios: maintaining a constant number of filters and progressively increasing the number of filters with depth.

1. **Keeping Filters Constant at 64**:

    - **Simplicity and Computational Efficiency**: This approach simplifies the architecture and reduces the number of parameters, making it well-suited for smaller datasets. It is computationally efficient, leading to faster training without sacrificing performance.
    - **Sufficient Feature Extraction**: Using 64 filters is sufficient for effectively distinguishing between 10 classes (9 disease categories and 1 healthy category) in datasets with moderate complexity.

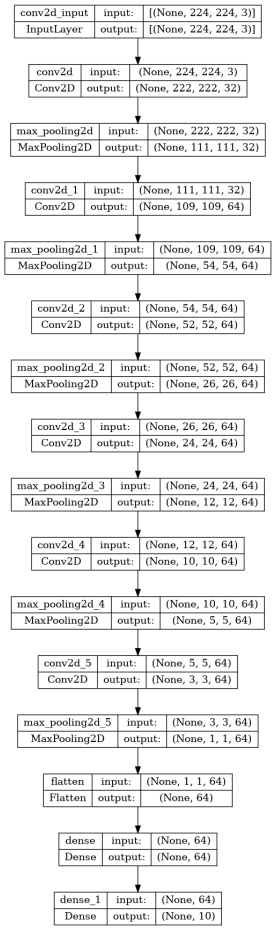

Figure 7.1: CNN Architecture.

2. **Increasing Filters with Depth**:

   - **Handling Complexity and Large Datasets**: For larger, more complex datasets, increasing the number of filters is essential to capture detailed and intricate patterns across layers.
   - **Feature Hierarchy**:
     - **Early Layers**: Capture basic features with fewer filters (e.g., 32).
     - **Middle Layers**: Capture more complex patterns with more filters (e.g., 64, 128).
     - **Deeper Layers**: Capture high-level features with even more filters (e.g., 256, 512).

7.1.8.2 Comparing Different Scenarios

- **Tomato Leaves Dataset (10,000+ images)**: A simpler dataset might perform well with a constant number of 64 filters.
- **Multi-Plant Dataset (72,000+ images)**: A more complex dataset requires a robust model with increasing filters for detailed feature extraction.

7.1.8.3 Key Takeaways

- **Dataset Size and Complexity**: Larger, complex datasets require deeper models with progressively increasing filters for improved feature extraction and performance.
- **Model Efficiency**: Smaller datasets benefit from simpler models with constant filters, striking the right balance between computational efficiency and accuracy.
- **Experimentation**: Finding the optimal configuration of filters is crucial and depends on the dataset's size and complexity.

7.1.9 Conclusion

Designing the CNN architecture according to the dataset's size and complexity is essential. Constant filters work effectively for smaller, simpler datasets, while larger, more complex datasets benefit significantly from increasing filters with depth to achieve optimal performance.

7.2 Transfer Learning with Pre-Trained Models)

7.2.1 General Overview

Transfer learning is a powerful technique in machine learning where a model trained on one task is re-purposed to improve performance on a related task. Let's break it down:

1. **What is Transfer Learning?**

   - Transfer learning involves taking a pre-trained model (usually developed for a specific task) and using it as a starting point for a different task.
   - Instead of training a neural network from scratch, we leverage the knowledge already captured by the pre-trained model.
   - This approach is particularly popular in deep learning due to the significant computational resources required for training deep neural networks.

2. **How Does Transfer Learning Work?**

   - Here's the basic process:
     - First, we train a base neural network (often called the base model) on a large dataset and a specific task (e.g., image classification).
     - Next, we repurpose the learned features (or transfer them) from the base model to a second neural network (the target model).
     - The target model is then fine-tuned on a smaller dataset related to a different task (e.g., a specific type of image classification).
   - The idea is that the features learned by the base model are general enough to be useful for both the original task and the new task.

3. **Why Use Transfer Learning?**

   - Transfer learning offers several benefits:
     - **Speed**: It accelerates training because we start with pre-trained weights.
     - **Performance**: Pre-trained models often capture useful features, leading to better performance on related tasks.
     - **Data Efficiency**: When we have limited data for the target task, transfer learning helps by leveraging knowledge from the base task.
     - **Resource Savings**: Training deep neural networks from scratch can be computationally expensive; transfer learning mitigates this.

4. **Examples of Transfer Learning**:
    - In computer vision:
        - We might use a pre-trained model (like VGG16 or ResNet) trained on ImageNet for a new image classification task.
        - Fine-tune it on your specific dataset (e.g., classifying dog breeds).
    - In natural language processing (NLP):
        - Pre-trained language models (such as BERT or GPT) can be fine-tuned for sentiment analysis, question answering, or other NLP tasks.

Keep in mind that this would be an appropriate case of transfer learning, where the feature learnings from the base model are general and applicable to both the original and target tasks. That will be a very powerful way to improve performance while saving time and resources!

Description and Fine-Tuning

Pre-trained models like VGG16 and VGG19, which are trained on the ImageNet dataset, are well-known for their powerful feature extraction capabilities. Fine-tuning these models involves adapting them to a new dataset, which can be achieved by adding layers, freezing some layers, or both.

1. **VGG16 and VGG19**: Pre-trained on the ImageNet dataset, known for their deep architectures and feature extraction capabilities.
2. **Fine-Tuning**: Adjusting a pre-trained model to a new dataset by adding new layers or/and retraining some of the existing layers.

Why Fine-Tuning

- **General Practice**: Fine-tuning the last few layers helps the model adapt its learned features to the new dataset while retaining the powerful features learned from the original dataset.

- **Benefit**: Helps the model learn specific features of the new dataset while leveraging pre-trained features from a large dataset like ImageNet.

7.2.2 Transfer Learning with Fine-Tuned VGG Architectures

In this work, we employed transfer learning techniques using pre-trained models to classify tomato leaf diseases. Specifically, we utilized the VGG16 and VGG19 architectures, which were fine-tuned for this task. Both architectures were pre-trained on the ImageNet dataset and then adapted to the tomato leaf dataset.

The choice of using VGG16 and VGG19 was driven by their established success in image classification tasks. Although the two architectures differ slightly in depth (VGG16 has 16 layers while VGG19 has 19), the overall approach of fine-tuning the models remains consistent. By freezing the pre-trained layers and adding new fully connected layers, we aimed to retain the general feature-extraction capabilities of the VGG models while allowing the network to specialize in tomato leaf disease classification.

The VGG models were adapted as follows:

1. We loaded the pre-trained VGG16 and VGG19 models, excluding their top (fully connected) layers.
2. The layers of the base models were frozen to retain the pre-trained weights.
3. New classification layers were added on top of the base model, including fully connected layers, dropout for regularization, and the final output layer for classification.

This fine-tuning approach allowed the model to focus on the disease-specific patterns within the tomato leaves, without losing the robustness of the pre-trained model's general feature extraction. The same architecture and methodology were applied to both the VGG16 and VGG19 models, ensuring consistency in our experimentation and evaluation.

Below is the code that illustrates this process for the VGG16 model, followed by a side-by-side comparison of the VGG16 and VGG19 architectures.

```
from tensorflow.keras.applications import VGG16

number_of_classes = 10

# Load the VGG16 model, excluding the top layers
base_model = VGG16(weights='imagenet', include_top=False, input_shape
    =(224, 224, 3))

# Freeze the base model layers
for layer in base_model.layers:
    layer.trainable = False

# Add new classification layers
model = tf.keras.Sequential([
    base_model,
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(512, activation='relu'),
    tf.keras.layers.Dropout(0.2),
    tf.keras.layers.Dense(256, activation='relu'),
    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.Dense(32, activation='relu'),
    tf.keras.layers.Dense(number_of_classes, activation='softmax')
])
```

Listing 7.2: Transfer learning using pre-trained VGG16 model with additional classification layers.

7.2.2.1 Overview of the Architecture

- **Base Model (VGG16/VGG19)**: The base VGG models (16 or 19 layers) provide robust feature extraction, learning from the general features of the input images, such as edges, textures, and simple patterns.
- **New Fully Connected Layers**: These layers enable the model to focus on

tomato leaf disease classification. They progressively reduce dimensionality and specialize the model by learning more complex features and patterns specific to the tomato leaves.

- **Dropout Layer**: A dropout layer with a 20% dropout rate is added to prevent overfitting and improve the model's generalization capabilities by randomly turning off neurons during training.

- **Output Layer**: The final dense layer uses a softmax activation function to classify the tomato leaves into 10 different classes, corresponding to various diseases.

7.2.2.2 VGG16 and VGG19 Architectures

Figure 7.2 shows the architectural comparison between VGG16 and VGG19. Although VGG19 has additional convolutional layers, both models are structured similarly in terms of feature extraction and classification. The main difference lies in the number of convolutional layers, which might provide VGG19 with a slight edge in capturing more complex features, though this also increases computational complexity.
The application of the same architecture in both VGG16 and VGG19 models ensures consistency in training and evaluation while allowing us to explore the effects of varying network depth on model performance. We will further discuss the results and motivations for using these architectures in later sections.

7.2.3 Explanation of Fine-Tuning

Purpose: Freezing the initial layers of the pre-trained model allows the model to retain the powerful feature extraction capabilities while adapting to new tasks with the added layers.
Why Not Freeze All Layers?:

- **General Practice**: Fine-tuning the last few layers helps adapt higher-level features more specific to the original dataset (ImageNet) to the new dataset (tomato leaves).

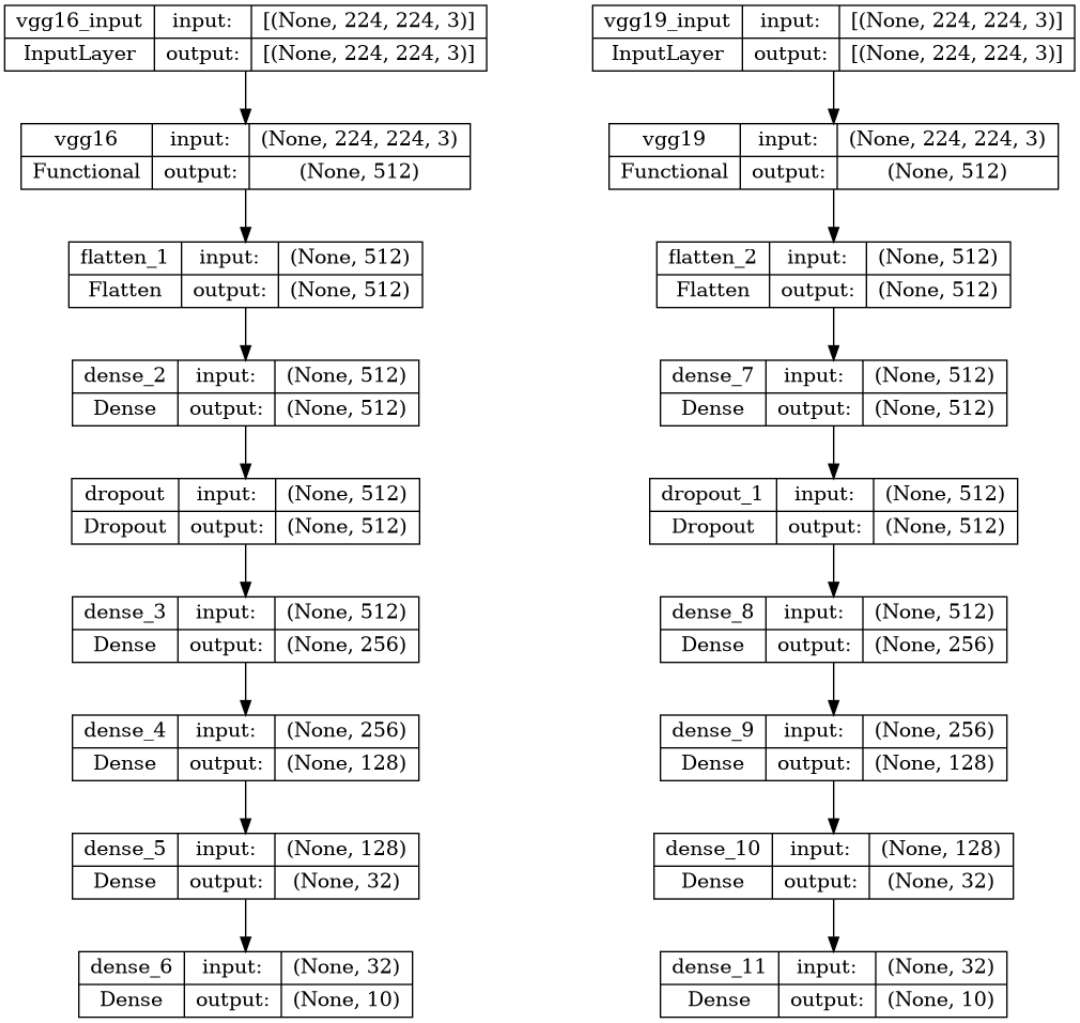

Figure 7.2: Comparison of VGG16 (left) and VGG19 (right) architectures fine-tuned for tomato leaf disease classification.

Selection of Values:

- **Dense Layer Units**: Typically start with a large number of units and decrease gradually to the number of classes.
- **Dropout Rate**: Adds regularization to prevent overfitting.

7.3 Model Compilation and Parameters

Once the architecture is defined, the model needs to be compiled with appropriate settings. The following steps are taken to compile the model:

```
cnn.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['
    accuracy'])
# Early stopping callback
from tensorflow.keras.callbacks import EarlyStopping

early_stopping = EarlyStopping(monitor='val_accuracy',
                               patience=20,
                               mode='max',
                               verbose = 1,
                               restore_best_weights=True)
# Train the model
history = cnn.fit(training_set, validation_data=validation_set, epochs
    =50, callbacks=[early_stopping])
```

Listing 7.3: Model compilation and training with early stopping callback for better convergence.

Explanation of Parameters

1. **Optimizer**: Adam optimizer is used for its efficiency and adaptability.
2. **Loss Function**: *categorical_crossentropy* is used for multi-class classification problems.
3. **Metrics**: *accuracy* is monitored during training to evaluate performance.

Early Stopping: Prevents overfitting by stopping the training process if the validation accuracy does not improve after a certain number of epochs (patience=20). This ensures that the best model weights are restored.

7.4 Visualizing Training and Validation Accuracy

Visualizing training and validation accuracy helps in understanding the model's learning process and identifying trends like overfitting or underfitting.

```
import matplotlib.pyplot as plt
# Plot training & validation accuracy values
plt.figure(figsize=[8,6])
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Model Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(['Train', 'Validation'], loc='best')
plt.show()
```

Listing 7.4: Visualization of training and validation accuracy across epochs.

7.5 Key Training Concepts and Parameters in Neural Network Training

1. **Optimizer**:
   - **What is an optimizer?**
     - An optimizer is an algorithm that adjusts the weights of a neural network to minimize the loss function during training. It updates the weights based on the gradients calculated during backpropagation.
     - In our case, we're using *tf.keras.optimizers.legacy.Adam(learning_rate=0.001)*, which initializes the Adam optimizer with a learning rate of 0.001.
     - The **Adam optimizer** is particularly effective for image classification tasks because it dynamically adjusts the learning rate for each parameter, leading to efficient updates and faster convergence.
2. **Monitoring Validation Accuracy**:
   - **Why monitor validation accuracy?**
     - Validation accuracy reflects how well the model generalizes to new, unseen data, providing a critical measure of the model's performance be-

yond the training set.

- By tracking this metric during training (*monitor='val_accuracy'*), we can ensure the model is not just memorizing the training data but is also capable of making accurate predictions on new data.

3. **Mode='max' in Early Stopping**:

   - **How does *mode='max'* work?**
     - When using *mode='max'*, training halts when the monitored metric, such as validation accuracy, ceases to improve.
     - For example, if validation accuracy increases consistently across epochs but then levels off or starts to decline, early stopping will trigger after a defined number of epochs without improvement (*patience*), preventing overfitting.

4. **The Role of Weights in the Model**:

   - **Purpose and significance of weights:**
     - Weights are the parameters in a neural network that are adjusted during training to minimize the loss function. They define the strength of connections between neurons and encapsulate the learned knowledge of the model.
     - By setting *restore_best_weights=True*, we ensure that if early stopping is activated, the model reverts to the weights configuration where the validation accuracy was highest, thus preserving the best-performing model.

5. **The Concept of Epochs**:

   - **What is an epoch?**
     - An epoch represents one complete pass through the entire training dataset. During an epoch, the model processes each training sample once.

- Training over multiple epochs allows the model to iteratively refine its predictions by adjusting the weights based on gradients computed from multiple passes through the data.

6. **Understanding Steps per Epoch**:

   - **What are steps per epoch?**
     - *steps_per_epoch* determines the number of batches processed during one epoch of training. It's calculated as the total number of samples divided by the batch size.
     - For instance, with *8800/32*, there are 275 batches per epoch, where each batch contains 32 samples.

7. **Validation Steps Explained**:

   - **What are validation steps?**
     - *validation_steps* specifies the number of batches to be processed from the validation dataset at the end of each epoch. Similar to *steps_per_epoch*, it ensures that validation accuracy is calculated over the entire validation dataset, divided into manageable batches.

8. **Batch size and Samples**:

   In the context of training, validation, and testing for a deep learning model, the terms batch size and samples refer to specific aspects of how data is processed. Let's break down what each term means, especially in the context of your dataset:

   (a) **Batch Size**:

   - **Batch size** refers to the number of images (or samples) that the model processes before updating its weights during training.
   - Instead of processing all the images at once (which would be computationally expensive), the model divides the dataset into smaller groups or **batches**. After each batch, the model performs a weight update based on the error (loss) computed for that batch.

- For example, if your **batch size** is set to 32, the model processes 32 images at a time, computes the loss and gradients, and updates the model's weights accordingly.
- This applies to all three sets: training, validation, and testing, but typically, batch size is most relevant for the **training** phase. During **validation** and **testing**, it helps with memory management and ensures that the model processes data in manageable chunks.
- **Smaller batch sizes** tend to provide a more stable training process, while **larger batch sizes** can speed up the training but may require more memory.

(b) **Samples**:

- **Samples** refers to the total number of images (or data points) in the dataset or a specific subset of the dataset (training, validation, or testing).
- In our case:
  - The **training set** contains **8,800 samples**, divided into 10 classes, with each class having 880 images.
  - The **validation set** contains **1,100 samples**, with 110 images per class.
  - The **testing set** contains **1,100 samples**, also with 110 images per class.
- Each **sample** is a single image that belongs to one of the 10 classes.

(c) **How Batch Size and Samples Are Related**:

- During training, the model processes the dataset in **batches**. For example, if the **batch size** is 32, the training process will divide the **8,800 samples** in the training set into batches of 32 images each.
  - The number of batches per epoch (one complete pass through the

training data) is computed as:

$$\text{steps\_per\_epoch} = \frac{\text{samples}}{\text{batch\_size}} = \frac{8800}{32} \approx 275 \text{ steps/updates per epoch}$$

– For the **validation** and **testing** sets, the concept is similar, but here, **batch size** mainly helps divide the **1,100 samples** into manageable parts during evaluation:

$$\text{validation\_steps} = \frac{1100}{32} \approx 35 \text{ steps during validation/testing}$$

(d) **Summary**:

- **Samples**: Total number of images in a dataset (e.g., 8,800 in training, 1,100 in validation, 1,100 in testing).
- **Batch size**: Number of images processed at a time during training or evaluation (e.g., 32 images per batch). The model's weights are updated after processing each batch.

Conclusion

This section henceforth elucidates the key concepts and parameters involved in the training of the CNN models, followed by a short context for some of the key terms relating to tomato leaf classification. The idea is for the reader to understand why each of these parameters has been set and how they result in the overall training.

7.6 Conclusion

- **Monitoring**: Regularly monitor training and validation performance.
- **Early Stopping**: Prevent overfitting and retain the best model configuration.
- **Visualization**: Aid in understanding and improving model performance.

By implementing this detailed methodology, a robust model for image classification can be developed, trained, and evaluated, ensuring it performs well on unseen data.

Chapter 8

Model Evaluation and Metrics

8.1 Core Metrics: Loss, Accuracy, Precision, Recall, F1-score

8.1.1 Understanding the Evaluation Framework

These conclusions are important before delving into the results and making final conclusions, and this requires an understanding of what benchmarks and evaluation metrics were used. The metrics form a basis upon which the effectiveness of the model was measured; hence, making proper understanding of them forms the basis for drawing correct implications from the results.

The primary metrics utilized during model training include Loss, Accuracy, Validation Loss, and Validation Accuracy. These metrics are universally recognized and provide an initial indication of a model's performance. Let's explore each of these in detail:

- **Loss**:
  - **Definition**: Loss is a measure of the error in the model's predictions. It quantifies the difference between the predicted output of the model and the actual target values.

  - **Purpose**: During training, the model attempts to minimize this loss, which means it is trying to make predictions that are as close as possible to the actual outputs.
  - **Interpretation**: A lower loss value indicates that the model is making more accurate predictions. However, while low loss is desirable, it does not always guarantee good performance, especially if the model overfits the training data.

- **Accuracy**:
  - **Definition**: Accuracy is the ratio of correctly predicted instances to the total number of instances. It provides a straightforward measure of how often the model makes correct predictions.
  - **Purpose**: Accuracy is an intuitive metric, often used as a primary performance indicator in classification tasks.
  - **Interpretation**: High accuracy suggests that the model is correctly predicting the majority of cases. However, it is important to consider the balance of classes; in imbalanced datasets, accuracy can be misleading, as it may reflect a bias toward the majority class.

- **Validation Loss**:
  - **Definition**: Validation Loss is the loss computed on a separate validation dataset that the model has not been trained on. It serves as a proxy for evaluating the model's performance on unseen data.
  - **Purpose**: By monitoring validation loss, we can gauge how well the model generalizes beyond the training data.
  - **Interpretation**: Ideally, validation loss should decrease along with training loss. If validation loss starts increasing while training loss continues to decrease, it is a sign that the model may be overfitting, learning the training data too well while failing to generalize.

- **Validation Accuracy**:
  - **Definition**: Validation Accuracy is the accuracy measured on the validation dataset. It shows how well the model performs on data that was not seen during training.
  - **Purpose**: This metric helps in assessing the model's ability to generalize. Like validation loss, it provides insights into potential overfitting.
  - **Interpretation**: Consistent validation accuracy with training accuracy indicates good generalization. A significant drop in validation accuracy compared to training accuracy is another indicator of overfitting.

While these metrics give a good starting point to estimate the performance of a model, they are not enough to tell the whole story. Loss and accuracy are especially limited and sometimes misleading. Further evaluation with a test set composed of completely unseen data is required to correctly judge how well the model has learned.

8.1.2 Loss VS Accuracy

To avoid confusion between the concepts of loss and accuracy, it's important to clarify their differences before discussing other metrics. These two metrics are often the first indicators we encounter and are commonly used as initial signs of a model's performance. However, it's crucial to understand that loss and accuracy are not complementary—they do not complement each other, nor are they inversely related.

The confusion arises because one might mistakenly assume that loss represents the proportion of errors made by the model and accuracy represents the proportion of correct predictions. For instance, if a model shows a loss of 0.25 and an accuracy of 0.93, one might wrongly expect their sum to equal 1. This misconception stems from a misunderstanding of what these metrics actually represent.

The key point to grasp is that **accuracy** and **loss** are two distinct metrics, each measuring different aspects of a model's performance. They are calculated independently, and their values do not sum to one. Understanding how each metric is derived and what it signifies is crucial for accurately interpreting model performance.

8.1.2.1 Accuracy

Definition: Accuracy measures the proportion of correctly classified instances among the total instances.

Calculation:

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}$$

8.1.2.2 Loss

Definition: Loss (or cost) is a measure of how well (or poorly) the model's predictions match the true labels. It is typically derived from a loss function that quantifies the error between predicted and true values.

Calculation: Loss is calculated using a specific loss function, such as cross-entropy loss for classification tasks. The cross-entropy loss for a single instance is given by:

$$\text{Loss} = -\sum_{i=1}^{N} y_i \log(p_i)$$

where:

- N is the number of classes,
- y_i is the true label (1 for the correct class, 0 for the others),
- p_i is the predicted probability for class i.

The total loss for a dataset is the average of the individual losses across all instances.

8.1.2.3 Relationship Between Accuracy and Loss

1. **Different Metrics**:
    - **Accuracy** simply counts the number of correct predictions.
    - **Loss** measures the magnitude of prediction errors and provides a more nuanced view of the model's performance.
2. **Nature of Calculation**:

- Accuracy is a discrete measure (correct/incorrect).
- Loss is a continuous measure, capturing how confident or wrong the predictions are.

3. **Interpretation**:
   - High accuracy indicates a high number of correct predictions.
   - Low loss indicates that the model's predictions are close to the true labels.
4. **Not Inversely Related**:
   - A model can have high accuracy but still have a significant loss if the correct predictions are not very confident.
   - Conversely, a model can have low loss but not necessarily high accuracy if it gets many predictions nearly correct.

8.1.2.4 Spoiler Alert for our Results

- **Training Accuracy: 0.9943181872367859**: Indicates that about 99.05% of the training instances are correctly classified.
- **Training Loss: 0.017940353602170944**: Indicates a small average error in the predictions on the training set.
- **Testing Accuracy: 0.9599999785423279**: Indicates that about 94.82% of the testing instances are correctly classified.
- **Testing Loss: 0.1253877580165863**: Indicates a moderate average error in the predictions on the testing set.

8.1.2.5 Summary

Accuracy and loss provide complementary information about the model's performance. High accuracy means the model is making a large number of correct predictions, while low loss means the model's predictions are close to the true labels. They do not sum

to one, as they are not inverse metrics of each other. Loss can provide more detailed insight into how well the model performs, especially when dealing with confidence in predictions.

8.1.3 Test Set Evaluation: Ensuring Model Generalization

Once a model has shown promising results on the training and validation datasets, the next crucial step is to evaluate its performance on a test set. The test set is composed of data that was not used during either the training or validation phases, making it an ideal candidate for assessing the model's generalization capabilities.

If the model performs well on the test set, with high accuracy and low loss, it suggests that the model has learned effectively and can make accurate predictions on new data. Conversely, if there is a significant drop in performance on the test set compared to the training and validation sets, it may indicate that the model has overfitted the training data. Overfitting occurs when the model memorizes the training data rather than learning generalizable patterns, leading to poor performance on new, unseen data.

8.1.4 Advanced Metrics: Precision, Recall, and F1-Score

While accuracy and loss are useful, they are not always sufficient, especially in scenarios involving imbalanced datasets or when the costs of different types of errors vary. To gain a more nuanced understanding of model performance, we turn to additional metrics: Precision, Recall, and F1-Score.

- **Precision**:
  - **Definition**: Precision is the ratio of true positive predictions to the total number of positive predictions made by the model (true positives + false positives).

$$\text{Precision} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Positives (FP)}}$$

  - **Purpose**: Precision answers the question, "Of all the instances that the model predicted as positive, how many were actually positive?"
  - **Interpretation**: High precision indicates that the model makes very few false positive errors, which is critical in applications where the cost of false positives is high, such as in medical diagnostics.

- **Recall**:
  - **Definition**: Recall (or Sensitivity) is the ratio of true positive predictions to the total number of actual positives (true positives + false negatives).

$$\text{Recall} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Negatives (FN)}}$$

  - **Purpose**: Recall answers the question, "Of all the actual positive instances, how many did the model correctly identify?"
  - **Interpretation**: High recall indicates that the model is good at identifying all positive instances, which is crucial in scenarios where missing a positive instance has severe consequences.

- **F1-Score**:
  - **Definition**: The F1-Score is the harmonic mean of precision and recall. It provides a single metric that balances the trade-off between precision and recall.

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

  - **Purpose**: The F1-Score is particularly useful when we need to strike a balance between precision and recall and when the class distribution is imbalanced.
  - **Interpretation**: A high F1-Score indicates that the model has a good balance between precision and recall, making it a robust metric for overall performance evaluation.

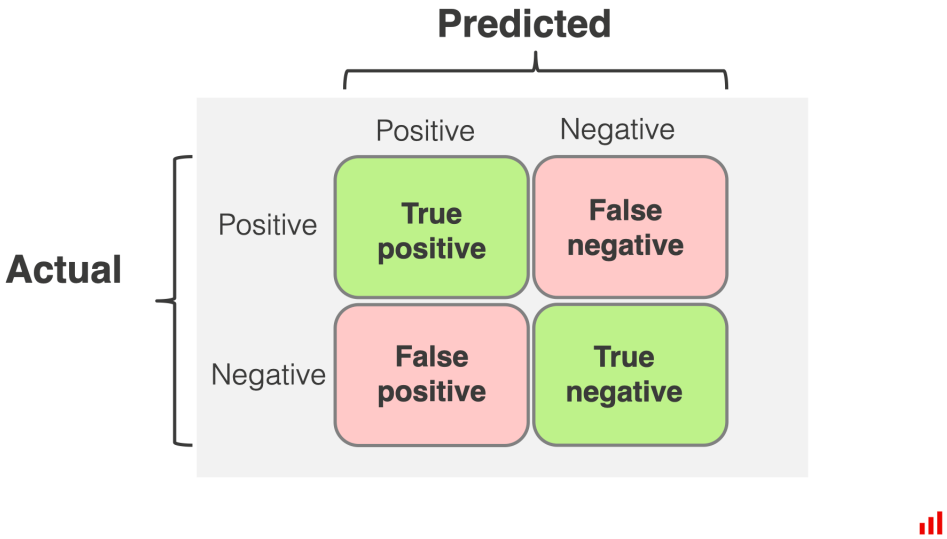

Figure 8.1: Confusion Matrix

8.1.5 Confusion Matrix and Its Importance

A **confusion matrix** as shown and on Figure 8.1 is a table used to evaluate the performance of a classification model. It provides insight into not just the accuracy, but also what types of errors are being made. The table consists of four main components:

1. **True Positive (TP)**: The model correctly predicts a positive class.
    - **Example**: The model correctly identifies a tomato leaf with *bacterial spot* as *bacterial spot*.
2. **True Negative (TN)**: The model correctly predicts a negative class.
    - **Example**: The model correctly identifies a healthy tomato leaf as healthy.
3. **False Positive (FP)** (Type I Error): The model incorrectly predicts a positive class when it should be negative.
    - **Example**: The model incorrectly identifies a healthy tomato leaf as having *leaf mold*.
4. **False Negative (FN)** (Type II Error): The model incorrectly predicts a negative class when it should be positive.

- **Example**: The model fails to identify a tomato leaf with *early blight* and instead predicts it as healthy.

8.1.6 Example with Tomato Leaf Disease Classification

Assume a scenario where the CNN model is trained to classify tomato leaf images into four categories: *Bacterial Spot*, *Early Blight*, *Leaf Mold*, and *Healthy*. Table 8.1 shows how the confusion matrix might look for a small set of predictions:

Actual/Predicted	Bacterial Spot	Early Blight	Leaf Mold	Healthy
Bacterial Spot	**TP** = 45	FN = 3	FN = 1	FN = 1
Early Blight	FP = 2	**TP** = 50	FN = 4	FN = 2
Leaf Mold	FP = 1	FP = 3	**TP** = 48	FN = 4
Healthy	FP = 1	FP = 2	FP = 3	**TN** = 54

Table 8.1: Confusion Matrix for the Classification Model

Interpretation:

- **True Positives (TP)**: Correct predictions where the actual class matches the predicted class.
- **False Positives (FP)**: Incorrect predictions where a different class was predicted.
- **False Negatives (FN)**: Incorrect predictions where a class was not identified correctly.
- **True Negatives (TN)**: Correctly identified as not belonging to a specific class (found in the "Healthy" row here).

These metrics and confusion matrix -which we will discuss later- components are essential for evaluating and improving the performance of the CNN model in accurately diagnosing tomato leaf diseases.

8.1.7 Aggregate Metrics: Macro and Weighted Average

In multi-class classification problems, it's often useful to compute aggregate metrics that provide a summary view of performance across all classes. Two such metrics are the Macro Average and Weighted Average.

- **Macro Average**:
  - **Definition**: Macro Average calculates the metric (e.g., Precision, Recall, F1-Score) independently for each class and then takes the average, treating all classes equally.

$$\text{Macro Average} = \frac{1}{n} \sum_{i=1}^{n} \text{Metric}_i$$

    where n is the number of classes, and Metric_i is the value of the metric (e.g., Precision, Recall, F1-Score) for class i.
  - **Purpose**: Macro Average is used when we want to assess the model's performance across all classes without considering class imbalance.
  - **Interpretation**: While it provides an overall picture, Macro Average can be misleading if the dataset is imbalanced, as it gives equal weight to all classes regardless of their frequency.

- **Weighted Average**:
  - **Definition**: Weighted Average calculates the metric for each class and then averages them, but it weights each class by its proportion in the dataset.

$$\text{Weighted Average} = \frac{\sum_{i=1}^{n} \text{Metric}_i \times \text{Support}_i}{\sum_{i=1}^{n} \text{Support}_i}$$

    where Support_i is the number of true instances for class i.
  - **Purpose**: This metric is particularly useful in imbalanced datasets, as it takes into account the varying sizes of each class.

– **Interpretation**: Weighted Average provides a more realistic measure of overall performance, especially in scenarios where some classes are under-represented.

8.1.8 Confidence

Another metric which is worth noting is **confidence**. We are going to see many references to this term later on our analysis, so it would be a good practice describing and understanding it. Confidence refers to the probability or certainty that a model assigns to its prediction for a particular class. Specifically, when a model classifies an image, it typically outputs a set of probabilities, one for each possible class. The confidence score for the predicted class is the highest of these probabilities, indicating how certain the model is that the image belongs to that class.

For example, if a model predicts that an image of a tomato leaf is 90% likely to be classified as "bacterial spot," the confidence in this prediction is 0.90 (or 90%). This means the model is quite certain that the image belongs to the "bacterial spot" class, as opposed to other possible classes like "early blight" or "leaf mold."

Confidence is a measure of the model's certainty but is not directly related to other metrics like precision, recall, or F1-score. Those metrics evaluate the performance of the model over multiple predictions, considering both true positives and errors, while confidence is associated with individual predictions. However, high confidence does not necessarily mean the prediction is correct; it's just a measure of the model's belief in its prediction.

8.1.9 Conclusion

Thus, using all these metrics jointly, such as Loss, Accuracy, Validation Loss, Validation Accuracy, Precision, Recall, F1-Score, Macro Average, and Weighted Average, we get an overall view of how much a model has learned and how it will perform on data that it hasn't seen. Together, all these metrics give enough insight into strengths and weaknesses to assess the model and guide further optimization efforts to improve

performance.

8.2 Classification Reports and Confusion Matrix Analysis

8.2.1 CNN Model Analysis

8.2.1.1 Detailed Analysis of the Classification Report

The classification report generated from the Convolutional Neural Network (CNN) model on the Figure 8.2 provides a wealth of information about the model's ability to classify various diseases found on tomato leaves, as well as to correctly identify healthy leaves. By analyzing key metrics such as precision, recall, and F1-score, we can assess the model's strengths and pinpoint areas that may require further attention. Below is a more detailed examination of these metrics and what they reveal about the model's performance.

	precision	recall	f1-score	support
Tomato___Bacterial_spot	0.95	0.94	0.94	110
Tomato___Early_blight	0.87	0.94	0.90	110
Tomato___Late_blight	0.96	0.92	0.94	110
Tomato___Leaf_Mold	0.99	0.98	0.99	110
Tomato___Septoria_leaf_spot	0.95	0.95	0.95	110
Tomato___Spider_mites Two-spotted_spider_mite	0.98	0.96	0.97	110
Tomato___Target_Spot	0.94	0.96	0.95	110
Tomato___Tomato_Yellow_Leaf_Curl_Virus	0.99	0.95	0.97	110
Tomato___Tomato_mosaic_virus	0.97	1.00	0.99	110
Tomato___healthy	0.99	1.00	1.00	110
accuracy			0.96	1100
macro avg	0.96	0.96	0.96	1100
weighted avg	0.96	0.96	0.96	1100

Figure 8.2: CNN Model: Classification Report

1. **Precision**:

   - **Definition and Importance**: Precision is defined as the ratio of correctly predicted positive observations to the total predicted positives. It is a critical metric in cases where the cost of false positives is high. In the context

of disease detection, a false positive could lead to unnecessary treatments, wasting resources, or even harming healthy plants.

- **Observations**:
  - **High Precision Across Most Classes**: The precision scores for the majority of the disease classes are notably high, with several diseases (e.g., **Tomato_Yellow_Leaf_Curl_Virus** and **Tomato_mosaic_virus**) achieving a perfect precision score of 1.00. This means that when the model predicts these diseases, it is always correct, which is a highly desirable outcome.
  - **Lower Precision for Tomato_Early_blight**: The precision for **Tomato_Early_blight** is 0.86, which, while still respectable, indicates that approximately 14% of the time, the model might incorrectly label a non-Early_blight leaf as Early_blight. This suggests that there may be some overlap or confusion between Early_blight and other diseases in the dataset, possibly due to similar visual characteristics.

2. **Recall**:

- **Definition and Importance**: Recall is the ratio of correctly predicted positive observations to all actual positives in the dataset. In simpler terms, it measures the ability of the model to find all relevant cases within a dataset. In disease detection, high recall is crucial because missing an actual case of disease (false negative) could lead to the disease spreading unchecked.
- **Observations**:
  - **Excellent Recall for Most Diseases**: Most diseases, such as **Tomato_Septoria_leaf_spot** (recall of 0.97) and **Tomato_healthy** (recall of 1.00), show very high recall values. This indicates that the model is very effective at identifying almost all true cases of these diseases when they are present.
  - **Slightly Lower Recall for Spider_mites**: The recall for **Tomato_Spider_mites_Two-spotted_spider_mite** is 0.93, suggest-

ing that in about 7% of the cases, the model failed to detect this disease when it was actually present. This might be due to the subtle nature of the visual symptoms of Spider_mites compared to other more visually distinct diseases.

3. **F1-Score**:

   - **Definition and Importance**: The F1-score is the harmonic mean of precision and recall, providing a single metric that balances the trade-off between precision and recall. This is particularly useful when we need to have a balanced approach, where neither false positives nor false negatives are overwhelmingly more important than the other.
   - **Observations**:
     - **High F1-Scores Indicate Balanced Performance**: The F1-scores across all categories are high, with several classes like **Tomato_Yellow_Leaf_Curl_Virus** and **Tomato_healthy** achieving a perfect score of 1.00. This suggests that the model is performing well in both identifying the diseases and minimizing false positives.
     - **Lower F1-Score for Tomato_Early_blight**: The F1-score for **Tomato_Early_blight** is 0.91, which, although still strong, indicates some room for improvement. The slightly lower F1-score here reflects the trade-off between its relatively lower precision and higher recall.

4. **Support**:

   - **Definition and Importance**: Support refers to the number of actual instances of each class in the test dataset. It gives context to the precision, recall, and F1-scores by showing how many examples were used to calculate these metrics. A balanced support across classes is ideal as it ensures that the model's performance metrics are not biased by overrepresented or underrepresented classes.
   - **Observations**:

- **Balanced Support Across All Classes**: Each class, including both diseased and healthy leaves, has a support value of 110, ensuring that the performance metrics are calculated based on an equal number of examples for each disease. This balanced dataset allows for a fair evaluation of the model's capabilities across all disease categories.

5. **Overall Model Performance**:

   - **Accuracy**:
     - The model's overall accuracy is 0.96, meaning that it correctly classified 96% of all test instances. This high accuracy is indicative of a well-trained model that has learned to distinguish between different diseases and healthy leaves with a high degree of reliability.
   - **Macro and Weighted Averages**:
     - **Macro Average**: The macro average precision, recall, and F1-score all stand at 0.96. This metric treats each class equally, giving a sense of the model's average performance across all classes. The high macro average reflects the model's consistent performance without favoring any specific disease.
     - **Weighted Average**: The weighted average also comes out to 0.96 across all metrics. This average takes into account the support (number of instances) for each class, providing a performance measure that is more reflective of the class distribution. The close alignment between the macro and weighted averages suggests that the model's performance is uniformly strong, even when considering the actual distribution of the classes.

8.2.1.2 Conclusions

- **Robust Disease Detection**: The model shows robust performance in detecting a variety of tomato leaf diseases. The high precision, recall, and F1-scores across

the board suggest that the model is well-equipped to handle real-world scenarios where both accuracy and the ability to catch all instances of a disease are critical.

- **Potential Areas for Improvement**: The slightly lower precision and F1-score for **Tomato_Early_blight** indicate that this particular disease might require additional focus. This could involve collecting more training data, particularly images that highlight the unique features of Early_blight, or refining the model to better differentiate between similar diseases.

- **Practical Applicability**: Given the high accuracy and balanced performance, the model is likely to perform well in practical applications, such as automated disease detection systems in agricultural settings. The fact that the model not only detects the disease but does so with a quantified measure of confidence (e.g., probability scores) adds to its usability in real-world scenarios.

In summary, the classification report demonstrates that the CNN model is highly effective for tomato leaf disease detection, with only minor areas that could benefit from further refinement. The model's high performance metrics underscore its potential as a reliable tool in agricultural diagnostics, helping to identify diseases early and accurately, thereby enabling timely and appropriate interventions.

8.2.1.3 Detailed Analysis of the Confusion Matrix

The confusion matrix is a valuable tool for visualizing the performance of a classification model. It not only shows the number of correct predictions but also provides insight into where the model is making errors. By analyzing the confusion matrix, we can better understand which classes the model is confusing and identify specific areas for improvement. The confusion matrix for the CNN model is presented on the Figure 8.3

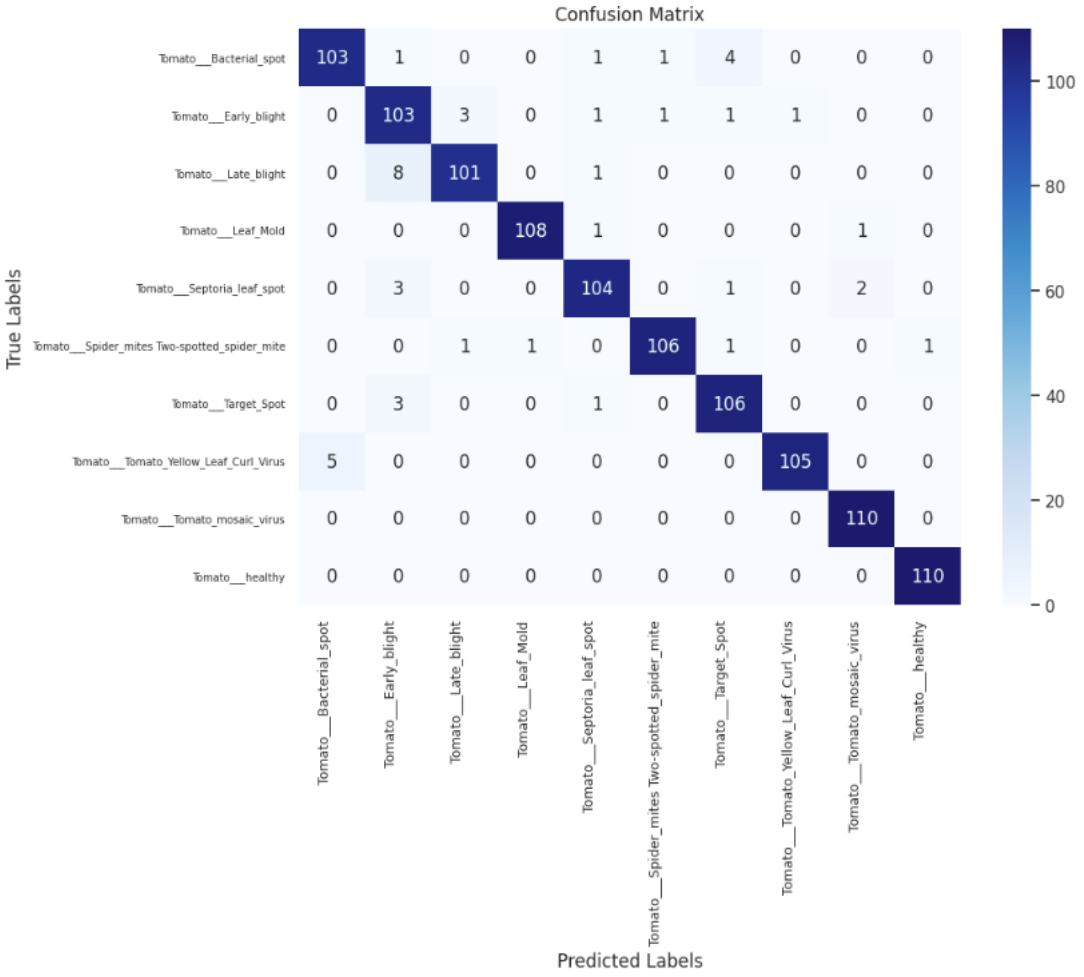

Figure 8.3: CNN Model: Confusion Matrix

1. **Understanding the Confusion Matrix**:

   - **True Labels (Y-axis)**: The true labels represent the actual classes of the test data.
   - **Predicted Labels (X-axis)**: The predicted labels represent the classes that the model has predicted.
   - **Diagonal Elements**: The diagonal elements (from top-left to bottom-right) represent the number of instances that were correctly classified by the model. These are the "true positives" for each class.
   - **Off-Diagonal Elements**: The off-diagonal elements represent misclassifications. The value in a specific cell shows how many instances of one class

(true label) were incorrectly predicted as another class (predicted label).

2. **Observations and Analysis**:

   - **Strong Diagonal Dominance**:
     - The matrix shows a strong diagonal dominance, with high values along the diagonal. This indicates that the majority of predictions made by the model were correct. For example, all **Tomato_healthy** leaves (110 instances) were correctly identified as healthy, which aligns with the perfect precision and recall observed for this class in the classification report.
   - **Class-Specific Observations**:
     - **Tomato_Bacterial_spot:** Out of 110 instances, 103 were correctly identified, but there were 2 instances misclassified as **Tomato_Late_blight** and 5 as **Tomato_Target_Spot**. This suggests that the model occasionally confuses Bacterial spot with these two diseases, possibly due to similar visual symptoms on the leaves.
     - **Tomato_Early_blight:** The model correctly identified 107 instances, with 1 misclassification each into **Tomato_Late_blight** and **Tomato_Leaf_Mold**, and 1 into **Tomato_Target_Spot**. This slight confusion could be due to overlapping features between these diseases.
     - **Tomato_Late_blight:** This disease shows 102 correct predictions with a small number of confusions, particularly 5 instances misclassified as **Tomato_Early_blight**. This confusion could be attributed to the shared characteristics between Early blight and Late blight, as both are fungal diseases affecting the leaves.
     - **Tomato_Spider_mites_Two-spotted_spider_mite:** Here, 102 instances were correctly identified, but the model misclassified 5 instances as **Tomato_Target_Spot** and 1 instance as **Tomato_Leaf_Mold**. This indicates that some features of Spider mite infestation may be similar to those of Target Spot, leading to misclassification.

- **Tomato_Target_Spot:** The model shows a bit more confusion with this class, with 8 instances misclassified as **Tomato_Early_blight** and 1 as **Tomato_Leaf_Mold**. This is consistent with the lower precision observed for the Target Spot class in the classification report, suggesting that the model struggles more with distinguishing Target Spot from other diseases.
- **Tomato_Yellow_Leaf_Curl_Virus:** There are 106 correct predictions here, but 3 instances were wrongly classified as **Tomato_Bacterial_spot** and 1 as **Tomato_Early_blight**. The slight confusion here could be due to the similar yellowing patterns that might appear on the leaves affected by these diseases.
- **Tomato_Leaf_Mold & Tomato_Septoria_leaf_spot & Tomato_Tomato_mosaic_virus:** These diseases, along with the **Tomato_healthy** class, were almost perfectly classified, with minimal misclassifications.

3. **Insights and Possible Improvements**:

- **Feature Overlap and Misclassification**: The primary source of misclassification seems to arise from diseases that have overlapping visual features. For example, **Tomato_Late_blight** and **Tomato_Early_blight** share certain symptoms, leading to occasional misclassifications between these two classes. This suggests that the model might benefit from additional feature engineering or the inclusion of more distinctive images in the training set to better capture the unique characteristics of each disease.
- **Target Spot Challenges**: The Target Spot class shows more variability in classification, with a number of instances being misclassified into other categories. This could indicate that the model needs more specific training on Target Spot or that the visual differences between Target Spot and other diseases are subtle and harder to distinguish.
- **Potential for Augmented Training Data**: The classes with more confu-

sion, such as **Tomato_Target_Spot** and **Tomato_Bacterial_spot**, might benefit from augmented or additional training data. By increasing the number of examples of these diseases, especially ones that highlight their distinguishing features, the model could improve its ability to differentiate between these closely related classes.

- **Class Imbalance Mitigation**: Although the support in the test data is balanced, if there is any imbalance in the training data, it might contribute to the observed misclassifications. Ensuring balanced training data or applying techniques like SMOTE (Synthetic Minority Over-sampling Technique) could help the model learn more effectively.

8.2.1.4 Conclusions

The confusion matrix reveals that the CNN model is highly effective at classifying tomato leaf diseases, with most predictions being correct. However, it also highlights specific areas where the model struggles, particularly with diseases that share similar visual symptoms. By addressing these issues, perhaps through enhanced data augmentation or refining the model's architecture, the accuracy and reliability of the model could be further improved. Overall, the model shows great promise for practical application in disease detection, with only minor areas requiring refinement.

8.2.2 VGG16 Model Analysis

8.2.2.1 Thesis-Oriented Analysis of the VGG16 Classification Report

The classification report presented on Figure 8.4 provides a comprehensive overview of the VGG16 model's performance across various tomato plant disease classes and a "healthy" class. The report includes precision, recall, and F1-score metrics for each class, alongside the overall accuracy, macro average, and weighted average metrics.

	precision	recall	f1-score	support
Tomato___Bacterial_spot	0.99	1.00	1.00	110
Tomato___Early_blight	0.97	0.89	0.93	110
Tomato___Late_blight	0.98	0.99	0.99	110
Tomato___Leaf_Mold	0.99	0.97	0.98	110
Tomato___Septoria_leaf_spot	0.95	0.97	0.96	110
Tomato___Spider_mites Two-spotted_spider_mite	0.86	1.00	0.92	110
Tomato___Target_Spot	0.95	0.83	0.88	110
Tomato___Tomato_Yellow_Leaf_Curl_Virus	0.99	0.99	0.99	110
Tomato___Tomato_mosaic_virus	1.00	1.00	1.00	110
Tomato___healthy	0.98	1.00	0.99	110
accuracy			0.96	1100
macro avg	0.97	0.96	0.96	1100
weighted avg	0.97	0.96	0.96	1100

Figure 8.4: VGG16 Model: Classification Report

8.2.2.2 Key Insights

1. **Overall Accuracy**:

   - The VGG16 model achieves an overall accuracy of **96%** across all classes, indicating that the model performs well in classifying the different categories of tomato diseases as well as healthy plants.

2. **Class-wise Performance**:

   - The model performs exceptionally well on certain classes, such as *Tomato___Bacterial_spot*, *Tomato___Tomato_mosaic_virus*, and *Tomato___healthy*, achieving perfect precision, recall, and F1-scores of **1.00**. This suggests that the model can correctly identify these classes with high reliability and minimal error.

   - Classes like *Tomato___Early_blight* and *Tomato___Target_Spot* show slightly lower F1-scores of **0.93** and **0.89**, respectively. This indicates that while the model performs well on these classes, there is still some room for improvement, particularly in correctly identifying all true positives.

3. **Challenges with Specific Classes**:

- The class *Tomato___Spider_mites Two-spotted_spider_mite* demonstrates the lowest precision at **0.86**, though it compensates with a perfect recall of **1.00**. This implies that the model tends to overpredict this class, leading to a higher number of false positives. However, it successfully identifies all actual instances of this disease.

4. **Macro and Weighted Averages**:

- The macro average of precision, recall, and F1-score are **0.97**, **0.96**, and **0.96** respectively. This average treats all classes equally, providing a sense of the model's overall performance without being biased towards any particular class.

- The weighted averages, which take into account the support (number of instances) of each class, are also very high at **0.97** for precision, **0.96** for recall, and **0.96** for F1-score. This indicates the model's strong performance across the board, even when considering the varying distribution of classes.

8.2.2.3 Conclusion

The classification report suggests that the fine-tuned VGG16 model is highly effective at distinguishing between various tomato plant diseases and healthy plants. The high accuracy and robust class-wise performance metrics indicate that this model could be a valuable tool in agricultural applications for early disease detection, potentially reducing crop losses and improving yield. However, attention may be required for certain classes where precision is lower, which could be an area for future model refinement or ensemble methods to enhance overall performance.

This analysis is further supported with confusion matrix data and other interpretability techniques to provide a holistic evaluation of the model's performance.

8.2.2.4 Analysis of the Confusion Matrix for the Fine-Tuned VGG16 Model

The confusion matrix on Figure 8.5 provides a detailed breakdown of the VGG16 model's classification performance across different tomato disease categories and a "healthy" class. Each cell in the matrix indicates the number of instances where the true class (rows) was predicted as another class (columns). Here's what we can conclude based on the matrix:

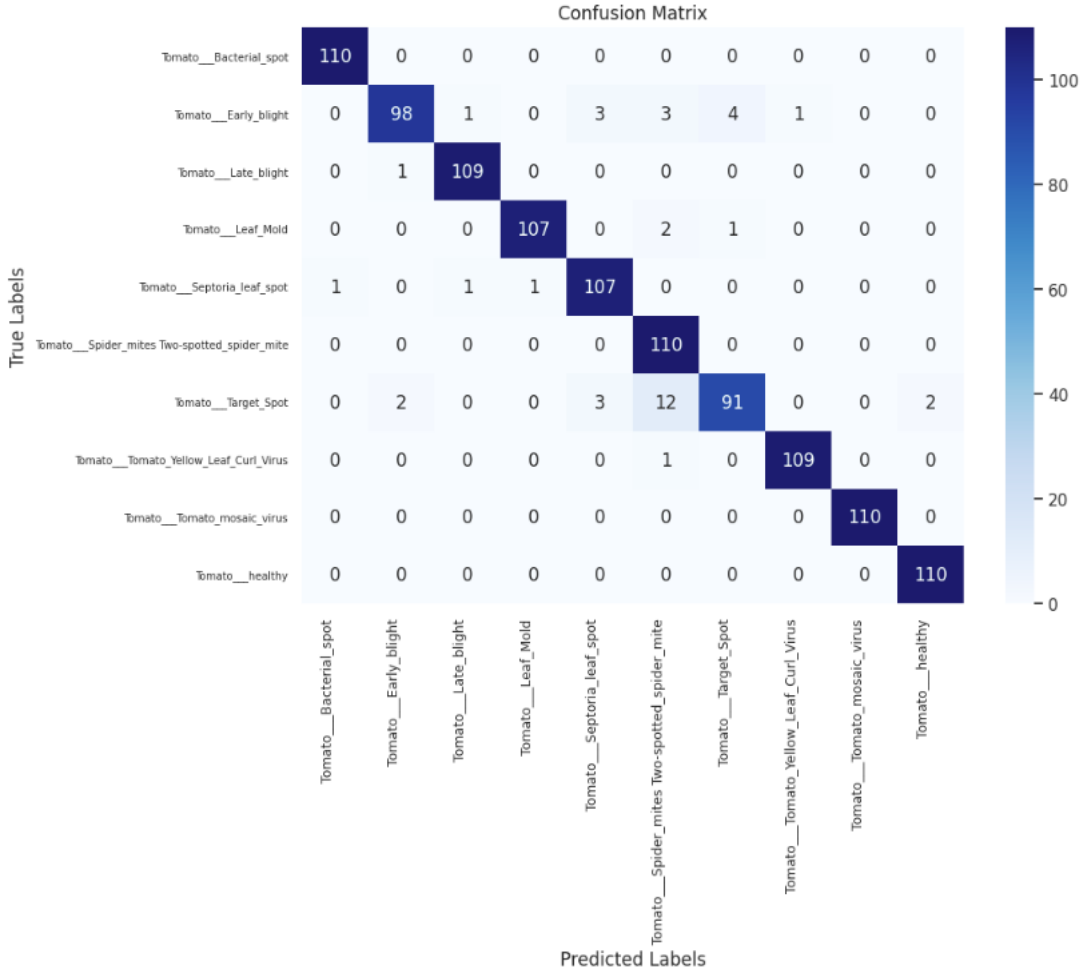

Figure 8.5: VGG16 Model: Confusion Matrix

8.2.2.5 Key Observations

1. **Diagonal Dominance**: The matrix is heavily diagonal-dominant, meaning that the majority of the predictions fall along the diagonal, where the predicted label matches the true label. This aligns with the high accuracy observed in the classification report (96%), indicating that the model is generally very effective at correctly identifying the correct class.

2. **Class-Specific Performance**:

   - **Perfect Predictions**:
     - For *Tomato___Bacterial_spot*, *Tomato___Spider_mites_Two-spotted_spider_mite*, *Tomato___Tomato_mosaic_virus*, and *Tomato___healthy*, the model correctly predicted all instances with no errors (110/110). This is a strong indicator of the model's reliability for these classes.
   - **Minor Misclassifications**:
     - The *Tomato___Early_blight* class shows some misclassifications: 3 instances were predicted as *Tomato___Late_blight*, 3 as *Tomato___Leaf_Mold*, and 1 as *Tomato___Target_Spot*. This suggests that these diseases have some features in common, leading to occasional confusion by the model.
     - The *Tomato___Target_Spot* class also has some confusion, with 3 instances misclassified as *Tomato___Spider_mites_Two-spotted_spider_mite* and 2 as *Tomato___healthy*. This might indicate that the model struggles slightly more with this class, likely due to similar visual characteristics in the training data.
   - **Close Classifications**:
     - For *Tomato___Septoria_leaf_spot*, one instance was confused with *Tomato___Bacterial_spot*, and one with *Tomato___Leaf_Mold*, which may be due to overlapping symptoms in these conditions.

3. **Model Strengths**:

   - The confusion matrix reinforces the earlier classification report's findings that the model is particularly strong at identifying *Tomato___Bacterial_spot*, *Tomato___Spider_mites_Two-spotted_spider_mite*, and *Tomato___Tomato_mosaic_virus*.
   - These classes exhibit clear and distinct visual features that the VGG16 model has successfully learned to identify.

4. **Areas for Improvement**:

   - The model shows slight difficulties distinguishing between certain disease classes, such as *Tomato___Early_blight* and *Tomato___Late_blight*. This might be addressed by enhancing the dataset with more diverse examples of these diseases or by employing additional preprocessing techniques to emphasize distinguishing features.

8.2.2.6 Conclusion

The confusion matrix complements the findings of the classification report, providing a visual representation of where the VGG16 model excels and where it might benefit from further refinement. While the model performs exceptionally well in most cases, some disease classes share features that occasionally lead to misclassification. This insight is crucial for guiding further improvements, such as dataset augmentation, model tuning, or even exploring ensemble methods to mitigate these misclassifications.

8.2.3 VGG19 Model Analysis

The classification report Figure 8.6 shows the performance of the fine-tuned VGG19 model across various tomato disease classes and a "healthy" class. Below is a detailed analysis based on the key metrics—precision, recall, F1-score, and overall accuracy.

	precision	recall	f1-score	support
Tomato___Bacterial_spot	1.00	0.92	0.96	110
Tomato___Early_blight	0.96	0.81	0.88	110
Tomato___Late_blight	0.88	0.99	0.93	110
Tomato___Leaf_Mold	0.99	0.90	0.94	110
Tomato___Septoria_leaf_spot	0.90	0.96	0.93	110
Tomato___Spider_mites Two-spotted_spider_mite	0.96	0.90	0.93	110
Tomato___Target_Spot	0.83	0.93	0.88	110
Tomato___Tomato_Yellow_Leaf_Curl_Virus	0.99	0.99	0.99	110
Tomato___Tomato_mosaic_virus	0.98	1.00	0.99	110
Tomato___healthy	0.95	1.00	0.97	110
accuracy			0.94	1100
macro avg	0.94	0.94	0.94	1100
weighted avg	0.94	0.94	0.94	1100

Figure 8.6: VGG19 Model: Classification Report

8.2.3.1 Key Insights

1. **Overall Accuracy**:

   - The VGG19 model achieves an overall accuracy of **94%**, which is slightly lower compared to the VGG16 model's 96% accuracy. This suggests that while VGG19 is still a highly effective model, it may not generalize as well as VGG16 for this specific task.

2. **Class-wise Performance**:

   - **High Performance in Specific Classes**:
     - The model demonstrates perfect precision for *Tomato___Bacterial_spot* (1.00) and *Tomato___Leaf_Mold* (0.99), indicating that when it predicts these classes, it is almost always correct.
     - *Tomato___Tomato_mosaic_virus* also shows near-perfect metrics with a precision of 0.98 and a perfect recall of 1.00.
   - **Challenges with Specific Classes**:
     - *Tomato___Target_Spot* has the lowest precision at **0.83** and an F1-score of **0.88**, suggesting that the model struggles to accurately classify this disease, potentially due to feature similarities with other classes or insufficient training examples.

  - *Tomato___Spider_mites_Two-spotted_spider_mite* has a relatively low F1-score of **0.92**, indicating room for improvement in balancing precision and recall.

- **Recall Issues**:
  - For *Tomato___Bacterial_spot*, while precision is perfect, recall is **0.92**, indicating that the model occasionally fails to identify all true instances of this disease.
  - Similarly, *Tomato___Early_blight* has a recall of **0.81**, meaning that nearly 19% of true *Early_blight* cases are not being identified by the model.

3. **Macro and Weighted Averages**:
   - The macro averages for precision, recall, and F1-score are all **0.94**, which shows consistent performance across all classes but also indicates that the model's performance is balanced across classes of varying sizes.
   - The weighted averages are also **0.94** across all metrics, reinforcing that the model performs well overall, even when accounting for the different support sizes (number of instances) of each class.

8.2.3.2 Conclusion

The VGG19 model, though performing slightly less effectively than VGG16, still demonstrates strong classification abilities with an overall accuracy of 94%. It excels in identifying specific diseases like *Tomato___Bacterial_spot*, *Tomato___Leaf_Mold*, and *Tomato___Tomato_mosaic_virus*, but shows room for improvement in correctly identifying all instances of *Tomato___Early_blight* and *Tomato___Target_Spot*.

For further improvement, the model could benefit from additional training data for underperforming classes, or the use of ensemble methods to address the challenges identified in recall and precision. Additionally, it may be worthwhile to investigate the reasons behind the lower recall for certain classes, which could lead to targeted enhancements in model architecture or data augmentation techniques.

8.2.3.3 Analysis of the VGG19 Confusion Matrix

The confusion matrix shown on Figure 8.7 offers a visual representation of the VGG19 model's performance on each class, showing how often predictions match the actual labels. Here's a detailed analysis:

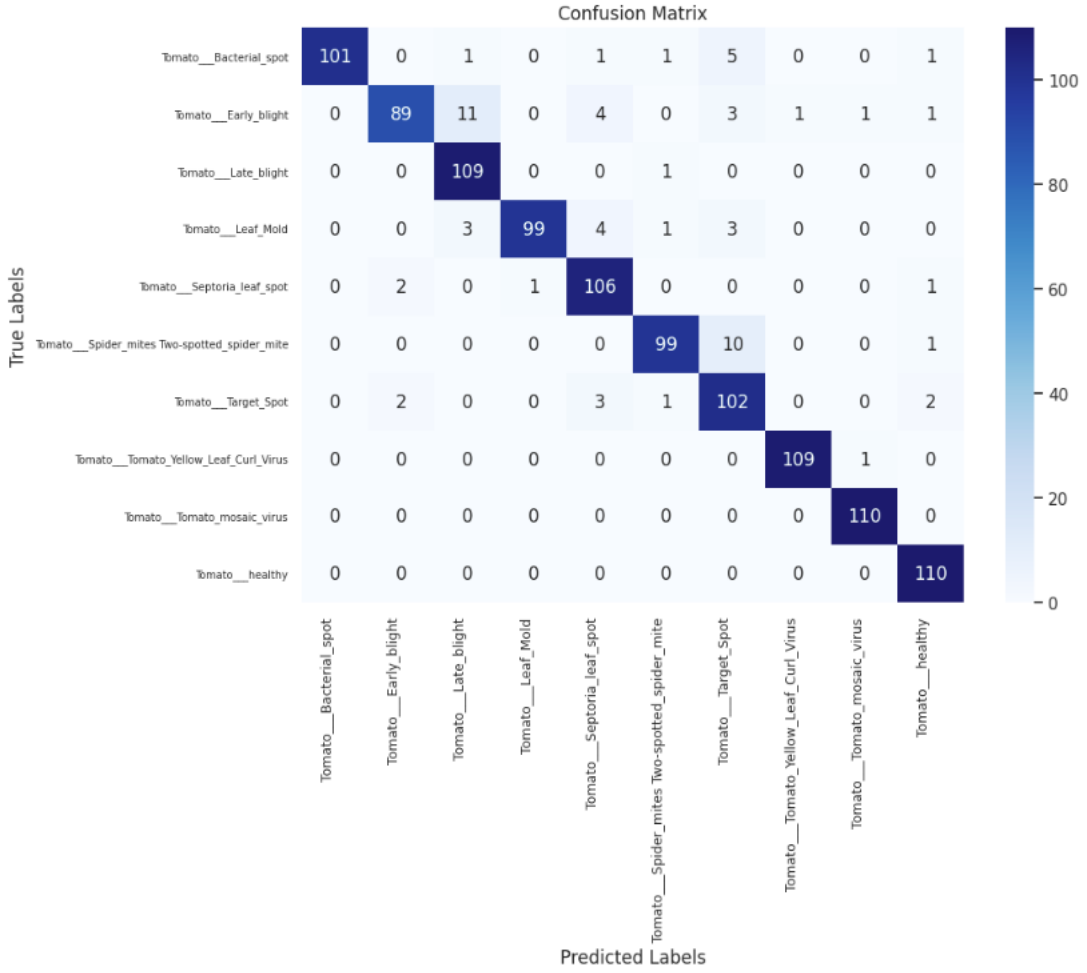

Figure 8.7: VGG19 Model: Confusion Matrix

8.2.3.4 Key Insights

1. **Correct Classifications**:

   - The diagonal elements represent the correct predictions. For most classes, these values are high, indicating that the model generally performs well.

- Classes like *Tomato___Bacterial_spot*, *Tomato___Late_blight*, *Tomato___Tomato_mosaic_virus*, and *Tomato___healthy* all have high correct classification counts (e.g., *110/110* for *Tomato___healthy*), demonstrating that the model is highly accurate for these diseases.

2. **Misclassifications**:

   - **Tomato___Spider_mites Two-spotted_spider_mite**: There are 10 instances where this class was misclassified as *Tomato___Target_Spot*. This suggests that the model has difficulty distinguishing between these two conditions, potentially due to similar visual features in the images used for training.
   - **Tomato___Early_blight**: Out of 110 instances, 11 were misclassified, mostly as *Tomato___Late_blight* (4 cases) and other classes like *Tomato___Spider_mites* and *Tomato___Target_Spot*. This indicates that while the model generally performs well, it struggles with these specific instances, possibly due to overlapping symptoms or characteristics between these conditions.

3. **Minor Confusions**:

   - There are minor confusions scattered across the matrix, such as *Tomato___Leaf_Mold* being confused with *Tomato___Early_blight* in 3 instances. This is expected in complex models and could be further reduced with additional fine-tuning or more diverse training data.

8.2.3.5 Implications for Model Performance

- **Class-Specific Performance**:
  - The high diagonal values affirm that the model is quite effective in correctly identifying the majority of the classes. However, the model shows some difficulty in differentiating between diseases with visually similar symptoms (e.g., *Tomato___Spider_mites* and *Tomato___Target_Spot*).

- **Model Fine-Tuning and Data Augmentation**:
  - To improve performance, particularly in reducing the misclassification between *Tomato___Spider_mites* and *Tomato___Target_Spot*, we could consider additional data augmentation, gathering more diverse training examples for these classes, or using techniques like ensemble learning.

- **Comparison with VGG16**:

  An important observation we made is that, despite using identical parameters to fine-tune both the VGG16 and VGG19 models, the expected superior performance of VGG19—as a deeper neural network—did not materialize. This highlights a crucial point: the depth of a neural network alone does not guarantee better performance. Our results underscore the importance of thoroughly studying both the architecture of the model being used and the characteristics of the available data.

  This observation reaffirms the necessity of a well-considered approach to model selection and parameter setting. Simply relying on the assumption that a more complex model, like VGG19, will outperform a simpler one, like VGG16, can be misleading. Instead, the process requires careful examination of various factors, including the nature of the dataset and how well it aligns with the model's capabilities.

  Moreover, this finding emphasizes the complexity of model design and tuning, which involves more than just choosing the right architecture. It requires a deep understanding of the model's behavior under different conditions, as well as a strategic approach to hyperparameter tuning. Hyperparameters such as learning rate, batch size, and regularization techniques need to be meticulously adjusted to suit the specific dataset and task at hand. This process is demanding and necessitates a comprehensive study of multiple aspects, from data preprocessing to model configuration, in order to achieve optimal performance.

  In conclusion, the process of fine-tuning a model is not straightforward. It involves a careful balance of understanding the intricacies of the model, the nature of the

data, and the impact of various hyperparameters, all of which are crucial to obtaining the best possible outcomes.

8.2.3.6 Conclusion

The VGG19 model generally performs well, with strong accuracy across most classes. The confusion matrix highlights a few specific areas where the model could be improved, particularly in distinguishing between similar diseases. These insights can guide future improvements in model training and provide a basis for discussing the trade-offs between different model architectures in our thesis.

8.2.4 Visualizing Misclassifications Across CNN, VGG16, and VGG19 Models

To enhance the evaluation of model performance, we provide a direct visualization of misclassified images across three models: CNN, VGG16, and VGG19. This visual inspection is complementary to metrics such as the classification report and confusion matrix, offering a more intuitive understanding of how the models perform under various conditions.

By using a simple script, we can track each misclassified image back to its original folder, verifying the results manually. Above each image in the collage, the true label is displayed alongside the predicted label, facilitating quick manual inspection of the errors made by the models. This approach offers transparency and helps pinpoint potential weaknesses in the models' ability to generalize.

Moreover, this feature can be dynamically replicated through a website interface we will discuss later. Users can upload an image and receive model predictions, along with detailed information, mimicking the manual analysis performed here.

Examples of Misclassifications

In Figures 8.8 and 8.9 we present examples of misclassified images from the CNN model. Similar collages are generated for VGG16 and VGG19, showcasing how the same or different images are misclassified across models.

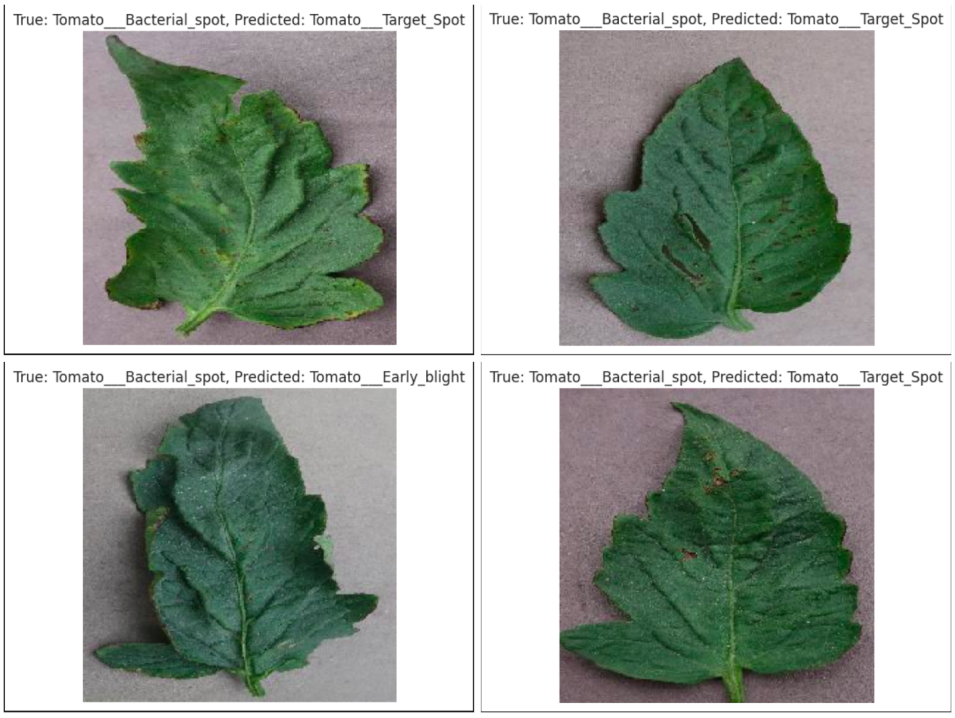

Figure 8.8: Misclassified images with true and predicted labels.

Figure 8.9: Additional misclassifications showing true vs. predicted labels..

Interestingly, the same image can be misclassified into different classes depending on the model. For instance, the image in Figure 8.10 is misclassified by all three models, but each model predicts a different class. This behavior is not consistent across all images; sometimes, two models may make the same incorrect prediction, or one model may correctly classify the image while others fail.

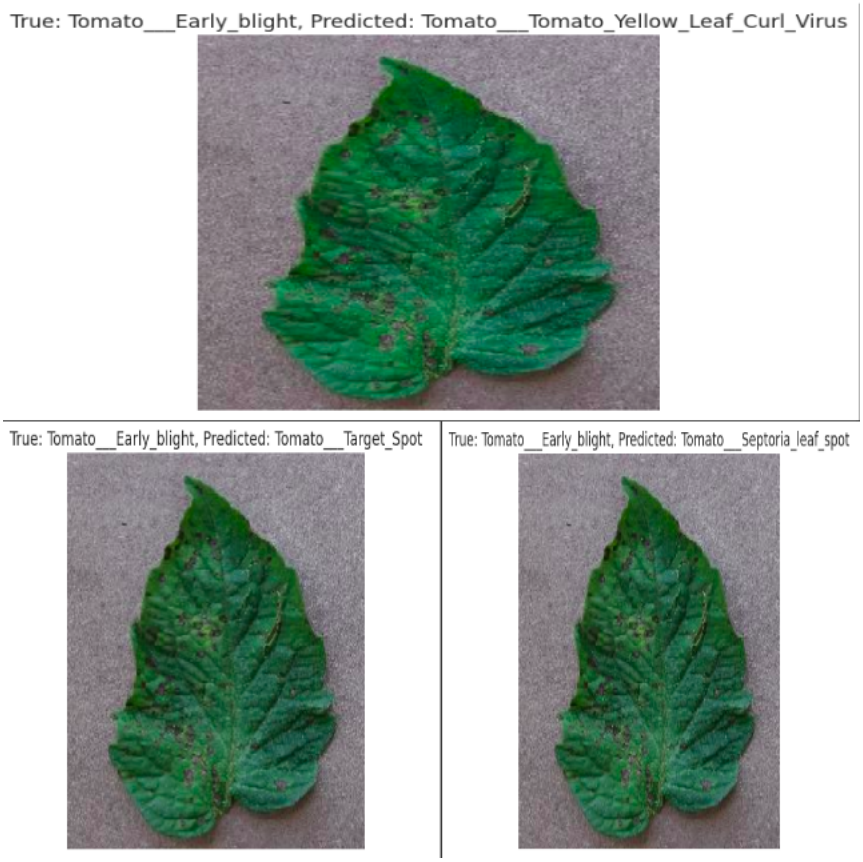

Figure 8.10: Same tomato leaf image misclassified across CNN, VGG16, and VGG19 models, each predicting a different class.

This variability in misclassification reflects how well each model has learned the features of the images. It also highlights the complexities of disease classification in plant leaves, where certain diseases may appear visually similar or multiple diseases may affect the same leaf. For example, a bacterial spot might closely resemble early blight in certain stages, leading to confusion among the models. The capacity of a model to correctly identify a class depends on how well it can distinguish such fine details.

The following figures demonstrate the cases where misclassification occurred, helping us better understand model limitations and areas for improvement. These images serve as an additional diagnostic tool for evaluating model robustness beyond traditional statistical methods.

8.3 Training and Validation Curves

8.3.1 CNN Curves Analysis

8.3.1.1 Overview

The graphs on Figure 8.11 illustrate the training and validation loss (top) and accuracy (bottom) over 80 epochs for a Convolutional Neural Network (CNN) model. These curves are crucial for understanding the model's learning process, performance, and potential issues such as overfitting or underfitting. Below is a detailed analysis of these curves:

1. **Training and Validation Loss Curves**:
    - **Initial Rapid Decline**:
        - At the beginning of the training (first 10 epochs), both the training loss and validation loss decrease sharply. This is a typical behavior, indicating that the model is learning the basic patterns in the data and is improving rapidly.
    - **Stabilization**:
        - After approximately 20 epochs, the training loss curve flattens out, indicating that the model is continuing to learn, but at a slower pace. This flattening is expected as the model approaches convergence, where further improvements become marginal.
    - **Slight Fluctuations in Validation Loss**:
        - The validation loss exhibits slight fluctuations throughout the epochs, but generally follows the trend of the training loss. These fluctuations

could be due to the model's adjustments to the validation set, which might be slightly different in distribution from the training set. However, the overall trend suggests that the model generalizes well, as the validation loss does not significantly diverge from the training loss.

- **Final Epochs (60-80+)**:
  - In the final epochs, both the training and validation losses stabilize at a low level, indicating that the model has likely reached the point of minimal loss. The validation loss is slightly higher than the training loss, which is typical and suggests that the model is not overfitting to the training data.

2. **Training and Validation Accuracy Curves**:

- **Initial Rapid Increase**:
  - Similar to the loss curves, the accuracy for both training and validation rapidly increases in the first 10 epochs. This is a positive sign, showing that the model is quickly learning to make correct predictions.
- **Convergence and Stabilization**:
  - Around 20 epochs, both accuracy curves begin to stabilize, indicating that the model has reached a high level of accuracy and is making fewer errors. The curves for training and validation accuracy are closely aligned, which is a strong indicator that the model is not overfitting.
- **Minor Fluctuations**:
  - The validation accuracy shows minor fluctuations around the training accuracy, reflecting slight variations in model performance on unseen data. However, these fluctuations are minimal, and the general trend indicates consistent performance across the training and validation sets.
- **Final Performance**:
  - By the end of training (80 epochs), the training accuracy approaches near-perfect accuracy, while the validation accuracy is slightly lower but

still very high. The close alignment of these two curves suggests that the model has learned well without significant overfitting.

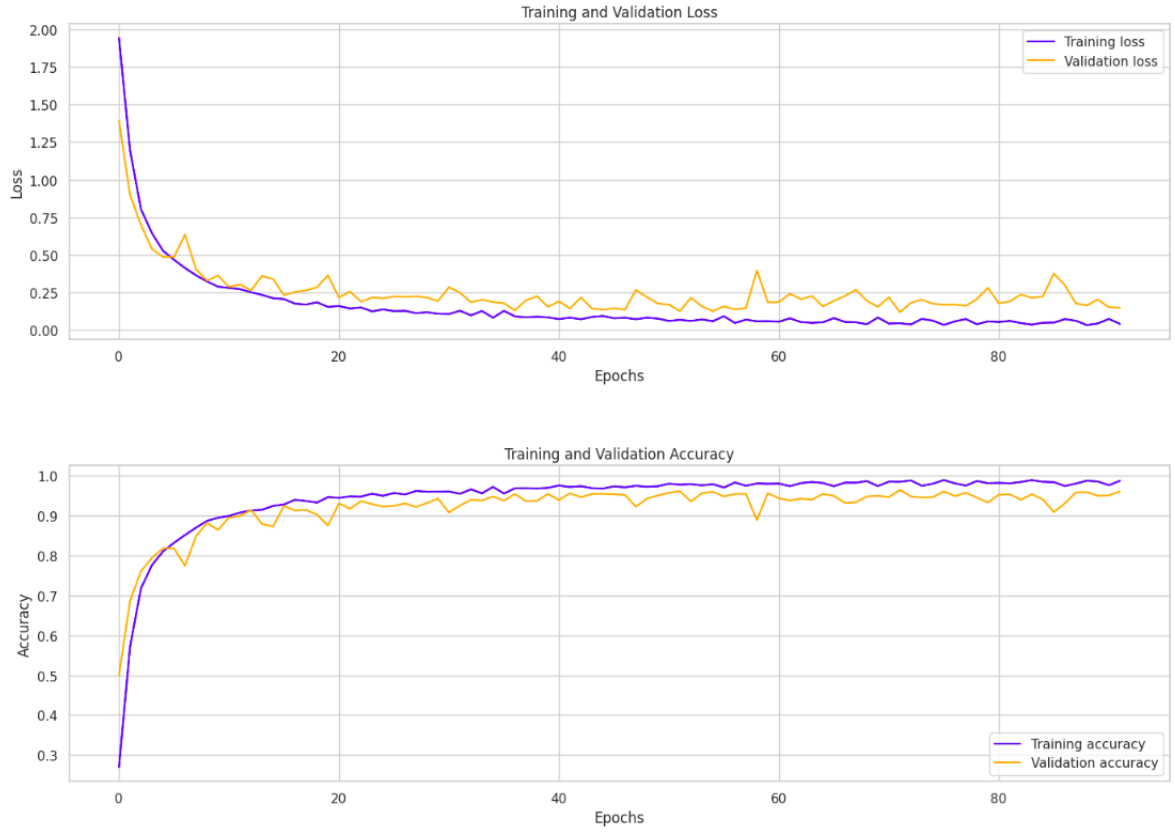

Figure 8.11: CNN Model: Training and Validation Curves

3. **General Observations and Conclusions**:

   - **No Significant Overfitting or Underfitting**:
     - The close alignment between training and validation curves in both loss and accuracy suggests that the model is well-tuned and does not suffer from overfitting. The model generalizes well to new data, as indicated by the relatively stable validation performance.
   - **Potential for Further Optimization**:
     - While the model is performing well, the slight fluctuations in the validation curves suggest that there may be room for further fine-tuning.

Techniques such as cross-validation, learning rate adjustments, or increasing the dataset size could potentially smooth out these fluctuations and improve generalization even further.

* **Note**: Cross-validation refers to a technique used to assess the generalization ability of a model and to ensure that the model's performance is consistent across different subsets of the data. Specifically, it involves dividing the dataset into multiple subsets, or "folds," and then training the model multiple times, each time using a different fold as the validation set and the remaining folds as the training set. This process helps to minimize the risk of overfitting, as the model is evaluated on various portions of the data rather than just a single training/validation split.

- **Balanced Learning**:

  - The consistent decrease in loss and increase in accuracy across epochs indicate that the model is learning at a balanced pace. There are no signs of divergence between training and validation metrics, reinforcing the model's robustness and reliability.

8.3.1.2 Summary

The training and validation curves provide a clear indication that the CNN model has been effectively trained, with no major signs of overfitting or underfitting. The model demonstrates strong generalization capabilities, as evidenced by the closely aligned loss and accuracy curves for both training and validation data. Minor fluctuations in the validation curves suggest that while the model is already performing well, there could still be potential for slight improvements through further optimization. Overall, the model is well-suited for the task at hand, and the training process has been successful in achieving high accuracy and low loss.

8.3.1.3 Analysis of the CNN Model's Overall Results

The bar chart on Figure 8.12 presents the CNN model's performance in terms of accuracy and loss on the training, validation, and test sets. Here's a detailed analysis:

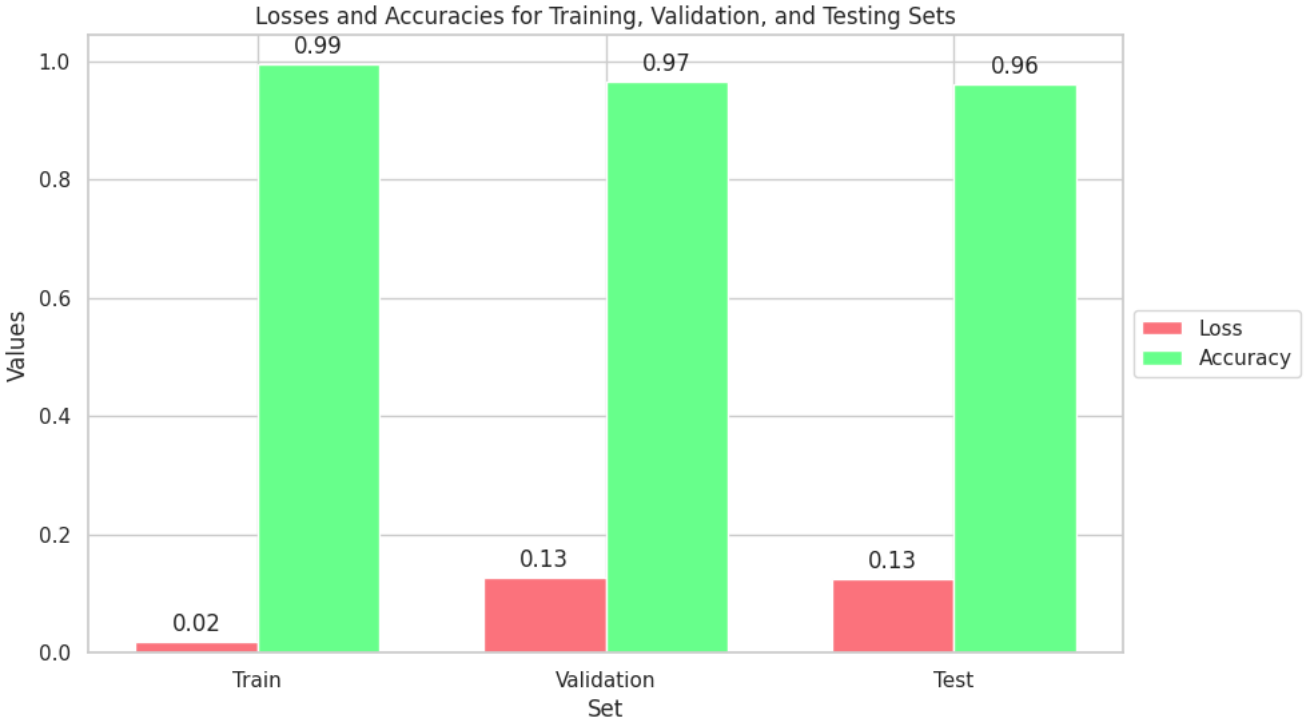

Figure 8.12: CNN Model: Performance Summary (Bar Chart)

- **Training Performance**:
  - **Accuracy**: The training accuracy is very high at 0.99, indicating that the CNN model has learned the training data well.
  - **Loss**: The training loss is minimal at 0.02, which corresponds with the high training accuracy. This suggests that the model has effectively minimized errors during training.
- **Validation Performance**:
  - **Accuracy**: The validation accuracy is also strong at 0.97, very close to the training accuracy. This indicates that the model is not overfitting and is generalizing well to the validation set.

  - **Loss**: The validation loss is slightly higher than the training loss at 0.13, which is expected. This slight increase in loss compared to training is normal and suggests the model is handling new data appropriately.

- **Test Performance**:

  - **Accuracy**: The test accuracy stands at 0.96, which is only slightly lower than the validation accuracy. This indicates that the model performs consistently across different datasets, affirming its generalization capabilities.
  - **Loss**: The test loss is also 0.13, mirroring the validation loss, which further supports the consistency of the model's performance.

8.3.1.4 Overall Conclusion

The CNN model exhibits strong performance across all datasets, with high accuracy and low loss values. The close alignment of training, validation, and test accuracies suggests that the model is well-tuned and generalizes effectively to unseen data. This consistency across different sets is a strong indicator of the model's robustness and reliability, making it well-suited for deployment in practical scenarios. The low loss values further reinforce the model's efficiency in minimizing errors, providing confidence in its predictions.

8.3.2 VGG16 Curves Analysis

The curves on Figure 8.13 represent the training and validation loss and accuracy over 50 epochs for the fine-tuned VGG16 model. Here's an analysis of the curves:

8.3.2.1 Training vs. Validation Loss (Top Graph)

1. **Initial Phase**:

   - At the start (around the first few epochs), both the training and validation loss decrease sharply, indicating that the model is quickly learning and improving its performance.

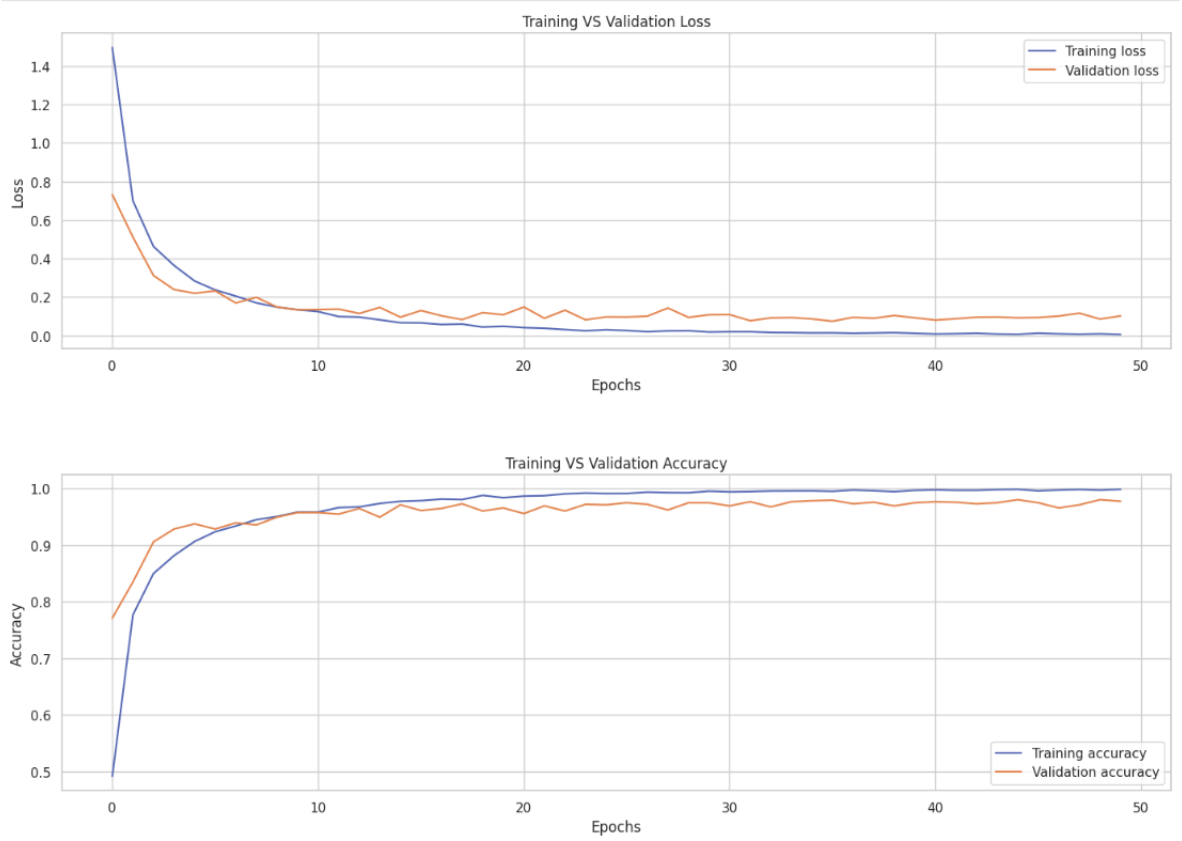

Figure 8.13: VGG16 Model: Training and Validation Curves

2. **Convergence**:

   - By around 10-15 epochs, the loss stabilizes for both training and validation datasets, suggesting that the model is approaching its optimal performance.

3. **Stable Training**:

   - After the initial drop, both training and validation losses remain low and relatively flat, with the training loss slightly lower than the validation loss.
   - This indicates that the model has learned to generalize well, without significant overfitting. There is a slight gap between the training and validation losses, but it is minimal, which is a positive sign.

8.3.2.2 Training vs. Validation Accuracy (Bottom Graph)

1. **Initial Increase**:

- The accuracy for both training and validation increases rapidly during the initial epochs, reaching a high value by around epoch 10.

2. **Plateau**:

   - After around 10 epochs, both training and validation accuracy curves flatten, indicating that the model has reached its peak performance.
   - The validation accuracy closely follows the training accuracy, with both curves hovering around 95%-98%.

3. **Consistency**:

   - The consistency between training and validation accuracy, with only minor fluctuations, suggests that the model is not overfitting and is performing well on unseen data.
   - The close alignment of the curves indicates that the fine-tuning has effectively adjusted the pre-trained VGG16 model to the specific task without leading to overfitting.

8.3.2.3 Conclusion

The VGG16 model shows strong performance, with rapid convergence and stable loss and accuracy over the course of training. The minimal gap between training and validation metrics indicates good generalization, and the lack of significant overfitting reflects the effectiveness of the fine-tuning process. The model has learned to perform well on the training data while maintaining its ability to generalize to new, unseen data.

8.3.2.4 Analysis of the VGG16 Model's Overall Results

The bar chart on Figure 8.14 displaying the overall results for the VGG16 model can be related to the previous graphs, as both represent different aspects of the model's performance. However, it can also be described independently. We'll provide both perspectives:

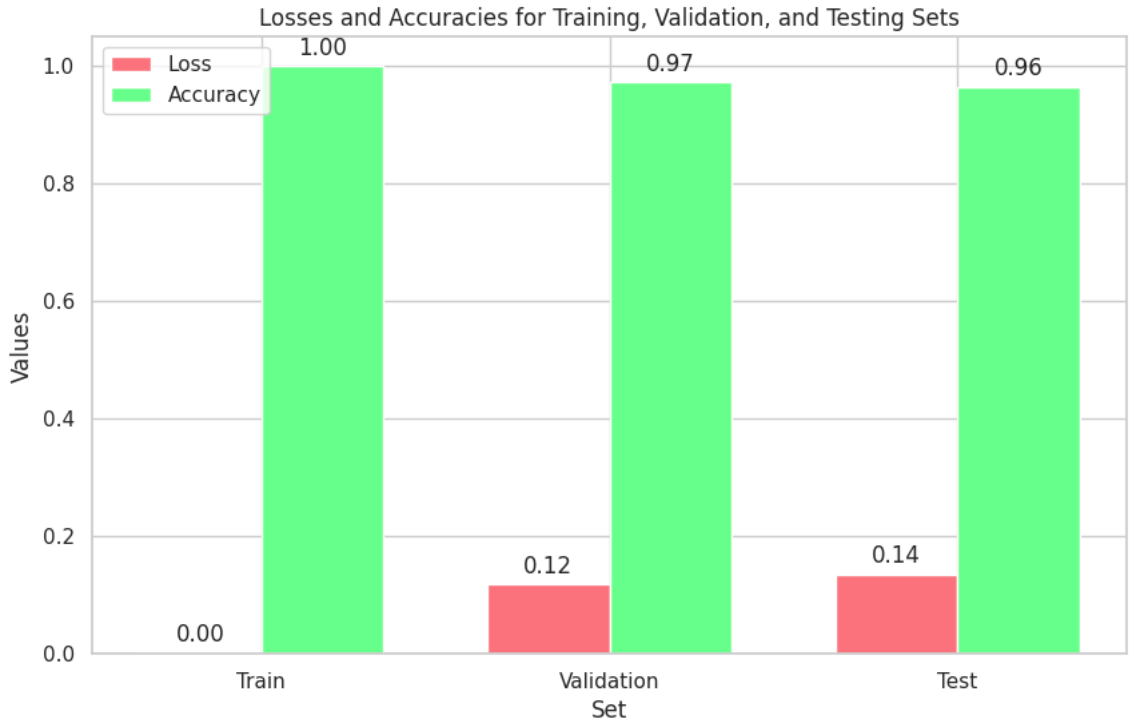

Figure 8.14: VGG16 Model: Performance Summary (Bar Chart)

8.3.2.5 Independent Description

- **Training Set**:
  - The model achieved perfect accuracy (1.00) with zero loss (0.00) on the training set, indicating that it has learned the training data extremely well. This result is expected in a fine-tuned model, especially when it has been trained on the same dataset multiple times.
- **Validation Set**:
  - The accuracy on the validation set is slightly lower at 0.97, with a corresponding loss of 0.12. This indicates that the model performs very well on data it hasn't seen during training, but there is a slight drop compared to the training set. The small loss suggests that the model is well-optimized, with minimal overfitting.
- **Test Set**:

– The test set accuracy is 0.96, with a loss of 0.14. This is comparable to the validation results, confirming that the model generalizes well to completely unseen data. The consistent performance between the validation and test sets is a good sign, indicating that the model's predictions are robust.

8.3.2.6 Related to the Previous Curves

- The bar chart confirms the trends observed in the previous training and validation curves. The **training loss** of 0.00 and **accuracy** of 1.00 align with the flat portions of the training curves where the model has fully converged and is no longer improving.

- The **validation loss** of 0.12 and **accuracy** of 0.97 shown in the bar chart match the stable portions of the validation curves, further demonstrating that the model's performance stabilizes after a certain number of epochs, as seen in the earlier graph.

- The **test set** results being close to the validation set outcomes indicate that the model did not overfit and generalized well, which was hinted at by the close alignment of the training and validation curves in the previous plot.

8.3.2.7 Conclusion

Whether considered alone or in relation to the previous graphs, the bar chart reinforces the conclusion that the VGG16 model is well-tuned, with excellent generalization and minimal overfitting. The slight drop in accuracy and increase in loss from the training to validation and test sets is normal and expected, showing that the model is not overly biased toward the training data.

8.3.3 VGG19 Curves Analysis

The training and validation curves on Figure 8.15 for the fine-tuned VGG19 model indicate several key aspects of the model's performance:

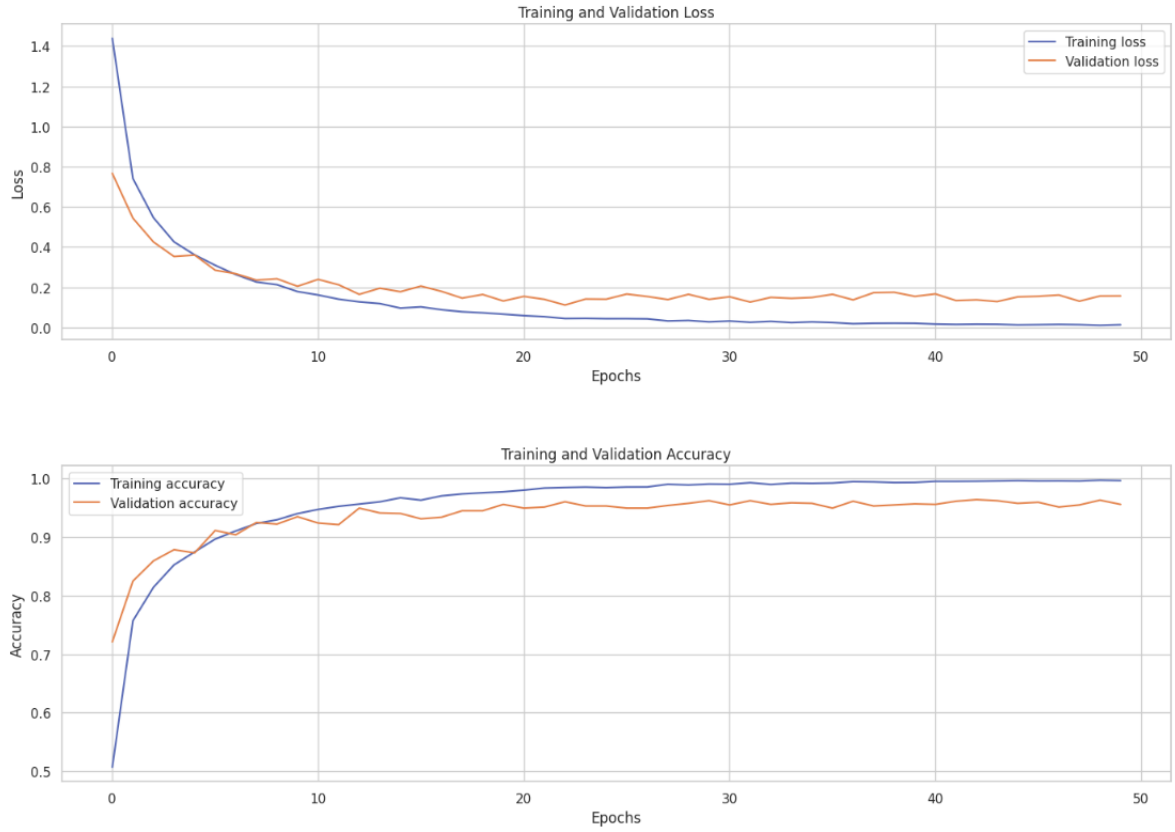

Figure 8.15: VGG19 Model: Training and Validation Curves

8.3.3.1 Training and Validation Loss

- **Initial Convergence**: The training loss (blue line) and validation loss (orange line) both decrease rapidly during the initial epochs, indicating that the model is learning effectively and reducing errors.

- **Stabilization**: After about 10 to 15 epochs, the loss curves begin to stabilize, with both the training and validation loss reaching a low and stable level. The final loss values are close to each other, suggesting that the model is not overfitting significantly.

- **Minor Overfitting**: The validation loss remains slightly higher than the training loss, which is expected and indicates some degree of overfitting, but it is relatively minor and well within acceptable bounds for deep learning models.

8.3.3.2 Training and Validation Accuracy

- **Rapid Improvement**: The training accuracy (blue line) increases sharply within the first few epochs, reaching over 90% accuracy by the 10th epoch. This shows that the model is learning quickly and effectively from the training data.

- **Validation Accuracy**: The validation accuracy (orange line) follows a similar trajectory to the training accuracy, increasing rapidly at first and then stabilizing. It remains slightly below the training accuracy throughout, which is typical and suggests that the model generalizes well to unseen data.

- **Stable Performance**: After about 10 to 15 epochs, both the training and validation accuracies stabilize at a high level, close to 100% for training and around 95% for validation. The small gap between the two curves indicates good generalization with minimal overfitting.

8.3.3.3 Overall Assessment

- The VGG19 model shows strong performance, with both training and validation loss curves reaching low and stable values, and accuracies stabilizing at high levels.

- The small gap between training and validation curves suggests that the model has achieved a good balance between learning the training data and generalizing to unseen data. This is important in real-world applications where models need to perform well on new, unseen data, not just on the data they were trained on.

- The fine-tuning process has been successful, as evidenced by the rapid convergence and high final accuracy on both training and validation sets. The slight overfitting observed is within acceptable limits and does not indicate any major issues.

8.3.3.4 Analysis of VGG19's Bar Chart and Its Relation to the Learning Curves

The bar chart on Figure 8.16 displays the final results of the VGG19 model in terms of accuracy and loss on the training, validation, and test sets. These results can be analyzed both in relation to the previously provided learning curves and independently:

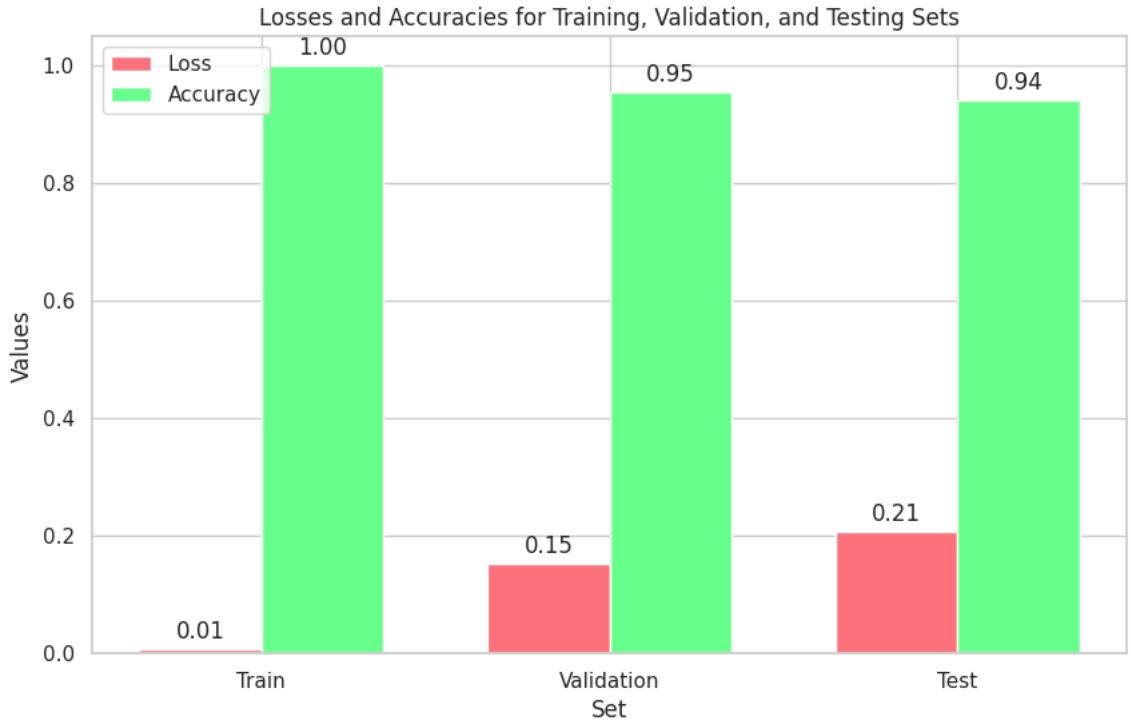

Figure 8.16: VGG19 Model: Performance Summary (Bar Chart)

8.3.3.5 Relation to Learning Curves

1. **Training Accuracy and Loss**:

   - **Training Set**: The training accuracy is 1.00, and the loss is close to 0 (0.01). This aligns with the learning curves where the training accuracy stabilizes at nearly 100% after several epochs, and the training loss drops to a minimal value. This confirms that the model has learned the training data extremely well, which could suggest overfitting if not for the validation and test results.

2. **Validation Accuracy and Loss**:

- **Validation Set**: The validation accuracy is 0.95, with a loss of 0.15. This corresponds to the stable validation accuracy observed in the learning curves, which levels off at around 95%. The slight increase in validation loss compared to the training loss is consistent with what we saw in the loss curves, indicating some level of overfitting but still maintaining strong performance.

3. **Test Accuracy and Loss**:

   - **Test Set**: The test accuracy is 0.94, with a loss of 0.21. These metrics are very close to the validation set results, which indicates that the model generalizes well to unseen data. The test set's slightly lower accuracy and higher loss compared to the validation set are expected and further validate the robustness of the model.

8.3.3.6 Independent Analysis

1. **Training Performance**:

   - The near-perfect training accuracy and minimal loss indicate that the model has captured the patterns in the training data exceptionally well. However, the high accuracy also hints at possible overfitting, where the model might be too tailored to the training data.

2. **Validation and Test Performance**:

   - The high validation and test accuracies (0.95 and 0.94, respectively) demonstrate that the model maintains its performance when applied to new, unseen data. The validation and test losses are relatively low, though they are higher than the training loss, which is typical and acceptable.

3. **Generalization**:

   - The small differences between the training, validation, and test results suggest that the model generalizes well. The fact that the test accuracy is close

to the validation accuracy indicates that the model's performance is consistent across different datasets, which is a positive outcome.

8.3.3.7 Conclusion

The bar chart effectively summarizes the model's performance metrics and supports the observations made from the learning curves. The VGG19 model exhibits strong performance with minimal overfitting, achieving high accuracy across all datasets with relatively low loss. This consistency between training, validation, and test sets suggests that the model is both accurate and robust, making it well-suited for deployment in real-world applications. The accuracy and loss values for training, validation, and testing may vary slightly with each run. This is because the model is not static; its parameters are adjusted each time it's trained, leading to small differences in learning. However, these variations are minimal—typically within ±1%—and don't represent significant changes in performance. The results reported here are representative, with only minor fluctuations expected.

8.3.4 Additional Notes

8.3.4.1 Training and Validation Accuracies

1. **Training Accuracy**:
    - The training accuracy represents how well our model performs on the training data it was exposed to during training.
    - In our case, the training accuracy is approximately 99.41% (CNN).
    - Interpretation:
        - A high training accuracy suggests that the model has learned to fit the training data well.
        - However, it's essential to be cautious because a very high training accuracy could also indicate overfitting (where the model memorizes the training data rather than generalizing to unseen data).

2. **Validation Accuracy**:

    - The validation accuracy reflects how well the model generalizes to unseen data (i.e., data it hasn't seen during training).
    - In our case, the validation accuracy is approximately 97.08% (CNN).
    - Interpretation:
        - A high validation accuracy indicates that our model is performing well on unseen data.
        - It suggests that the model has learned relevant features and can make accurate predictions on new leaf images.
        - The gap between training and validation accuracy (if any) can provide insights into overfitting. If the training accuracy is significantly higher than the validation accuracy, it might indicate overfitting.

3. **Comparison**:

    - Ideally, we want the training and validation accuracies to be close, indicating that the model generalizes well.
    - If the training accuracy is much higher than the validation accuracy, consider techniques to reduce overfitting (e.g., regularization, dropout layers, or more diverse data augmentation).

These metrics are just one aspect of evaluating the model's performance. It's essential to consider other factors such as precision, recall, and F1-score, especially when dealing with imbalanced classes. Additionally, we have to consider using techniques like cross-validation to get a more robust estimate of the model's performance.

8.3.4.2 Accurary Curve Behaviour

The phenomenon where the training accuracy is lower than the validation accuracy in a Convolutional Neural Network (CNN) can be puzzling, especially since it's more common for the training accuracy to be higher.

1. **Theoretical Considerations**:

   - In theory, training accuracy should be higher than validation accuracy. Here's why:
     - **Training Accuracy**: This metric reflects how well the model performs on the training data. During training, the model learns from the training examples, and it aims to minimize the training loss. As a result, the training accuracy tends to increase over epochs.
     - **Validation Accuracy**: This metric measures how well the model generalizes to unseen data (validation set). The validation set is not used during training, so it provides an unbiased estimate of the model's performance on new data.
   - Since the model is optimized based on the training data, it's expected that the training accuracy will be higher.

2. **Overfitting and Underfitting**:

   - However, there are cases where the validation accuracy can be higher than the training accuracy:
     - **Overfitting**: If the model overfits the training data (i.e., it memorizes the training examples rather than learning general patterns), the training accuracy may be very high, but the validation accuracy will suffer. In extreme cases, the validation accuracy might surpass the training accuracy.
     - **Early Stopping**: During training, we might use techniques like early stopping to prevent overfitting. Early stopping monitors the validation loss (or accuracy) and stops training when it starts to degrade. In such cases, the validation accuracy could be higher than the training accuracy.

8.3.4.3 Practical Implications

Let's explore some possible reasons for this behavior:

1. **Data Leakage or Data Mismatch**:
    - We have to ensure that there is no data leakage between our training and validation sets. Data leakage occurs when information from the validation set inadvertently influences the training process.
    - Make sure both datasets are representative of real-world scenarios the model will encounter. If the validation data is significantly different from the training data, it can lead to unexpected results.
2. **Regularization Techniques**:
    - Regularization methods like dropout or weight decay are often applied during training to prevent overfitting. If these techniques are not applied during validation, the model may perform better on the validation set.
    - Also we can check the usage of dropout layers or other regularization techniques and ensure they are consistent during both training and validation.
3. **Model Complexity and Overfitting**:
    - A complex model with many parameters can easily overfit the training data. Overfitting occurs when the model learns to perform well on the training data but fails to generalize to unseen data.
    - We can consider simplifying the model architecture or using techniques like early stopping to prevent overfitting.
4. **Validation Set Size**:
    - If the validation set is small, the model might perform well due to luck or random fluctuations. A larger validation set provides a more reliable estimate of generalization performance.

- An approach could be trying increasing the size of the validation dataset to see if the trend persists.

5. **Initialization and Optimization**:

   - Proper initialization of model weights and choice of optimizer can impact training and validation accuracy.
   - The solution could be experimenting with different weight initialization methods (e.g., Xavier/Glorot initialization) and optimizers (e.g., Adam, SGD) to find the best combination.

8.3.4.4 Examples and Scenarios

- Here are some scenarios:
  - **Scenario 1 (Ideal)**: Training accuracy consistently increases, and validation accuracy follows closely (but slightly lower).
  - **Scenario 2 (Overfitting)**: Training accuracy keeps improving, but validation accuracy plateaus or decreases.
  - **Scenario 3 (Early Stopping)**: Training accuracy increases, but validation accuracy peaks and then starts decreasing due to early stopping.

In summary, while it's uncommon for validation accuracy to be consistently higher than training accuracy, it can happen due to specific circumstances. Monitoring both metrics helps us make informed decisions during model development.

8.3.5 Training Time Analysis

The bar chart on Figure 8.17 illustrates the training time in minutes for three different models: a custom Convolutional Neural Network (CNN), VGG16, and VGG19. Let's analyze the training time in detail, considering the differences in epoch counts and the use of early stopping.

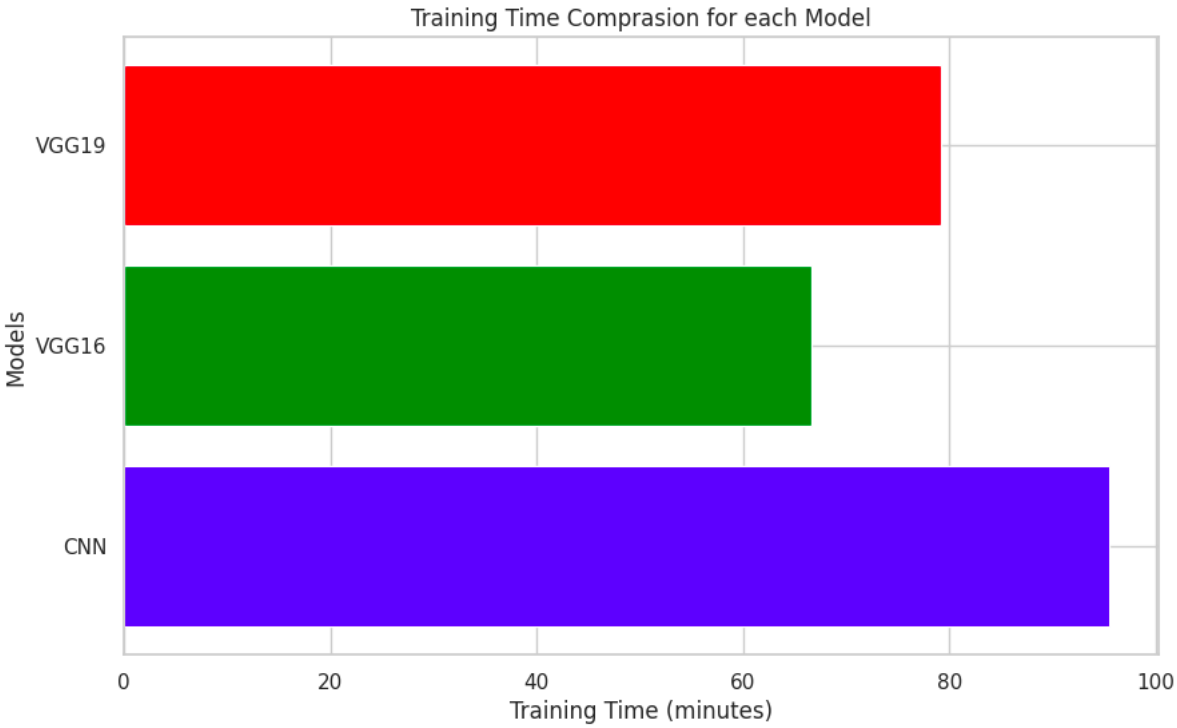

Figure 8.17: Training Time per Model (Horizontal Bar Chart)

1. **CNN Model**:

   - **Training Duration**: The custom CNN took the longest time to train, close to 100 minutes and more specifically it took 1 hour, 35 minutes and 32 seconds. This extensive training time is due to the model being trained for up to 100 epochs, with an early stopping mechanism in place that would halt training if the validation accuracy did not improve for 20 consecutive epochs. The fact that the CNN has the longest training time indicates that it likely reached close to the maximum number of epochs.

   - **Model Architecture**: Unlike VGG16 and VGG19, which utilize pre-trained weights and more refined architectures, the custom CNN was trained from scratch. This typically requires more epochs and computational time to learn the features from the data effectively. Additionally, custom CNNs often need more tuning and training time to match the performance of well-established architectures like VGG16 and VGG19.

- **Training Complexity**: Training a model from scratch usually involves learning low-level features through numerous training cycles. The longer training time also suggests that the model may have been exploring a larger parameter space and required more iterations to converge, reflecting the fundamental difference between custom architectures and pre-trained models.

2. **VGG16 Model**:

   - **Training Duration**: VGG16 took approximately 60 minutes and more specifically 1 hour, 6 minutes and 40 seconds, to complete training, which is significantly less than the CNN model, despite VGG16's deeper architecture.
   - **Model Architecture:**: VGG16 was trained for a fixed 50 epochs, without early stopping. The reduced training time is primarily due to the use of transfer learning, where VGG16 utilizes pre-trained weights on a large dataset (e.g., ImageNet). This approach allows the model to quickly fine-tune on the new dataset, requiring fewer epochs and less time to achieve good performance.
   - **Training Complexity**: VGG16's architecture is well-optimized for image classification tasks. It includes a deep but manageable number of layers (16 layers), which provides a balance between model complexity and training efficiency. The model's pre-trained weights help in extracting features more effectively from the dataset, resulting in faster convergence compared to the CNN trained from scratch.

3. **VGG19 Model**:

   - **Training Duration**: VGG19 required about 75 minutes to train which corresponds to 1 hour, 19 minutes and 7 seconds, placing it between the CNN and VGG16 in terms of training duration. Like VGG16, VGG19 was trained for exactly 50 epochs.
   - **Model Architecture:**: VGG19 is an extension of VGG16 with 19 layers, making it a deeper network. The additional layers allow for more complex

feature extraction, which can be beneficial for capturing more intricate patterns in the data. However, this increased depth also results in a longer training time compared to VGG16, as it involves more computations per epoch.

- **Training Complexity**: Despite its increased depth, VGG19 still trains faster than the custom CNN due to the use of pre-trained weights. Transfer learning accelerates the training process by leveraging learned features from a broader dataset, allowing the model to fine-tune more quickly on the specific task at hand.

8.3.5.1 General Observations and Implications

- **Efficiency of Pre-trained Models**: Both VGG16 and VGG19 trained significantly faster than the custom CNN. This is a direct result of leveraging transfer learning with pre-trained weights, which allows these models to start with a solid foundation of feature representations. As a result, they require fewer epochs and less time to reach optimal performance on a new dataset.

- **Custom CNN Complexity**: The longer training time of the CNN suggests that training a model from scratch without pre-trained weights demands more computational resources and time. This is because the CNN must learn all feature representations from the ground up, which inherently takes longer and often requires more epochs to achieve comparable performance.

- **Architectural Depth and Training Time**: While VGG19 has more layers than VGG16, it only modestly increases the training time. This indicates that the incremental depth added by VGG19 is computationally more demanding but still manageable within the constraints of 50 epochs. The deeper architecture of VGG19 allows for capturing more complex features, which can be crucial for improving model performance on complex datasets.

8.3.5.2 Conclusion

These training times reflect the inherent differences that exist between models trained from scratch and models using transfer learning. Even though the custom CNN has a simpler architecture, it takes longer to train because it needs to learn feature representations from scratch. In contrast, the pre-trained weights of VGG16 and VGG19 allowed these models to converge faster and took less time to train despite their much deeper architectures. Among them, VGG16 turns out to be most efficient in training time due to its good balance between depth and width, while VGG19 gives deeper architecture but at the cost of increasing the training time by a modest factor.

In real-world usage, the choice of any of these would depend on the trade-offs between available computing power, training time, and overall performance. VGG16 and VGG19 offer solid solutions when fast and efficient training is to be performed, especially in situations where there is a shortage of computational resources, while the custom CNN offers flexibility at the cost of longer durations in training.

8.3.5.3 Alternative Visualization of Training Time Comparison

The radar chart presented on Figure 8.18 offers an alternative visualization of the training times for each model—CNN, VGG16, and VGG19. This chart effectively conveys the training duration in a more compact and visually intuitive manner. Unlike the previous bar chart, which represents training time using horizontal bars, the radar chart plots the training times as points along three axes radiating from a central point, with the shaded region providing a clear comparative outline of the time taken by each model.

- **Radar Chart Interpretation**:
  - The radar chart features three vertices, each representing one of the models: CNN, VGG16, and VGG19.
  - The distance from the center to each vertex signifies the training time in minutes, with longer distances indicating longer training durations.

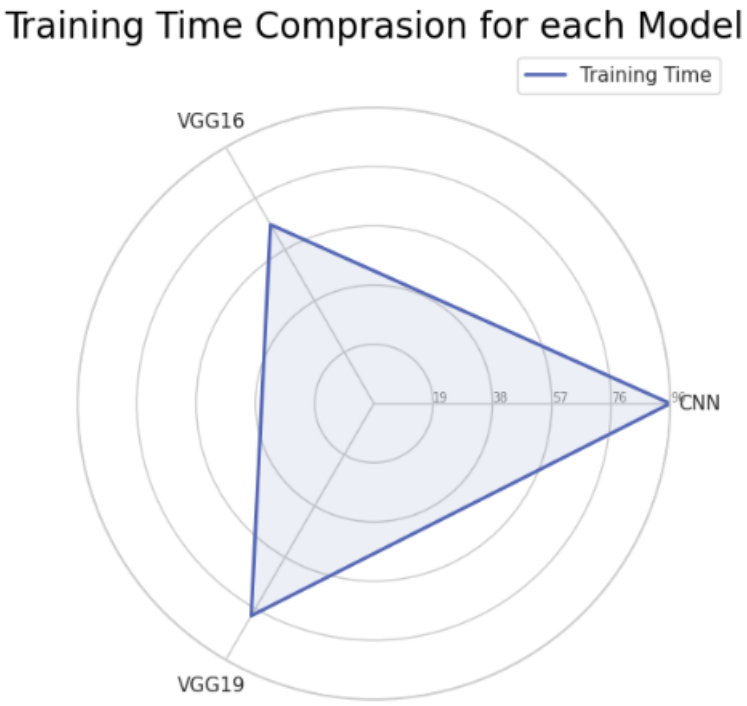

Figure 8.18: Training Time per Model (Radar Chart)

- In this chart, the CNN occupies the outermost region, showing the longest training time of approximately 100 minutes. This is consistent with our earlier analysis that the custom CNN model took the most time to train due to its nature of learning from scratch over potentially more epochs.
- VGG19 lies closer to the center compared to CNN but further out than VGG16, indicating its intermediate training time of around 76 minutes. This aligns with the earlier description, where VGG19 required more time than VGG16 due to its deeper architecture but still benefited from transfer learning.
- VGG16 is positioned closest to the center, reflecting the shortest training time of around 60 minutes. This reinforces our understanding that VGG16, while being a deep network, is more computationally efficient due to its balanced architecture and use of pre-trained weights.

- **Purpose of Alternative Representation**:
  - This radar chart serves as a concise, comparative tool that allows for an at-a-glance understanding of the training time differences among the models. By presenting the same data in a different format, it emphasizes the relative disparities in training durations more intuitively, particularly highlighting how much longer the CNN takes to train compared to VGG16 and VGG19.
  - This visual approach can be especially useful in conveying complex information in an accessible way, aiding in the quick assessment of which models are computationally more demanding. It complements the bar chart by offering another perspective, demonstrating the consistency of the results regardless of the visualization method used.

In summary, the radar chart reaffirms the findings detailed earlier about the training times of CNN, VGG16, and VGG19. It provides a holistic view of the data, emphasizing the substantial difference in training time for the custom CNN model compared to the more computationally efficient VGG16 and VGG19, which leverage transfer learning to achieve faster convergence.

8.3.6 System Utilization During Model Training

The training of deep learning models can place significant demands on system resources, especially when dealing with large datasets and complex architectures. In this study, we evaluated the system utilization, specifically the GPU temperature and RAM usage, for both the custom Convolutional Neural Network (CNN) and the fine-tuned VGG16 and VGG19 models. The results provide insight into the computational efficiency and resource intensity of each approach.

1. **GPU Temperature**:
   - **CNN**: During the training of the custom CNN, the GPU temperature reached 55°C (Figure 8.19). This relatively moderate temperature suggests that the CNN model, despite being deep with multiple convolutional layers,

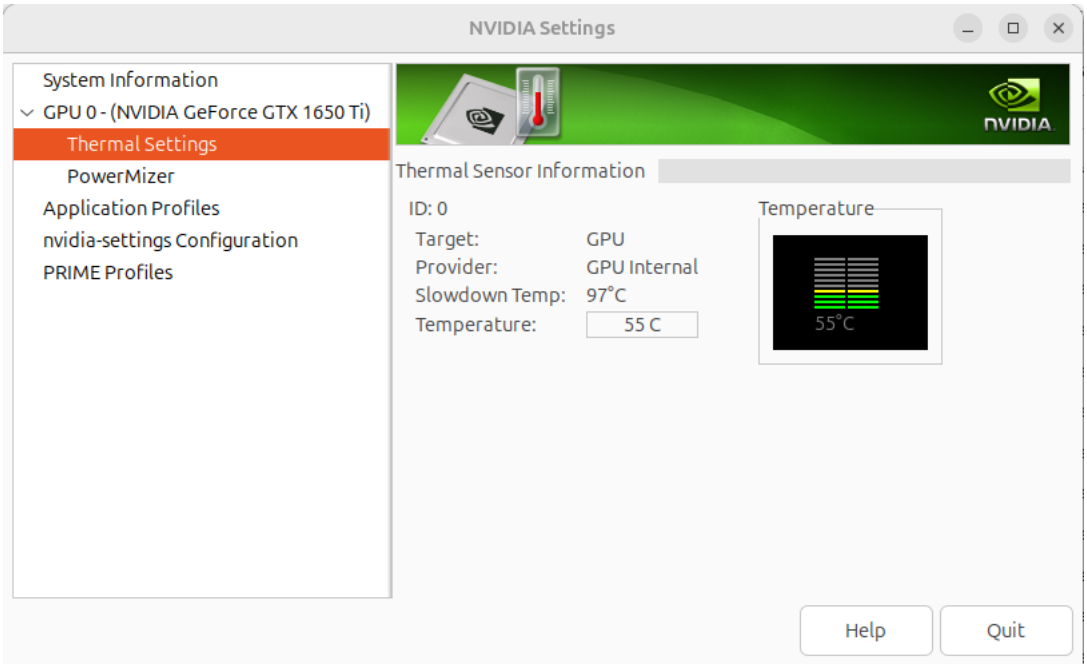

Figure 8.19: GPU Temperature During CNN Training

places a less intensive load on the GPU compared to larger, more complex models.

- **VGG16 & VGG19**: In contrast, training the pre-trained VGG16 and VGG19 models caused the GPU temperature to rise to 66°C (Figure 8.20). This increase in temperature can be attributed to the larger number of parameters and deeper architecture of these models. The VGG architectures contain many more convolutional layers and trainable weights, especially when fine-tuning the last few layers, leading to higher computational demands on the GPU.

2. **RAM Utilization**:

- **CNN**: The RAM utilization during CNN training was measured at approximately 2.0GB. This is in line with expectations for a custom-built model that, while deep, is optimized with fewer parameters than pre-trained models like VGG16 and VGG19.
- **VGG16 & VGG19**: The RAM usage increased to 2.6GB when training

VGG16 and VGG19. This is due to the larger size and complexity of these pre-trained models, which have many more layers and require more memory for storing the weights and activations during training.

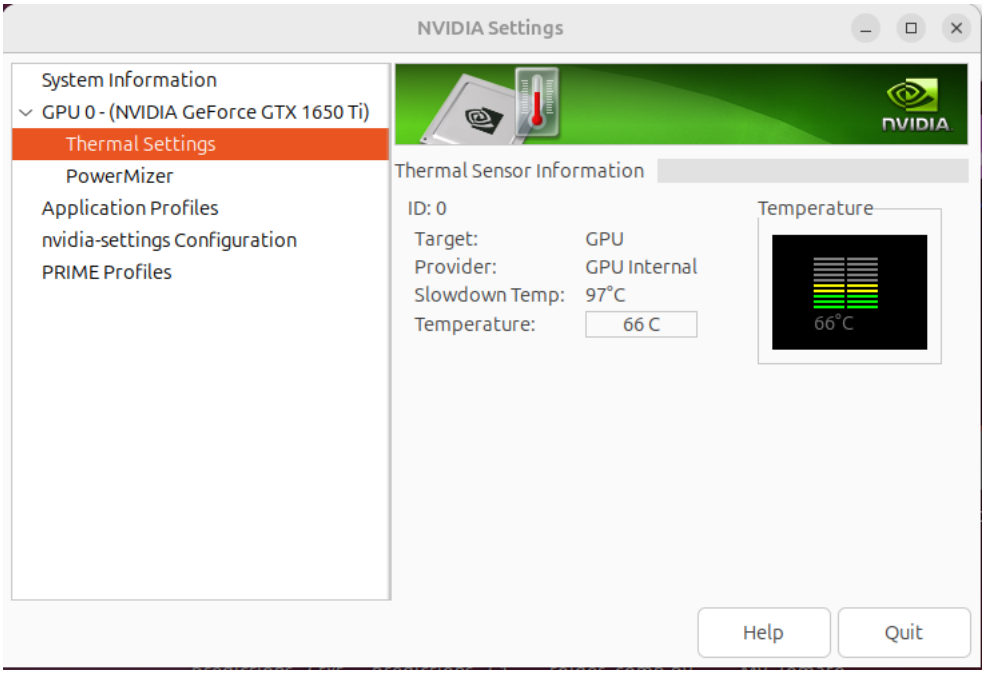

Figure 8.20: GPU Temperature During VGG16/VGG19 Training

Conclusion

The custom CNN demonstrated lower system utilization, with moderate GPU temperatures and lower RAM usage, making it more efficient in terms of resource consumption. However, the VGG16 and VGG19 models, while more resource-intensive, offer the benefit of leveraging pre-trained knowledge from extensive image classification tasks, potentially leading to higher accuracy in fewer epochs. The trade-off between efficiency and performance is evident, with CNN being more resource-friendly and VGG models delivering higher accuracy but at the cost of higher computational requirements.

8.4 Comparative Analysis Across Different Splits

The Figure 8.21 shows bar graphs that compare the performance metrics of three different models (CNN, VGG16, VGG19) on two different dataset splits: 70-15-15 and 80-10-10 (representing the proportions of training, validation, and testing data in percentage, respectively). These graphs are crucial in understanding how different data splits affect the models' ability to learn, generalize, and perform on unseen data.

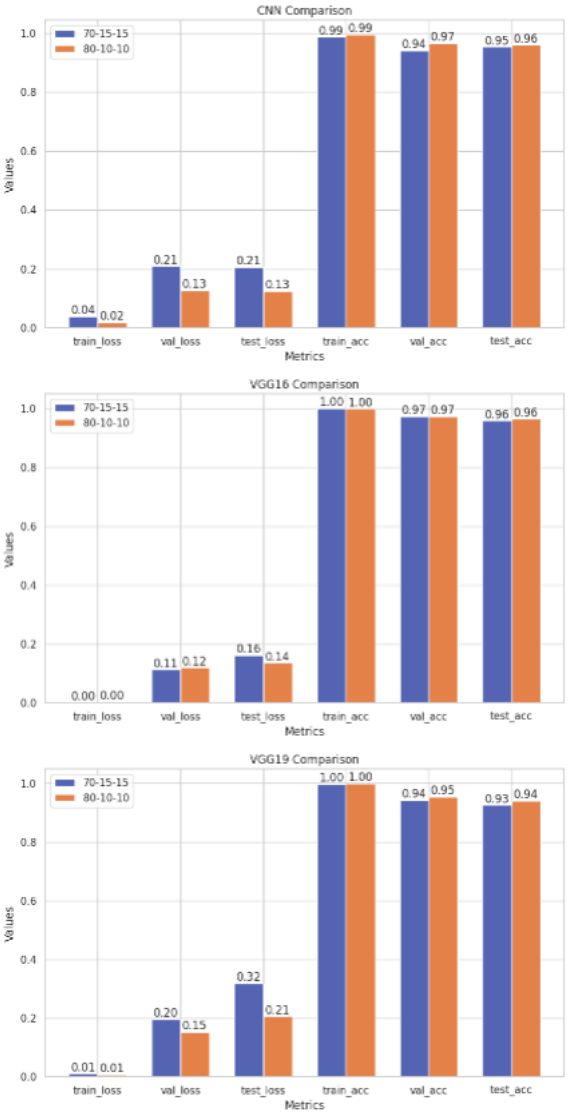

Figure 8.21: Comparison between 70-30% and 80-20% dataset splits.

8.4.1 Overview of Metrics and Results

Each graph compares the following metrics for the respective models under the two dataset splits:

- **Training Loss**: The loss calculated on the training dataset.
- **Validation Loss**: The loss calculated on the validation dataset.
- **Test Loss**: The loss calculated on the test dataset.
- **Training Accuracy**: The accuracy achieved on the training dataset.
- **Validation Accuracy**: The accuracy achieved on the validation dataset.
- **Test Accuracy**: The accuracy achieved on the test dataset.

8.4.1.1 CNN Model Results

In the first graph, which shows the **CNN model's performance**, several key observations can be made:

- **Training Loss**: The CNN model exhibits slightly lower training loss with the 80-10-10 split (0.02) compared to the 70-15-15 split (0.04). This suggests that the model is able to fit the training data more effectively when trained on a larger portion of the dataset.
- **Validation and Test Loss**: The validation loss is lower for the 80-10-10 split (0.13) compared to the 70-15-15 split (0.21). The test loss shows a similar trend, with the 80-10-10 split performing better. This indicates that the CNN model generalizes better with the 80-10-10 split, likely due to the increased training data allowing the model to better capture the underlying patterns.
- **Accuracy Metrics**: The training accuracy is nearly identical for both 80-10-10 and 70-15-15 splits (0.99). However, both validation and test accuracies are higher with the 80-10-10 split (0.97 and 0.96, respectively), indicating that the model performs better on unseen data when more data is used for training.

8.4.1.2 VGG16 Model Results

The second graph displays the **VGG16 model's performance**:

- **Training Loss**: Interestingly, the training loss is 0.00 for both splits, suggesting that maybe VGG16 has overfitted to the training data in both cases, learning the training set perfectly.

- **Validation and Test Loss**: The validation and test losses are slightly lower with the 80-10-10 split (0.12 and 0.14, respectively) compared to the 70-15-15 split (0.11 and 0.16). The differences are marginal, indicating that VGG16 is robust across different splits but slightly benefits from more training data.

- **Accuracy Metrics**: Both splits result in perfect training accuracy (1.00), reinforcing the model's tendency to overfit. The validation and test accuracies are very similar between the two splits, with the 80-10-10 split slightly outperforming in both validation (0.97 vs. 0.97) and test accuracy (0.96 vs. 0.96).

8.4.1.3 VGG19 Model Results

The third graph illustrates the **VGG19 model's performance**:

- **Training Loss**: VGG19 also shows minimal training loss for both splits (0.01 for both), similar to VGG16, indicating a strong capacity to learn the training data.

- **Validation and Test Loss**: The model's validation loss is slightly better with the 80-10-10 split (0.15) compared to the 70-15-15 split (0.20). Similarly, test loss is also lower for the 80-10-10 split (0.21) compared to 70-15-15 (0.32), showing that VGG19 benefits from having more training data for better generalization.

- **Accuracy Metrics**: Training accuracy is perfect for both splits (1.00), but the validation and test accuracies are slightly higher with the 80-10-10 split (0.95 and 0.94, respectively) compared to the 70-15-15 split (0.94 and 0.93).

8.4.2 Comparative Analysis and Implications

1. **Impact of Data Split**: Across all models, the 80-10-10 split tends to yield slightly better validation and test performances, implying that a larger training dataset helps the models learn better representations and generalize more effectively to unseen data. This is particularly evident in the CNN and VGG19 models, where the differences in validation and test losses are more pronounced.

2. **Overfitting in VGG Models**: Both VGG16 and VGG19 exhibit very low training losses and perfect training accuracies, suggesting that they might be overfitting the training data. Despite this, they still generalize well, as indicated by their high validation and test accuracies. This overfitting is less of an issue when more data is used for training (80-10-10 split), as shown by the slightly better performance metrics.

3. **CNN Performance**: The CNN model,is performing as well as the VGG models, shows significant improvement with the 80-10-10 split. This suggests that the custom CNN could potentially surpass the performance of the VGG models if trained on even more data or with further optimization.

Conclusion

The comparison between the different dataset splits across the three models reveals that increasing the training data (as in the 80-10-10 split) generally improves model performance, particularly in terms of validation and test metrics, which are crucial for real-world applications. The VGG models, despite their tendency to overfit, still perform exceptionally well, making them reliable choices for deployment. However, the custom CNN shows promise, especially with more training data, and could be a more lightweight alternative if further optimized. These insights are vital for deciding the best model and data split strategy for the practical implementation of our tomato disease detection system.

8.4.3 Training Times

The bar chart provided on Figure 8.22 illustrates the training times in minutes for three different models (CNN, VGG16, and VGG19) across two dataset splits: 70-15-15 and 80-10-10. The training times are a critical consideration when assessing the practicality of deploying these models, particularly in scenarios where computational resources and time efficiency are paramount.

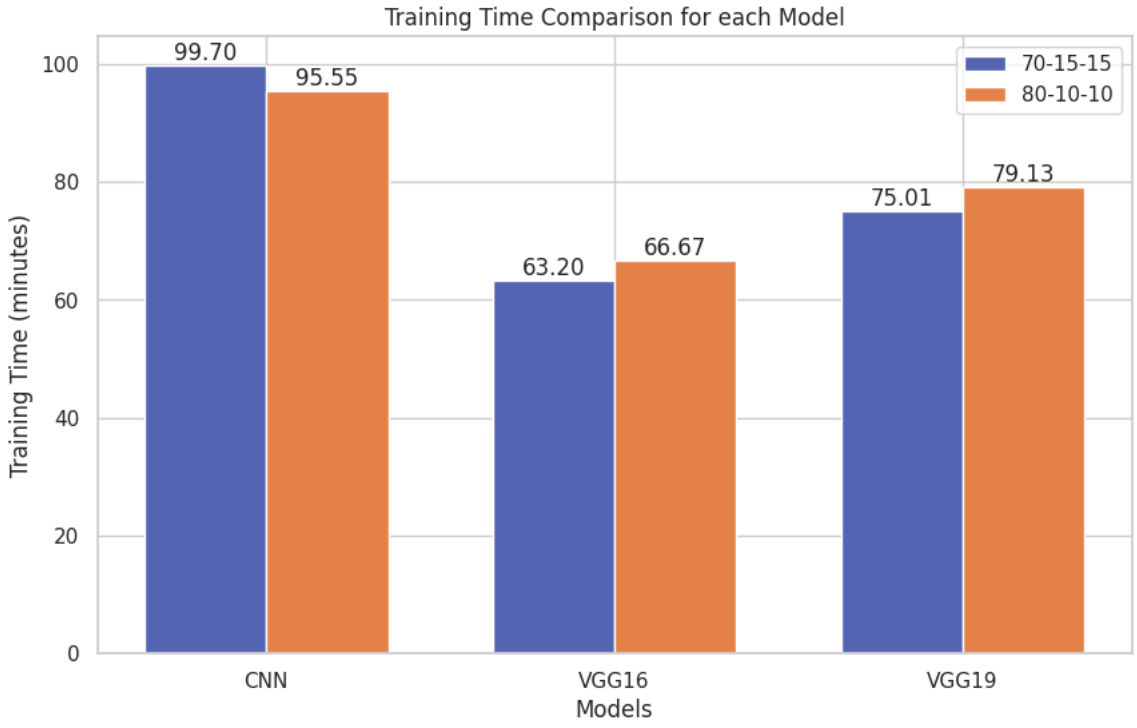

Figure 8.22: Training Time per Model (Different Dataset Splits)

8.4.3.1 Key Observations

1. **Training Time for CNN**:

   - **70-15-15 Split**: The CNN model took approximately 99.70 minutes to train.
   - **80-10-10 Split**: The training time slightly decreased to 95.55 minutes with the 80-10-10 split.

- **Explanation**: The CNN's training time is the longest among all the models, primarily because it is designed to run for up to 100 epochs, depending on early stopping criteria. The slight decrease in training time with the 80-10-10 split might be attributed to the model achieving early stopping more quickly due to better generalization from having more training data.

2. **Training Time for VGG16**:

   - **70-15-15 Split**: VGG16 completed training in 63.20 minutes.
   - **80-10-10 Split**: The training time increased to 66.67 minutes.
   - **Explanation**: VGG16 has a more standardized training time since it runs for 50 epochs without early stopping. The slight increase in training time with the 80-10-10 split is likely due to the increased amount of training data, which requires more computation per epoch.

3. **Training Time for VGG19**:

   - **70-15-15 Split**: VGG19 took 75.01 minutes to train.
   - **80-10-10 Split**: The training time increased further to 79.13 minutes.
   - **Explanation**: Similar to VGG16, VGG19 also runs for 50 epochs, and the increase in training time with the 80-10-10 split is again attributed to the additional training data. VGG19 generally takes longer to train than VGG16, likely due to its deeper architecture, which has more parameters to optimize.

8.4.3.2 Comparative Analysis

1. **Impact of Dataset Split**:

   - Across all models, the 80-10-10 split results in longer training times compared to the 70-15-15 split. This is expected as more training data typically increases the computational load for each epoch. The increase is modest for the VGG models but more noticeable for the CNN model, indicating that

the CNN's early stopping mechanism is more sensitive to the amount of training data.

2. **Impact of Model Architecture/Complexity**:

   - The CNN model, being custom-built and possibly less optimized compared to the VGG architectures, takes the longest to train. Its flexibility in running for up to 100 epochs contributes to this extended training time, although early stopping helps mitigate excessive training duration.
   - VGG16 is the most efficient in terms of training time, likely due to its relatively simpler architecture compared to VGG19, and it benefits from fewer epochs being required.
   - VGG19, while taking longer than VGG16, remains more efficient than CNN but demonstrates the trade-off between model complexity (i.e., depth and parameter count) and training duration.

8.4.3.3 Combined Consideration

- **Training Time vs. Dataset Split**: The results indicate that while increasing the training set size (from 70% to 80%) does enhance the model's exposure to data, leading to potentially better performance, it also imposes a higher computational cost, as evidenced by the increased training times. This trade-off must be balanced depending on the availability of computational resources and the urgency of the training process.

- **Epoch Count Consideration**: The fact that VGG16 and VGG19 are trained for a fixed 50 epochs, regardless of the split, highlights their stability in training duration, although this comes at the cost of potentially longer training times as the dataset size increases. The CNN, on the other hand, with its early stopping mechanism, could offer a more adaptive training process but still incurs high computational costs due to its architecture.

8.4.3.4 Conclusion

Training time analysis provides useful insights into computational efficiency for each model on different dataset splits. While the custom CNN is the most time-consuming, it may offer more flexibility through early stopping, which can prevent unnecessary computation. The VGG models are far more efficient, and especially VGG16, therefore might be appealing in cases where training time is a critical factor. However, the slight increase in training time with an 80-10-10 split on all models brings out the issue of balancing dataset size with available computational resources and desired speed of deployment of models. In most real-world applications, these factors are very crucial for optimizing model performance since training time can be directly translated to operation efficiency.

8.5 Model Performance Analysis

8.5.1 Overview

The two bar charts on Figure 8.23 illustrate the loss and accuracy performance of three different models— a custom CNN, VGG16, and VGG19—across the training, validation, and testing datasets. These graphs provide insight into how each model performed and generalizes to new data. Below is a detailed analysis:

1. **Loss Comparison**:
    - **Training Set**:
        - The loss on the training set is lowest for the VGG16 model, followed by VGG19, with the custom CNN showing the highest loss among the three.
        - This suggests that VGG16, even not being the deepest network among the three, has better capacity to minimize the loss during training, possibly fitting the training data more closely than the other models.

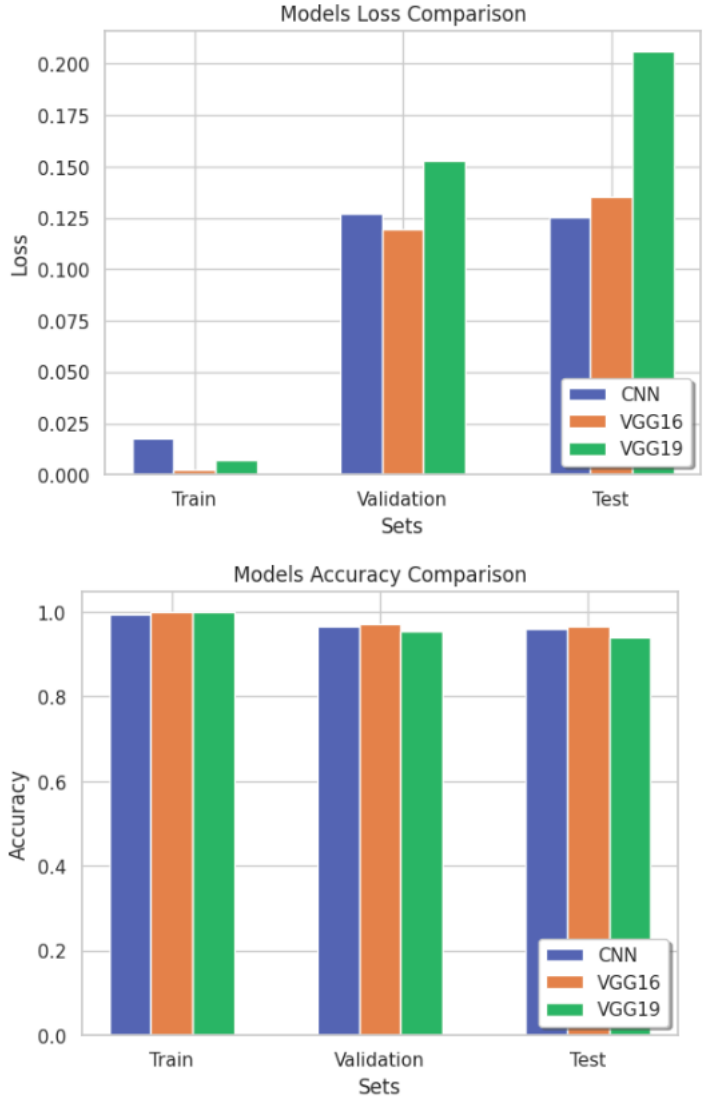

Figure 8.23: Loss and Accuracy Comparison Across Models and Different Sets

- **Validation Set**:
  - On the validation set, the losses for all models are higher than on the training set, which is expected as the model is exposed to unseen data.
  - Here, VGG19 shows the highest loss, followed by CNN, with VGG16 having the lowest validation loss.
  - The significant increase in validation loss for VGG19 compared to its training loss suggests that VGG19 may be overfitting the training data, leading to poorer generalization on new, unseen data.

  - The custom CNN's relatively lower validation loss indicates better generalization and suggests that it might have a better balance between fitting the training data and generalizing to new data.

- **Testing Set**:
  - The loss on the test set is again highest for VGG19, followed by VGG16, with the custom CNN showing the lowest loss.
  - This pattern reinforces the observation that the deeper VGG19 model is struggling to generalize, whereas the custom CNN, despite its simpler architecture, is more robust in handling unseen data.

2. **Accuracy Comparison**:

- **Training Set**:
  - All models exhibit very high accuracy on the training set, with slight differences. VGG19 and VGG16 show marginally higher accuracy than the custom CNN.
  - High training accuracy across all models indicates that they all have sufficient capacity to learn the training data well.
- **Validation Set**:
  - Validation accuracy is slightly lower than training accuracy for all models, as expected. However, the custom CNN and VGG16 models are very close in performance, with VGG19 slightly lagging.
  - This suggests that while VGG19 fits the training data well, it does not generalize as effectively as the other two models.
- **Testing Set**:
  - Similar to the validation set, the custom CNN and VGG16 maintain high accuracy on the test set, with VGG19 showing a slight drop.
  - The close performance of the custom CNN and VGG16 on unseen data (validation and test sets) indicates that these models are well-tuned and

capable of generalizing, whereas VGG19, despite its complexity, may be prone to overfitting.

3. **General Observations and Conclusions**:

   - **Overfitting in VGG19**:
     - The VGG19 model, while powerful, shows signs of overfitting as indicated by the substantial increase in loss and slight drop in accuracy on the validation and test sets compared to the training set.
     - This overfitting may be due to its deeper architecture, which has a higher capacity to learn intricate patterns in the training data but struggles to maintain this performance on new data.
   - **Robustness of the Custom CNN**:
     - The custom CNN, despite being a simpler model compared to VGG16 and VGG19, demonstrates strong generalization abilities. This is evident from its low loss and high accuracy on the validation and test sets.
     - The model's design is well-suited for the specific task at hand, balancing complexity and generalization.
   - **VGG16 as a Balanced Option**:
     - VGG16 performs well across all sets, with lower losses and high accuracy, indicating that it may strike a good balance between model complexity and generalization.
     - It could be seen as a more reliable choice if computational resources and model interpretability are considerations.

Summary

The comparison between the custom CNN, VGG16, and VGG19 models highlights different strengths and weaknesses. While the VGG19 model is the most complex and performs best on the training data, it suffers from overfitting, leading to higher losses

and slightly lower accuracy on validation and test sets. The custom CNN, though simpler, demonstrates robust performance across all datasets, making it a strong candidate for deployment. VGG16 offers a good compromise, with consistently high accuracy and moderate loss, suggesting it could be a balanced choice for this task.

8.5.2 Comparison of Test Loss and Accuracy Between Models

The bar chart on Figure 8.24 compares the test accuracy and test loss for three models: CNN, VGG16, and VGG19. The metrics are evaluated on a testing set, which consists of unseen data. Here's a detailed analysis of these results:

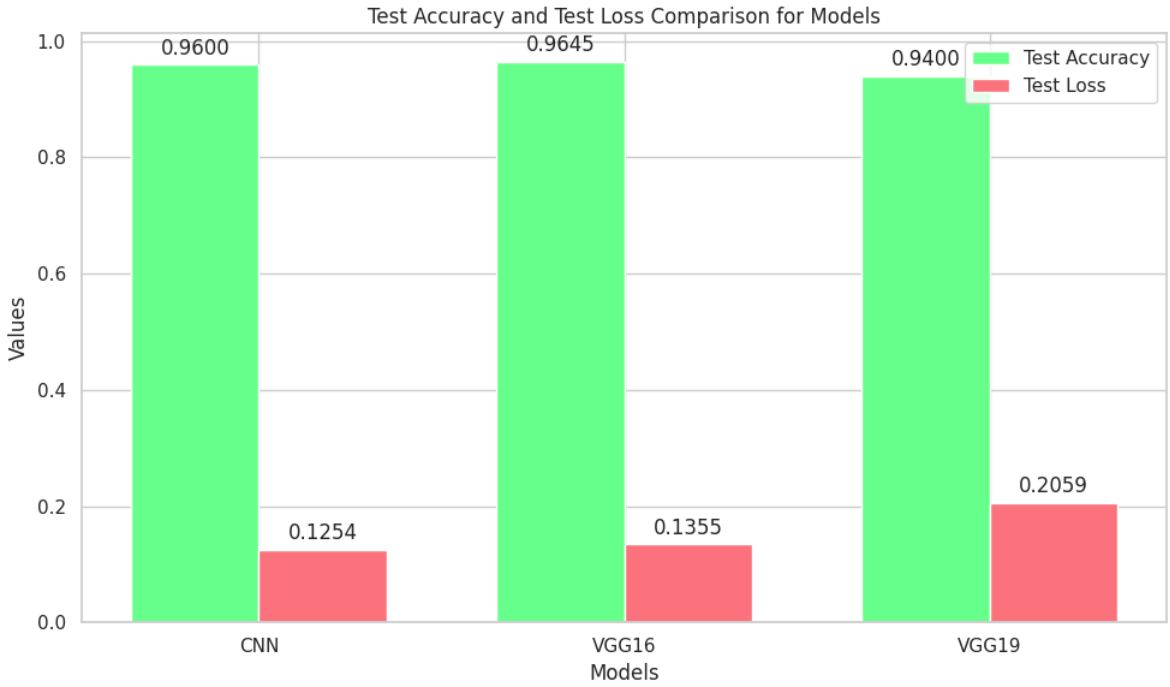

Figure 8.24: Accuracy and Loss Comparison Across Models (Test Dataset)

- **Test Accuracy**:
  - **CNN**:
    - **Accuracy**: 96.00%
    - **Comment**: The CNN model achieved a high accuracy, indicating that it generalizes well to unseen data. This result suggests that the model has

learned robust features during training, leading to strong performance on the test set.

  - **VGG16**:
    * **Accuracy**: 96.45%
    * **Comment**: VGG16 slightly outperforms CNN in terms of test accuracy, reaching 96.45%. This marginal improvement can be attributed to the more sophisticated architecture of VGG16, which might be better at capturing complex patterns in the data.
  - **VGG19**:
    * **Accuracy**: 94.00%
    * **Comment**: VGG19 shows a lower test accuracy (94.00%) compared to both CNN and VGG16. Despite being a deeper network, it does not perform as well, which could be due to overfitting or the increased complexity making it harder to generalize as effectively on the unseen data.

- **Test Loss**:
  - **CNN**:
    * **Loss**: 0.1254
    * **Comment**: CNN has the lowest test loss, which complements its high accuracy. A low test loss indicates that the predictions are not only correct but also confident, which is crucial for a reliable model.
  - **VGG16**:
    * **Loss**: 0.1355
    * **Comment**: VGG16, despite having the highest accuracy, shows a slightly higher test loss than CNN. This suggests that while VGG16 makes slightly more correct predictions, the confidence in those predictions might be a bit lower compared to CNN.

  - **VGG19**:
    - **Loss**: 0.2059
    - **Comment**: VGG19 has the highest test loss, which aligns with its lower accuracy. This indicates that the model might struggle with certain aspects of the test data, leading to less confident predictions and potential overfitting during training.

- **Comparative Analysis**:

  1. **Model Performance**:
     - **VGG16** emerges as the top performer in terms of test accuracy, albeit with a slightly higher test loss compared to CNN. This suggests that VGG16 is able to capture the most relevant patterns in the data, making it the most accurate model for this task.
     - **CNN** shows a strong balance between accuracy and loss, making it a reliable model with confident predictions.
     - **VGG19** lags behind in both accuracy and loss, suggesting that its increased complexity may not be necessary for this specific task and could lead to overfitting.
  2. **Generalization**:
     - The results indicate that while more complex models like VGG19 have the potential for high accuracy, they may not always generalize better, as seen in the case of this comparison. Simpler models like CNN and VGG16 can sometimes offer a better balance of performance and confidence.
  3. **Overfitting**:
     - The higher test loss of VGG19, despite its complexity, suggests that it might be overfitting to the training data. This is a common issue with deeper networks that have more parameters, as they can memorize the training data rather than generalize from it.

Conclusion

The comparison shows that **VGG16** achieves the best test accuracy, making it the most accurate model on unseen data. However, **CNN** is not far behind, offering a better trade-off between accuracy and confidence (as reflected by its lower test loss). **VGG19**, despite being a deeper model, does not perform as well, highlighting the importance of model simplicity and the risk of overfitting when dealing with complex architectures.

For tasks where confident predictions are crucial, CNN might be preferable, while for maximizing accuracy, VGG16 could be the better choice. However, VGG19's performance suggests it may not be the best option for this particular problem.

8.5.3 Model Ensemble

8.5.3.1 What is a model ensemble?

A **model ensemble** is a machine learning technique that combines predictions from multiple models to create a stronger, more accurate model. The idea is that each model might have different strengths and weaknesses, and by combining them, we can balance out individual errors, leading to better overall performance.

8.5.3.2 Why do we use it?

We use model ensembles to improve **accuracy** and **robustness** of predictions. No single model is perfect, and combining multiple models often helps capture different aspects of the data, leading to more reliable and accurate results.

8.5.3.3 What are the benefits of it?

1. **Better Accuracy**: Combining models often leads to better performance than using just one model. The ensemble can make fewer errors by averaging out the mistakes of individual models.

2. **Reduction in Overfitting**: If one model overfits (performs very well on the

training data but poorly on new data), the other models may balance this out, leading to more generalizable predictions.

3. **Increased Robustness**: If one model is weak in certain areas, other models in the ensemble might cover for it, making the final prediction more stable.

8.5.3.4 How is it used?

In our case, we are combining the predictions of three models:

1. A **CNN** model,
2. A **VGG16** model,
3. A **VGG19** model.

These models make independent predictions, and we use a technique called **majority voting** to determine the final prediction. For each data point, we count the prediction each model makes, and the class that gets the most votes becomes the final prediction.

Figure 8.25 shows the classification report of an ensemble model applied to a test dataset. The report includes key metrics: precision, recall, F1-score, and support for each class, as well as overall accuracy and average metrics. Here's a detailed analysis of the results:

	precision	recall	f1-score	support
Tomato___Bacterial_spot	1.00	0.98	0.99	110
Tomato___Early_blight	0.95	0.95	0.95	110
Tomato___Late_blight	0.97	0.99	0.98	110
Tomato___Leaf_Mold	0.99	0.98	0.99	110
Tomato___Septoria_leaf_spot	0.96	0.99	0.98	110
Tomato___Spider_mites Two-spotted_spider_mite	0.99	0.98	0.99	110
Tomato___Target_Spot	0.96	0.94	0.95	110
Tomato___Tomato_Yellow_Leaf_Curl_Virus	0.99	1.00	1.00	110
Tomato___Tomato_mosaic_virus	1.00	1.00	1.00	110
Tomato___healthy	0.99	1.00	1.00	110
accuracy			0.98	1100
macro avg	0.98	0.98	0.98	1100
weighted avg	0.98	0.98	0.98	1100

Figure 8.25: Model Ensemble: Classification Report

1. **Tomato_Bacterial_spot**:
    - **Precision**: 1.00, **Recall**: 0.98, **F1-Score**: 0.99
    - **Comment**: The model is highly precise in identifying bacterial spot, with very few false positives, and has excellent recall, indicating almost all true bacterial spot cases are correctly identified.
2. **Tomato_Early_blight**:
    - **Precision**: 0.95, **Recall**: 0.95, **F1-Score**: 0.95
    - **Comment**: Early blight is classified well with a good balance between precision and recall, reflecting a solid performance.
3. **Tomato_Late_blight**:
    - **Precision**: 0.97, **Recall**: 0.99, **F1-Score**: 0.98
    - **Comment**: Late blight shows a slightly higher recall than precision, indicating that almost all actual cases are detected, with minimal false positives.
4. **Tomato_Leaf_Mold**:
    - **Precision**: 0.99, **Recall**: 0.99, **F1-Score**: 0.99
    - **Comment**: The model performs exceptionally well on leaf mold, demonstrating near-perfect precision and recall.
5. **Tomato_Septoria_leaf_spot**:
    - **Precision**: 0.96, **Recall**: 0.99, **F1-Score**: 0.97
    - **Comment**: The high recall suggests that nearly all Septoria leaf spot cases are detected, with very few missed, though the precision is slightly lower, indicating a few more false positives.
6. **Tomato_Spider_mites_Two-spotted_spider_mite**:
    - **Precision**: 0.99, **Recall**: 0.99, **F1-Score**: 0.99

- **Comment**: The model handles spider mite cases excellently, with very high precision and recall, indicating reliable identification.

7. **Tomato_Target_Spot**:
   - **Precision**: 0.96, **Recall**: 0.94, **F1-Score**: 0.95
   - **Comment**: Target spot shows a slight drop in recall, suggesting a few cases are missed, but overall, the performance is still strong.
8. **Tomato_Yellow_Leaf_Curl_Virus**:
   - **Precision**: 0.99, **Recall**: 1.00, **F1-Score**: 0.99
   - **Comment**: The model is highly effective in detecting yellow leaf curl virus, with perfect recall and very high precision.
9. **Tomato_Tomato_mosaic_virus**:
   - **Precision**: 1.00, **Recall**: 1.00, **F1-Score**: 1.00
   - **Comment**: Mosaic virus detection is flawless, with perfect precision and recall, indicating that the model made no errors for this class.
10. **Tomato_healthy**:
    - **Precision**: 0.99, **Recall**: 1.00, **F1-Score**: 1.00
    - **Comment**: The model accurately identifies healthy plants with almost no mistakes, as shown by its high precision and perfect recall.

8.5.3.5 Overall Model Performance

- **Accuracy**: 98%
  - **Comment**: The model achieves an impressive accuracy of 98%, indicating that the majority of predictions are correct.
- **Macro Average**:

  - **Precision**: 0.98, **Recall**: 0.98, **F1-Score**: 0.98
  - **Comment**: The macro average shows that, on average, the model performs consistently well across all classes, treating each class equally.

- **Weighted Average**:
  - **Precision**: 0.98, **Recall**: 0.98, **F1-Score**: 0.98
  - **Comment**: The weighted average takes into account the support (number of instances) for each class and confirms that the model performs well even when considering the class distribution.

8.5.3.6 Conclusion

The ensemble model achieves excellent performance across all classes, with most F1-scores close to 1.00, indicating a well-balanced and effective classifier. The high accuracy and strong precision, recall, and F1-scores across the board suggest that the ensemble approach successfully leverages the strengths of each individual model, resulting in improved overall performance. The few minor discrepancies, such as slightly lower precision or recall in some classes, do not significantly detract from the overall effectiveness of the model. This result demonstrates the success of the ensemble strategy in achieving robust and reliable classification, particularly in a multi-class scenario like this one.

8.5.4 ROC (Receiver Operating Characteristic) Curve

The **ROC curve** is a graphical representation used to evaluate the performance of a binary or multi-class classifier. It shows the trade-off between the **True Positive Rate (Recall)** and the **False Positive Rate (FPR)** at various threshold settings. It helps to understand how well the classifier distinguishes between classes, particularly in binary classification problems, but can be extended to multi-class problems.

8.5.4.1 Components of ROC Curve

1. **True Positive Rate (TPR)**: Also called **Recall** or **Sensitivity**, it tells us the proportion of actual positives that were correctly identified.

$$\text{TPR} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

   It answers the question: "Out of all actual positive samples, how many did the classifier identify as positive?"

2. **False Positive Rate (FPR)**: This is the proportion of actual negatives that were incorrectly classified as positive.

$$\text{FPR} = \frac{\text{False Positives}}{\text{False Positives} + \text{True Negatives}}$$

   It answers the question: "Out of all actual negative samples, how many did the classifier incorrectly classify as positive?"

3. **Threshold**: A classification model outputs a probability score for each sample, and the **threshold** is the probability value above which a sample is classified as positive (and below which it is classified as negative). The ROC curve shows how performance changes as you vary this threshold.

8.5.4.2 How to Interpret the ROC Curve?

- **X-axis**: The **False Positive Rate (FPR)**, which ranges from 0 to 1.
- **Y-axis**: The **True Positive Rate (TPR)**, which also ranges from 0 to 1.

A point on the ROC curve represents the **(FPR, TPR)** for a particular threshold. As you vary the threshold from 0 to 1, the curve traces out the performance of the classifier.

8.5.4.3 Key Points to Consider

1. **The diagonal line** from (0, 0) to (1, 1) represents random guessing. This is because, with random guessing, the False Positive Rate increases proportionally with the True Positive Rate. An **AUC (Area Under the Curve) of 0.5** represents this situation, meaning the model has no discrimination capability (no better than random chance).

2. **The closer the curve is to the top-left corner** (FPR=0, TPR=1), the better the classifier. This indicates:

   - High True Positive Rate (high Recall)
   - Low False Positive Rate (few misclassified negatives)

3. **Area Under the ROC Curve (AUC)**: This is a single number that summarizes the performance of the classifier. It can be interpreted as the probability that a randomly chosen positive instance is ranked higher by the classifier than a randomly chosen negative instance. The values of AUC range from:

   - **1.0**: Perfect classifier (ideal)
   - **0.9-1.0**: Excellent performance
   - **0.8-0.9**: Good performance
   - **0.7-0.8**: Fair performance
   - **0.5-0.7**: Poor performance
   - **0.5**: No better than random guessing

8.5.4.4 Why Use the ROC Curve?

- **Threshold independence**: Unlike many metrics that require choosing a fixed threshold (e.g., accuracy), the ROC curve evaluates classifier performance across all possible thresholds. This is helpful when you're interested in how well your model ranks predictions rather than relying on a specific threshold.

- **Comparing models**: The ROC curve, combined with the AUC score, allows easy comparison between multiple models. A model with a higher AUC consistently performs better across different thresholds.

- **Handling imbalance**: While the ROC curve is useful, it's less informative when dealing with **imbalanced datasets**, because the False Positive Rate may be misleadingly low when the negative class dominates. In such cases, the **Precision-Recall curve** (which you used in your earlier code) can be more informative.

8.5.4.5 Example of ROC Curve Behavior

- A **perfect classifier** would have a TPR of 1 and an FPR of 0, placing its ROC curve right at the top-left corner of the plot with an AUC of 1.0.

- A **random classifier** has an ROC curve that follows the diagonal from (0, 0) to (1, 1), with an AUC of 0.5.

- A **poor classifier** might perform worse than random guessing, leading to a curve below the diagonal and an AUC of less than 0.5 (indicating the model is likely misclassifying positive and negative classes).

8.5.4.6 ROC Curve Example Visualization

- **In a well-performing model**: The curve quickly rises towards a high True Positive Rate while keeping the False Positive Rate low and the area under the curve (AUC) approaches 1, signifying good discrimination ability.

- **In a weak model**: The curve remains closer to the diagonal, indicating poor performance (closer to random guessing).

In summary, the **ROC curve** helps to evaluate a classifier's ability to balance between catching true positives while avoiding false positives at different threshold levels. It's particularly useful for binary classification and comparing classifiers.

8.5.4.7 ROC Curve for CNN and VGG models

Looking at the ROC curve on Fgiure 8.26, here are the conclusions we can draw:

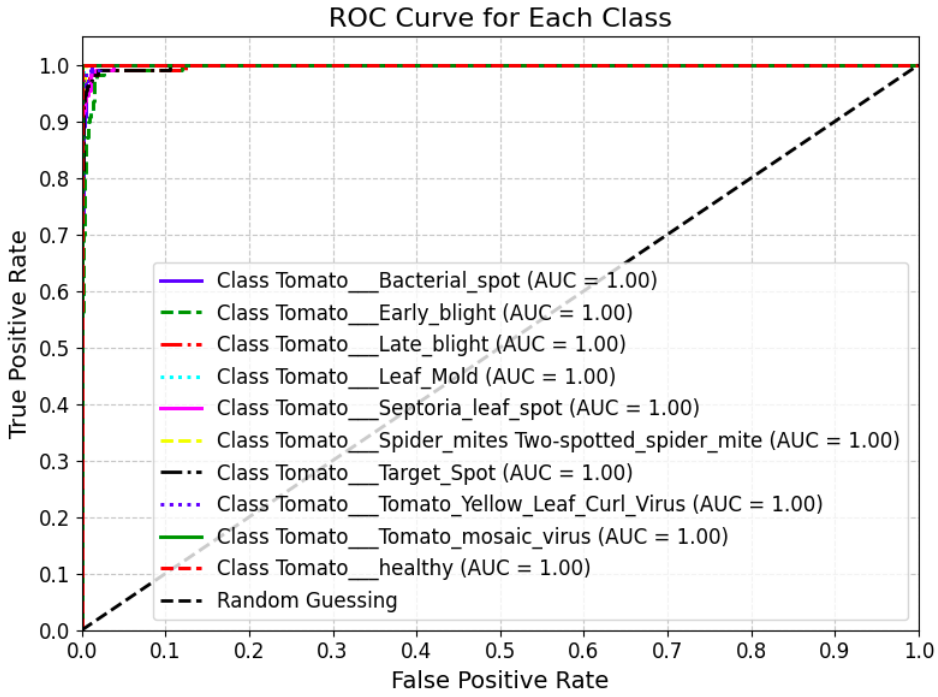

Figure 8.26: ROC Curve for Each Class.

Key Observations

1. **AUC (Area Under the Curve) of 1.00 for All Classes**:
   - Each class has an **AUC of 1.00**, which means the model has a **perfect classification performance** for every class.
   - An AUC of 1.00 indicates that the classifier perfectly distinguishes between the positive and negative classes for all categories.
2. **ROC Curves Hugging the Top-Left Corner**:
   - All the curves are tightly clustered near the top-left corner of the plot. This is the ideal behavior for a classifier, where the **True Positive Rate (TPR)** is maximized and the **False Positive Rate (FPR)** is minimized.

- This means the model achieves a **high True Positive Rate** (close to 1) while keeping the **False Positive Rate** (close to 0) very low, even at different thresholds.

3. **Diagonal Line (Random Guessing)**:

   - The dashed diagonal line represents the performance of a random classifier (AUC = 0.5).
   - Since all the ROC curves for the classes are well above this line, it confirms that the model is significantly better than random guessing.

In summary, the ROC curve shows **exceptional model performance** across all classes, but you should also ensure this is not due to overfitting by testing it on new, unseen data as we have done.

8.6 Loss and Accuracy Analysis

8.6.1 Training and Validation Loss/Accuracy for CNN, VGG16, and VGG19 (2 Graphs)

The charts presented in Figure 8.27 provide an in-depth comparison of the training and validation loss, as well as accuracy across 50 epochs, for three different models: a custom CNN, VGG16, and VGG19. These graphs are crucial for understanding the learning dynamics, convergence behavior, and generalization capability of each model. Below is a detailed analysis:

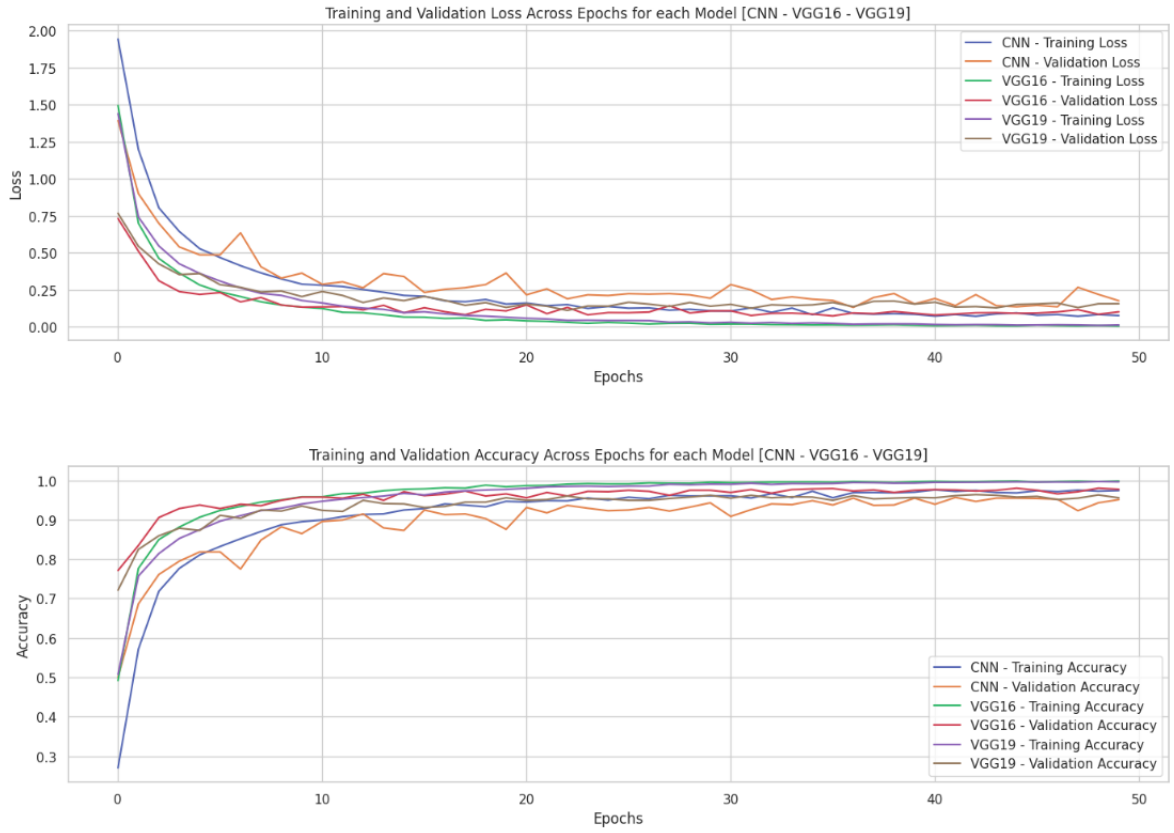

Figure 8.27: Overall Performance Analysis (Two Graphs: Loss and Accuracy)

1. **Training and Validation Loss Across Epochs**:

   - **Initial Convergence (First 10 Epochs)**:
     - All three models demonstrate a sharp decline in training and validation loss during the first 10 epochs, indicating that the models are learning quickly from the data.
     - The custom CNN starts with the highest initial loss but catches up rapidly. VGG19 and VGG16 start with slightly lower losses and converge faster initially.
   - **Post-Initial Convergence (After 10 Epochs)**:
     - **CNN**:
       * The custom CNN model shows a smooth and continuous reduction in both training and validation loss, but the validation loss remains

consistently higher than the training loss throughout the training process. This indicates that while the model is learning well, there might be slight overfitting as the validation loss doesn't decrease as smoothly as the training loss.

- **VGG16**:
  - VGG16 maintains a stable loss curve after the initial drop, with validation loss closely tracking the training loss. This suggests a good balance between model complexity and its ability to generalize, as both losses remain low and close to each other.
- **VGG19**:
  - VGG19 shows the most significant gap between training and validation loss after the initial convergence, which is more pronounced compared to VGG16 and the custom CNN. This divergence indicates potential overfitting, where the model performs exceptionally well on the training data but struggles to maintain similar performance on the validation data.

- **Final Epochs (After 40 Epochs)**:
  - Towards the end of the training, the loss curves for all models show minor fluctuations, particularly in validation loss, which is expected as the models reach the limits of their learning capacity.
  - VGG19 continues to show higher validation loss than training loss, reinforcing the observation of overfitting. VGG16 and the custom CNN, while having slightly lower training loss, exhibit better generalization, with VGG16 being the most stable among the three.

2. **Training and Validation Accuracy Across Epochs**:

- **Initial Accuracy Growth (First 10 Epochs)**:
  - All models show rapid increases in both training and validation accuracy within the first few epochs. The custom CNN starts with the lowest accuracy but quickly catches up, indicating effective learning.

  - VGG16 and VGG19 start with relatively high initial accuracy and improve quickly, reflecting the advantages of transfer learning in these pre-trained models.

- **Post-Initial Growth (After 10 Epochs)**:
  - **CNN**:
    * The custom CNN achieves a consistent and steady increase in accuracy, peaking around 90-95%. However, the gap between training and validation accuracy is slightly more prominent than in VGG16, suggesting slight overfitting.
  - **VGG16**:
    * VGG16 displays a near-parallel increase in training and validation accuracy, with both metrics stabilizing around 95-97%. The close alignment between these curves suggests excellent generalization with minimal overfitting.
  - **VGG19**:
    * VGG19 achieves high training accuracy, consistently above 95%, but its validation accuracy curve shows more fluctuations compared to VGG16. The gap between training and validation accuracy towards the later epochs hints at overfitting.

- **Final Epochs (After 40 Epochs)**:
  - By the end of the training process, VGG16 and the custom CNN show convergence of training and validation accuracy, indicating that these models have learned the training data well while still generalizing effectively to the validation data.
  - VGG19, however, despite achieving high training accuracy, shows a slightly lower and less stable validation accuracy curve, reinforcing concerns about overfitting.

8.6.1.1 Summary of Observations

1. **Model Convergence and Learning Efficiency**:

   - All three models demonstrate efficient learning, as indicated by the rapid decrease in loss and increase in accuracy during the initial epochs.
   - VGG19, due to its deeper architecture, initially shows promising results but quickly diverges between training and validation metrics, suggesting that while it learns the training data very well, it might be overfitting.

2. **Overfitting in VGG19**:

   - The VGG19 model exhibits the most significant signs of overfitting, with a noticeable gap between training and validation loss, as well as fluctuating validation accuracy, particularly in the later epochs.

3. **Generalization in VGG16 and Custom CNN**:

   - VGG16 appears to be the most well-balanced model, showing close alignment between training and validation metrics, indicative of strong generalization capabilities.
   - The custom CNN also generalizes well, though it shows slightly more overfitting compared to VGG16, evidenced by the small but consistent gap between training and validation metrics.

4. **Overall Model Performance**:

   - While VGG19 might be more powerful in theory, its performance on unseen data suggests that it is not as robust as VGG16 or the custom CNN for this specific task. VGG16, with its stable performance and lower risk of overfitting, stands out as the most reliable model among the three, followed closely by the custom CNN.

8.6.1.2 Conclusion

The provided analysis illustrates the importance of balancing model complexity with the ability to generalize. While more complex models like VGG19 can achieve higher training accuracy, they are prone to overfitting, leading to poorer performance on validation and test datasets. In contrast, models like VGG16 and the custom CNN, which strike a better balance between complexity and generalization, are likely to be more reliable choices for practical deployment in real-world scenarios.

8.6.2 Combined Loss/Accuracy Curves for CNN, VGG16, and VGG19 (1 Graph)

The Figure 8.28 graph combines both loss and accuracy curves for training and validation sets across 50 epochs for three different models: a custom CNN, VGG16, and VGG19. This comprehensive visualization allows us to observe the relationships between loss and accuracy, and between training and validation performance, all within a single plot. Here's a detailed analysis:

1. **Initial Observations (First Few Epochs)**:
    - **Loss Curves**:
        - All models begin with high loss values, which is expected during the initial training phase.
        - The custom CNN (blue line) starts with the highest initial loss, while VGG19 (grey line) and VGG16 (green line) start with lower initial losses. This suggests that the VGG models, due to their pre-trained nature, begin with a more advantageous position.
        - A sharp decrease in loss is observed for all models within the first 5 epochs, which is typical as the models rapidly learn basic features of the dataset.

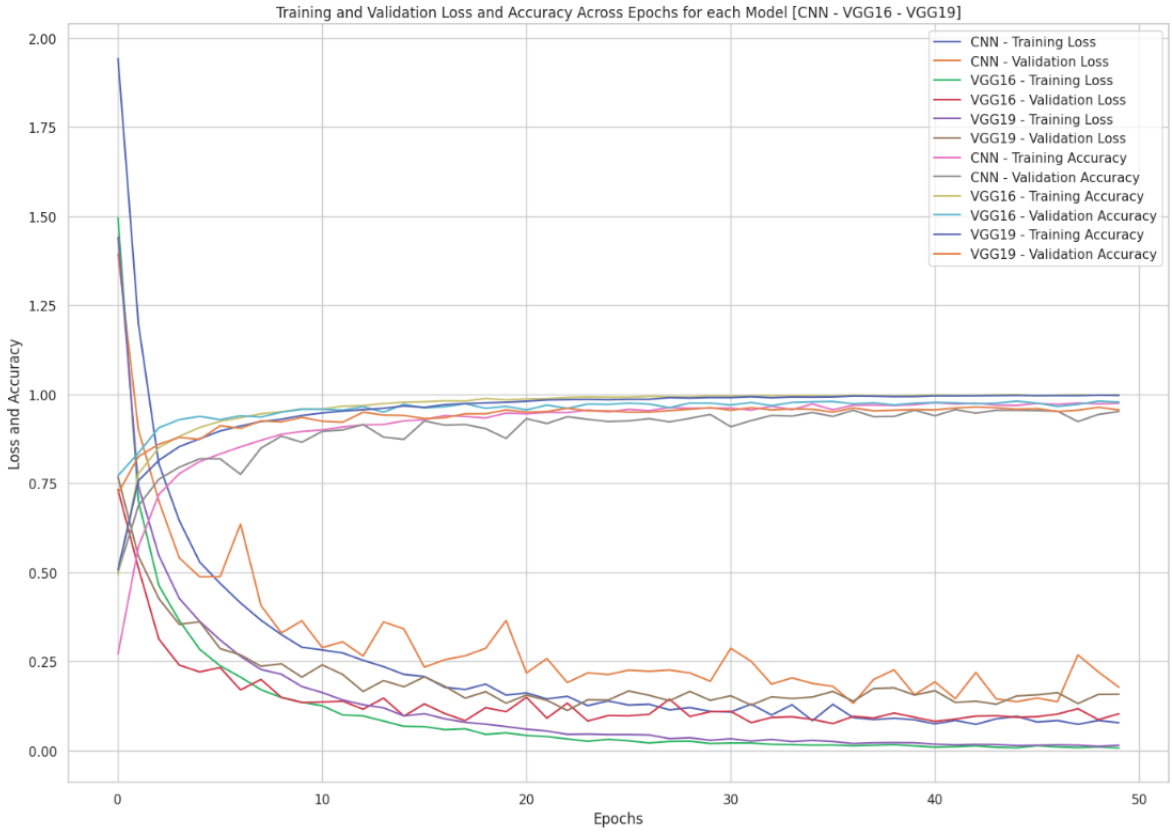

Figure 8.28: Overall Performance Analysis (Combined Graph: Loss and Accuracy)

- **Accuracy Curves**:
  - The accuracy curves like the loss but in the opposite direction exhibit rapid growth within the first few epochs.
  - VGG16 (beige) and VGG19 (dark blue) show an early advantage, reflecting their transfer learning benefits. The custom CNN, while starting lower, quickly catches up.

2. **Mid-Epoch Performance (10-30 Epochs)**:

- **Loss Stabilization**: After the initial rapid drop, the loss curves for all models begin to stabilize.
  - **CNN (Blue)**:
    * The custom CNN model shows a stable decrease in training loss, with validation loss following a similar pattern but at a slightly

higher level. This indicates that the model continues to learn but shows minor signs of overfitting as the validation loss does not decrease as steadily.

- **VGG16 (Green)**:
  - VGG16 exhibits the most stable loss curves among the three models. Both training and validation losses converge closely, indicating good generalization with minimal overfitting.
- **VGG19 (Grey)**:
  - VGG19 shows a more fluctuating validation loss compared to its training loss, indicating overfitting. The model learns the training data well but struggles to maintain consistency on unseen validation data.

- **Accuracy Consolidation**: The accuracy curves start to plateau, with the models reaching their peak performance.
  - **VGG16 (Beige)**:
    - VGG16 maintains high and consistent accuracy across both training and validation sets, showing excellent generalization. The accuracy lines remain close together, indicating minimal overfitting.
  - **VGG19 (Dark Blue)**:
    - VGG19 achieves high training accuracy, but the gap between training and validation accuracy begins to widen, reflecting overfitting.
  - **CNN (Rose)**:
    - The custom CNN reaches high accuracy, though it shows a slightly wider gap between training and validation accuracy than VGG16, again hinting at overfitting.

3. **Late-Epoch Observations (After 30 Epochs)**:

- **Final Performance Trends**:
  - **CNN (Blue)**:

    - The custom CNN continues to show good performance, with training loss gradually reducing and validation loss stabilizing slightly above it. The accuracy for both training and validation remains high, though with some divergence, indicating mild overfitting.
  - **VGG16 (Green)**:
    - VGG16 continues to demonstrate robust generalization, with both loss and accuracy curves for training and validation remaining closely aligned. This model shows the least fluctuation, suggesting it has learned the task well and is likely to generalize effectively to new data.
  - **VGG19 (Grey)**:
    - VGG19, despite high training accuracy, shows more instability in its validation loss and accuracy, reinforcing the observation that it may be overfitting. The model's validation performance does not match its training performance as closely as the other models, which could limit its real-world applicability.

8.6.2.1 Key Insights

1. **Model Generalization**:

   - **VGG16** emerges as the most balanced model, with closely aligned training and validation metrics across the board, indicating strong generalization and minimal overfitting.
   - The **custom CNN** also shows good generalization, though with slightly more overfitting than VGG16, as indicated by the divergence between training and validation metrics.

2. **Overfitting in VGG19**:

   - **VGG19** consistently shows signs of overfitting, as evidenced by the gap between training and validation metrics. Despite achieving high training

accuracy, its validation performance is less stable and lower than that of VGG16, which suggests that it may struggle with new, unseen data.

3. **Training Dynamics**:

   - All models learn quickly within the first few epochs, but VGG16 maintains a superior balance between learning capacity and generalization, making it the most reliable model in this comparison.

8.6.2.2 Conclusion

In summary, this combined visualization underscores the importance of monitoring both loss and accuracy simultaneously to assess a model's performance. **VGG16** stands out as the most reliable model for this task due to its consistent performance across training and validation datasets. The custom **CNN** model also performs well but exhibits mild overfitting. **VGG19**, while powerful, demonstrates a tendency to overfit, which may limit its effectiveness in real-world applications where generalization to unseen data is crucial.

NOTE: The example and graph presented here are essentially the same as those discussed in the previous section. However, unlike before, we have not separated them into two distinct graphs—one for loss and the other for accuracy. Instead, both metrics are combined into a single graph to clearly demonstrate how closely their curves align. By doing so, we can observe that the curves track each other closely without significant discrepancies, which might have caused confusion when viewed separately. Consequently, it is expected that the results and observations in this section mirror those from the previous one, making the analyses appear similar.

8.6.3 Training Loss and Accuracy Across Epochs

Figure 8.29 consists of two graphs, each depicting the training performance of three different models: a custom Convolutional Neural Network (CNN), VGG16, and VGG19, over 50 epochs. These graphs are crucial for understanding the behavior and efficacy

of each model during the training process, and they directly relate to our thesis on disease detection in tomato plants using machine learning.

8.6.3.1 Top Graph: Training Loss Across Epochs

The first graph plots the **training loss** against the number of epochs for each of the three models. Here's a detailed analysis:

- **CNN (Blue Line)**: The custom CNN model starts with the highest loss at the beginning, close to 2.0, which indicates the model initially had a significant error in its predictions. However, as training progresses, the loss decreases sharply and continues to gradually decline, stabilizing at a lower value around the 20th epoch. Despite this improvement, the final loss value is higher compared to the VGG16 and VGG19 models, suggesting that the CNN model, although effective, is not as optimized as the pre-trained models for this specific task.
- **VGG16 (Orange Line)**: The VGG16 model starts with a lower initial loss compared to the CNN, indicating that it has a better starting point, likely due to its pre-training on a large image dataset. The loss decreases more rapidly and reaches a lower stable point than the CNN, demonstrating better learning efficiency and generalization capability. The curve flattens out sooner, indicating that VGG16 has converged and learned the features required for the task efficiently.
- **VGG19 (Green Line)**: Similar to VGG16, the VGG19 model also begins with a lower initial loss and follows a trend similar to VGG16. The loss decreases rapidly and reaches a point of stability, with its final loss value being quite similar to that of VGG16. The proximity of the VGG16 and VGG19 loss curves suggests that both models perform comparably in minimizing the loss, although subtle differences in architecture may lead to slight variations in the training process.

8.6.3.2 Bottom Graph: Training Accuracy Across Epochs

The second graph on the same Figure 8.29, shows the **training accuracy** over the same 50 epochs for the three models:

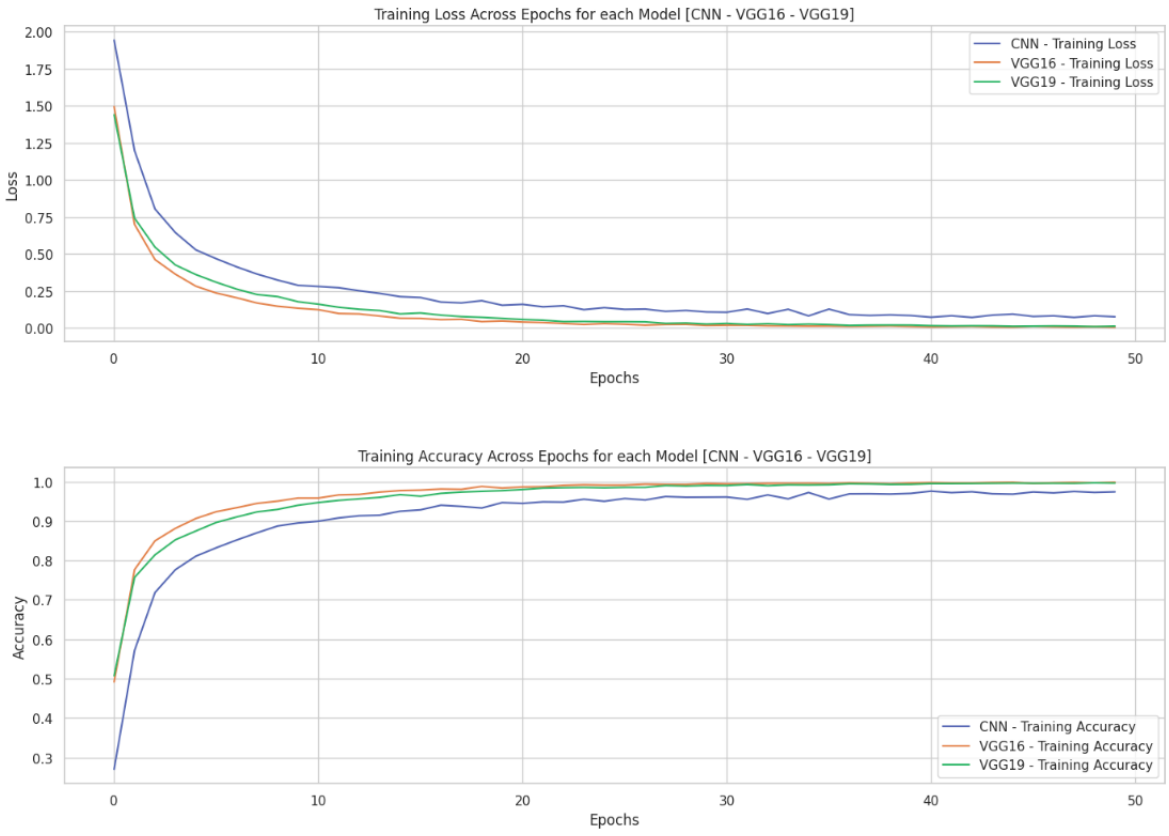

Figure 8.29: Training Set: Loss and Accuracy Over Epochs (Separate Graphs)

- **CNN (Blue Line)**: The CNN model begins with a relatively low accuracy, just above 0.3, indicating that its initial predictions were mostly incorrect. However, the accuracy improves significantly as training progresses, with a steep rise in the early epochs. The model eventually stabilizes at an accuracy just above 0.9, indicating that it learned to correctly identify the diseases with a good degree of accuracy, though it still falls short of the performance of the VGG models.

- **VGG16 (Orange Line)**: The VGG16 model starts with a much higher accuracy than the CNN, which can be attributed to the advantages of transfer learning. The accuracy curve rises quickly and plateaus near 1.0 within the first 20 epochs. This indicates that VGG16 has rapidly learned the necessary features and is capable of making highly accurate predictions early in the training process.

- **VGG19 (Green Line)**: The accuracy curve for VGG19 is very similar to that of VGG16, starting at a high initial value and quickly reaching near-perfect ac-

curacy. This reinforces the observation that both VGG16 and VGG19 are well-suited for the task and benefit from their pre-trained weights, allowing them to generalize effectively with fewer epochs.

8.6.3.3 Conclusion and Implications

These graphs illustrate a comparative performance analysis between a custom CNN model and two pre-trained models (VGG16 and VGG19) when trained on a dataset of tomato leaf images for disease classification:

- **Performance of Pre-trained Models**: Both VGG16 and VGG19 outperform the custom CNN model, achieving lower training loss and higher accuracy with fewer epochs. This highlights the effectiveness of transfer learning in image classification tasks, particularly when using complex architectures like VGG16 and VGG19 that have been pre-trained on large, diverse datasets.

- **Custom CNN Model**: While the custom CNN shows significant improvement over time, it requires more epochs to reach a comparable level of accuracy. This suggests that while custom models can be effective, they may require more data, fine-tuning, or more complex architectures to compete with well-established pre-trained networks.

- **Implications for Application**: The superior performance of VGG16 and VGG19 implies that these models could be more reliable for real-world deployment in our web application for diagnosing tomato plant diseases. Their rapid convergence and high accuracy make them suitable candidates for integration into systems that require quick and accurate disease detection.

  This analysis provides a clear understanding of the training dynamics of the models we explored, supporting our thesis's argument regarding the utility of ML and AI in agricultural disease management. The insights gained from these graphs are valuable in demonstrating the trade-offs between custom and pre-trained models, ultimately guiding the choice of model for practical applications.

8.6.4 Validation Loss and Accuracy Across Epochs

The graphs provided on Figure 8.30 illustrate the validation loss and validation accuracy across epochs for three models: CNN, VGG16, and VGG19. Let's break down the observations and conclusions based on these curves.

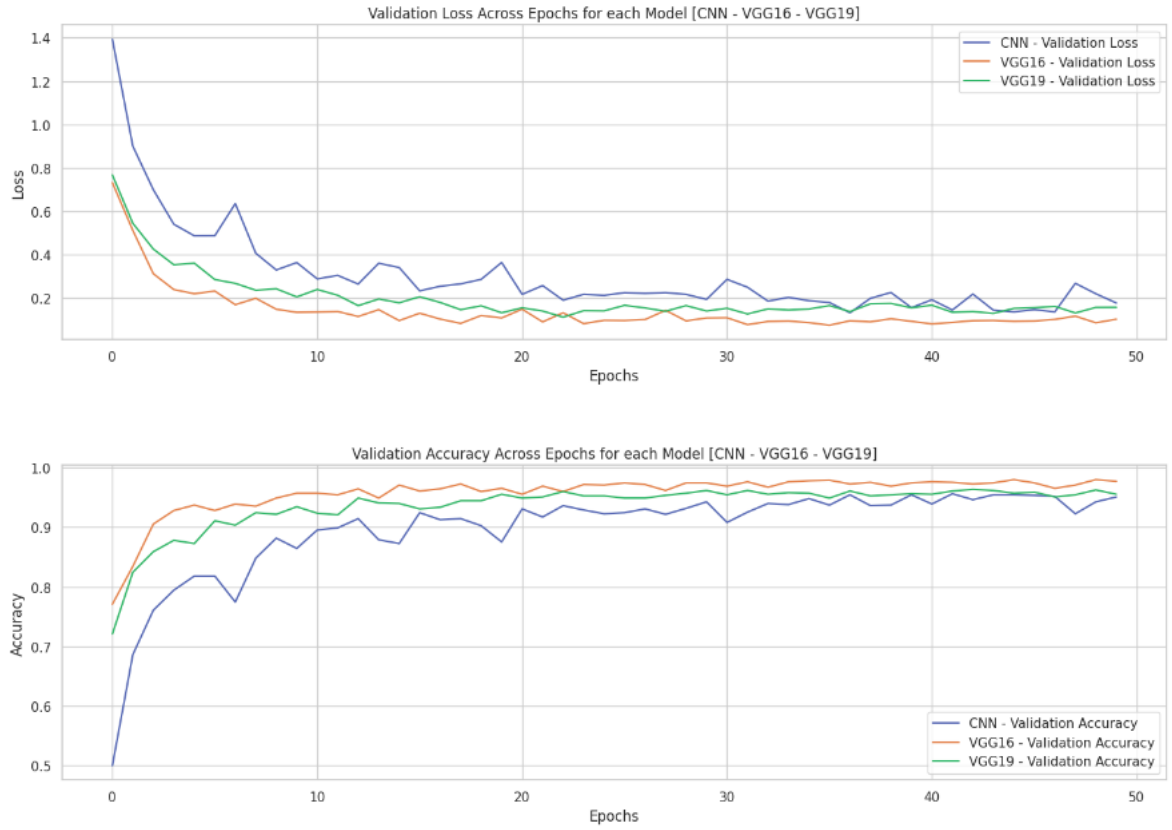

Figure 8.30: Validation Set: Loss and Accuracy Over Epochs (Separate Graphs)

8.6.4.1 Validation Loss

- **CNN**: The validation loss for the CNN model starts relatively high but decreases significantly over the epochs. Although it fluctuates slightly, the overall trend shows a steady decline, indicating that the model is improving its predictions on unseen data.

- **VGG16**: The validation loss for VGG16 is consistently lower than that of CNN, with a smoother curve that indicates more stable learning. This suggests that

VGG16 is not only learning effectively but also generalizing well to the validation data.

- **VGG19**: VGG19 shows a validation loss curve similar to VGG16 but slightly higher. Despite being a deeper network, VGG19's performance here doesn't surpass that of VGG16, hinting at possible overfitting. This means that while VGG19 learns very well on the training data, it struggles a bit more when it comes to validation data, suggesting that it might be overfitting to the training set.

8.6.4.2 Validation Accuracy

- **CNN**: The validation accuracy curve for CNN starts lower than the others but increases rapidly, approaching a high accuracy. However, it stabilizes slightly below the curves for VGG16 and VGG19. This shows that while CNN is effective, it is slightly less accurate in its predictions compared to the VGG models.

- **VGG16**: VGG16 demonstrates the best validation accuracy, with a curve that is consistently high and stable across epochs. The close alignment between its validation accuracy and loss indicates a well-balanced model that performs consistently across both training and validation data.

- **VGG19**: Although VGG19 also achieves high validation accuracy, its curve is a bit more erratic compared to VGG16. This further supports the observation of overfitting; VGG19 may perform exceptionally well on the training set, but its performance on the validation set is less consistent, leading to more fluctuations.

8.6.4.3 Combined Observations

When examining these curves together, it's clear that **VGG16** is the most reliable model, balancing high accuracy with low and stable loss across validation data. **VGG19**, despite being a deeper network, seems to overfit more, achieving high training accuracy but not generalizing as well on validation data. **CNN** is very close to VGG16 in performance, but slightly behind, making it a solid yet slightly less optimal choice compared to VGG16.

8.6.4.4 Importance of Combined Graphs

These observations, however, are equally poignant, especially to the fact that the training and validation curves should go together. Observations of the graphs separately can be misleading since this does not give a picture about the generalization capability of the model. The slight overfitting in VGG19, for example, would not have been spotted unless the metrics for training and validation are put side by side. Plotting all metrics together provides a broader view regarding model performance and allows us to draw more sound conclusions. This is actually the necessary holistic approach that should be followed in order for our models not only to be accurate but also robust and generalizable.

Chapter 9

Streamlit Web Application for Disease Detection

9.1 Streamlit Overview

After building and saving the trained CNN model for tomato leaf disease detection, the next step is to deploy this model in a user-friendly interface. Testing images one by one through code is not efficient or user-friendly, particularly for real-world applications. Thus, we created an interactive web application using Streamlit, allowing users to upload an image of a tomato leaf and receive a prediction of the disease. Additionally, based on the predicted disease, the application suggests appropriate treatments to prevent and eradicate the disease.

Streamlit is an open-source Python library that allows one to quickly create interactive and beautiful web applications. The purpose of Streamlit, in essence, is to take data scripts and convert them into shareable web apps with minimal effort, exercising simplicity in the most appealing way.

9.1.1 Why Use Streamlit?

- **Simplicity**: Streamlit allows developers to build and deploy web applications with only a few lines of code.

- **Interactivity**: It supports interactive widgets, making it easier to create user inputs, such as file uploaders and buttons.
- **Real-time Updates**: Streamlit apps update in real-time as users interact with widgets, providing immediate feedback.
- **Integration**: It seamlessly integrates with various Python libraries such as TensorFlow, NumPy, and Pandas.

9.1.2 Features of Streamlit

- **Widgets**: Easy to create sliders, buttons, file uploaders, and more.
- **Data Display**: Effortlessly display data using tables, charts, and other visual elements.
- **Layouts and Theming**: Customize the appearance and layout of your app.
- **Real-time Data Processing**: Automatically reruns scripts as users interact with the app, providing real-time feedback.
- **Deployment**: Streamlit apps can be deployed on various platforms, including Streamlit Sharing, Heroku, and AWS.

9.1.3 Streamlit vs Django and Flask

In this thesis, we employed Streamlit to deploy a machine learning model aimed at identifying diseases in tomato plants. To understand why Streamlit was the preferred choice for this project, it's important to compare it with other web frameworks such as Django and Flask.

- **Streamlit**:
  - **Purpose**: Streamlit is designed for **data science and machine learning applications**, allowing researchers and developers to quickly transform Python scripts into interactive web applications. This feature is invaluable

for projects that involve data analysis or model deployment, such as the disease classification model developed in this thesis.

  - **Features**:
    - Easy integration with **data visualization tools** like Matplotlib, Seaborn, and Plotly, which are essential for displaying the results of machine learning models.
    - Minimal coding requirements for front-end design, making it highly efficient for rapid prototyping.
    - Users can directly upload images of tomato leaves and receive **real-time disease classification** and treatment suggestions, making it ideal for agricultural use.
  - **Use Cases**: Streamlit's simplicity and specialization make it ideal for projects like this one, where the goal is to quickly build an interactive interface for a machine learning model without the complexity of full-stack web development.

- **Django**:
  - **Purpose**: Django is a **full-stack web framework** that offers comprehensive solutions for building complex, feature-rich web applications. It provides built-in tools for database management, user authentication, and templating, making it suitable for large-scale applications where multiple components need to work together.
  - **Features**:
    - Strong emphasis on security and scalability, with robust support for databases and user management.
    - Follows the **Model-View-Template (MVT)** architecture, making it ideal for applications requiring complex workflows or database interactions.

  - **Use Cases**: While Django is powerful, its complexity is unnecessary for this project, which focuses on delivering a streamlined interface for disease diagnosis.

- **Flask**:

  - **Purpose**: Flask is a **micro-framework** that offers greater flexibility than Django but provides fewer built-in tools. It allows developers to build lightweight web applications and APIs with minimal overhead.
  - **Features**:
    * Flask is highly modular, enabling developers to choose the components they need, but requires more manual configuration compared to Django.
    * It is lightweight and ideal for building simple APIs or web services.
  - **Use Cases**: Flask is well-suited for simple applications and APIs but would require additional setup and configuration to match the functionality provided by Streamlit in this project.

9.1.3.1 Why Streamlit Was the Better Choice for This Thesis

In the context of this thesis, where the goal was to create a **machine learning-driven application for diagnosing diseases in tomato leaves**, Streamlit proved to be the most appropriate tool for several reasons:

1. **Ease of Use**: Streamlit allowed us to convert our Python scripts and machine learning models into an interactive web application with minimal effort, enabling rapid development without needing to manage complex front-end or back-end tasks.

2. **Visualization Support**: The ability to seamlessly integrate data visualizations, such as displaying model predictions and performance metrics, made it easy to interpret and present the results of our machine learning models.

3. **Real-Time Interaction**: Streamlit provided an intuitive interface where users could upload images, receive immediate diagnoses, and view treatment recommendations, making the application highly practical for **real-world agricultural use**.

4. **Focus on Data Science**: Unlike Django or Flask, Streamlit is purpose-built for data-driven applications, aligning perfectly with the machine learning and AI-driven objectives of this research.

By using Streamlit, we were able to make the machine learning model accessible to users in a way that is both interactive and easy to use, helping bridge the gap between **research** and **practical application in agriculture**.

9.2 Running the Streamlit Application

Once the Streamlit application is built, running it is straightforward. Following the steps below we achieve to start an Streamlit app and launch it in a web browser:

1. **Install Streamlit**:

   - If Streamlit is not already installed, we can do so using *pip3*. Open a terminal or command prompt and run the following command:

   ```
   $ pip3 install streamlit
   ```

   - This will install Streamlit and any required dependencies.

2. **Import Streamlit in Your Script**:

   - In the Python script, we have to ensure that Streamlit is imported. For example:

   ```
   import streamlit as st
   ```

   - This import statement allows us to access Streamlit's functions and widgets within the application.

3. **Run the Streamlit Application**:

   - To run the Streamlit application, we can use the following command in the terminal and specifically in the directory the python script is located:

```
$ streamlit run [script_name].py
```

   - Replace *[script_name].py* with the actual name of the Python script. In our case the script is located to (./Thesis/Website/) and would be:

```
$ streamlit run predictions.py
```

4. **Localhost Server and Web Browser**:

   When we run the command, Streamlit automatically starts a local development server. We will see output in our terminal indicating that the server is running and displaying a URL, typically something like *http://localhost:8501*. Streamlit will also automatically open this URL in our default web browser, displaying the web application. The web page that will appear in our case is shown on Figure 9.1.

5. **Accessing the Web Application**:

   The web application will be accessible through the provided URL in our browser. The localhost server acts as a temporary server hosted on our own machine, allowing us to interact with the application as if it were deployed on a public server. As long as the server is running, we can interact with the app, upload images, and receive predictions.

6. **Stopping the Server**:

   To stop the Streamlit server, simply go back to the terminal where it's running and press *Ctrl+C*. This will terminate the server process and close the connection to the localhost.

Conclusion

This subsection provides a step-by-step guide on how to run an Streamlit application and interact with it through a web browser, making it easy for users to test and deploy

their applications.

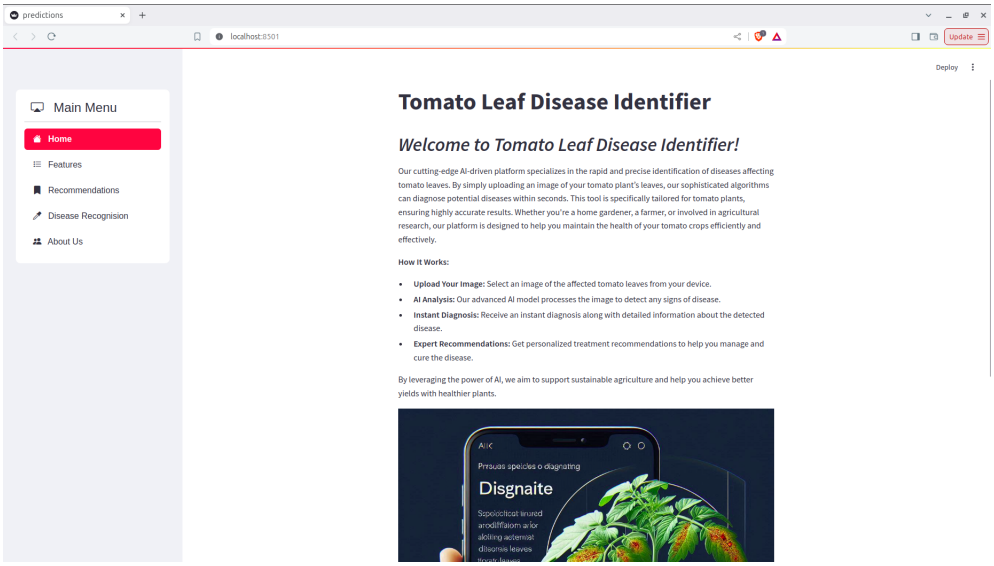

Figure 9.1: Tomato Leaf Disease Identifier: Main Page

9.3 Workflow of the Web Application

9.3.1 Disease Recognition Page

1. **File Upload**: Users can navigate to the *Disease Recognition* tab and upload an image of a tomato leaf using a file uploader. The image can be selected from local files or dragged and dropped into the uploader box. This tab is shown in the Figure 9.2.

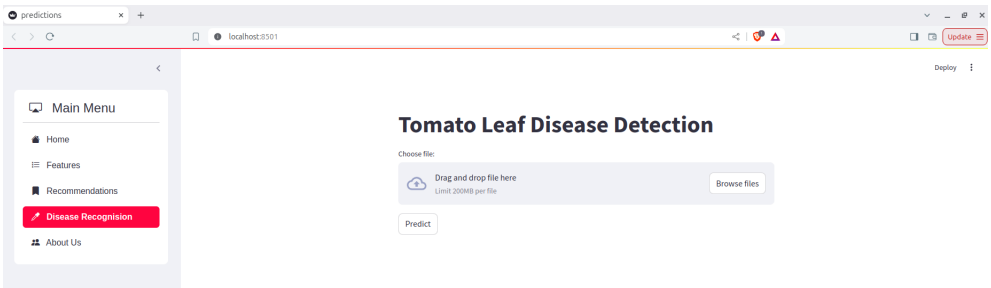

Figure 9.2: Tomato Leaf Disease Identifier: Image Upload Tab

2. **Prediction Button**: After uploading the image, users click the **Predict** button.

3. **Display Results**: The application displays the uploaded image and the model's prediction, including the confidence percentage. Based on the predicted disease, the application also provides a set of treatment recommendations. On Figure 9.3 we can see the result of the above process.

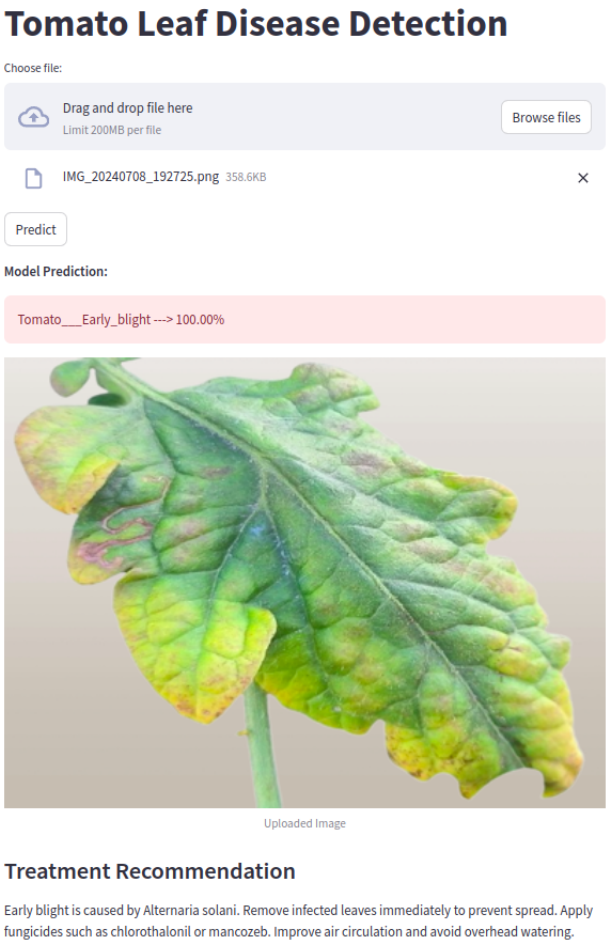

Figure 9.3: Tomato Leaf Disease Identifier: Prediction Results Page

9.3.2 Background Process Explanation

Here is a general description of how the prediction and recommendation process works:

1. **Model Loading**:

- When a user uploads an image and clicks "Predict," the web application loads the pre-trained CNN model for tomato leaf disease detection.

2. **Image Processing**:

   - The uploaded image is resized to the required input dimensions (224x224 pixels).
   - The image is then converted to a numpy array and normalized by dividing by 255 to match the input format expected by the CNN model.

3. **Prediction**:

   - The processed image is expanded to create a batch (even if it contains only one image).
   - The model makes a prediction, producing an array of probabilities for each possible disease class.
   - The highest probability is identified, and the corresponding disease label is selected.

4. **Confidence Calculation**:

   - The maximum probability value is converted to a percentage to indicate the confidence level of the prediction.

5. **Treatment Recommendation**:

   - Based on the predicted disease, a pre-defined dictionary of treatment recommendations provides the appropriate measures to manage the disease.

6. **Result Display**:

   - The predicted disease and confidence percentage are displayed.
   - The uploaded image is shown alongside the prediction.
   - The recommended treatment for the predicted disease is provided.

9.4 Understanding Website Behavior and Results Interpretation

A crucial aspect of these disease detection systems is how they communicate their predictions and confidence to users. Beyond simply classifying a leaf as "healthy" or "diseased," modern machine learning models provide visual cues that reflect the certainty of their predictions. These visual indicators help users assess the reliability of the results, allowing for more informed decision-making. For example, the use of color-coded frames around predictions—along with a displayed confidence percentage—provides a clear, intuitive way to interpret the model's findings.

In this analysis, we explore how these visualizations enhance the user experience and support the decision-making process. We will discuss several scenarios based on model outputs, explaining how varying levels of confidence in predictions are conveyed to the user. These visual indicators—green, red, and yellow frames—along with their corresponding confidence scores, provide users with valuable insights into the model's prediction process. By integrating visual cues into disease detection systems, machine learning models offer an intuitive way for users to quickly assess the reliability of predictions, helping them make timely and informed decisions. Whether through automated disease identification or manual follow-up inspections, this approach enhances the practical application of machine learning in agriculture, particularly for disease management in tomato crops.

9.4.1 Healthy Leaves: High Confidence and Visual Clarity

In one case, illustrated by Figure 9.4, the model predicts that a tomato leaf is healthy, presenting a green frame around the image. This green frame is significant as it signals to the user that the model is highly confident in its classification, typically with a confidence score approaching 100%. The green color is intentionally chosen to indicate safety, implying that no immediate action is needed for the plant. This visual indication, coupled with a high confidence percentage, reassures users that the model has correctly identified the leaf as free from disease.

However, it's important to note that confidence percentages can sometimes vary. When the confidence score is lower, even for a healthy leaf, as seen in Image , the green frame might still appear, but this should prompt users to consider performing a manual inspection. A lower confidence level suggests that the image may not perfectly align with the healthy leaf category in the training dataset, making it worthwhile to double-check the prediction.

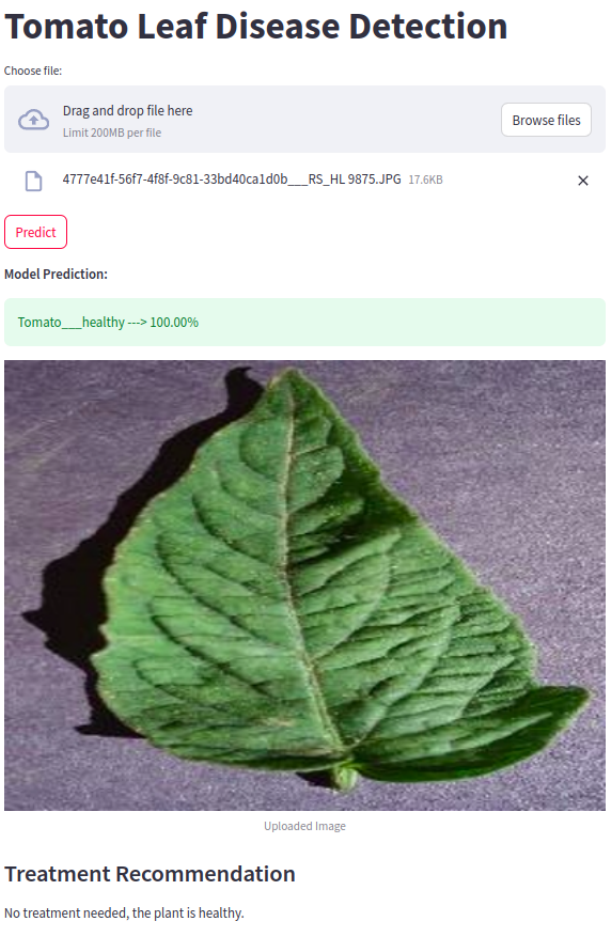

Figure 9.4: Healthy Leaf Detection

9.4.2 Diseased Leaves: Red Frames and Urgent Action

Moving from healthy to diseased leaves, Figure 9.5 showcases a scenario where the model detects a disease, such as early blight, and displays a red frame around the leaf image. The red frame is an immediate alert for users, indicating that action is neces-

sary to prevent further damage to the crop. In this case, the model not only highlights the disease but also provides treatment recommendations based on the specific diagnosis. Additionally, a confidence percentage accompanies the prediction, informing users about how certain the model is about the disease classification. A high confidence score would affirm the model's diagnosis, making it easier for farmers to take swift action. If the confidence score is lower, users might still rely on the model's prediction but would benefit from cross-referencing with other methods or manually inspecting the leaves.

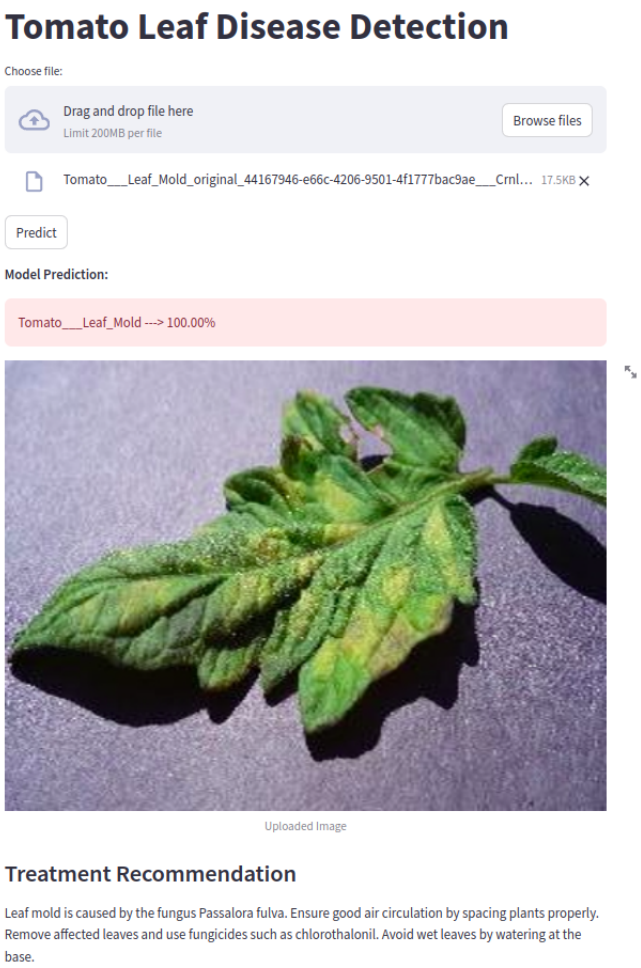

Figure 9.5: Disease Leaf Detection

9.4.3 Uncertainty: Yellow Frames and Low Confidence

A particularly intriguing case arises when the model's confidence level falls below a certain threshold, as shown in Figure 9.6. Here, the model places a yellow frame around the image, indicating uncertainty in its prediction. In this example, the system detected early blight but only assigned a confidence score of 52.84%. The yellow frame serves as a cautionary signal, advising users that the model could not make a definitive prediction. In situations like this, the recommendation is for users to conduct a manual inspection to verify the model's output. The yellow frame acts as a bridge between certainty and uncertainty, alerting users to exercise additional care in diagnosing the plant. While it doesn't imply the prediction is necessarily wrong, it highlights that the system needs further verification.

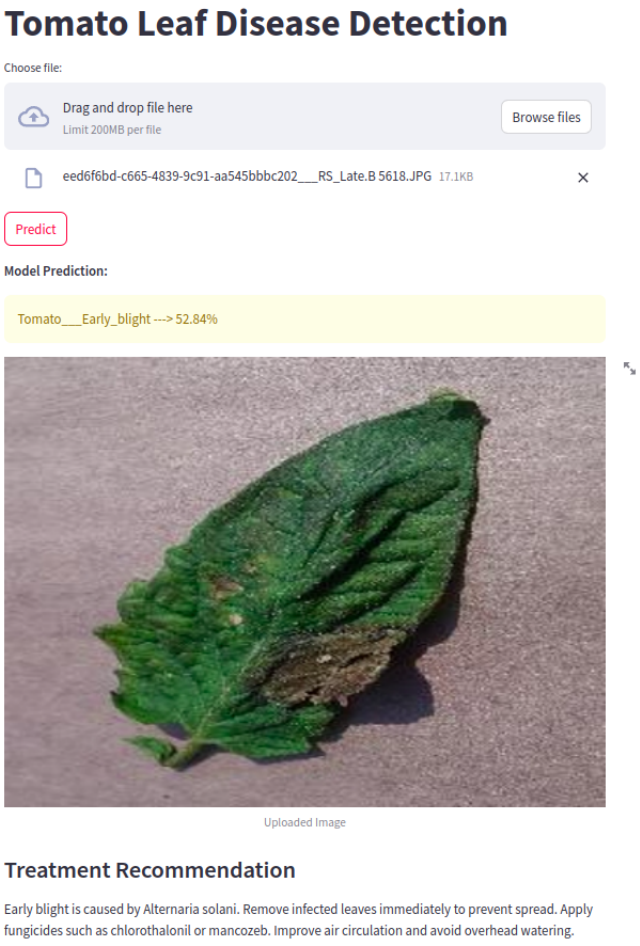

Figure 9.6: Low Confidence Prediction

9.4.4 Robustness of the Model: Moderate Confidence Predictions

Finally, in Figure 9.7, we see the model once again predicting that the leaf is healthy, with a confidence score of 80.85%. While this percentage is lower than the nearly perfect confidence levels seen in previous healthy leaf cases, it still demonstrates the model's ability to correctly identify a non-diseased leaf with a reasonable degree of certainty. This scenario reinforces the robustness of the model, especially as it deals with a variety of leaf images from different regions and environmental conditions.

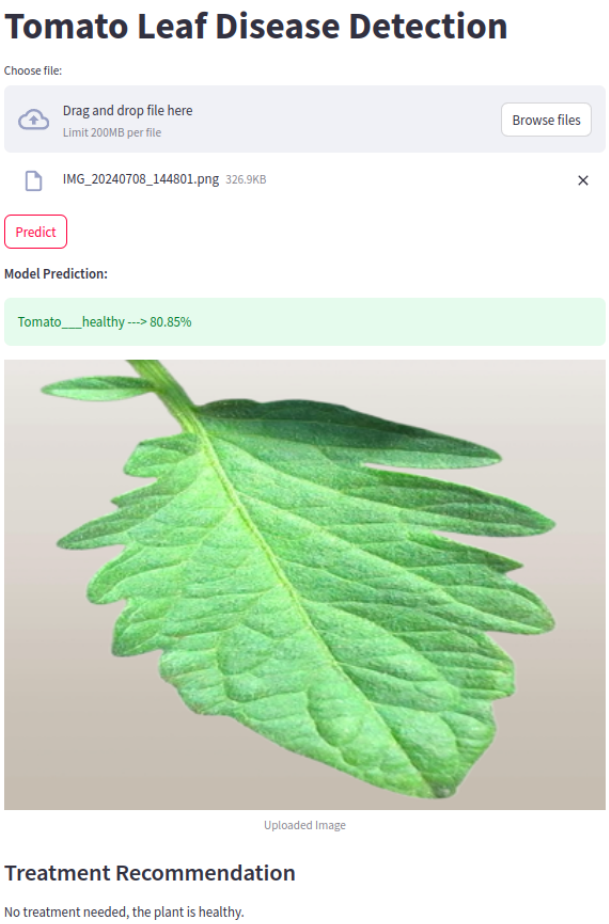

Figure 9.7: Model Robustness: Accurate Classification Across Diverse Leaf Images

9.4.5 Conclusion: Visual Cues and Model Confidence as Decision-Making Tools

These visual indicators—green, red, and yellow frames—along with their corresponding confidence scores, provide users with valuable insights into the model's prediction process. By integrating visual cues into disease detection systems, machine learning models offer an intuitive way for users to quickly assess the reliability of predictions, helping them make timely and informed decisions. Whether through automated disease identification or manual follow-up inspections, this approach enhances the practical application of machine learning in agriculture, particularly for disease management in tomato crops.

9.5 Summary

In general, the given web application using Streamlit provides an interface for uploading an image of a tomato leaf and, based on a series of processes in the background that involve image preprocessing and model prediction, outputs the most likely diagnosis together with the treatment recommendations. This interactive tool greatly improves usability, adding practical value by using the previously trained model in a user-friendly, efficient way.

Chapter 10

Thesis Enhancement: Tomato Leaf Disease Detection

10.1 Image Collection and Preprocessing

In our endeavor to create a robust model for detecting tomato leaf diseases, we collected images from a real-world garden setting. This garden, is meticulously maintained, and during the tomato season, we had the opportunity to capture a variety of tomato leaf conditions. Utilizing a Xiaomi Poco X4 GT smartphone, we took a total of 131 photos, comprising both diseased and healthy leaves. The photos were taken under different lighting conditions, with 90 captured in the morning and the remaining 41 in the afternoon.

10.1.1 Xiaomi Poco X4 GT Specifications

To ensure comprehensive documentation, the detailed specifications of the Xiaomi Poco X4 GT used for image collection are provided at the Table 10.1:

10.2 Image Preprocessing

The images we captured underwent meticulous preprocessing to enhance the accuracy of disease detection. This preprocessing was crucial to eliminate background noise and

Feature	Specification
Processor Model	MediaTek Dimensity 8100
Processor Cores	4+4
Screen Size	6.6”
Resolution	2460 x 1080 pixels
Refresh Rate	144 Hz
Display Type	IPS, Full HD
Rear Camera	Triple
Rear Camera Lenses	Macro 2MP, Wide-angle 64MP, Super Wide-angle 8MP
Camera Features	HDR, Night Mode, Slow Motion

Table 10.1: Specifications of the Device

focus solely on the leaf in question. We organized the images into three distinct folders based on the preprocessing steps applied:

1. **Original Images**: This folder contains the raw images as captured by the smartphone, without any modifications.

2. **Cropped Images**: In these images, we manually cropped the photos to focus as much as possible on the specific leaf intended for disease detection. This step was essential to reduce interference from other leaves and background elements present in the original images.

3. **Background Removed Images**: These images were further processed to remove any remaining background elements, ensuring that only the leaf was present. This step aimed to completely eliminate any distractions and provide the most accurate input for the model. In place of the removed background, a neutral background was added. This background was intentionally chosen to be a very pale beige or light brown, ensuring that it was devoid of any features that could cause interference or confuse the model. By using this neutral background behind the central image of the tomato leaf, the focus was solely on the leaf itself. This approach was consistent with the already defined training, validation, and testing sets, ensuring that the model concentrated on the relevant features of the leaf without being influenced by any extraneous information from the background.

10.3 Results and Observations

The experiments compared the model's performance across three distinct image sets: *Cropped*, *Cropped and Background Removed*, and *Original*, to assess how various preprocessing steps affected the accuracy and confidence of tomato leaf disease detection. The focus was on how these preprocessing techniques influenced prediction consistency (Figure 10.1) and confidence (Figure 10.2).

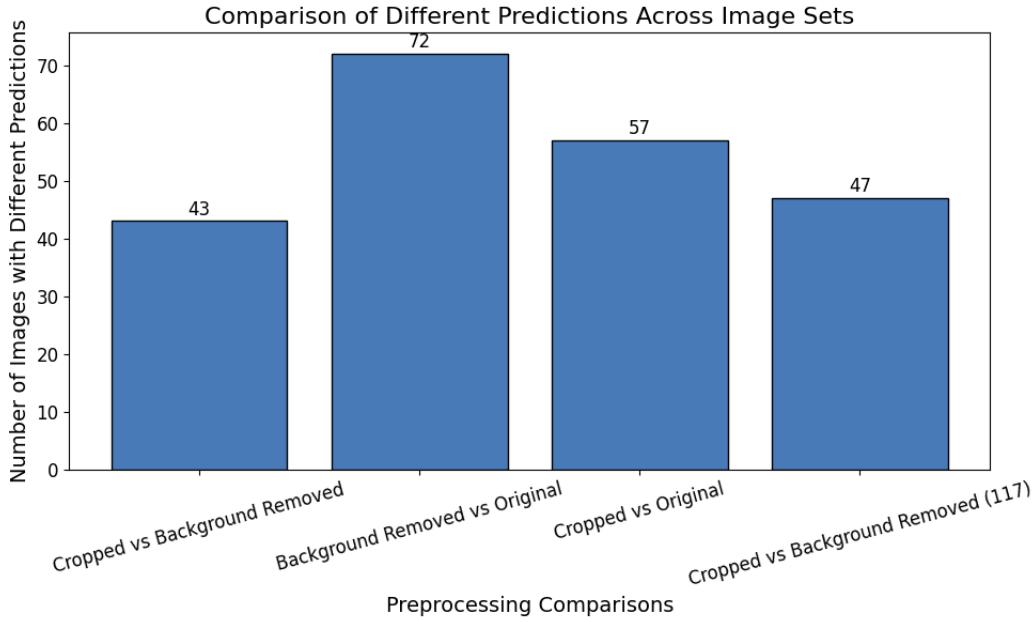

Figure 10.1: Distribution of Different Predictions Across Preprocessing Techniques

1. **Cropped vs. Background Removed (102 images total)**:
   - **43 images** exhibited different predictions between the *Cropped* and *Background Removed* sets.
   - Notably, there was a more significant **rise** in confidence for many images:
     - **35 images** experienced a confidence increase, with an **average rise** of **26.46%**.
     - **64 images** saw a confidence drop, with an **average decrease** of **16.47%**.

Key Insights:

Even though more images showed a drop in confidence, the **magnitude** of the confidence **rise was more substantial** than the decrease. A manual inspection revealed that the confidence drops were generally small, suggesting the model retained certainty in most of its predictions despite losing some background context. On the other hand, the confidence gains were significant in several images, indicating that removing the background often allowed the model to focus more precisely on leaf features. This trend suggests that while background removal can occasionally reduce confidence, it often results in a more focused and confident prediction where the rise is meaningful.

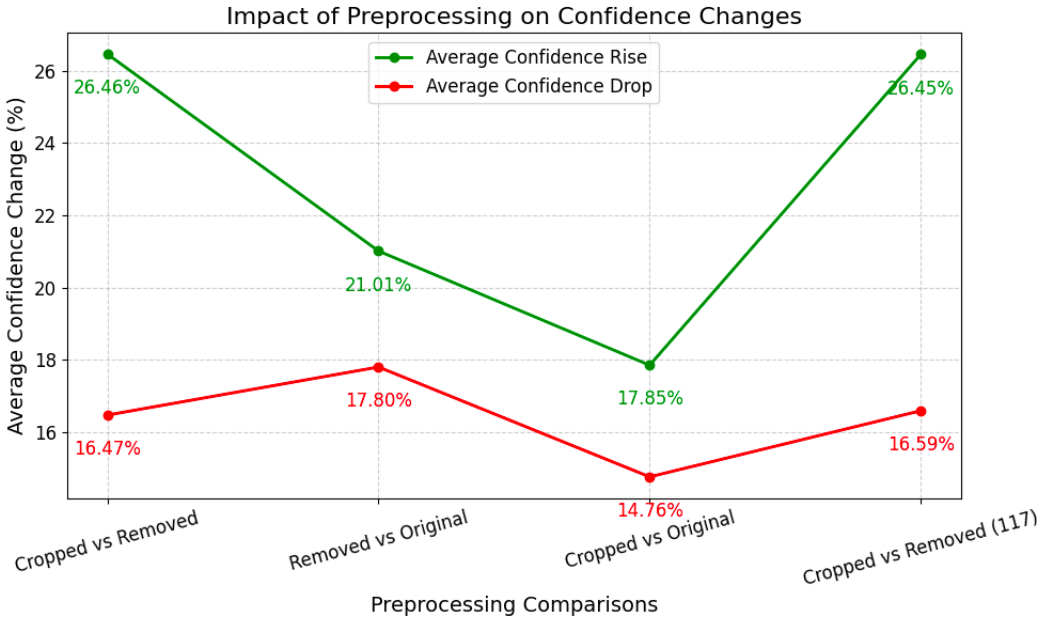

Figure 10.2: Average Confidence Changes After Preprocessing Adjustments

2. **Background Removed vs. Initial (102 images total)**:

   - **72 images** had different predictions when comparing the *Background Removed* images with the *Original* unprocessed images.
   - The changes in confidence were as follows:
     - **21 images** showed a rise in confidence, with an **average increase** of **21.01%**.

  - **80 images** showed a confidence drop, with an **average decrease** of **17.80%**.

Key Insights:

While the majority of images showed a decrease in confidence, it is important to note that **the rise in confidence, though less frequent, was often more significant** than the drops. The **larger rise in confidence** suggests that background removal, while occasionally stripping away useful context, generally provides more clarity to the model in terms of distinguishing leaf diseases. The fact that confidence improvements were more pronounced in this comparison, particularly when contrasted with the *Cropped vs. Original* dataset (discussed next), highlights the potential benefit of background removal as a preprocessing step.

3. **Cropped vs. Initial (102 images total)**:

   - **57 images** showed different predictions between the Cropped images and the Original unprocessed ones.
   - Confidence levels fluctuated as follows:
     - **32 images** saw a rise in confidence, with an **average increase** of **17.85%**.
     - **66 images** experienced a confidence drop, with an **average decrease** of **14.76%**.

Key Insights:

The differences between the *Cropped* and *Original* sets were relatively smaller compared to the *Background Removed* comparisons. While cropping helped focus the model on the leaf, it didn't lead to significant improvements. The fact that both the number of images with increased confidence and the magnitude of those rises were **less pronounced** than in the *Background Removed vs. Initial* comparison suggests that simply cropping the images did not provide the same level of benefit. This indicates that while cropping was somewhat helpful, it was not enough to make a substantial difference in model confidence or accuracy.

4. **(Augmented): Cropped vs. Background Removed (117 images total)**:

   - **47 images** had different predictions when comparing Cropped and Background Removed sets across a slightly larger dataset of 117 images.
   - Confidence levels behaved similarly:
     - **41 images** experienced a rise in confidence, with an **average increase** of **26.45%**.
     - **73 images** showed a confidence drop, with an **average decrease** of **16.59%**.

   Key Insights:
   The trend here reflects that even though more images saw a confidence drop, the **confidence rises were both more frequent and more significant**. This confirms the earlier observation that **background removal**, rather than simple cropping, provided a clearer benefit by enabling the model to focus on disease features. Despite some confidence drops, the consistent rise in a significant number of images suggests that background removal plays a critical role in improving prediction reliability, especially compared to simple cropping.

Overall Conclusions

From the experiments and results, several key conclusions can be drawn:

1. **Magnitude of Confidence Rise vs. Drop**: Even though more images showed confidence decreases, the **confidence rises were more significant** in magnitude. A manual inspection confirmed that the **confidence drops were relatively small**, often not affecting the model's certainty in a meaningful way. On the other hand, the **confidence rises**, especially after background removal, were much more substantial, indicating that this preprocessing step provided the model with clearer information on disease features.

2. **Cropped vs. Original Performance**: The comparison between Cropped and Original images showed **no substantial improvement** in model performance,

suggesting that while cropping the image helps by focusing the model on the leaf, it does not significantly enhance prediction confidence or accuracy.

3. **Background Removal's Impact**: The **largest confidence rise** occurred in the comparison between Background Removed and Initial images, demonstrating that background removal can greatly help the model focus on the relevant parts of the image. Even though more images showed a drop in confidence, the fact that the rises were larger in magnitude suggests that background removal is an effective preprocessing step, even though it occasionally strips away useful context.

4. **Cropped vs. Background Removed**: The **largest difference** in predictions was observed in the comparison between Cropped and Background Removed images. This suggests that cropping alone is not sufficient to maximize model confidence, and that **removing the background entirely allows the model to perform more effectively**, with greater confidence in key cases.

In summary, while background removal sometimes reduces confidence, it **generally leads to a more significant rise** in confidence where it matters. Cropping alone offers limited improvement, but the combination of careful cropping and background removal appears to provide the most significant boost in model performance.

Dataset Variations and Their Impact on Model Performance

Another critical observation that emerged during our analysis relates to the dataset used for training compared to the dataset we created through our own image collection and preprocessing. Specifically, we noticed that the model struggled to accurately classify leaves from our custom dataset with high confidence, often failing to correctly identify the leaf category. This occurred despite the preprocessing techniques we applied, as discussed in earlier sections.

Upon further investigation into the differences between the two datasets, we identified a key factor contributing to this discrepancy. The issue was not related to image resolution or technical specifications but rather to the intrinsic characteristics of the tomato leaves themselves. In particular, we observed that the tomato leaves in Greece,

where our custom dataset was sourced, have distinct morphological differences compared to those in the original dataset.

In Greece, the tomato plants commonly cultivated tend to have thinner and narrower leaves, whereas the leaves in the original dataset are typically thicker and broader. This variance in leaf shape, shown in Figure 10.3, could account for the model's difficulty in generalizing predictions across both datasets. The model was trained on leaf images with a specific shape and thickness, making it less adept at recognizing the narrower leaf shapes prevalent in our local dataset.

This finding underscores the importance of building a more diverse and representative dataset. Although the model achieved respectable confidence levels in certain cases, its performance highlighted the need for greater variability in the training data. As we previously discussed, having a diverse dataset is essential to developing a robust model capable of making accurate predictions across different environmental conditions, leaf variations, and tomato breeds.

To improve future performance, it will be crucial to expand the dataset by incorporating images of tomato leaves from a variety of sources, including:

- Different tomato breeds (e.g., cherry tomatoes, heirloom tomatoes, beefsteak tomatoes).
- Various countries and regions, to account for geographical variations in leaf morphology.
- Different stages of growth and health conditions (e.g., diseased vs. healthy leaves, different disease severities).
- Diverse environmental settings, including different lighting conditions, angles of capture, and weather effects (e.g., dry vs. humid climates).

This expansion will enable us to develop a more versatile and accurate model, adaptable to a wide range of scenarios and capable of performing optimally across diverse datasets.

Such improvements are vital not only for this project but also for future analyses aimed at enhancing the accuracy and generalizability of tomato leaf disease detection models.

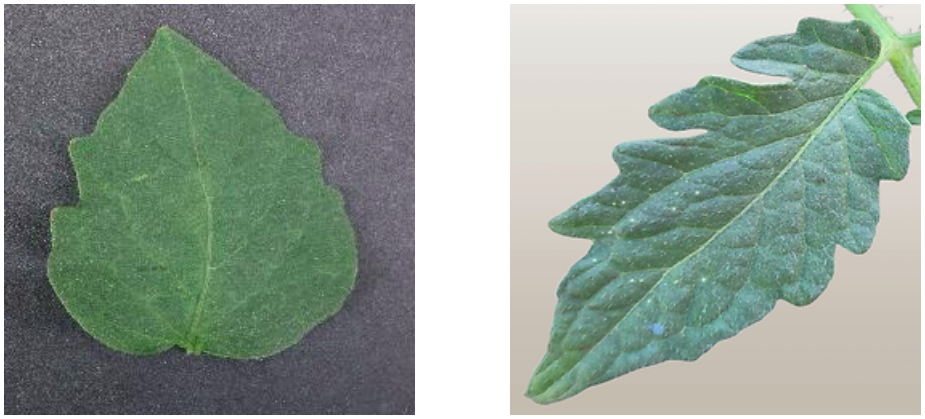

Figure 10.3: Comparison of Tomato Leaf Morphology: The left image shows a broader, thicker tomato leaf from the original dataset, while the right image displays a thinner, narrower leaf from the custom dataset sourced in Greece.

10.4 Summary

Our approach in the thesis covered the effort put in to construct, test and validate the model for disease detection in tomato leaves. Collecting real-world images and this time, with the difference this time being from a different region as opposed to the one we had in the dataset, expanding the diversity, performing various pre-processing techniques and detailed experimentation ensured that there would be a deep analysis of the model's performance. It also included manual classification and evaluation with peer-validated data for a deeper understanding of the accuracy and robustness of the model, thus contributing significantly to our learning and to the field of machine learning in agriculture.

Chapter 11

Potential Improvements and Future Work

Based on the current research, which acts as a solid foundation in AI-driven plant disease management, many avenues of enhancement and expansion are possible. This section highlights some important areas of further improvement and future exploration that can be done to widen the applicability, effectiveness, and impact of the model. It is with such enhancement that the research would, therefore, have a wider coverage of the agricultural challenge to make the developed solutions more comprehensive and user-friendly towards more substantial benefits to the global farming community.

1. **Expansion of the Dataset**:
    - **Incorporate Additional Crops**: While the focus is currently on tomato plants, expanding the dataset to include other crops could make the model more versatile and applicable to a wider range of agricultural scenarios.
    - **Inclusion of More Disease Classes**: The model could be improved by training it on a more comprehensive dataset that includes a greater variety of diseases and pest infestations. This would enhance its diagnostic capabilities.
    - **Geographical Diversity**: The dataset could be expanded to include images from different geographical regions, ensuring that the model is robust and applicable in various climates and agricultural conditions.

2. **Model Enhancement**:

    - **Exploring Advanced Architectures**: Investigate the performance of more recent and advanced deep learning architectures such as EfficientNet, ResNet variants, or Vision Transformers, which might offer better accuracy and efficiency.
    - **Ensemble Learning**: An ensemble of multiple models (e.g., combining the custom CNN with VGG16, VGG19, and other models) could be explored to improve classification accuracy by leveraging the strengths of different architectures.
    - **Model Optimization**: Techniques such as hyperparameter tuning, pruning, and quantization could be applied to optimize the model for better performance and reduced computational overhead, especially for deployment on mobile or edge devices.

3. **Real-Time and Mobile Integration**:

    - **Mobile Application Development**: Building on the idea of a web application, a dedicated mobile application could be developed, allowing farmers to diagnose diseases on the go with their smartphones.
    - **Real-Time Image Processing**: Implementing real-time image processing capabilities within the mobile app or the web application could enhance the user experience, providing instant feedback and recommendations.

4. **User Experience and Interface Improvement**:

    - **Interactive Features**: The web and mobile applications could be made more interactive by integrating features such as voice commands, multilingual support, or an AI assistant to guide users through the diagnosis process.
    - **Feedback Loop**: Implement a feedback system where users can provide information about the accuracy of the diagnosis and the effectiveness of the recommended treatments. This feedback could be used to further train and improve the model.

5. **Integration with IoT and Smart Farming**:

    - **IoT Integration**: The model could be integrated with IoT devices such as drones or smart cameras that continuously monitor crops and provide real-time disease detection and alerts.
    - **Predictive Analytics**: Incorporating weather data, soil conditions, and other environmental factors into the model could allow it to not only diagnose current diseases but also predict potential future outbreaks.

6. **Cross-Disciplinary Collaboration**:

    - **Collaboration with Agronomists and Plant Pathologists**: Working closely with experts in agriculture and plant pathology could help in refining the model's recommendations and expanding its utility in real-world farming.
    - **Economic Impact Analysis**: Assessing the economic benefits of using AI-driven tools in disease management could provide a strong case for wider adoption among farmers and agricultural businesses.

7. **Ethical Considerations and Accessibility**:

    - **Fairness and Bias**: Ensure that the model does not exhibit bias towards certain types of plants or diseases due to the nature of the dataset. This can be mitigated by diversifying the training data and validating the model across different conditions.
    - **Accessibility**: Efforts should be made to make the tool accessible to small-scale farmers in developing regions, possibly through partnerships with NGOs or agricultural organizations.

8. **Longitudinal Studies**:

    - **Long-Term Performance Evaluation**: Conduct longitudinal studies to evaluate the model's performance over time and in different seasons, ensuring its reliability and consistency in various agricultural cycles.

By addressing these areas, the research can be significantly enhanced, providing even greater value to the agricultural community and advancing the field of AI in plant disease management.

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