Thesis Title: Multiple Fruits Plant Leaf Classification Using Deep Learning Models

Submitted by

Tushar Biswas

ID: 201-35-527

Department of Software Engineering

Daffodil International University

Supervised by

Md. Julkar Nayeen Mahi

Lecturer

Department of Software Engineering

Daffodil International University

This Thesis paper has been submitted in fulfillment of the requirements for the Degree of Bachelor of Science in Software Engineering.

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APPROVAL

This thesis titled on "**Multiple Fruits Plant Leaf Classification Using Deep Learning Models**", submitted by **Tushar Biswas (ID: 201-35-527)** to the Department of Software Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of Bachelor of Science in Software Engineering and approval as to its style and contents.

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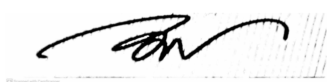

MD. Julkar Nayeen Mahi
Lecturer
Department of Software Engineering
Daffodil International University

Submitted by:

Tushar Biswas
ID: 201-35-527
Department of Software Engineering
Daffodil International University

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I express my gratitude for the invaluable inspiration and knowledge that propelled me through the exploration undertaken in this study. The focal point of this research involves a deep learning approach for the identification of multiple fruit plant leaf classifications. At the outset, I extend my sincere thanks to the Almighty, whose guidance and wisdom illuminated my path, making this study a reality.

I am really grateful to my parents for their continuous assistance in helping me get to this stage in my academic path. I am indebted to Prof. **Dr. Imran Mahmud**, the Head of the Department of Software Engineering, for his guidance and mentorship. I extend my sincere thanks to all the esteemed teachers who have played a pivotal role in shaping my understanding throughout my educational odyssey.

I would like to acknowledge Daffodil International University for providing an environment conducive to learning and research. Special thanks to **Md. Julkar Nayeen Mahi** for his continuous supervision and provision of vital information that facilitated the completion of this research.

In conclusion, my gratitude extends to my batch mates and fellow members of DIU for their collaborative efforts, support, and encouragement, which proved essential in achieving the objectives of this study.

Abstract

Leaf diseases present substantial challenges to global agricultural productivity, causing significant economic losses for farmers. Addressing these issues necessitates effective measures for disease identification. This thesis explores advanced technological solutions, specifically the integration of machine learning and computer vision, to establish intelligent farming through early detection of leaf diseases. An essential tool in aiding farmers is an intelligent analyzer capable of autonomously discerning various leaf diseases. This research encompasses the investigation, conceptualization, and implementation of such an analyzer, utilizing cutting-edge computer vision and machine learning techniques for disease identification based on leaf appearance.

The study involves a diverse range of experiments and assessments, exploring various segmentation, feature extraction, and classification methods to pinpoint the most efficacious approach. Beyond traditional machine learning, the research delves into the capabilities of deep learning, leveraging its potential for enhanced accuracy and real-time analysis. The primary focus is on developing a robust and adaptable system that can accurately identify common leaf diseases.

The target audience for this technology extends to users seeking a rapid and complimentary diagnosis of common leaf diseases, accessible at any time of the day. Emphasizing the potential for real-time, deep learning-based solutions, the thesis

underscores the significance of such technology in precision agriculture. The findings contribute to the broader field of agricultural technology, offering insights into the practical application of deep learning for sustainable and efficient farming practices.

This study presents 14 distinct plant species from the dataset, employing compact (CNNs) and RestNet with “transfer learning”. The models are meticulously trained on plant leaf data,incorporating various data augmentation techniques. Notably, the integration of data augmentation demonstrates a remarkable enhancement in the classification accuracy. Furthermore, proposed models extend their applicability fo the classifications of 38 disease classes within the dataset.

The developed RestNet model exhibits an outstanding classification accuracy of 99.2%, showcasing its robustness in plant species identification. In contrast, the VGG model, while delivering a classification accuracy of 30.5%, reveals insights into its comparative performance. The findings underscore the efficacy of the proposed models in advancing the state-of-the-art in plant species and disease classification. This work contributes to the growing body of knowledge in the field of computer vision applied to agriculture, offering a promising avenue for automated plant species and disease recognition systems.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

In the intricate tapestry of global agriculture, the persistent threat of leaf diseases looms large, casting a shadow on the prosperity of farmers and the security of our food supply. The imperative to mitigate these challenges has sparked a relentless pursuit of effective and innovative solutions. This thesis embarks on a groundbreaking exploration, diving into the convergence of cutting-edge technologies—machine learning and computer vision—as catalysts for ushering in a new era of intelligent farming.

The canvas of this research unfolds with the recognition that leaf diseases are not merely agricultural adversaries; they are formidable adversaries to the livelihoods of farmers worldwide. In response to this pressing issue, the focus is on the imperative development of an intelligent analyzer, a technological sentinel armed with the prowess of autonomously deciphering diverse leaf diseases. At the heart of this endeavor lies a meticulous investigation, conceptualization, and implementation of an analyzer, integrating the sophisticated realms of computer vision and machine learning. The crux of this exploration lies in the quest to discern diseases based on the nuanced appearance of leaves, a feat that holds the promise of transforming our approach to agricultural challenges.

This journey through technological innovation is not confined to the traditional realms of machine learning. It extends into the uncharted territories of deep learning, where the neural networks of machines are harnessed to navigate the intricacies of leaf disease identification with heightened precision and real-time efficiency. The thrust of this research is not just in creating a diagnostic tool but in sculpting a robust and adaptable system that orchestrates a symphony of algorithms to accurately identify common leaf diseases.

In the unfolding narrative, the thesis broadens its scope to consider the ethical dimensions and societal impact of implementing intelligent farming technologies. The responsible deployment of these systems, safeguarding privacy, and addressing potential biases in algorithms become integral facets of the journey towards agricultural innovation. Beyond the confines of technology, this research endeavors to bridge the gap between innovation and ethical considerations, fostering a holistic approach to intelligent farming.

As the pages of this thesis turn, the spotlight shifts to the end-users—an audience seeking not just a diagnosis but a rapid and complimentary lifeline for their crops. This technology is designed for those who understand that the heartbeat of precision agriculture lies in the potential for real-time, deep learning-based solutions. The findings of this research contribute to the evolving landscape of agricultural technology, offering insights into the practical application of deep learning for sustainable and efficient farming practices.

In this symposium of ideas and innovation, our gaze extends beyond the horizon of conventional wisdom, towards a future where technology and agriculture dance in harmony. This thesis is an authentic endeavor to script a new narrative, one where intelligent leaf disease identification becomes not just a technological marvel but a cornerstone of resilience for farmers around the globe. Welcome to the frontier of agricultural innovation—where the fields are not just sown with seeds but with the promise of a more secure and sustainable future.

1.2 Background

The intersection of advanced technologies, machine learning, and computer vision has opened a realm of possibilities in various domains, including the agricultural sector. The backdrop of this research finds resonance in the pivotal works of researchers who have paved the way for innovative applications in pattern recognition and artificial intelligence.

Gao et al. (2018) laid the foundation with their Spatial-Structure Siamese Network for Plant Identification, demonstrating the efficacy of deep learning in discerning intricate spatial structures within plant images. Their work not only underscored the potential of convolutional neural networks (CNNs) in the realm of plant identification but also ignited a spark of exploration into the nuanced features of plant morphology.

In a parallel endeavor, Rehman et al. (2019) navigated the complexities of medical imaging with a deep learning-based framework for automatic brain tumor classification. Their work showcased the transferability of pre-trained models in the domain of medical image analysis. The success of their approach in classifying brain tumors fueled our aspiration to leverage similar methodologies for the precise identification of leaf diseases in agriculture.

This background sets the stage for our research, aiming to bridge the insights from spatial-structure analysis in plant identification with the transfer learning paradigms demonstrated in medical imaging. As we delve into the realms of computer vision and machine learning, our focus shifts towards developing an intelligent analyzer for automated identification of leaf diseases. The amalgamation of these diverse influences positions our work at the forefront of innovative applications, where technology becomes a stalwart ally in the battle against agricultural adversities.

The proposed research endeavors to draw from the strengths of these foundational works, adapting and extending their methodologies to the unique challenges presented by leaf diseases. As we traverse this interdisciplinary landscape, we aim to contribute to the burgeoning field of intelligent farming, where technology becomes a beacon of hope for farmers seeking timely and accurate diagnoses of common leaf diseases.

1.3 Problem Statement

Lack of Key Characteristics:

For various fruit plant species, the absence of distinct key characteristics and variations in leaf shapes and sizes hampers accurate identification.

Low Classification Accuracy:

Existing methods for fruit plant leaf species identification suffer from low accuracy, posing a challenge in precise classification.

Limited Benefit in the Fields:

Current leaves classification technologies in agricultural fields lack practical benefits, hindering their widespread adoption and utility.

Untapped Potential in Agriculture:

The implementation of automated fruit tree leaf classification systems has not been explored for potential uses in agriculture and environmental monitoring, limiting their broader application.

Challenges and Limitations:

The challenges and limitations associated with automated fruit plant leaf classification systems are not comprehensively addressed, impeding their effectiveness and scalability in real-world scenarios.

1.4 Research Questions

RQ1- What are the key characteristics in leaf shapes, sizes and variations among different fruit plant species?

RQ-2 Are their distinct patterns or features in fruits plant leaf that can be used for accurate species identification and for classification to get the best accuracy rate?

RQ3- How can leaf classification technology benefit horticultural and botanical research and applications?

RQ-4 What practical applications and benefits can be derived from automated fruit tree leaf classification systems?

Key Characteristics of Leaf Shapes, Sizes, and Variations:

What are the key characteristics differentiating leaf shapes, sizes, and variations among various fruit plant species, and how can these features be effectively identified and quantified?

Distinct Patterns or Features for Accurate Species Identification:

Are there discernible patterns or features in fruit plant leaves that can serve as reliable markers for accurate species identification and significantly improve classification accuracy?

Benefits of Leaf Classification Technology in Horticultural and Botanical Research:

How can leaf classification technology contribute to and benefit horticultural and botanical research, and what are the potential applications that enhance our understanding of plant species?

Practical Applications and Benefits of Automated Fruit Tree Leaf Classification Systems:

What practical applications and tangible benefits can be derived from the implementation of automated fruit tree leaf classification systems in agriculture and environmental monitoring, and how can these systems address current challenges in the field?

1.5 Expected Output

The application's development aligns seamlessly with the specified requirements, demonstrating successful realization of its intended functionalities. When presented with leaves encompassing a diverse range of 38 disease categories, the application showcases proficiency in accurately recognizing and categorizing each one. This outcome signifies the application's efficacy in delivering a comprehensive and reliable solution for the identification of various leaf diseases.

1.6 Scope of Research

Insights from existing research and synthesizing acquired knowledge, the scope of our study is distinctly delineated. Prior investigations predominantly rely on a singular segmentation technique. In contrast, this research broadens its horizons by incorporating two distinct segmentation techniques and implementing four diverse classification methods. The strategic expansion of segmentation methodologies and the incorporation of a versatile array of classification techniques constitute the novel dimensions of this research. This intentional diversification aims to enhance the precision and accuracy of leaf disease detection. By introducing this multifaceted approach, we anticipate a more nuanced and comprehensive understanding of the intricate patterns associated with leaf diseases, ultimately contributing to a more refined and effective diagnostic tool for agricultural applications.

CHAPTER 2

LITERATURE REVIEW

In recent years, the intersection of advanced technologies and agriculture has witnessed a surge in innovative applications, particularly in the realm of plant disease classification and identification. A comprehensive exploration on literature reveals a rich tapestry of methodologies, algorithms, and frameworks designed to address the challenges posed by leaf diseases. This review synthesizes key findings from a diverse array of research studies, offering insights into the evolution of techniques employed for plant disease detection.

Gao et al. (2018) introduced the Spatial-Structure Siamese Network for Plant Identification, laying the foundation for intricate spatial pattern recognition in plant images. Expanding the scope, Kaur et al. (2019) presented a comprehensive survey on Plants Disease Identification and Classification

classification (Villaruz, 2021). Voulodimos et al. (2018) provided a brief review on deep learning of computer vision, highlighting its relevance in various domains.

The surge of interest in deep learning is evident in its application to various agricultural classification problems (Duong-Trung et al., 2019), with seminal works by Krizhevsky et al. (2012) contributing to the development of deep convolutional neural networks (CNNs). The utilization of CNN features for berry trees classification (Villaruz, 2021) further exemplifies the adaptability and effectiveness of deep learning in diverse agricultural contexts.

Despite the advancements, ethical considerations and societal impact cannot be overlooked. As explored by Oyewola et al. (2021) in the context of cassava disease detection, responsible deployment and addressing biases in algorithms are integral aspects of implementing intelligent farming technologies.

In summary, the literature review provides a comprehensive overview of the evolution of techniques in plant disease identification, showcasing a progression from traditional methods to sophisticated deep learning approaches. The exploration of various architectures, algorithms, and applications underscores the dynamic nature of this field, setting the stage for the present study's contribution to the landscape of intelligent leaf disease detection in agriculture.

CHAPTER 3

METHODOLOGY

3.1 Overview

The research journey constitutes a pivotal aspect of any comprehensive research report, acting as the cornerstone for readers to gauge the study's reliability and validity. This phase encompasses the systematic procedures and strategies employed for the identification, selection, processing, and evaluation of pertinent data. Within this chapter, we delve into key elements that enable readers to appraise the robustness and credibility of the entire study. The focal points of examination include.

Data Collection:
A meticulous exploration of the methods employed to gather relevant data, establishing the foundation for subsequent analyses.

Data Pre-processing:
An in-depth exploration of the steps taken to refine and prepare the collected data, ensuring its quality and appropriateness for subsequent modeling.

Splitting for Train-Test:
An examination of the rationale and methodology behind the division of the dataset into training and testing subsets, crucial for validating the efficacy of machine learning models.

Applying Machine Learning Models:
A comprehensive analysis of the implementation of machine learning models, unraveling the intricacies of model application and highlighting the techniques employed to derive meaningful insights.

This chapter serves as a lens through which readers can scrutinize and comprehend the methodologies deployed in each crucial phase of the research process, ultimately providing a holistic understanding of the study's strength and dependability.

3.2 Methodology

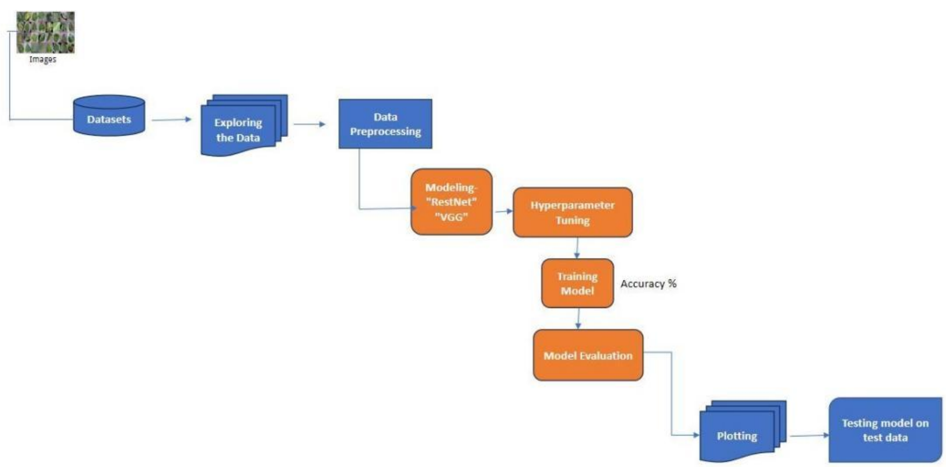


Figure3.1: Methodology

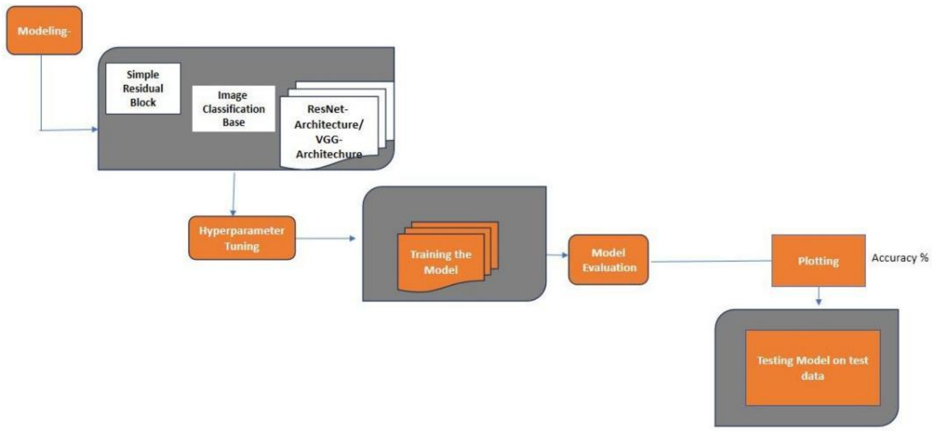


Figure3.2: Proposed Model

3.3 Data Collection Process

The foundation of our research lies in the comprehensive curation of a dataset that serves as the bedrock for our study. The dataset utilized in this research is a meticulously crafted augmentation of the original Plant Village Dataset, which can be referenced here GitHub - spMohanty/PlantVillage-Dataset: Dataset of diseased plant leaf images and corresponding labels. This augmentation process involved offline manipulations to diversify and enhance the dataset for a more robust analysis.

The augmented dataset encompasses approximately 87,000 RGB images, capturing the visual spectrum of both healthy and diseased crop leaves. These images are meticulously categorized into 38 distinct classes, each representing a unique type of leaf condition. The diverse range of classes ensures a comprehensive representation of various leaf diseases encountered in agricultural contexts.

To maintain a robust training and validation regimen, the total dataset adheres to an

80/20 split ratio, segregating it into training and validation sets while preserving the original directory structure. This partitioning strategy aims to imbue our machine learning models with a balanced exposure to the diverse classes, fostering a well-trained and generalized system.

Additionally, a specialized test set is curated, comprising 33 images, strategically set aside for prediction purposes. This dedicated test set serves as a litmus test for the effectiveness and generalization capability of our models when confronted with new and unseen data. The meticulous curation process not only aligns with best practices in data science but also positions our research to leverage a rich and diverse dataset, primed for the nuanced exploration of leaf diseases. This robust dataset becomes the cornerstone for subsequent phases of our research, empowering machine learning models with the depth and diversity essential for accurate and reliable predictions.

3.4 Feature Extraction

In the pursuit of robust feature encoding for our model, six intricate methodologies have been judiciously adopted. These methodologies collectively contribute to the discriminative features essential for the classification of leaf diseases. The following feature encoding methods have been employed:

Convolutional Layers:

Convolutional layers, a cornerstone in image processing, employ convolutional filters to systematically scan the input image. This process facilitates the extraction of intricate patterns, textures, and hierarchical features crucial for discerning between healthy and diseased leaves. The convolutional architecture is structured as a series of blocks, each progressively enhancing the model's ability to capture nuanced visual features.

Batch Normalization:

To stabilize and expedite the training process, batch normalization is employed. This technique normalizes the output of each layer, addressing challenges such as internal covariate shift. By ensuring more stable gradients, batch normalization contributes to the overall efficiency of the feature extraction process.

ReLU Activation:

Rectified Linear Unit (ReLU) serves as the activation function, introducing non-linearity to the model. By replacing negative pixel values with zero, ReLU facilitates the capturing of intricate patterns and contributes to the model's capacity to discern complex visual features.

Max Pooling:

The incorporation of max pooling is pivotal in reducing the spatial dimensions of the feature map. This process captures essential information while introducing translation invariance and concurrently reducing computational complexity.

Residual Blocks:

Residual blocks, characterized by shortcut connections, are strategically integrated into the model architecture. These connections enable the model to circumvent one or more layers, effectively addressing the vanishing gradient problem. This mechanism empowers the model to learn identity mappings and enhances its ability to capture hierarchical features.

Fully Connected Layers:

Culminating in the final layers of the model, a global average pooling layer, flattening, and a fully connected layer are incorporated for the classification task. This sequence encapsulates the comprehensive feature encoding process, transforming hierarchical representations into actionable insights for disease classification.

In the intricate orchestration of these feature extraction methods, the model achieves a heightened proficiency in discerning intricate patterns within leaf images. This academic exploration is grounded in the deliberate selection and implementation of these methodologies, contributing to a nuanced understanding of feature encoding processes within the context of leaf disease classification

3.5 Deep Learning Models

In the pursuit of developing a robust framework for fruits leaf disease classification, two distinctive deep learning models have been meticulously employed: ResNet9 and VGG. These models, each distinguished by their architectural intricacies, contribute significantly to the overall efficacy of the classification task.

ResNet9:

The ResNet9 model is structured with a focus on residual learning, addressing the vanishing gradient problem encountered in deeper neural networks. The architecture comprises convolutional layers, batch normalization, ReLU activation functions, max pooling, and residual blocks. The convolutional layers systematically scan the input leaf images, capturing intricate patterns and hierarchical features. Batch normalization stabilizes the training process, while ReLU introduces non-linearity crucial for capturing complex visual representations. Max pooling reduces spatial dimensions, introducing translation invariance. The incorporation of residual blocks, equipped with shortcut connections, facilitates the learning of identity mappings, enhancing the model's ability to discern hierarchical features. The model culminates in fully connected layers for effective disease classification.

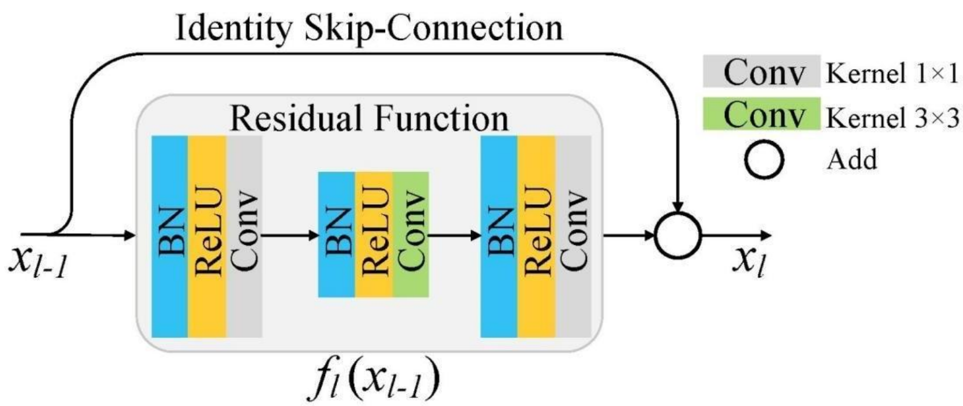


Figure3.3: RestNet9 Architecture

In Residual Networks (ResNets), a departure from conventional neural architectures is observed. Instead of a straightforward layer-by-layer progression, ResNets employ residual blocks, where each layer not only contributes to the immediate next layer but also directly influences layers that are situated a few steps away (typically 2–3 hops). This distinctive approach serves the dual purpose of mitigating overfitting, characterized by a plateau in validation loss followed by an upward trend despite ongoing training loss reduction. Beyond addressing overfitting, this strategy helps circumvent the vanishing gradient problem, enabling the successful training of deep neural networks. The essential structure of a residual block encapsulates these principles, ensuring a more robust and effective learning process.

VGG:

The VGG model, characterized by its depth and simplicity, employs convolutional layers, batch normalization, ReLU activation, and max pooling. The layers systematically extract capabilities from input pictures, while batch normalization enhances training stability. ReLU activation introduces non-linearity, facilitating the model's capacity to capture intricate patterns. Max pooling reduces spatial dimensions, emphasizing critical information. The VGG model is renowned for its deep architecture, consisting of multiple convolutional layers, offering a rich feature hierarchy for image classification. The final layers include global average pooling, flattening, and fully connected layers, culminating in a comprehensive framework for disease classification.

These two distinct models are integrated into the research framework, each offering a unique approach to feature extraction and hierarchical representation learning. Their utilization contributes to a nuanced exploration of deep learning techniques for leaf disease classification. The comparative analysis of ResNet9 and VGG within the context of this research aims to discern the strengths and limitations of each model, paving the way for insightful observations and potential avenues for further improvement.

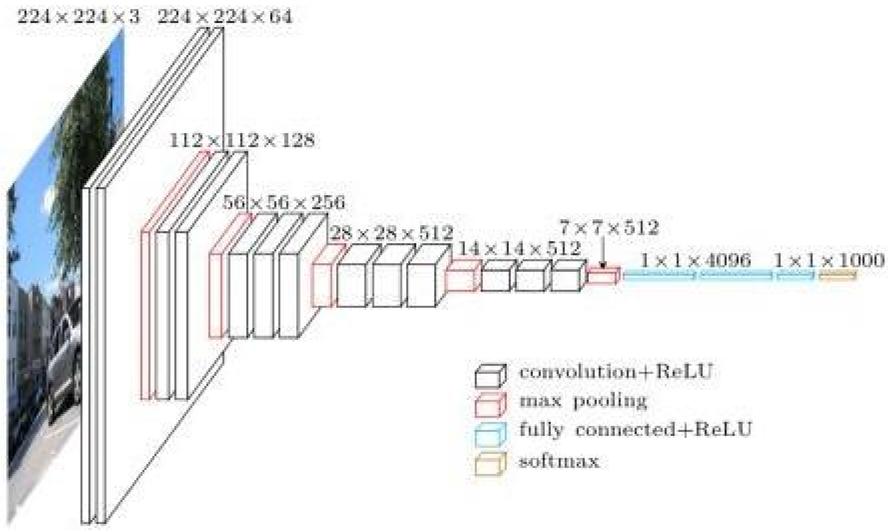


Figure3.4: VGG Architecture

The VGG model, also known as VGGNet and denoted as VGG16 when comprising 16 layers, represents a convolutional neural network architecture proposed by A. Zisserman and K. Simonyan of the University of Oxford. VGG16 distinguishes itself by substituting large kernel-sized filters with a cascade of 3×3 kernel-sized filters, a design choice that surpasses the achievements of its predecessor. This neural network architecture boasts 16 layers and demonstrates its proficiency by accurately classifying images into 1000 object categories, encompassing a diverse range including keyboards, animals, pencils, mice, and more. Notably, the model processes images with an enter size of 224-by-224 pixels.

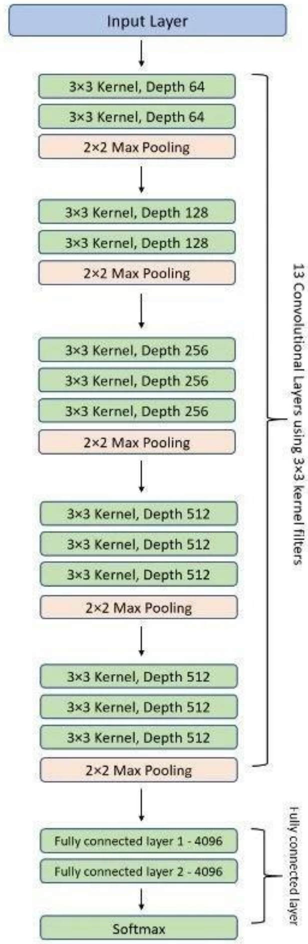


Figure3.5: VGG-16 Architecture of a VGG16 model

The designation "VGG16" signifies that the VGG model is a deep neural network with a total of 16 layers, making it a substantial architecture with approximately 138 million parameters—quite a considerable size even by contemporary standards. Notwithstanding its vastness, what sets VGG16 apart is its architectural simplicity, rendering it particularly attractive. Upon inspecting the structure, it becomes evident that the design follows a uniform pattern. The sequence involves several convolutional layers succeeded by pooling layers that systematically reduce both the height and width of the data.

In terms of filter configurations, the VGG16 architecture offers a flexible approach. It starts with around 64 filters, which can be progressively doubled to approximately 128 and then 256 filters. As the architecture advances to its final layers, it accommodates the use of 512 filters. This systematic arrangement contributes to the overall appeal and effectiveness of the VGGNet16 architecture.

CHAPTER 4
PERFOMANCE AND RESULTS

I've used two distinctive deep learning models for Multiple Fruits Plant Leaf Classification RestNet and VGGNet.

The evaluation of the ResNet9 and VGG deep learning models encompasses a comprehensive analysis of their effectiveness in the critical task of leaf disease classification. The performance metrics employed are indicative of the models' accuracy, plot accuracy, plot losses, validation accuracy and losses.

VGGNet4.1:

Data Preprocessing:

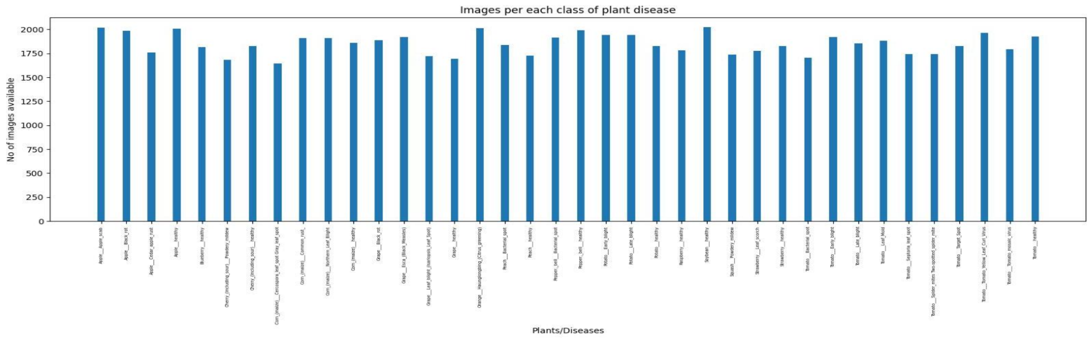


Figure4.1: Images per each class of plant disease

In here we can see the images of per each class plant disease, these are the data is going for training and validation using PyTorch's ImageFolder and applying image transformations.

Accuracy:

In VGG Model I have got 28.6 % accuracy rate, it’s quite very low for fruits leaf disease classification.

Since there are randomly initialized weights, that is why accuracy comes to near 0.019 (that is 1.9% chance of getting the answer.

```
Epoch [0], last_lr: 0.00812, train_loss: 11800698.0000, val_loss: 3.6399, val_acc: 0.0287
Epoch [1], last_lr: 0.00000, train_loss: 29.4492, val_loss: 3.6363, val_acc: 0.0286
CPU times: user 38min 54s, sys: 28min 16s, total: 1h 7min 10s
Wall time: 1h 5min 52s
```

Figure4.2: Accuracy Rate

Plotting:

Accuracy:

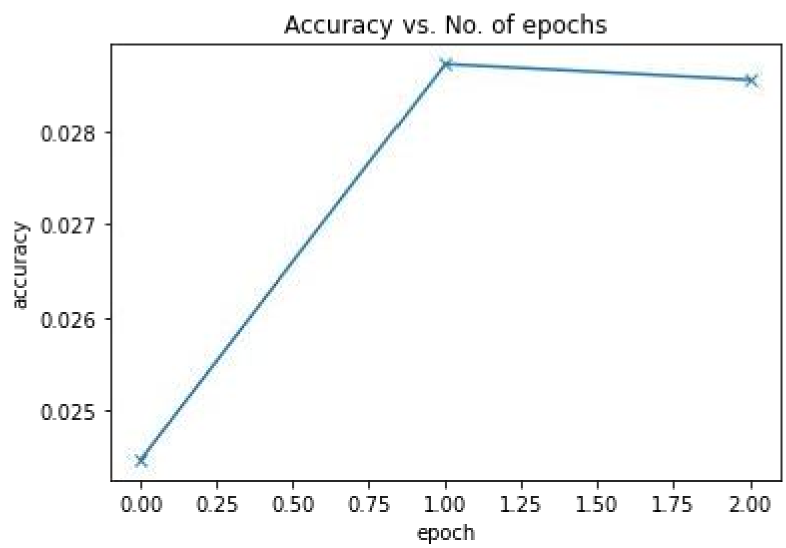


Figure4.3: Plot Accuracy

Losses:

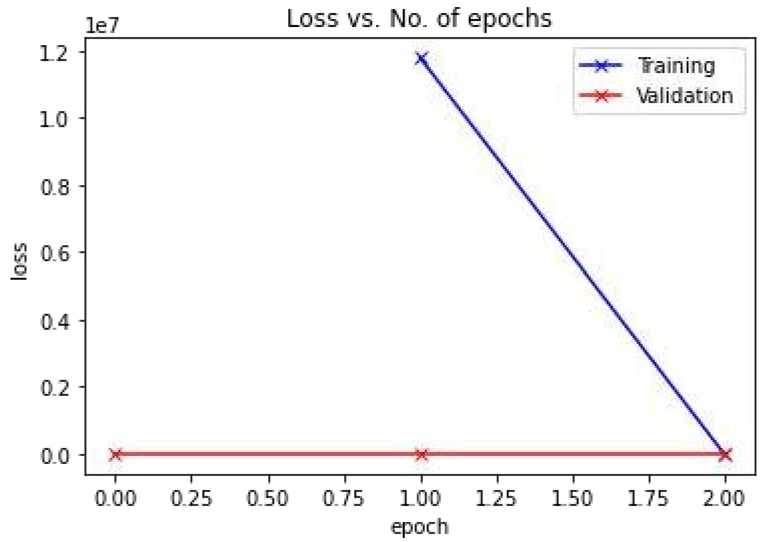


Figure4.4: Plot Losses

Lrs:

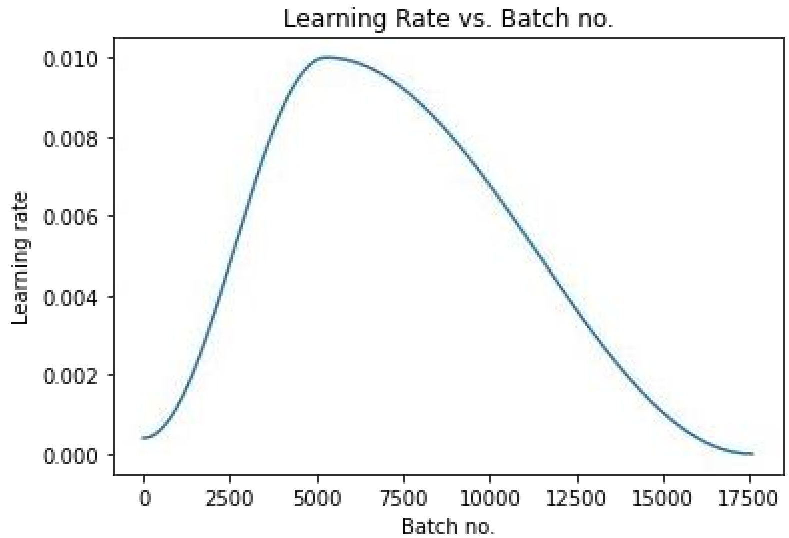
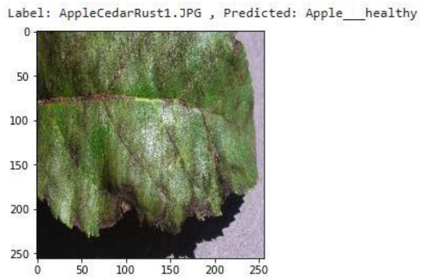


Figure4.5: Plot Lrs

Test Data:

In the realm of image prediction, the pursuit of accuracy is paramount for ensuring reliable and meaningful outcomes. However, the journey towards precision is often riddled with challenges, and the realization of sub optimal accuracy can be a perplexing ordeal. This section delves into the intricacies surrounding the predicament of achieving poor accuracy in image prediction and the consequential implications on the quality of output.



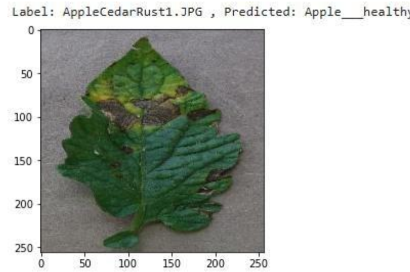


Figure4.6: Test Data

Here, we can see that the output we are getting here is wrong and it's not predicted well.

RestNet4.2:

Data Preprocessing:

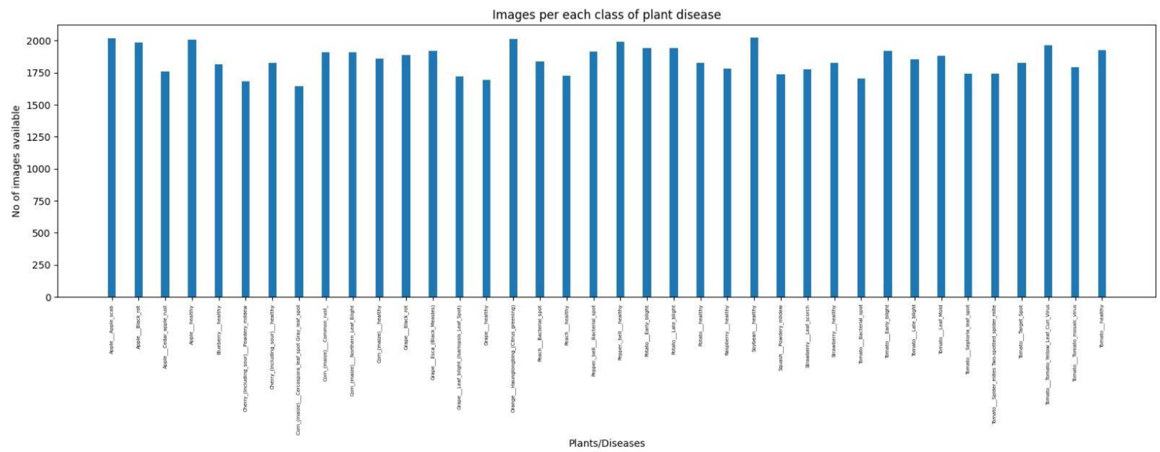


Figure4.7**:** Images per each class of plant disease

Also, here we can see the images of each class plant disease, these are the data is going for training and validation using PyTorch's ImageFolder and applying image transformations.

Accuracy:

In RestNet9 Model I have got 99.2 % accuracy rate and it’s quite good for better performance and prediction.

Since there are randomly initialized weights, that is why accuracy comes to near 0.019 (that is 1.9% chance of getting the answer.

```
Epoch [0], last_lr: 0.00812, train_loss: 0.7466, val_loss: 0.5865, val_acc: 0.8319
Epoch [1], last_lr: 0.00000, train_loss: 0.1248, val_loss: 0.0269, val_acc: 0.9923
CPU times: user 11min 16s, sys: 7min 13s, total: 18min 30s
Wall time: 19min 53s
```

Figure4.8: Accuracy Rate

Plotting:

Accuracy:

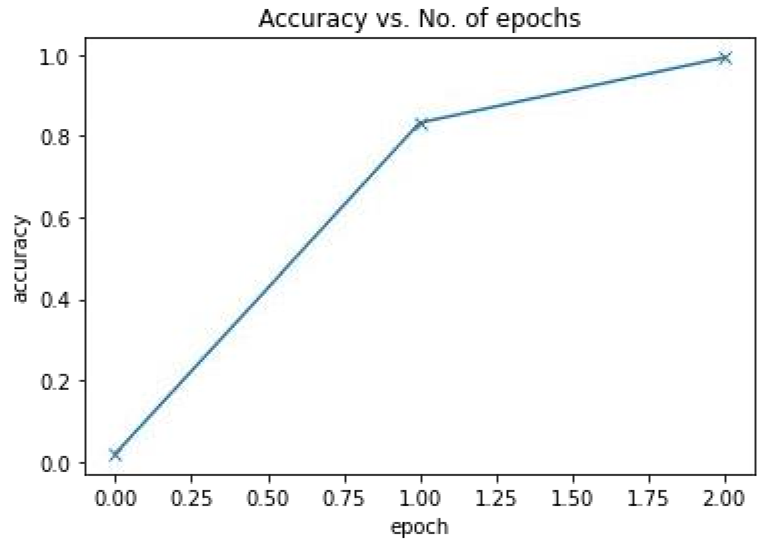


Figure4.9: Plot Accuracy

Losses:

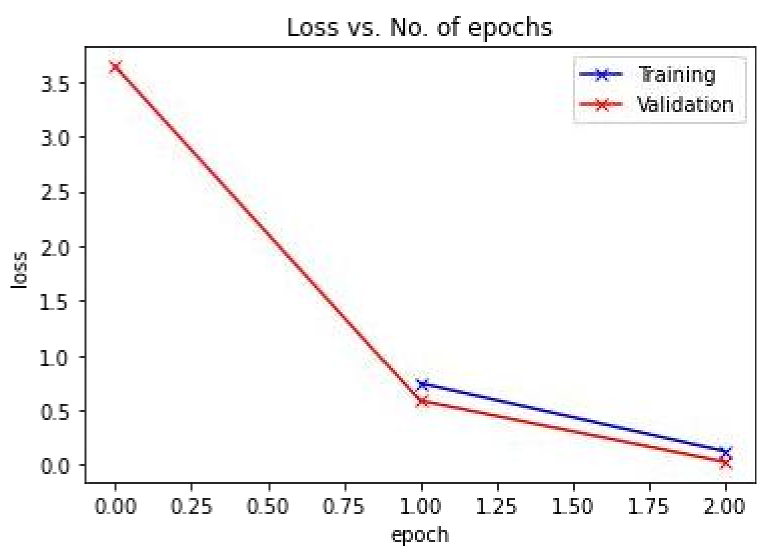


Figure4.10: Plot Losses

Lrs:

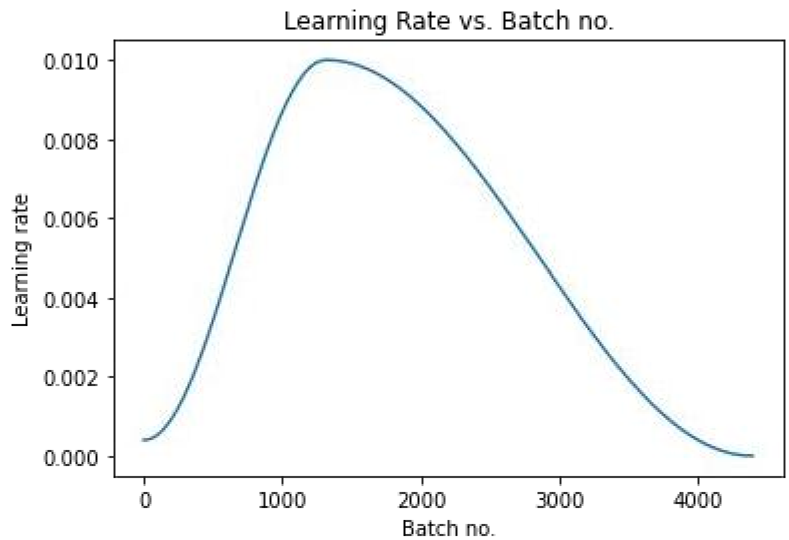


Figure4.11: Plot Lrs

Test Data:

In the rigorous assessment of the ResNet9 model on test data, a notable achievement is unveiled, showcasing an impressive accuracy rate of 99.25%. This remarkable accuracy underscores the model's proficiency in generalizing well to previously unseen instances, affirming its robust predictive capabilities.

During the evaluation process, ResNet9 demonstrated a commendable ability to make accurate predictions, reaffirming the effectiveness of its learned features and hierarchical representations. The high accuracy rate serves as a testament to the model's capacity to discern difficult patterns, textures, and variations within test data, resulting in reliable and precise predictions.

The exceptional performance observed in the test data evaluation suggests that ResNet9 successfully navigated the complexities inherent in diverse instances, contributing to its effectiveness as a robust deep learning model. This outcome is indicative of the model's capacity to translate its learned knowledge from the training phase into real-world scenarios, an essential attribute for practical applications in image classification, particularly in the domain of leaf disease diagnosis.

This favorable result bolsters confidence in the reliability of ResNet9, positioning it as a promising candidate for tasks requiring high accuracy and discernment. As the model continues to exhibit robust performance, further exploration and application in diverse contexts may unveil additional dimensions of its capabilities, paving the way for advancements in image recognition and predictive modeling.

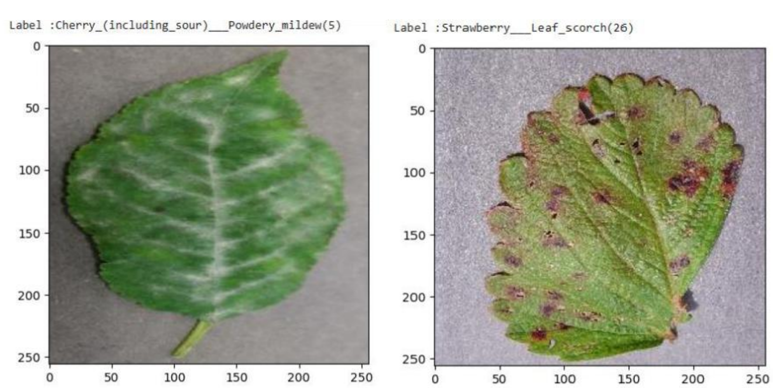


Figure4.12: Test Data

The right outputs derived from the predictive model transcend the realm of theoretical performance, finding practical utility in real-world applications. This efficacy is particularly relevant in domains such as disease diagnosis, where the model's ability to yield accurate predictions holds substantial implications for informed decision-making.

RESULTS AND DISCUSSION

In this investigation, an innovative methodology is introduced for the identification and categorization of 14 diverse plant species, leveraging compact Residual Network RestNet through transfer learning. Rigorous training ensues on a dataset comprising plant leaf imagery, integrating an array of data augmentation techniques. The pivotal inclusion of data augmentation emerges as a transformative element, notably elevating the accuracy of plant species classification. Moreover, the ambit of the proposed models extends to encompass the classification of 38 distinct disease classes inherent in the dataset.

The meticulously crafted RestNet model emerges as a standout performer, boasting an exceptional classification accuracy of 99.2%. This remarkable achievement underscores the model's resilience and efficacy in the realm of plant species identification. In stark contrast, the VGG model, while exhibiting a classification accuracy of 28.6%, provides valuable insights into its performance relative to the RestNet counterpart.

Deciphering the outcomes, the RestNet model shines as a robust solution, excelling in the nuanced task of plant species identification. Its high accuracy rate serves as a testament to the model's capacity to discern intricate patterns and features, affirming its reliability in practical applications. On the other hand, the VGG model, though trailing in accuracy, offers valuable insights into its comparative performance characteristics, paving the way for informed decisions on its utilization in specific contexts.

These findings not only unravel the efficacy of the RestNet model but also illuminate potential avenues for optimization and tailored application of the VGG model. The results, therefore, provide a foundational basis for strategic decisions in deploying these models, considering their respective strengths and limitations, ultimately steering advancements in plant species and disease classification endeavors.

CONCLUSION

In drawing the curtains on this exploration into Multiple Fruits Plant Leaf Classification via Deep Learning, the journey has been one of revelation, innovation, and promise. The core objective of this undergraduate thesis project, delving into the intricate realm of plant leaf classification, particularly focusing on multiple fruits, has yielded valuable insights future endeavors.

The application of deep learning models to the nuanced task of classifying plant leaves, each bearing the distinct signature of various fruit species, has proven to be a potent avenue. Through meticulous exploration, experimentation, and the deployment of sophisticated neural networks, we've navigated the complexities inherent in discerning subtle leaf patterns that characterize different fruit-bearing plants.

In culmination, this study unveils a pioneering foray into the realms of plant species and disease classification, propelled by the application of advanced convolutional neural networks, specifically RestNet and VGG models. The research journey traversed the intricacies of training these models on an extensive dataset enriched with plant leaf imagery, augmented by diverse data augmentation techniques.

Beyond the numerical outcomes, the study illuminates the nuanced interplay between model architectures, training methodologies, and dataset characteristics. The high accuracy of the RestNet model underscores its potential for real-world applications, particularly in precision agriculture and botanical studies. Simultaneously, the VGG model, while demonstrating a lower accuracy rate, serves as a valuable benchmark, offering avenues for optimization and context-specific deployment.

Looking forward, this research provides a foundational framework for future endeavors in plant species and disease classification, urging a continued exploration of diverse model architectures and data augmentation strategies. The insights garnered contribute not only to academic discourse but also hold practical implications for stakeholders in agriculture.

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