MULTI LABEL FOLIAR DISEASE CATEGORIZATION IN APPLE ORCHARDS USING DEEP LEARNING

A Thesis Submitted
In Partial Fulfillment of the Requirements
for the Degree of

MASTER OF TECHNOLOGY

in

Artificial Intelligence

by

SAURABH SINGH
(Roll No. 2K22/AFI/20)

Under the Supervision of
Dr. RAHUL KATARYA
(Professor, Dept. of Computer Science & Engineering)

To the
Department of Computer Science and Engineering

DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering)
Shahbad Daulatpur, Main Bawana Road, Delhi-110042. India

May, 2024

DELHI TECHNOLOGICAL UNIVERSITY

(Formerly Delhi College of Engineering)
Shahbad Daulatpur, Main Bawana Road, Delhi-42

CANDIDATE'S DECLARATION

I, Saurabh Singh, Roll No. 2K22/AFI/20 student of M.Tech (Artificial Intelligence), hereby certify that the work which is being presented in the thesis entitled "**Multi Label Foliar Disease Categorization in Apple Orchards Using Deep Learning**" in partial fulfillment of the requirements for the award of the Degree of Master of Technology in Artificial Intelligence in the Department of Computer Science and Engineering, Delhi Technological University is an authentic record of my own work carried out during the period from August 2022 to June 2024 under the supervision of Dr. Rahul Katarya (Professor, Department of Computer Science and Engineering). This work has not previously formed the basis for the award of any Degree, Diploma Associateship, Fellowship or other similar title or recognition.

Place: Delhi **Candidate's Signature**

This is to certify that the student has incorporated all the corrections suggested by the examiners in the thesis and the statement made by the candidate is correct to the best of our knowledge.

Signature of Supervisor **Signature of External Examiner**

DELHI TECHNOLOGICAL UNIVERSITY

(Formerly Delhi College of Engineering)
Shahbad Daulatpur, Main Bawana Road, Delhi-42

CERTIFICATE

I hereby certifiy that **Saurabh Singh** (Roll No. 2K22/AFI/20) has carried out the research work presented in the thesis titled "**Multi Label Foliar Disease Categorization in Apple Orchards Using Deep Learning**", for the award of Degree of Master of Technology from Department of Computer Science and Engineering, Delhi Technological University, Delhi under my supervision. To the best of my knowledge this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

Place: Delhi
Date:

Dr. Rahul Katarya
(SUPERVISOR)

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering)
Bawana Road, Delhi-110042

ACKNOWLEDGEMENT

I wish to express my sincerest gratitude to **Dr. Rahul Katarya** for his continuous guidance and mentor-ship that he provided during this project. He showed me the path to achieving targets by explaining all the tasks to be done and explained to me the importance of this work as well as its industrial relevance. He was always ready to help me and clear doubts regarding any hurdles in this project. Without his constant support and motivation, this project would not have been successful.

Place: Delhi **Saurabh Singh**

Date:

ABSTRACT

The accurate detection and classification of foliar diseases in apple orchards are crucial for ensuring crop health and optimizing yield. Traditional methods of disease identification, which rely heavily on visual inspection by experts, are not only time-consuming but also prone to errors and lack scalability. This research introduces a robust deep learning model leveraging the MobileNetV2 architecture, enhanced with custom layers and advanced data processing techniques, to address these challenges through automated multi-label classification of foliar diseases. Utilizing the FGCV 2021 dataset, comprising over 23,000 high-resolution images labeled for multiple diseases, the model demonstrates superior performance in recognizing complex disease patterns under varied environmental conditions.

The study employs extensive data augmentation techniques including rotations, flips, and color adjustments to enhance model generalization across different lighting and background scenarios. The training process is optimized through adaptive learning rate adjustments and early stopping mechanisms to prevent overfitting, thus ensuring the model's robustness. Performance evaluation metrics such as accuracy, precision, recall, and F1-score consistently indicate that the proposed model outperforms existing benchmarks, achieving an accuracy of 92.46%, and an F1-score of 90.87%.

The implications of this research are significant, offering a scalable and efficient tool for real-time disease monitoring in apple orchards. This not only aids in timely and effective disease management but also potentially reduces economic losses and improves agricultural sustainability. Future work will focus on expanding the dataset to include more diverse environmental conditions and exploring real-time deployment scenarios to enhance the practical applicability of the model in precision agriculture. Another area could be adapting this solution to a wider range of crops and diseases, as well as integrating with other evolving technologies like IoT or drones for effective and larger-scale crop monitoring.

TABLE OF CONTENTS

List of Tables

List of Figures

CHAPTER 1
INTRODUCTION

In the field of agriculture, it is of great importance to ensure the health and productivity of crops to maintain food security and economic stability around the world. Apple is one of the most widely consumed commodity and represents a significant agricultural market around the world and the cultivation of apples is one of the major agricultural activities worldwide, contributing significantly to the economy and food supply. However, the productivity and health of apple orchards are continually threatened due to foliar diseases[1], which can lead to great loss to the farmers if not handled promptly and effectively[2]. The amount and quality of the produce is also negatively impacted by foliar diseases. Conventional disease management strategies rely heavily on manual human inspection and expertise, which are not sustainable, labor-intensive, and time-consuming.

In recent years the advancement in the field of Artificial Intelligence(AI)[3] and Machine Learning(ML)[4] has been pivotal in solving many real-life problems like plant disease detection, computer vision, social network analysis, medical analysis, etc. [5][6][7][8][9][10][11][12]. Deep learning[13] techniques applied in the field of agriculture have demonstrated encouraging outcomes, providing new tools for quick and precise disease identification. Using this technology, this study hopes to not only improve the accuracy in diagnosing diseases but also greatly cut down on the labor-intensive nature and time associated with traditional methods. This introduction outlines the motivation, challenges, objectives, and significance of developing such a model, setting the stage for a deeper exploration of leveraging deep learning to revolutionize disease management in apple orchards.

1.1 Motivation

In agriculture, ensuring the crops health is very important for maximizing the yield and the quality of produce. Foliar disease is one of the biggest threats to the apple industry. It can greatly lower yields, lower the quality of apples produce, and hence can cause great economic loss to the apple cultivators around the world. Traditional ways of finding diseases often depend on experts visual inspection which are often time consuming, prone to errors and aren't always useful on a large scale. Deep learning is one way to possibly address these problems. Deep learning can help automatically identify and classify diseases, leading to early detection and management of diseases. This would help in reduction of manual labour, economic loss, food wastage and less chemical treatments by automating the process of disease identification and classification. As a result, the procedure is not only more economical and efficient but also lessens the environmental impact of chemical use by early disease detection and management, which would help supports sustainable farming practices around the world.

1.2 Objective

The main objective of this study is to develop a deep learning based model capable of multi-label[14] foliar disease classification with high accuracy and efficiency. The proposed framework should be able to analyse photo and spot patterns in the images to correctly classify it to particular disease based on the symptoms and pattern identified by the model. This study's key objectives are summarized below:

- To conduct an extensive literature review on recent research in the field of plant disease detection, specifically focusing on apple foliar diseases, utilizing deep learning techniques.
- To design and implement a deep learning based model for multi-label foliar disease classification in apple plants.
- To validate how effectively the model works using different performance evaluation metrics like accuracy, precision, recall and F1-Score and how it stands up against the other recent work done in the field of multi-label foliar disease classification.

1.3 Challenges

Building a framework which is both accurate and efficient is one of the biggest challenge while working with deep learning based models. Working on building a framework for multi-label foliar disease classification we faced multiple challenges which are discussed below:

- **Variability of Images:** In the real world the images can vary significantly in terms of background, lightning and maturity can greatly affect the performance and accuracy of the model.
- **Multi-label Classification:** Identifying multiple diseases on single leaf and classifying it correctly is a complex process and requires deep understanding of the process and flow to build a framework. It also requires appropriate dataset which aligns with multi label classification.
- **Generalization:** Developing a model that not only performs well on the dataset but can also generalize to unseen images from different environments is crucial for practical application of proposed framework.
- **Computational Resources:** Training deep learning models on large datasets requires substantial computational power and memory, which is one of the limiting factor for extensive experimentation.

1.4 Thesis Organization

This thesis is organized into several chapters to provide a structured and comprehensive discussion of the research:

- **Chapter 2: Related Work -** This chapter covers recent existing research work done in the field of application of deep learning towards foliar disease detection, highlighting key methods and findings that form the base for current research work.
- **Chapter 3: Proposed Methodology -** Detailed explanation of the different steps involved like data pre-processing, data augmentation, etc and the architecture of the proposed framework.
- **Chapter 4: Experiments and Results -** Presentation of the experimental setups, including the detailed analysis of the results obtained from the model testing.
- **Chapter 5: Conclusion and Future Work -** Summary of the research findings and recommendations for future research directions that can enhance the effectiveness and applicability of the model.

CHAPTER 2
RELATED WORK

2.1 Literature Survey

Recently, a lot of progress has been made in the field of agriculture using deep learning[15][16] to find and predict different leaf diseases in apple orchards. A lot of work has gone into making new frameworks and techniques that not only make it easier to diagnose diseases but are also capable of multi-label foliar disease classification with just one framework. This literature review covers a wide range of studies that examine the use of deep learning for detecting plant diseases, with a specific focus on diseases affecting apple leaves. Here some of the recent work using deep learning are discussed below:

In 2024, Tianyu Fang et al.[17] suggested a new, light bilinear convolutional neural network (CNN)[18] structure called BLSENet for classifying apple foliar diseases. Strategy called feature fusion and attention mechanism was added to the model. BLSENet incorporates Squeeze-and-Excitation (SE)[19] modules within both of its subnetworks. These modules enhance the precision of feature extraction and recognition leading to better performance and accuracy.

The Holistic Self-Distillation (HSD) method and the Squeeze and Excitation Network were used by Jingxuan Su et al. [20] to propose a model in the year 2023 that could predict multiple diseases in the same apple leaf. This method combines knowledge of labels with knowledge of space, which leads to better accuracy and performance. Another author, Barsha et al.[21], came up with a CNN-based model in the year 2023 that could also detect multiple diseases. The proposed model has a multilayer CNN architecture, and it works very well, as shown by its 91% accuracy, 89% precision, 85% recall, and 88.34% F1-Score.

In the year 2023 another study by Mamta Gehlot et al.[22] introduced EffiNet-TS, a composite architecture that includes the EffiNet-Teacher classifier, Decoder, and EffiNet-Student classifier, built upon EfficientNetV2. The model achieved an impressive F1 score of 0.989, an accuracy of 0.990, and a validation loss of 0.045 on the Plant Village dataset. Despite its superiority over the ResTS architecture, it highlighted the need for improvements in both the quantity and quality of the plant disease datasets. Another study by Rabbia Mahum et al.[23] proposed a method using an Efficient DenseNet[24] for classifying potato leaves into five categories, achieving a high accuracy of 97.2% with the Plant Village Dataset supplemented by manually gathered data. The focus was specifically on potato diseases in this study.

In another study by Manzhou Li et al. [25] the author proposed an integrated model that combines single-stage and two-stage target detection networks. The single-stage network is built upon the YOLO[26] with internal structure optimization. The two-stage network, on the other hand, is based on the Faster R-CNN (Region Convolutional Neural Network)[27]. The model, tested on a self-made dataset of 7199 images across six species, achieved an accuracy of 85.2%. Another study by Sheng Yu et al. [28] developed a novel network that integrates inception convolution with vision transformers, achieving accuracy rates of 99.94% on Plant Village, 99.22% on ibean, 86.89% on AI2018, and 77.54% on PlantDoc datasets This model outperformed state-of-the-art models showing promising results. Raghu Ramamoorthy et al.[29] proposed a framework utilizing MobileNetV1[30] as the base model for leaf disease detection in plants showing an accuracy of 95% on the plant village dataset.

It was suggested by Vibhor Kumar Vishnoi et al.[31] in 2022 that we use a Convolutional Neural Network (CNN)-based model with fewer layers and different data augmentation techniques to improve the performance and generalization of the network. When tested on the PlantVillage dataset, this method showed an amazing 98% accuracy. This method is notable for less computational and storage space.

In the year 2022, Helong Yu et al.[32] did another study and came up with a model called MSO-ResNet. This model is based on ResNet50[33] and includes a number of improvements in the architecture making it more robust and reliable. In 2022, Haiqing Wang et al.[34] conducted a study where they proposed a lightweight model for plant disease detection. This model is based on the advanced YOLOV5 architecture and has demonstrated superior accuracy and performance compared to other existing techniques. Kush Vora et al. [35] suggested a CNN-based ensemble model for finding multiple diseases. This model did a good job of classifying foliar diseases into multiple labels and classes. The proposed framework was Ensemble of MobileNet, Xception[36], and InceptionResNet[37].

In the year 2022 a study by Ahmed Elaraby et al.[38] proposed a framework based on AlexNet[39] and particle swarm optimization for feature selection showing significant improvement in accuracy from 95.6 to 98.83 with PSO. Muhammad Hammad Saleem et al.[40] proposed a model Region-Based Fully Convolutional Network (RFCN)[41] for plant disease categorization. In this study, they also studied the effect of hyperparameter tuning and data augmentation on the performance of the model.

In 2021, Peng Wang et al.[42] enhanced deep CNN-based network by incorporating an attention mechanism. This advancement resulted in an impressive accuracy of 98.92%. However, they encountered difficulties in accurately distinguishing between identical diseases, leading to misclassifications. The study by The 2021 research conducted by Prakhar Bansal et, al[43] titled "Disease Detection in Apple Leaves Using Deep Convolutional Neural Network" showcased a collection of pre-trained models combined with picture augmentation approaches. The employed models, namely DenseNet121[44], EfficientNetB7[45], and EfficientNet NoisyStudent[46], exhibited a 96.25% accuracy when applied to a dataset sourced from Cornell University. The study was distinguished by its exceptional precision and efficacy in identifying multiple diseases.

Xiaofei Chao et al.[47] in there study in 2021 proposed a method for enhancing the apple disease classification by using a fusion of Squeeze-and-Excitation modules with the Xception network, as well as creating a compact network called SE_miniXception. The proposed model showed exceptional performance showing accuracy of 99.40% and showing more sensitivity towards key features.

Dhruvil Shah et al.[48] in there study proposed a model called ResTS (Residual Teacher/Student)[49] that is based on a CNN architecture. The model consists of a decoder and two classifiers. The proposed model exhibited superior performance when compared to the state-of-the-art Teacher-student architecture. In a separate study conducted in 2021, Adesh V. Panchal et al.[50] performed a comparative analysis on four models: Inception-v3[51], ResNet50, VGG16, and VGG19[52]. Additional hyperparameter tuning was conducted to achieve improved results, and the corresponding insights were shared.

Hee-Jin Yu et al.[53] conducted a study in 2020 that proposed a model named leaf spot attention network (LSA-Net) for apple foliar disease detection showing high accuracy equivalent to 89.4%. In another study by Xiaofei Chao et al.[54] proposed a method for apple apple disease detection using a deep convolutional neural network, combining DenseNet and Xception, with global average pooling and support vector machine for classifying achieving a high accuracy of 98.82%.

These works collectively demonstrate the dynamic and rapidly changing nature of deep learning applications in agriculture, namely in the detection and categorization of diseases in apple orchards. In Table 2.1, we highlight these key works and each of these studies provide distinctive perspectives and approaches towards foliar disease detection. A lot of the work was done on finding a single disease on the leaf, but a plant may have more than one disease at the same time. The main aim of this research work is to build a framework that can tell the difference between different diseases based on their symptoms on a single-leaf image. The study utilizes the Plant Pathology 2021[55] dataset, which consists of multi-label images, to present a model capable of distinguishing between individual diseases among multiple disease symptoms in a single leaf image.

Table 2.1- Literature Survey of Recent Deep Learning Based Apple Foliar Disease Detection

Year, Reference	**Model Used**	**Performance**	**Dataset Used**	**Classification Type**	**Pros**	**Cons**
2024, [17]	Bilinerar CNN	Accuracy-93.3	14582 Images dataset from College of AI	Single Label Classification	Better performance achieved due to attention mechanism and feature fusion strategy.	Complexity introduced by the bilinear feature fusion and SE module.
2023, [20]	Squeeze-and-Excitation Networks with holistic self distillation	Accuracy-98.22%(FGCV7) and 90.72%(FGCV8) F1-Score-89.61(FGCV8)	FGCV8 and FGCV7	**Multi Label classification**	Model is capable of multi-label classification.	Complexity introduced by adding Holistic Self Distillation.
2023, [21]	CNN	Accuracy 91% and f1_score 0.88	FGVC8	**Multi Label classification**	Model is capable of multi-label classification.	Focuses only on single disease classification.
2023, [23]	Efficient NetV2	F1 score: 0.989, Accuracy: 0.990	Plant Village dataset	Single Label Classification	Better performance compared to the state-of-the-art architecture of ResTS.	Dataset does not depict real world agricultural setting. Leaf organ of plant is only considered for disease detection.
2023 [24]	Efficient DenseNet	Accuracy 97.2%	Plant Village Dataset+manually gathered data	Single Label Classification	Computationally fast and efficient.	Focuses only on potato leaf disease detection. Dataset quality is questionable.

Year, Reference	Model Used	Performance	Dataset Used	Classification Type	Pros	Cons
2023, [25]	YOLO+ RCNN	Accuracy 85.2%	Self-made dataset of 7199 images.	Single Label Classification	Computationally fast and efficient.	Dataset quality and quantity is of concern..
2023, [28]	Inception Convoluti-on and vision Transform-er.	Accuracy (PlantVillage): 99.94, Accuracy(ibean): 99.22, Accuracy(AI 2018):86.89, Accuracy (PlantDoc):77.54	PlantVillage, ibean leaf image, AI2018, PlantDoc Dataset	Single Label Classification	Model performed better compared to the state-of-the-art models.	Leaf organ of plant is only considered for disease detection.
2023, [29]	Mobile-NetV1	Accuracy: 95%	Plant Village dataset.	Single Label Classification	Simple and efficient.	Leaf organ of plant is only considered for disease detection.
2022, [31]	CNN	Accuracy - 98%	Plant Village dataset.	Single Label Classification	Lower storage and computational requirements	The dataset is not sourced from a standard source, therefore the quality of the data is questionable.
2022, [32]	MSO-ResNet (Multistep Optimization ResNet)	Average precision-0.957, recall-0.957, and F1-score-0.957.	Dataset with 11397 taken from Kaggle and Google.	Single Label Classification	High recognition performance, strong robustness, improved accuracy and speed.	The dataset is not sourced from a standard source, therefore the quality of the data is questionable.

Year, Reference	**Model Used**	**Performance**	**Dataset Used**	**Classification Type**	**Pros**	**Cons**
2022, [34]	Optimized YOLOv5	Precision 93.73, Recall 92.94, Accuracy (PlantDoc): 90.26% Accuracy (Peanut Rust): 92.57%	Plant Village dataset, PlantDoc, and self-made Peanut Rust dataset.	Single Label Classification	Lower storage and computationally fast compared to other networks.	Dataset does not depict real world agricultural setting. Leaf organ of plant is only considered for disease detection.
2022, [35]	Ensemble of MobileNet + Xception +Inception ResNet	Accuracy-0.8731, Precision-0.8905, Recall-0.91, and F1-score-0.9001	FGCV8	**Multi Label Classification**	Model is capable of multi-label classification.	Complexity introduced due to ensemble of three models.
2022, [38]	AlexNet +PSO	Accuracy 98.83	The dataset consists of nearly 13,000 images of 5 crop species.	Single Label Classification	Improvement in accuracy of model with PSO.	Room to enhance the quality of dataset.
2022, [40]	Region-Based Fully Convolutional Network (RFCN)	mAP 93.8%	NZDLPlantDisease-v1	Single Label Classification	Focuses on other organs of plants like fruits, stems, etc. instead of just leaves.	Disease detection for multiple organs is not considered. The dataset is limited to fields from New Zealand.
2021, [42]	CA-ENet	Accuracy - 98.92%	3,000 images from Plant Village and 5,170 images from Northwest A&F University.	Single Label Classification	High accuracy, robust and fewer parameters.	Miss-classification between similar diseases

Year, Reference	**Model Used**	**Performance**	**Dataset Used**	**Classification Type**	**Pros**	**Cons**
2021, [43]	DenseNet121, EfficientNetB7, EfficientNet NoisyStudent	Accuracy - 96.25%	3642 images from Plant Pathology 2020 and Plant Village dataset	Single Label Classification	High accuracy and performance.	Focuses only on two foliar diseases belonging to four classes.
2021, [47]	SE_Xception, SE_miniXception	SE_Xception: 99.40% accuracy; SE_miniXception: 97.01% accuracy.	Dataset with 2975 images of five apple leaf diseases and healthy leaves.	Single Label Classification	High accuracy, improved sensitivity to principal features, lightweight model.	Dataset quality and quantity is of concern..
2021, [48]	CNN	F1-score of .991	PlantVillage dataset	Single Label Classification	Model performed better compared to the state of art Teacher/ Student architecture.	Leaf organ of plant is only considered for disease detection. Model is memory intensive and slow.
2021,[50]	CNN	Accuracy- 93.5%	PlantVillage dataset.	Single Label Classification	Model is simple and efficient.	Additional data could have enhanced the model's performance. Leaf organ of plant is only considered for disease detection.
2020, [53]	LSA-Net	Accuracy- 89.4%	404 images provided by Apple research institute	Single Label Classification	Better performance than other state-of-the-art methods. Focus on leaf	Leaf organ of plant is only considered for disease detection.

Year, Reference	Model Used	Performance	Dataset Used	Classification Type	Pros	Cons
					spot areas for accurate identification	
2020, [54]	Deep Convolutional Neural Network	Accuracy- 98.35%.	2970 images of apple tree leaf diseased validated by experts.	Single Label Classification	High accuracy, fast convergence, small number of parameters, high robustness.	Dataset quality and quantity is of concern..

2.2 Datasets

Good quality datasets are very crucial while working with any model based on machine learning or deep learning. Similarly while working in the field of Plant Pathology datasets play a crucial role and the model will tend to perform better provided more and more quality data is fed to the model while training. The utilization of these datasets is crucial for the development, training, and validation of the models designed to identify and categorize leaf diseases. They function as a benchmark for assessing the efficiency of various models and facilitate comparative studies and technological advancement. Some of the widely used datasets in the field of apple foliar disease detection are listed in Table 2.2.

Table 2.2- Datasets Used in Apple Foliar Disease Detection

Dataset Name	No. of Images	Year Released
FGCV-8[55]	23249	2021
FGCV-7[56]	3,651 RGB images	2020
Plant Village Dataset[57]	3171 RGB images of apple leaves	2015
Apple Leaf Disease Identification Data set (ALDID)[42]	81700	-

The availability of these datasets has greatly advanced the field of plant pathology by offering a wide range of high-quality data sources for training advanced models.

They enable the investigation of different algorithmic methodologies, ranging from traditional machine learning methods to sophisticated deep learning based frameworks. In this research, we utilize these datasets, particularly the FGCV8 2021 dataset, to develop and validate a deep-learning model for detecting multiple foliar diseases in apple orchards.

2.3 Limitation in Existing Work

Through this extensive literature survey we could see great advancement has been made in the field of agriculture utilizing deep learning, yet certain limitations exists. Going through the studies we could identify some limitations in existing work which are discussed below:

- **Generalization:** The majority of the research has been conducted using datasets that may not accurately reflect a practical real-world scenario. This issue significantly affects the generality of the algorithms, making them unfit for practical applications.
- **Multiple Disease Detection**: There has been limited focus on identifying multiple diseases at once on a single part of a plant, like a leaf. This study aims to fill that gap by developing methods that can detect multiple diseases simultaneously on one plant organ.
- **Limited scope:** The majority of research conducted in this field concentrates solely on diseases that impact plant leaves, disregarding other organs of plants such as stems or fruits. It is important to expand disease detection to consider different organs of the plant, rather than solely focusing on the leaves.
- **Accuracy Speed Trade-off:** Most existing studies prioritize how well they can recognize diseases, often at the expense of how quickly or efficiently these recognition can be made. This focus can limit the usefulness of these methods in real-world applications where both speed and accuracy are important.
- **Small datasets:** For deep learning models to perform well and be accurate, they need large and diverse datasets. Currently, there are only a few small datasets available for plant disease detection, which is a significant

limitation that needs to be addressed to improve model performance and accuracy.

In response to these limitations our proposed framework tries to address these limitation and extend work towards multi label foliar disease categorization using deep learning through which proposed framework would be capable of to identify an individual disease from multiple disease symptoms on a single leaf image.

2.4 Problem Statement

The accurate and timely detection of foliar diseases in apple orchards is crucial for maintaining crop health and optimizing yields. Traditional methods of disease detection rely heavily on manual inspection and expert knowledge and are often labor-intensive, time-consuming, and subject to human error.

With the advancements in the field of deep learning, it offers great opportunity to build a framework capable of detecting and classifying diseases accurately. However, while working in the real world we may face numerous challenges like variations in lighting, leaf orientation, background clutter, etc. which can badly affect the accuracy and performance of the model. Also, in real world setting multiple diseases may be existing on same leaf. With the multiple diseases existing on same leaf, the complexity is increased and the model should be able to correctly spot the patterns and classify each individual disease accurately

Also, it is crucial for these model to work efficiently, which calls for building a framework that offers a balance between performance and computational requirements. Thus, the main goal of this study is to develop a highly effective and efficient framework capable of multi-label foliar disease classification in apple orchards even under challenging and real world setting. This model should be be capable of deployable in resource-constrained environments, usually seen in agricultural settings, and it should also able to handle the complexity of multiple disease symptoms per image with high accuracy and precision.

CHAPTER 3

PROPOSED METHODOLOGY

This section discussed about the proposed methodology towards multi-label foliar disease classification in apple orchards using deep learning. In the proposed framework we have utilized FGCV8 2021 dataset and used state-of-the-art MobileNetV2 model to build the proposed predictive network. The Fig 3.1 shows the architecture of proposed framework. In coming sub-sections we have discussed about data acquisition, pre-processing, network architecture and model training and validation.

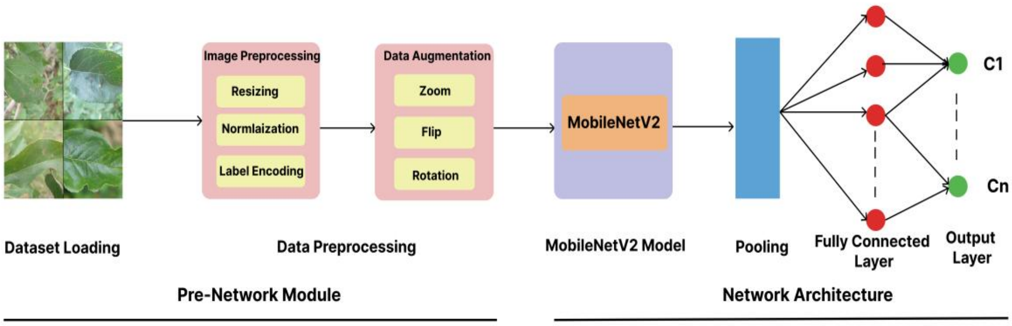


Fig. 3.1- Proposed Model Architecture for Foliar Disease Detection

3.1 Data Acquisition

The data acquisition process involves collecting and analyzing data following systematic and standardized steps so as to effectively use it in different areas of application like research, technical analysis, etc. In the field of deep learning and machine learning, data acquisition involves several critical steps as discussed below:

1. Data Identification:

- **Defining Requirements:** Based on the field of research and direction first we need to determine the type of data required. For our research in field of plant pathology, images of diseased and healthy plants are required.
- **Sources:** Potential resources needs to be identified as per the requirements based on the research work. This can be publicly either

publicly available datasets or proprietary dataset owned by individual, company, etc. If no relevant data is found which aligns with our research work it could involve creating our own dataset.

2. **Data Collection:**
   - **Gathering Data:** Collect the data which is relevant to research work from the identified sources. This could involve downloading dataset from the source or making our own dataset through experimental setup like photographing leaves under different conditions.
3. **Data Validation and Cleaning:**
   - **Validation:** This step involves checking the data for accuracy and completeness. This helps ensure that the collected data meets the quality standards related to the field of work performed in this study.
   - **Cleaning:** The gathered data must be free of inaccurate or irrelevant data which is not related to field of work. This cleaning step guarantees that the data of high quality is provided to the model for the training process, resulting in improved performance and accuracy of the model.

In our study, we have utilized the Plant Pathology FGCV8 2021 dataset, which consists of nearly 23000 high quality images consisting of both healthy and diseased images of apple leaves. The final collected data undergoes different data pre-processing steps and fed to the model for training and validation which are discussed in coming sub-sections.

3.2 Data Pre-processing

Data pre-processing is one of the critical step while building any model in the field of deep learning or machine learning. The main aim of this is to convert the raw data into a form that is suitable to be fed to the model directly for further processing and analysis. This helps to standardize and improve the quality of data fed to the model which further helps enhance the performance and accuracy of the model. In the coming sub-sections we have discussed the some of the data pre-processing techniques that we have utilized while building the model.

3.2.1 Image Pre-processing

Proper preparation of the images is critical to ensure that the model trains effectively and efficiently on the dataset. The steps followed are discussed below:

- **Resizing:** All the images in the dataset are resized to a uniform dimension as per the requirements of the model. In this study we have resized the images to 224x224 pixels for compatibility with MobileNetV2 model. This helps ensure that consistent input is fed to the model which helps the model to learn effectively from the data provided.
- **Normalization:** Normalization is the process of scaling input within a range of 0 to 1. In this case for all the images pixel values are scaled to range 0 to 1 by dividing each pixel value by 255 i.e. the maximum pixel value for 8-bit image. This helps the model to converge faster by reducing skewness in the pixel value distribution and maintains numerical stability.
- **Label Encoding:** Label encoding helps transform categorical values to numerical value where each numerical value represents a class. In this study we have used MultiLabelBinarizer which aligns with our research work multi-label foliar disease categorization. Encoding helps neural network to learn the desired output format.

3.2.2 Data Augmentation

Data augmentation[58] is a technique used in the field of deep learning and machine learning to artificially generate more data from the existing data by making random and realistic modification to the original data. This helps model to generalize better to new and unseen data. Some of the data augmentation techniques used in building our model is discussed below:

- **Zoom:** A zoom augmentation randomly zooms into the image which would which could help model generalize and learn better to slight variations which is highly possible in real world scenario.
- **Flip:** In this step images are flipped horizontally and vertically. This step increases the diversity of training data by simulating different

orientations of leaves as they might occur naturally in real world scenario. It helps the model become invariant to the orientation of the leaf in real-world scenarios.

- **Rotation:** Images are rotated by a range of angles (e.g., -25 to 25 degrees). This variation introduces a range of perspectives and angles, mimicking the way leaves might be viewed under natural conditions, thus aiding the model in recognizing diseases regardless of the leaf's orientation in the image.

3.3 Network Architecture

In the proposed framework, the MobileNetV2[59] architecture serves as the backbone of the neural network model for classifying foliar diseases in apple orchards. The different layers used in network are shown in Fig 3.2 and are discussed below:

- **Input Layer-** This layer serves as entry point for input data. Input Shape: [256, 256, 3] indicating images of size 256x256 pixels with 3 color channels (RGB).
- **MobilenetV2 Layer-** Acts as the backbone for feature extraction. MobileNetV2 is a pre-trained model that uses depthwise separable convolutions to efficiently process images.
- **GlobalAveragePooling2D-** Applies global average pooling[60] over the spatial dimensions (height and width) of the input tensor from the last convolution layer. This reduces each of the feature maps to a single number by averaging out each map.
- **Dense-** Fully connected layer that applies a linear transformation to the incoming data followed by a ReLU activation. Often used to learn non-linear combinations of the high-level features extracted by the convolution layers.

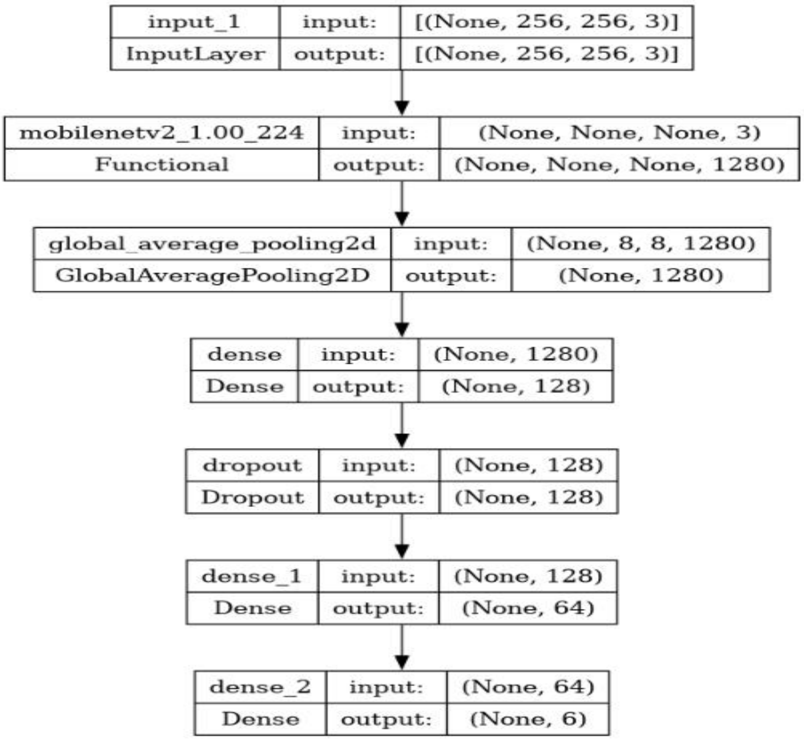


Fig. 3.2- Layered Architecture of proposed model

- **Dropout-** A dropout[61] regularization layer that randomly sets a fraction of input units to 0 at each update during training time, to help prevent model from over-fitting.
- **Output Layer-** The final fully connected layer that outputs the predictions for the task with Sigmoid Activation function which is suitable for multi-label classification, allowing independent probabilities for each class.

3.3.1 MobilenetV2 Model

MobileNetV2 is chosen for its compact architecture, which provides a balance between efficiency and accuracy, making it particularly well-suited for applications requiring low latency or operating under computational constraint. This model leverages depthwise separable convolutions that significantly reduce the number of parameters resulting in reduced computational cost compared to conventional convolutional layers. The model's lightweight nature guarantees quicker inference times, which is essential for deploying it in real-time disease detection systems under natural field conditions.

In MobileNetV2 the core architecture consist of two different types of blocks: the residual block with a stride of one and another block with a stride of two for reducing the spatial dimensions. Each of these two block contains three layers. The first layer consists of 1x1 convolution layer with ReLU6 activation function, which is used for channel-wise transformation and non-linear activation. The second layer is a depthwise convolution, which applies a single filter per input channel, enabling efficient spatial filtering. The third layer is another 1x1 convolution, but it notably excludes any non-linear activation function like ReLU. This is based on the factor that reintroducing ReLU at this stage could diminish the network's ability to capture complex patterns. This architecture leverages these layers within its blocks to enhance computational efficiency while maintaining robustness in feature extraction, making it highly suitable for resource-constrained environments. The Fig. 3.3 shows the architecture of two blocks.

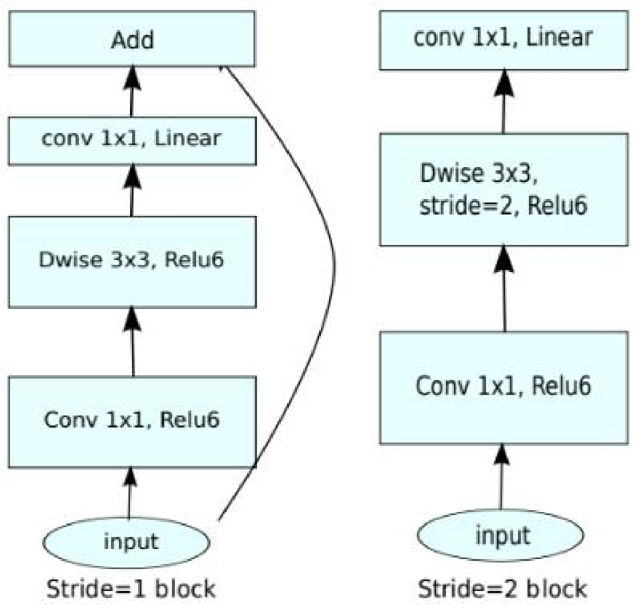


Fig 3.3: Layerwise structure of two blocks of MobileNetV2[59]

3.3.2 Optimizer

In our study we have used ADAM[62] optimizer while training our model. It stands for "Adaptive Moment Estimation" and combines the best properties of the AdaGrad[63] and RMSProp algorithms to handle sparse gradients on noisy problems.

Adam is well-suited for problems with large datasets and/or many parameters. Some of the key features of adam optimizer are:

- **Adaptive Learning Rates**: Adam modifies the learning rate for each parameter separately using estimations of the first and second moments of the gradients, which correspond to the mean and variance, respectively. This allows it to handle varying gradients and sparse data more effectively than algorithms with a constant learning rate.
- **Efficiency:** Adam optimizer demonstrates high computational efficiency and has relatively low memory demands. It is suited for problems with large data or parameters and is invariant to the diagonal gradient rescale.

The Algorithm of ADAM optimizer is as defined in Fig. 3.4 showing different steps and operations. The different parameters required are as mentioned below with optimal values as mentioned in bracket:

- β1 — This is used for decaying the running average of the gradient (0.9).
- β2 — This is used for decaying the running average of the square of gradient (0.999).
- α — Step size parameter (0.001).
- ε- It is to prevent *Division from zero* error. (10^-8).

Require: α: Stepsize
Require: $\beta_1, \beta_2 \in [0, 1)$: Exponential decay rates for the moment estimates
Require: $f(\theta)$: Stochastic objective function with parameters θ
Require: θ_0: Initial parameter vector
$m_0 \leftarrow 0$ (Initialize 1st moment vector)
$v_0 \leftarrow 0$ (Initialize 2nd moment vector)
$t \leftarrow 0$ (Initialize timestep)
while θ_t not converged **do**
$t \leftarrow t + 1$
$g_t \leftarrow \nabla_\theta f_t(\theta_{t-1})$ (Get gradients w.r.t. stochastic objective at timestep t)
$m_t \leftarrow \beta_1 \cdot m_{t-1} + (1 - \beta_1) \cdot g_t$ (Update biased first moment estimate)
$v_t \leftarrow \beta_2 \cdot v_{t-1} + (1 - \beta_2) \cdot g_t^2$ (Update biased second raw moment estimate)
$\widehat{m}_t \leftarrow m_t/(1 - \beta_1^t)$ (Compute bias-corrected first moment estimate)
$\widehat{v}_t \leftarrow v_t/(1 - \beta_2^t)$ (Compute bias-corrected second raw moment estimate)
$\theta_t \leftarrow \theta_{t-1} - \alpha \cdot \widehat{m}_t/(\sqrt{\widehat{v}_t} + \epsilon)$ (Update parameters)
end while
return θ_t (Resulting parameters)

Fig 3.4: Algorithm for ADAM optimizer[62]

```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 256, 256, 3)]     0

 mobilenetv2_1.00_224 (Func  (None, None, None, 1280   2257984
 tional)                     )

 global_average_pooling2d (  (None, 1280)              0
 GlobalAveragePooling2D)

 dense (Dense)               (None, 128)               163968

 dropout (Dropout)           (None, 128)               0

 dense_1 (Dense)             (None, 64)                8256

 dense_2 (Dense)             (None, 6)                 390

=================================================================
Total params: 2430598 (9.27 MB)
Trainable params: 2396486 (9.14 MB)
Non-trainable params: 34112 (133.25 KB)
_________________________________________________________________
```

Fig 3.5: Summary of model with details on number of parameters.

3.4 Model Training and Validation

The training was conducted on the pre-processed FGCV8 2021 dataset, which had undergone extensive augmentation to enhance model generalization capabilities. The dataset was split into training and validation sets, with 90% of the data used for training and 10% reserved for validation. This split ensured that the model could be trained extensively while also being evaluated against unseen data. The training was performed over 50 epochs using the Adam optimizer. The learning rate was initially set at 0.001 and adjusted dynamically based on the plateau in validation loss to ensure efficient convergence. Fig 3.5 shows the the detail of model along with the total trainable and non-trainable parameters associated with the model.

During training, callbacks such as ModelCheckpoint and EarlyStopping were implemented to save the best model and halt training when the validation loss ceased to decrease, enhancing training efficiency. Model performance was evaluated using accuracy, precision, recall, and F1-score to provide a comprehensive view of its capabilities across various thresholds and conditions. Validation during training allowed for continuous monitoring of model behavior, ensuring that adjustments could be made promptly to optimize performance.

CHAPTER 4
EXPERIMENTAL RESULT AND ANALYSIS

This section discusses about the experimental setup which was used for conducting this research work followed by discussion on dataset and the framework to assess the effectiveness of the network framework proposed. Finally, the comparative study against existing work in the field of multi-label foliar disease classification and analysis of performance of model against different metrics is discussed.

4.1 Experimental Setup

All the experiments related to this research were conducted on the Kaggle platform, which offers a highly user-friendly interface for Artificial Intelligence and Machine Learning related tasks. The collection of diverse datasets and powerful computational resources makes it highly suitable for working on complex tasks related to AI/ML. In this research work, Python is used as a programming language. Python provides added advantage because of availability of libraries and frameworks like TensorFlow, PyTorch, and Scikit-learn which help in tasks related to Artificial Intelligence and Machine Learning.

This study work utilized Two NVIDIA T4 GPUs, to speed up the training process, and handle the tasks requiring high computational power. The GPUs helped in training the models by utilizing parallel processing capabilities. The use of GPU acceleration resulted in significant reduction in training time, allowing for efficient experimentation and iterative development.

4.2 Dataset Description

In this study, we have used the FGCV8 Plant Pathology 2021 dataset for training and validating our model which consists of approximately 23,000 high-quality images showcasing various apple foliar diseases. This dataset stands out for its diversity, covering multiple disease categories and including images with non-homogeneous backgrounds, different leaf maturity stages, and varied lighting conditions. The main advantage of using this dataset over other datasets is that it consists of images exhibiting multiple disease symptoms on a single leaf and mimics the complexity of real-world scenarios. Fig. 4.1 shows images from the plant pathology 2021 dataset with multiple foliar diseases.

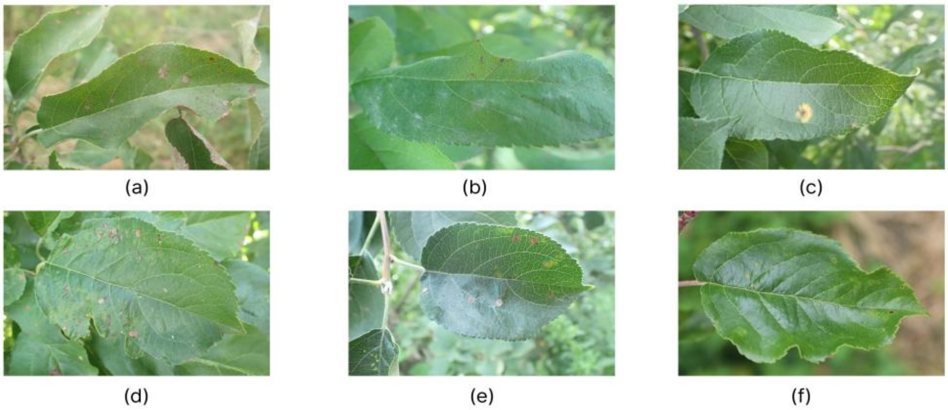


Fig. 4.1- Apple leafs with multi foliar diseases from Plant Pathology 2021(FGCV 8) dataset- (a) scab, frog_eye_leaf_spot and complex, (b) powdery_mildew and complex, (c) rust and frog_eye_leaf_spot, (d) frog_eye_leaf_spot and complex, (e) scab and frog_eye_leaf_spot, (f) rust and complex

4.3 Performance Evaluation Metrics

In order to access the performance of proposed model it is necessary to determine how effective a model is. Performance metric help in analyzing how well models perform in a variety of tasks, like classification, regression, etc. This section discusses various performance evaluations metrics which we have used in our study to evaluate our model.

- **Accuracy-** Accuracy is the proportion of correctly predicted observations among the total number of cases examined. It can be deceptive for datasets that are not balanced, but it works well for balanced datasets.

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}$$

- **Precision-** Precision indicates the proportion of positive predictions that were actually correct. When the cost of false positives is high, it is imperative.

$$\text{Precision} = \frac{\text{Number of True Positives}}{\text{Number of Predicted Positives}}$$

- **Recall-** Recall indicates the proportion of actual positives that were correctly identified. When the cost of false negatives is high, it becomes crucial.

$$\text{Recall} = \frac{\text{Number of True Positives}}{\text{Number of Actual Positives}}$$

- **F1 Score-** The precision and recall weighted average is the F1 score. When you have to account for both false positives and false negatives, it is helpful.

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

4.4 Result Comparison and Analysis

The proposed model using MobileNetV2 as backbone architecture demonstrates superior performance compared to other state-of-the-art methods working towards multi-label foliar disease classification. These state-of-the-art models include an Ensemble CNN combining MobileNet, Xception, and InceptionResNet; a Multi-Layer CNN; and a Squeeze Excitation network with Holistic Self Distillation(HSD).

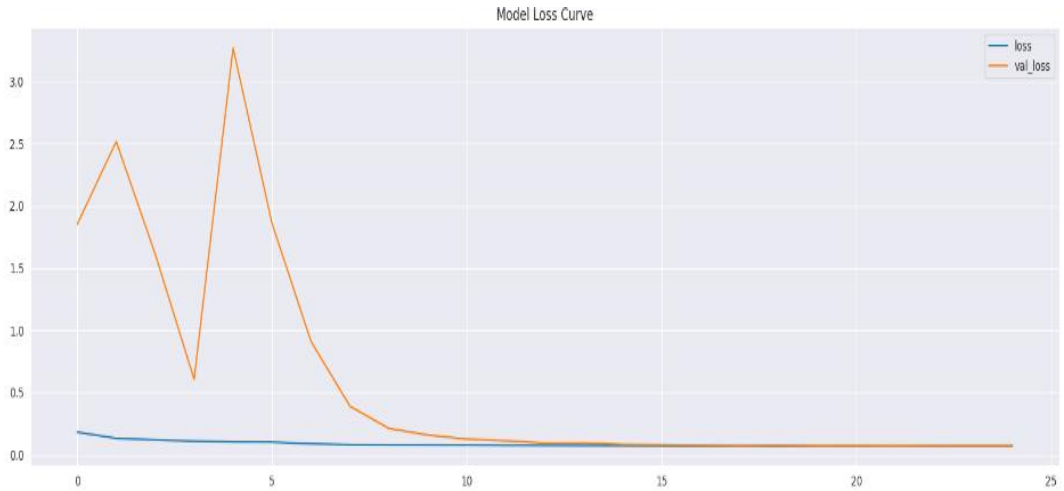


Fig. 4.2- Graph showing proposed model's loss across different epochs.

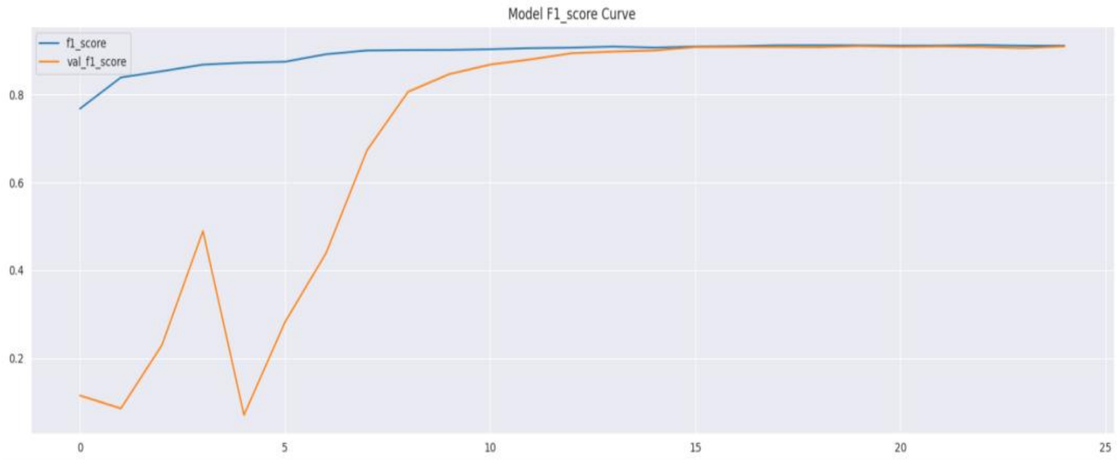


Fig. 4.3- Graph showing proposed model's F1-Score across different epochs.

The Fig 4.2 shows the variation of loss and validation loss for the proposed model across different epochs. The detailed results analysis is discussed below based on different performance metrics used in this study:

- **Accuracy-** The Proposed Model exhibits the highest accuracy at 92.46%, indicating its superior capability in correctly classifying test data compared to the other models. The Multi-Layer CNN follows closely at 91%, while the Ensemble CNN and the Squeeze Excitation network show lower accuracies of 87.31% and 90.72%, respectively.
- **F1-Score-** The F1-Score, which balances precision and recall, is highest for the Proposed Model at 90.87%. This suggests that it not only accurately identifies the positive class but also maintains a lower rate of false positives and false negatives. The Ensemble CNN, despite its lower accuracy, achieves a competitive F1-score of 90.01%, indicating effective balance despite fewer correct predictions overall. The other two models have somewhat lower F1-scores, with the Multi-Layer CNN at 88.34% and the Squeeze Excitation network at 89.61%. The Fig. 4.3 shows the variation of F1-Score across different epochs for proposed model.
- **Precision-** Precision is exceptionally high in the Proposed Model at 93.11%, indicating that when it predicts an instance as positive, it is correct more often than the other models. This is particularly important

in applications where the cost of a false positive is high. The other models display relatively lower precision, ranging from 89% to 90.03%.

- **Recall-** The recall of the Proposed Model is 90.81%, which is higher than that of the Multi-Layer CNN and Squeeze Excitation network, but slightly higher than the 90% of the Ensemble CNN. This indicates that the Proposed Model is slightly better at identifying all positive samples.

The improvements in recall and precision are especially significant because they point to a very trustworthy model that reduces false positives and negatives while simultaneously correctly identifying the diseases, which is essential for timely and efficient crop disease management. In conclusion, these findings support the effectiveness of the proposed model based on MobileNetV2 in precisely detecting the presence of disease and assisting in effective agricultural management. The Fig. 4.4 shows the comparison of performance of proposed model against other state-of-art-models.

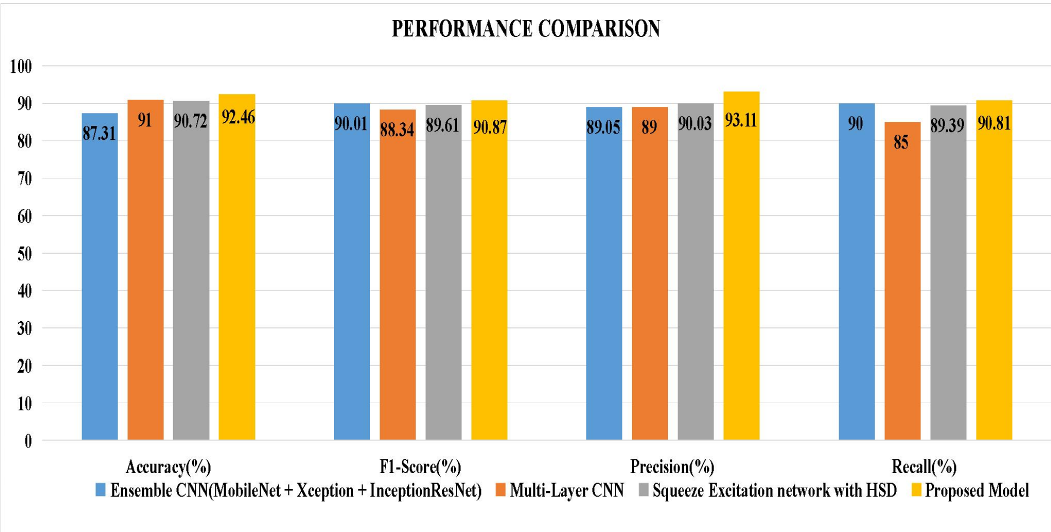


Fig. 4.4- Comparison of Proposed Model with other state of art model for multi label foliar disease classification- Ensemble CNN(MobileNet + Xception + InceptionResNet) [35], Multi-Layer CNN[21] and Squeeze Excitation network with HSD[20]

CHAPTER 5
CONCLUSION AND FUTURE WORK

5.1 Conclusion

This research study focuses on the development of a framework capable of multi-label foliar disease classification in apple orchards. The proposed framework utilizing MobileNetV2 as backbone architecture shows the capability of a deep learning model that can efficiently and accurately identify foliar diseases.

The results obtained for the proposed model against different performance evaluation metrics show the effectiveness of deep learning based models. The accuracy of 92.46%, an F1-score of 90.87%, a Precision of 93.11%, and a Recall of 90.81% show the robustness of the proposed model compared against different metrics. The improvements in recall and precision in comparison to other state-of-the-art models are especially significant because they point to a very trustworthy model that reduces false positives and negatives while simultaneously correctly identifying the diseases.

Overall, this research work highlights the potential of using advanced tools and technology like deep learning to improve the detection and management of plant diseases. The proposed framework could prove to be highly beneficial to apple cultivators around the world by helping in early disease detection and management leading to reduced crop damage and economic loss.

5.2 Limitation

The proposed framework based on MobileNetV2 for multi-label foliar disease categorization has demonstrated superior performance and accuracy in comparison to other state-of-the-art models. However, there are certain fields and area that must be understood and acknowledged to identify the potential areas for improvement in coming future. Some of the limitations are discussed below:

- **Data Dependency:** The performance of the deep learning based model relies heavily on the quality and diversity of the dataset i.e. better the data the more effective and accurate the model will be. While the FGCV 2021 dataset is comprehensive, it is still limited to images collected under specific conditions, which might not encompass all possible variations in disease presentation in different geographic or climatic conditions.
- **Generalization Ability:** While the model performs well on the dataset used, its ability to generalize to completely new environments or different types of plants has not been extensively tested. This could be a significant limitation if the model is applied in a broader agricultural context without additional training.
- **Computational Resources:** Although MobileNetV2 is designed for efficiency, training deep learning models and processing large datasets still require substantial computational resources, which may not be readily available in all potential application scenarios, particularly in resource-limited settings.
- **Detection of New Diseases:** The current model is trained to detect diseases included in the FGCV 2021 dataset. However, its capability to identify new or emerging diseases that were not part of the training data is limited, which could affect its utility over time as new threats to crop health emerge.

5.3 Future Scope

The Future scope for this study using deep learning could be very promising and vast in the field of agriculture advancement and plant pathology. As we move forward there are various fields to which this work could be extended and some of them are discussed below:

- **Expanding Dataset Diversity:** As we know more the quality dataset better deep learning models tend to perform. So, one immediate area could be to expand the data source to include more diversity in term of environment condition, plant varieties and stages of disease progression.

Also including data from different geographic regions and different apple orchards could further help model generalize better and improved performance. Also collecting image during different season and time of day could also help further fine tune the performance of the model.

- **Real-Time Detection System-** Integrating the existing work with other cutting edge technologies like IoT and drone could further help in efficient and timely intervention leading to less crop wastage and reduced economic to the cultivators.
- **Fine-Tune Model:** Combining MobileNetV2 with other models or use of much more complex deep learning models could further help improve accuracy and performance of the model. Also fine-tuning of existing model could be explored to better performance.
- **Feedback Loops for Continuous Learning:** Establishing mechanisms for continuous learning, where the model can update itself based on new data collected in the field, could help maintain its accuracy over time. This approach would involve developing an infrastructure for data collection, model retraining, and deployment that can operate dynamically.

These could be the significant area which could involve future research work and further help unlock the potential of deep learning in the field of agriculture leading to more sophisticated, reliable and useful tools for the farmers and agronomists around the world. This ongoing evolution will play a crucial role in advancing sustainable agriculture and ensuring food security in the face of global challenges.

In summary, although the present study has effectively illustrated the efficacy of MobileNetV2 in the classification of foliar diseases, there are enough prospects for advancement and creativity in the utilization of deep learning to help create robust and sustainable farming systems in the future.

REFERENCES

1. Turechek, William W. "Apple diseases and their management." *Diseases of Fruits and Vegetables Volume I: Diagnosis and Management* (2004): 1-108.
2. Savary, Serge, Andrea Ficke, Jean-Noël Aubertot, and Clayton Hollier. "Crop losses due to diseases and their implications for global food production losses and food security." *Food security* 4, no. 4 (2012): 519-537.
3. Nilsson, Nils J. *Principles of artificial intelligence*. Springer Science & Business Media, 1982.
4. Sarker, Iqbal H. "Machine learning: Algorithms, real-world applications and research directions." *SN computer science* 2, no. 3 (2021): 160.
5. Gupta, Anunay, Shreyansh Gupta, and Rahul Katarya. "InstaCovNet-19: A deep learning classification model for the detection of COVID-19 patients using Chest X-ray." *Applied Soft Computing* 99 (2021): 106859.
6. Nandanwar, Himanshu, and Rahul Katarya. "Deep learning enabled intrusion detection system for Industrial IOT environment." *Expert Systems with Applications* 249 (2024): 123808.
7. Anjum, and Rahul Katarya. "HateDetector: Multilingual technique for the analysis and detection of online hate speech in social networks." *Multimedia Tools and Applications* (2023): 1-28.
8. Katarya, Rahul, and Om Prakash Verma. "An effective collaborative movie recommender system with cuckoo search." *Egyptian Informatics Journal* 18, no. 2 (2017): 105-112
9. Jain, Lokesh, and Rahul Katarya. "Discover opinion leader in online social network using firefly algorithm." *Expert systems with applications* 122 (2019): 1-15.
10. S. Kumar, A. Mallik, " COVID-19 Detection from Chest X-rays Using Trained Output Based Transfer Learning Approach". Neural processing letters, 55(3), 2405-2428 (2023)4. S. Kumar, A Mallik, S.S Sengar, “Community detection in complex networks using stacked autoencoders and crow search algorithm”. The Journal of Supercomputing, 79(3), 3329-3356 (2023).

11. D. Kurchaniya, S. Kumar, "Two stream deep neural network based framework to detect abnormal human activities", Journal of Electronic Imaging 32 (4), 043021-043021 (2023).
12. A. Mallik, S. Kumar, “Word2Vec and LSTM based deep learning technique for context-free fake news detection”. Multimedia Tools and Applications, 83, 919–940, (2024).
13. Hao, Xing, Guigang Zhang, and Shang Ma. "Deep learning." *International Journal of Semantic Computing* 10, no. 03 (2016): 417-439.
14. Read, Jesse, and Fernando Perez-Cruz. "Deep learning for multi-label classification." *arXiv preprint arXiv:1502.05988* (2014)
15. Kamilaris, Andreas, and Francesc X. Prenafeta-Boldú. "Deep learning in agriculture: A survey." *Computers and electronics in agriculture* 147 (2018): 70-90.
16. Singh, Saurabh, and Rahul Katarya. "Exploring the Deep Learning Techniques in Plant Disease Detection: A Review of Recent Advances." In *International Conference on Advances in Data-driven Computing and Intelligent Systems*, pp. 265-277. Singapore: Springer Nature Singapore, 2023.
17. Fang, Tianyu, Jialin Zhang, Dawei Qi, and Mingyu Gao. "BLSENet: A Novel Lightweight Bilinear Convolutional Neural Network Based on Attention Mechanism and Feature Fusion Strategy for Apple Leaf Disease Classification." *Journal of Food Quality (*2024).
18. O'shea, Keiron, and Ryan Nash. "An introduction to convolutional neural networks." *arXiv preprint arXiv:1511.08458* (2015).
19. Hu, Jie, Li Shen, and Gang Sun. "Squeeze-and-excitation networks." In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 7132-7141. 2018
20. Su, Jingxuan, Sean Anderson, and Lyudmila Mihaylova. "Holistic Self-Distillation with the Squeeze and Excitation Network for Fine-grained Plant Pathology Classification." In *2023 26th International Conference on Information Fusion (FUSION)*, pp. 1-7. IEEE, 2023.

21. Biswas, Barsha, and Rajesh Kumar Yadav. "Multilayer Convolutional Neural Network Based Approach to Detect Apple Foliar Disease." In *2023 2nd International Conference for Innovation in Technology (INOCON)*, pp. 1-5. IEEE, 2023.
22. Gehlot, Mamta, and Geeta Chhabra Gandhi. "“EffiNet-TS”: A deep interpretable architecture using EfficientNet for plant disease detection and visualization." *Journal of Plant Diseases and Protection* 130, no. 2 (2023): 413-430.
23. Mahum, Rabbia, Haris Munir, Zaib-Un-Nisa Mughal, Muhammad Awais, Falak Sher Khan, Muhammad Saqlain, Saipunidzam Mahamad, and Iskander Tlili. "A novel framework for potato leaf disease detection using an efficient deep learning model." *Human and Ecological Risk Assessment: An International Journal* 29, no. 2 (2023): 303-326.
24. Huang, Gao, Shichen Liu, Laurens Van der Maaten, and Kilian Q. Weinberger. "Condensenet: An efficient densenet using learned group convolutions." In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 2752-2761. 2018
25. Li, Manzhou, Siyu Cheng, Jingyi Cui, Changxiang Li, Zeyu Li, Chang Zhou, and Chunli Lv. "High-Performance Plant Pest and Disease Detection Based on Model Ensemble with Inception Module and Cluster Algorithm." *Plants* 12, no. 1 (2023): 200.
26. Redmon, Joseph, Santosh Divvala, Ross Girshick, and Ali Farhadi. "You only look once: Unified, real-time object detection." In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 779-788. 2016.
27. Ren, Shaoqing, Kaiming He, Ross Girshick, and Jian Sun. "Faster r-cnn: Towards real-time object detection with region proposal networks." *Advances in neural information processing systems* 28 (2015).
28. Yu, Sheng, Li Xie, and Qilei Huang. "Inception convolutional vision transformers for plant disease identification." *Internet of Things* 21 (2023): 100650.

29. Ramamoorthy, Raghu, E. Saravana Kumar, R. Ch A. Naidu, and K. Shruthi. "Reliable and Accurate Plant Leaf Disease Detection with Treatment Suggestions Using Enhanced Deep Learning Techniques." *SN Computer Science* 4, no. 2 (2023): 158
30. Howard, Andrew G., Menglong Zhu, Bo Chen, Dmitry Kalenichenko, Weijun Wang, Tobias Weyand, Marco Andreetto, and Hartwig Adam. "Mobilenets: Efficient convolutional neural networks for mobile vision applications." *arXiv preprint arXiv:1704.04861* (2017).
31. Vishnoi, Vibhor Kumar, Krishan Kumar, Brajesh Kumar, Shashank Mohan, and Arfat Ahmad Khan. "Detection of apple plant diseases using leaf images through convolutional neural network." *IEEE Access* 11 (2022): 6594-6609.
32. Yu, Helong, Xianhe Cheng, Chengcheng Chen, Ali Asghar Heidari, Jiawen Liu, Zhennao Cai, and Huiling Chen. "Apple leaf disease recognition method with improved residual network." *Multimedia Tools and Applications* 81, no. 6 (2022): 7759-7782.
33. He, Kaiming, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. "Deep residual learning for image recognition." In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 770-778. 2016.
34. Wang, Haiqing, Shuqi Shang, Dongwei Wang, Xiaoning He, Kai Feng, and Hao Zhu. "Plant disease detection and classification method based on the optimized lightweight YOLOv5 model." *Agriculture* 12, no. 7 (2022): 931.
35. Vora, Kush, and Dishant Padalia. "An ensemble of convolutional neural networks to detect foliar diseases in apple plants." *arXiv preprint arXiv:2210.00298* (2022).
36. Chollet, François. "Xception: Deep learning with depthwise separable convolutions." In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 1251-1258. 2017.
37. Szegedy, Christian, Sergey Ioffe, Vincent Vanhoucke, and Alexander Alemi. "Inception-v4, inception-resnet and the impact of residual connections on learning." In Proceedings of the AAAI conference on artificial intelligence, vol. 31, no. 1. 2017.

38. Elaraby, Ahmed, Walid Hamdy, and Madallah Alruwaili. "Optimization of Deep Learning Model for Plant Disease Detection Using Particle Swarm Optimizer." *Computers, Materials & Continua* 71, no. 2 (2022).
39. Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "ImageNet classification with deep convolutional neural networks." *Communications of the ACM* 60, no. 6 (2017): 84-90.
40. Saleem, Muhammad Hammad, Johan Potgieter, and Khalid Mahmood Arif. "A performance-optimized deep learning-based plant disease detection approach for horticultural crops of new zealand." *IEEE Access* 10 (2022): 89798-89822.
41. Dai, Jifeng, Yi Li, Kaiming He, and Jian Sun. "R-fcn: Object detection via region-based fully convolutional networks." *Advances in neural information processing systems* 29 (2016).
42. Wang, Peng, Tong Niu, Yanru Mao, Zhao Zhang, Bin Liu, and Dongjian He. "Identification of apple leaf diseases by improved deep convolutional neural networks with an attention mechanism." *Frontiers in Plant Science* 12 (2021): 723294.
43. Bansal, Prakhar, Rahul Kumar, and Somesh Kumar. "Disease detection in apple leaves using deep convolutional neural network." *Agriculture* 11, no. 7 (2021): 617.
44. Huang, Gao, Zhuang Liu, Laurens Van Der Maaten, and Kilian Q. Weinberger. "Densely connected convolutional networks." In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 4700-4708. 2017.
45. Tan, Mingxing, and Quoc Le. "Efficientnet: Rethinking model scaling for convolutional neural networks." In *International conference on machine learning*, pp. 6105-6114. PMLR, 2019.
46. Xie, Qizhe, Minh-Thang Luong, Eduard Hovy, and Quoc V. Le. "Self-training with noisy student improves imagenet classification." In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 10687-10698. 2020.
47. Chao, Xiaofei, Xiao Hu, Jingze Feng, Zhao Zhang, Meili Wang, and Dongjian He. "Construction of apple leaf diseases identification networks based on xception fused by SE module." *Applied Sciences* 11, no. 10 (2021): 4614.

48. Shah, Dhruvil, Vishvesh Trivedi, Vinay Sheth, Aakash Shah, and Uttam Chauhan. "ResTS: Residual deep interpretable architecture for plant disease detection." *Information Processing in Agriculture* 9, no. 2 (2022): 212-223.
49. Li, Xuewei, Songyuan Li, Bourahla Omar, Fei Wu, and Xi Li. "Reskd: Residual-guided knowledge distillation." *IEEE Transactions on Image Processing* 30 (2021): 4735-4746.
50. Panchal, Adesh V., Subhash Chandra Patel, K. Bagyalakshmi, Pankaj Kumar, Ihtiram Raza Khan, and Mukesh Soni. "Image-based plant diseases detection using deep learning." *Materials Today: Proceedings* 80 (2023): 3500-3506.
51. Szegedy, Christian, Vincent Vanhoucke, Sergey Ioffe, Jon Shlens, and Zbigniew Wojna. "Rethinking the inception architecture for computer vision." In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 2818-2826. 2016.
52. Simonyan, Karen, and Andrew Zisserman. "Very deep convolutional networks for large-scale image recognition." *arXiv preprint arXiv:1409.1556* (2014).
53. Yu, H. J., and C. H. Son. "Leaf spot attention network for apple leaf disease identification, in 2020 IEEE." In *CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, pp. 229-237. 2020.
54. Chao, Xiaofei, Guoying Sun, Hongke Zhao, Min Li, and Dongjian He. "Identification of apple tree leaf diseases based on deep learning models." *Symmetry* 12, no. 7 (2020): 1065.
55. Thapa, Ranjita; Zhang, Kai; Snavely, Noah; Belongie, Serge; Khan, Awais. (2021). Plant Pathology 2021 - FGVC8 (2021).
56. Christine Kaeser-Chen, Fruit Pathology, Maggie, Sohier Dane. (2020). Plant Pathology 2020 - FGVC7. Kaggle. https://kaggle.com/competitions/plant-pathology-2020-fgvc7.
57. Hughes, David, and Marcel Salathé. "An open access repository of images on plant health to enable the development of mobile disease diagnostics." arXiv preprint arXiv:1511.08060 (2015).
58. Perez, Luis, and Jason Wang. "The effectiveness of data augmentation in image classification using deep learning." *arXiv preprint arXiv:1712.04621* (2017).

59. Sandler, Mark, Andrew Howard, Menglong Zhu, Andrey Zhmoginov, and Liang-Chieh Chen. "Mobilenetv2: Inverted residuals and linear bottlenecks." In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 4510-4520. 2018.
60. Lin, Min, Qiang Chen, and Shuicheng Yan. "Network in network." *arXiv preprint arXiv:1312.4400* (2013).
61. Srivastava, Nitish, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. "Dropout: a simple way to prevent neural networks from overfitting." *The journal of machine learning research* 15, no. 1 (2014): 1929-1958.
62. Kingma, Diederik P., and Jimmy Ba. "Adam: A method for stochastic optimization." arXiv preprint arXiv:1412.6980 (2014).
63. Duchi, John, Elad Hazan, and Yoram Singer. "Adaptive subgradient methods for online learning and stochastic optimization." *Journal of machine learning research* 12, no. 7 (2011).

List of Publication

1. Singh, Saurabh, and Rahul Katarya. "Exploring the Deep Learning Techniques in Plant Disease Detection: A Review of Recent Advances." In *International Conference on Advances in Data-driven Computing and Intelligent Systems*, pp. 265-277. Singapore: Springer Nature Singapore, 2023.

Certicate of Participation:

2nd International Conference on Advances in Data-driven Computing and Intelligent Systems (ADCIS 2023)

Organized by
BITS Pilani, K K Birla, Goa Campus, India
Co-organized by
National Forensic Sciences University, Goa
Technically Sponsored by
Soft Computing Research Society
September 21-23, 2023

Certificate of Participation

This is to certify that **Saurabh Singh** has presented the paper titled **Exploring The Deep Learning Techniques in Plant Disease Detection: A Review of Recent Advances** authored by **Saurabh Singh, Rahul Katarya** in the 2nd International Conference on Advances in Data-driven Computing and Intelligent Systems (ADCIS 2023) held during September 21-23, 2023.

SCRS\ADCIS2023\748

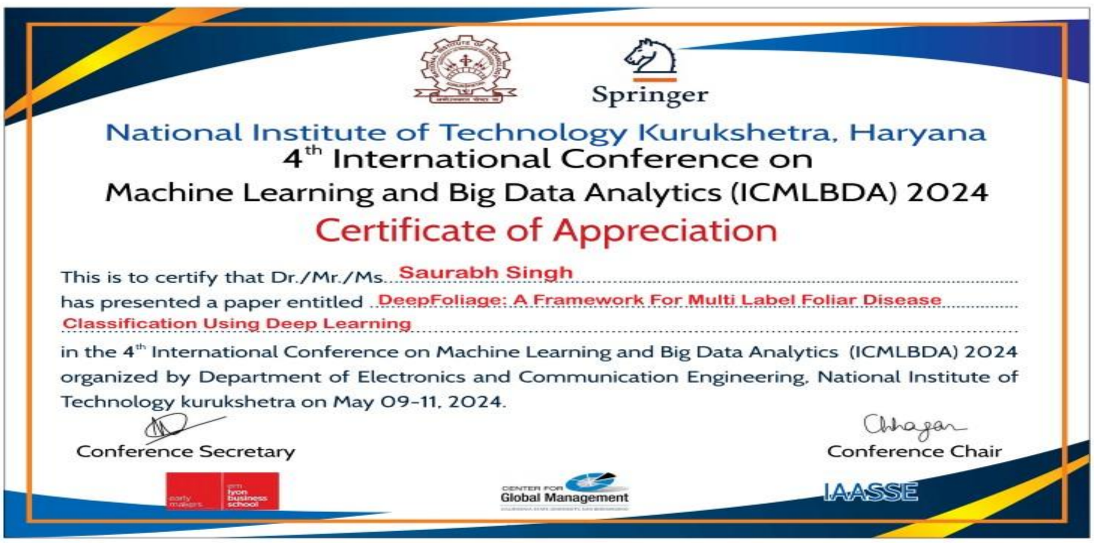
Dr. Lokesh Chouhan
General Chair

Dr. Snehanshu Saha
General Chair

Dr. Jagdish Chand Bansal
General Chair

2. Singh, Saurabh, and Rahul Katarya. "DeepFoliage: A Framework For Multi Label Foliar Disease Classification Using Deep Learning." In 4th *International Conference on Machine Learning and Big Data Analytics*, NIT Kurukshetra, 2024.

Certificate of Participation:



Springer

National Institute of Technology Kurukshetra, Haryana
4th International Conference on
Machine Learning and Big Data Analytics (ICMLBDA) 2024
Certificate of Appreciation

This is to certify that Dr./Mr./Ms. Saurabh Singh
has presented a paper entitled DeepFoliage: A Framework For Multi Label Foliar Disease Classification Using Deep Learning
in the 4th International Conference on Machine Learning and Big Data Analytics (ICMLBDA) 2024 organized by Department of Electronics and Communication Engineering, National Institute of Technology kurukshetra on May 09-11, 2024.

Conference Secretary

Conference Chair

DELHI TECHNOLOGICAL UNIVERSITY

(Formerly Delhi College of Engineering)

Shahbad Daulatpur, Main Bawana Road, Delhi-42

PLAGIARISM VERIFICATION

Title of the Thesis : **Multi Label Foliar Disease Categorization in Apple Orchards Using Deep Learning.**

Total Pages : **39**

Name of the Scholar : **Saurabh Singh, (2K22/AFI/20)**

Supervisor : **Prof. Rahul Katarya**

Department : **Department of Computer Science and Engineering**

This is to report that the above thesis was scanned for similarity detection. Process and outcome are given below:

Software used: **Turnitin** Similarity Index: **11%** Total Word Count: **9346**

Place: Delhi

Date:

Candidate's Signature **Signature of Supervisor**

PAPER NAME

Thesis Chap1-5 Saurabh.pdf

WORD COUNT	CHARACTER COUNT
9346 Words	**53746 Characters**
PAGE COUNT	FILE SIZE
37 Pages	**822.0KB**
SUBMISSION DATE	REPORT DATE
May 28, 2024 9:52 AM GMT+5:30	**May 28, 2024 9:53 AM GMT+5:30**

11% Overall Similarity

The combined total of all matches, including overlapping sources, for each database.

- 5% Internet database
- 6% Publications database
- Crossref database
- Crossref Posted Content database
- 7% Submitted Works database

Excluded from Similarity Report

- Bibliographic material
- Quoted material
- Cited material
- Small Matches (Less then 10 words)

11% Overall Similarity

Top sources found in the following databases:

- 5% Internet database
- 6% Publications database
- Crossref database
- Crossref Posted Content database
- 7% Submitted Works database

TOP SOURCES

The sources with the highest number of matches within the submission. Overlapping sources will not be displayed.

1	Saurabh Singh, Rahul Katarya. "Chapter 21 Exploring the Deep Learnin... Crossref	2%
2	louisdl.louislibraries.org Internet	<1%
3	medium.com Internet	<1%
4	Brown University on 2024-04-14 Submitted works	<1%
5	Satish Kumar, Rohit Kumar, Saad. "Real-Time Detection of Road-Base... Crossref	<1%
6	Imperial College of Science, Technology and Medicine on 2017-09-15 Submitted works	<1%
7	link.springer.com Internet	<1%
8	mdpi.com Internet	<1%

9	Jie Ding, Cheng Zhang, Xi Cheng, Yi Yue, Guohua Fan, Yunzhi Wu, Youh... Crossref	<1%
10	Sunway Education Group on 2023-06-20 Submitted works	<1%
11	The University of the West of Scotland on 2024-04-19 Submitted works	<1%
12	Brunel University on 2023-09-13 Submitted works	<1%
13	Liverpool John Moores University on 2024-03-12 Submitted works	<1%
14	University of Florida on 2024-04-24 Submitted works	<1%
15	assets.researchsquare.com Internet	<1%
16	cs.nott.ac.uk Internet	<1%
17	Saeed Iqbal, Adnan N. Qureshi, Jianqiang Li, Imran Arshad Choudhry, T... Crossref	<1%
18	Arab Academy for Science, Technology & Maritime Transport CAIRO o... Submitted works	<1%
19	Sharad Hasan, Sarwar Jahan, Md. Imdadul Islam. "Disease Detection o... Crossref	<1%
20	University of Essex on 2024-01-02 Submitted works	<1%

21	University of Hull on 2024-04-02 Submitted works	<1%
22	University of Surrey on 2024-05-21 Submitted works	<1%
23	mobt3ath.com Internet	<1%
24	webthesis.biblio.polito.it Internet	<1%
25	J. Sequeira. "Semantics Driven Resampling of the OSA-UCS", 14th Inter... Crossref	<1%
26	Swiss School of Business and Management - SSBM on 2024-05-15 Submitted works	<1%
27	Technical University of Košice on 2024-05-28 Submitted works	<1%
28	University of Ulster on 2023-08-31 Submitted works	<1%
29	Van-Thanh Hoang, Kang-Hyun Jo. "PydNet: An Efficient CNN Architect... Crossref	<1%
30	Xiamen University on 2022-12-26 Submitted works	<1%
31	export.arxiv.org Internet	<1%
32	hal.archives-ouvertes.fr Internet	<1%

33	srmist on 2024-01-30 Submitted works	<1%
34	tnsroindia.org.in Internet	<1%
35	Adnane Ait Nasser, Moulay A. Akhloufi. "A Hybrid Deep Learning Archit... Crossref	<1%
36	Asia Pacific University College of Technology and Innovation (UCTI) on... Submitted works	<1%
37	Federation University on 2023-10-06 Submitted works	<1%
38	Hong Kong University of Science and Technology on 2024-04-29 Submitted works	<1%
39	Ila Kaushik, Nupur Prakash, Anurag Jain. "Plant disease detection usin... Crossref	<1%
40	Mepco Schlenk Engineering college on 2024-04-19 Submitted works	<1%
41	Rumi, Roisul Islam. "An End-to-End Hybrid Approach to Automatic and ... Publication	<1%
42	Teena Varma, Prajwal Mate, Noamaan Abdul Azeem, Sanjeev Sharma, ... Crossref	<1%
43	University of Northampton on 2024-05-13 Submitted works	<1%
44	University of Portsmouth on 2024-05-22 Submitted works	<1%

45	University of Sunderland on 2024-05-21 Submitted works	<1%
46	Yeditepe University on 2024-01-08 Submitted works	<1%
47	comsis.org Internet	<1%
48	en.d2l.ai Internet	<1%
49	mdpi-res.com Internet	<1%
50	scpe.org Internet	<1%
51	researchgate.net Internet	<1%

Thesis Chap1-5 Saurabh.pdf

My Files

My Files

Delhi Technological University

Document Details

Submission ID

trn:oid:::27535:60146686

Submission Date

May 28, 2024, 9:52 AM GMT+5:30

Download Date

May 28, 2024, 9:57 AM GMT+5:30

File Name

Thesis Chap1-5 Saurabh.pdf

File Size

822.0 KB

37 Pages

9,346 Words

53,746 Characters

How much of this submission has been generated by AI?

0%

of qualifying text in this submission has been determined to be generated by AI.

Caution: Percentage may not indicate academic misconduct. Review required.

It is essential to understand the limitations of AI detection before making decisions about a student's work. We encourage you to learn more about Turnitin's AI detection capabilities before using the tool.

Frequently Asked Questions

What does the percentage mean?

The percentage shown in the AI writing detection indicator and in the AI writing report is the amount of qualifying text within the submission that Turnitin's AI writing detection model determines was generated by AI.

Our testing has found that there is a higher incidence of false positives when the percentage is less than 20. In order to reduce the likelihood of misinterpretation, the AI indicator will display an asterisk for percentages less than 20 to call attention to the fact that the score is less reliable.

However, the final decision on whether any misconduct has occurred rests with the reviewer/instructor. They should use the percentage as a means to start a formative conversation with their student and/or use it to examine the submitted assignment in greater detail according to their school's policies.

How does Turnitin's indicator address false positives?

Our model only processes qualifying text in the form of long-form writing. Long-form writing means individual sentences contained in paragraphs that make up a longer piece of written work, such as an essay, a dissertation, or an article, etc. Qualifying text that has been determined to be AI-generated will be highlighted blue on the submission text.

Non-qualifying text, such as bullet points, annotated bibliographies, etc., will not be processed and can create disparity between the submission highlights and the percentage shown.

What does 'qualifying text' mean?

Sometimes false positives (incorrectly flagging human-written text as AI-generated), can include lists without a lot of structural variation, text that literally repeats itself, or text that has been paraphrased without developing new ideas. If our indicator shows a higher amount of AI writing in such text, we advise you to take that into consideration when looking at the percentage indicated.

In a longer document with a mix of authentic writing and AI generated text, it can be difficult to exactly determine where the AI writing begins and original writing ends, but our model should give you a reliable guide to start conversations with the submitting student.