A COMPARATIVE ANALYSIS OF DEEP LEARNING MODELS FOR MANGO LEAF DISEASE DETECTION AND CLASSIFICATION

Abstract

Mango (Mangiferaindica) being an economically and nutritionally significant tropical fruit, yet its cultivation is threatened by several foliar diseases such as anthracnose, powdery mildew, bacterial canker and so on. However, this is an automatic identification for mango plant disease and classification has vied an important role within agriculture exploitation digital image process techniques. Basically, traditional detection methods rely on manual inspection, which is labor-intensive, subjective, and often delayed. Advances in deep learning (DL) provide opportunities for automated, accurate, and scalable solutions. This study presents a comparative analysis of deep learning models for mango leaf disease classification using a dataset of 4,000 images across seven classes: healthy, anthracnose, powdery mildew, bacterial canker, gall midge, dieback, cutting weevil, and sooty mold. Four models namely: Custom CNN, LeafNet, AlexNet, and VGG19, were trained and evaluated using accuracy, precision, recall, and F1-score. Results show that Custom CNN and LeafNet achieved the highest performance (99.5% across all metrics), followed by VGG19 (99.0%) and AlexNet (88.0%). The study also introduces a vein-pattern-based segmentation approach that enhances feature localization. The findings highlight the potential of AI-driven frameworks for early mango disease detection, with implications for improving crop management, reducing yield losses, and supporting sustainable agricultural practices.

Keywords: CNN; Multiclass Classification; Neural Networks; Image Pre-processing; Transfer Learning

1. Introduction

Mango is among the most important tropical fruits worldwide, prized for both its nutritional value and its significant economic potential [1]. Cultivation is widespread across tropical and subtropical regions, where mango production supports food security, rural livelihoods, and international trade.

Mango Leaves (MLs) are the potential source of minerals, viz. nitrogen, potassium, phosphorus, iron, sodium, calcium, magnesium, and vitamins, viz. A, B, E, and C. A major bio-acromolecule present in mango leaves is protein. MLs can be utilized as an alternative source of livestock feeding in developing countries for alleviating the food shortage for livestock. Extracts of the MLs have been utilized for traditional medicines to cure diabetes, bronchitis, diarrhea, asthma, kidney, scabies, respiratory problems, syphilis, and urinary disorders. MLs Oil (MLO) contains monoterpenes, sesquiterpenes, minor quantities of other analogues, and trace amounts of non-terpenoid hydrocarbons and oxygenated hydrocarbons. There is scattered compilation of literature on mango seeds, mango leaves, and mango bark, but irrespective of mango involvements it starts from its leaf. Because the health condition of the leaf determines the beneficial economic importance of the mango tree [2]. Nevertheless, it has nutritional composition involving protein and different oil extracts. It can be utilized as an alternative source of livestock feeding in developing countries for alleviating food shortage for livestock.

Consequently, mango crops face serious threats from foliar diseases that collectively account for 30 – 40% yield losses each year. These diseases often go undetected in their early stages because symptoms are difficult to recognize with the unaided eye. The manifestations vary considerably: some produce white or black patches on leaves and young fruits, others cause powdery fungal growth, while certain infections specifically target young shoots and emerging leaves. If not detected early, these conditions spread rapidly and cause severe damage, underscoring the urgent need for timely and accurate diagnosis.

Traditional disease detection techniques mostly depend on farmers or agricultural scientists doing ongoing visual inspections. This method works well in small-scale settings, but it is slow, labor-intensive, and requires specialized knowledge, which makes it unfeasible for commercial orchards or huge farms. Moreover, regular monitoring and expensive resources are frequently needed for correct diagnosis, which can be difficult for smallholder farmers [3]. Spots, blights, anthracnose, scabs, and greasy spots are common diseases of mango leaves. Although the most common diagnostic technique, specialist eye examination, is still time-consuming and resource-intensive, accurate detection of these disorders is essential for efficient management strategies and sustaining production [4].

New methods for detecting plant diseases have been made possible in recent years by developments in digital imaging and artificial intelligence (AI). Deep learning (DL) and computer vision applications have revolutionized agricultural diagnosis. High-accuracy illness categorization is made possible by DL models, especially Convolutional Neural Networks (CNNs), which have shown the capacity to automatically extract intricate information from leaf images, including textures, edges, and vein patterns. Opportunities to scale disease surveillance, lessen need on human expertise, and promote sustainable agricultural practices are presented by these technologies [1].

Mangos have nutritional value in addition to their economic significance; they provide proteins and oil extracts, and in developing nations, they are also used as an additional source of animal feed. This emphasizes even more how crucial it is to shield mango crops from losses brought on by illness. The viability of DL-based models for early detection and classification of mango leaf diseases like powdery mildew, anthracnose, dieback, and bacterial canker has been shown in recent research [5]. However, most approaches rely on generic segmentation methods and often ignore structural cues like leaf vein patterns, which could improve localization of diseased regions.

Building on these insights, this study proposes a deep learning approach for accurate detection and classification of mango leaf diseases. Using a dataset of images spanning seven disease classes, we investigate the performance of four models: a Custom CNN, LeafNet, AlexNet, and VGG19. The study also explores an enhanced CNN training strategy that incorporates an exponential moving average function with temporal constraints and an optimized gradient approach. By systematically comparing model performance, this research aims to identify the most effective architecture for mango leaf disease detection and contribute toward practical, scalable solutions for early crop protection.

2. Review of Related Works

In recent years, the application of computer vision in agriculture has produced notable progress in crop monitoring and plant disease detection. Early studies on mango leaf diseases relied primarily on traditional machine learning approaches. [6] applied a Convolutional Neural Network (CNN), noting that most prior research used conventional algorithms such as Support Vector Machines (SVM) and K-Nearest Neighbors (KNN), with limited recognition of mango-specific diseases. Similarly, [7] employed KNN and Artificial Neural Networks (ANN) on a 4,000-image dataset, highlighting the role of proper care and maintenance in disease prevention but achieving only moderate performance. These early efforts revealed the limitations of handcrafted features and traditional models for complex, multi-class classification problems.

The emergence of deep learning (DL) significantly advanced the field. [5] demonstrated the potential of CNNs by classifying three mango leaf diseases with 90.36% accuracy using the SKUAST-J dataset. [8] extended this work with a larger dataset of 4,000 images across seven disease classes, comparing CNN, VGG16, and InceptionV3. Their results showed VGG16 achieving 96.87% accuracy, outperforming both CNN and InceptionV3. [1] proposed a DL-based automated inspection system that incorporated transfer learning with models such as VGG16, MobileNet, GoogleNet, YOLOv8, and EfficientNet, achieving high accuracy across multiple diseases including anthracnose, bacterial canker, gall midge, powdery mildew, and sooty mold. These studies collectively illustrate the strength of CNN-based architectures and transfer learning in capturing complex visual patterns from mango leaves.

Alongside conventional CNNs, optimized and hybrid deep learning methods have been explored to further improve performance. [9] proposed a CNN architecture optimized with a crossover-based levy flight distribution algorithm, integrating MobileNetV2 for feature extraction and SVM for classification, achieving superior accuracy compared to state-of-the-art methods. [10] also compared hybrid models, combining deep learning with ensemble approaches such as SVGD, reporting 97.7% accuracy. [11] advanced this idea through an ensemble stacked DL framework that aggregated multiple deep neural networks with a machine learning model, achieving 98.57% accuracy. [12] employed a hybrid DL method to classify eight mango leaf diseases, including red rust, on a dataset of

4,873 images, obtaining 93.01% accuracy and demonstrating scalability for real-time applications. These studies highlight how hybrid and ensemble methods can balance accuracy and generalization, although often at the cost of increased computational complexity.

Another research focus has been lightweight and efficient architectures for practical deployment. [13] introducedLeafNet, a compact CNN specifically designed for mango leaf disease detection. LeafNet achieved 98.55% accuracy while using fewer parameters than AlexNet and VGG16, making it more efficient and less prone to overfitting. Similarly, [14] leveraged the Fast.ai framework with ResNet18 for transfer learning, showing how lightweight pretrained models could maintain strong accuracy with reduced training costs. These works are particularly relevant for resource-constrained environments where real-time deployment is needed.

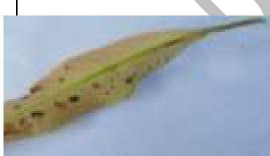
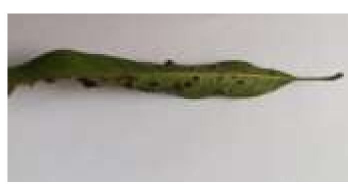
Efforts have also been directed toward segmentation and dataset development, as the foundation of reliable DL performance lies in high-quality image data. [15] employed a fully convolutional network for disease segmentation, while [16] introduced a novel segmentation approach based on vein patterns, validated with SVM, to enhance recognition accuracy. [17] proposed a dataset from Sahelian mango orchards in Senegal, with the goal of deploying CNN-based models such as VGG16, Unet, and MobileNet in mobile applications for field diagnosis. [18] developedMangoLeafBD, the first public dataset of Bangladeshi mango leaves, emphasizing the importance of standardized datasets for reproducibility. [19] performed a systematic analysis of multiple pretrained models, including VGG19, InceptionV3, ResNet152V2, DenseNet121, and Xception, with InceptionV3 achieving the highest accuracy of 99.87%. These studies underscore the necessity of robust datasets and advanced segmentation techniques for achieving generalizable results.

Beyond image-based methods, non-visual approaches have also been explored. [20] proposed an ultrasonic sensor-based technique for detecting bacterial canker and phoma blight, achieving 90% accuracy. While innovative, such methods remain less scalable compared to image-based DL approaches.

Taken together, the reviewed literature demonstrates significant progress in mango leaf disease detection, with CNNs and transfer learning establishing themselves as dominant techniques. Hybrid models and lightweight networks further extend the applicability of DL to real-time agricultural settings, while dataset development and segmentation innovations provide critical support for model generalization. However, important research gaps remain. Many studies focus on a limited number of disease classes, often three to four, restricting their practical relevance. Segmentation approaches, though improving, have not been consistently integrated into classification pipelines, particularly those leveraging vein pattern structures. Furthermore, there is a trade-off between accuracy and efficiency: while some models achieve very high accuracy, they are computationally heavy, whereas lightweight models sacrifice performance.

This study addresses these gaps by conducting a comparative analysis of four models—Custom CNN, LeafNet, AlexNet, and VGG19—on a balanced dataset of 4,000 images spanning seven disease classes. In addition, it introduces a segmentation approach based on leaf vein patterns to enhance disease localization. By combining comparative benchmarking with domainspecific innovations, this work contributes toward the development of scalable, accurate, and efficient frameworks for early mango disease detection in precision agriculture.

2.1 Mango Leaf Classes (Healthy and Unhealthy Leaf)

0			**Healthy Mango Leaf**
1			**Anthracnose Leaf**
2			**Gall Midge Leaves**

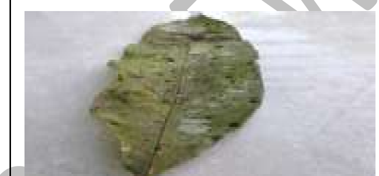
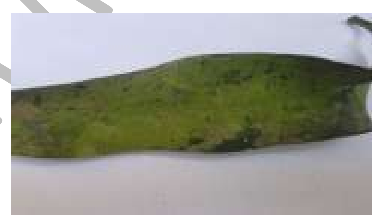
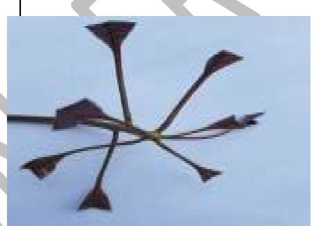
3			**Die Back Leaves**
4			**Bacterial Canker Leaves**
5			**Sooty Mold Leaves**
6			**Powdery Mildew Leaves**
7			**Cutting Weavil leaves**

Figure 1

System Workflow

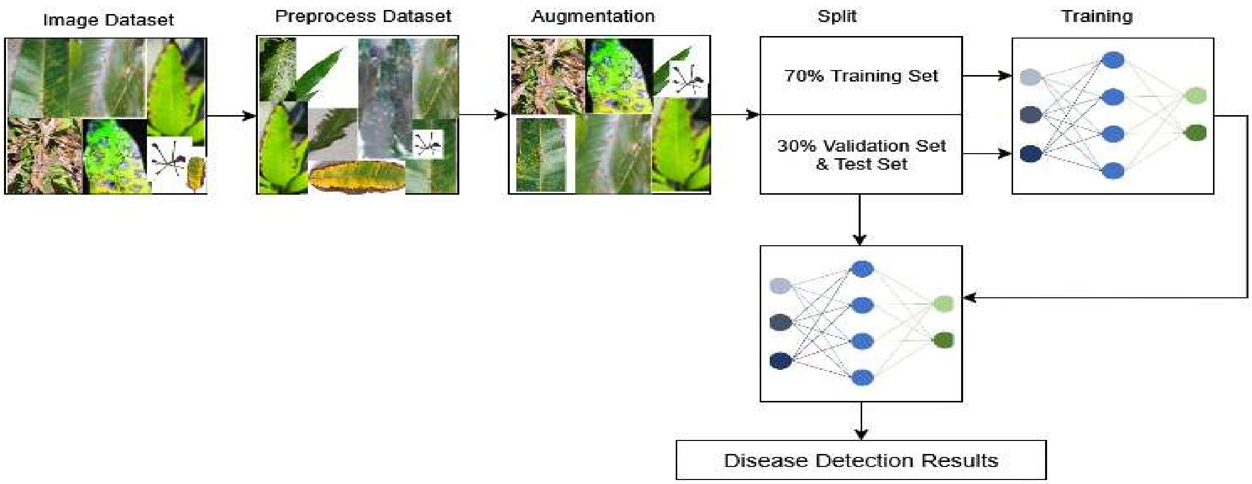


Figure 2

3.0 Methodology

3.1 Dataset Description

This study utilized a publicly available dataset of mango leaves sourced from Kaggle (https://www.kaggle.com/datasets/aryashah2k/mango-leaf-disease-dataset). The dataset contained 4,000 images, equally distributed across seven classes from zero count: healthy, anthracnose, powdery mildew, bacterial canker, gall midge, dieback, cutting weevil, and sooty mold, with approximately 500 images per class. The dataset was selected for its balance across categories, which supports robust model training and reduces bias during classification.

Methodology Process

The overall methodology is summarized in Figure 3, which outlines the sequence of tasks:

i. Image collection from the Kaggle dataset.
ii. Data preprocessing and augmentation to enhance dataset consistency and diversity.
iii. Dataset splitting into training and testing subsets.
iv. Model training using Custom CNN, VGG19, AlexNet, and LeafNet.
v. Performance evaluation using classification metrics and confusion matrices.
vi. Prediction output, representing the identified disease class for each test image

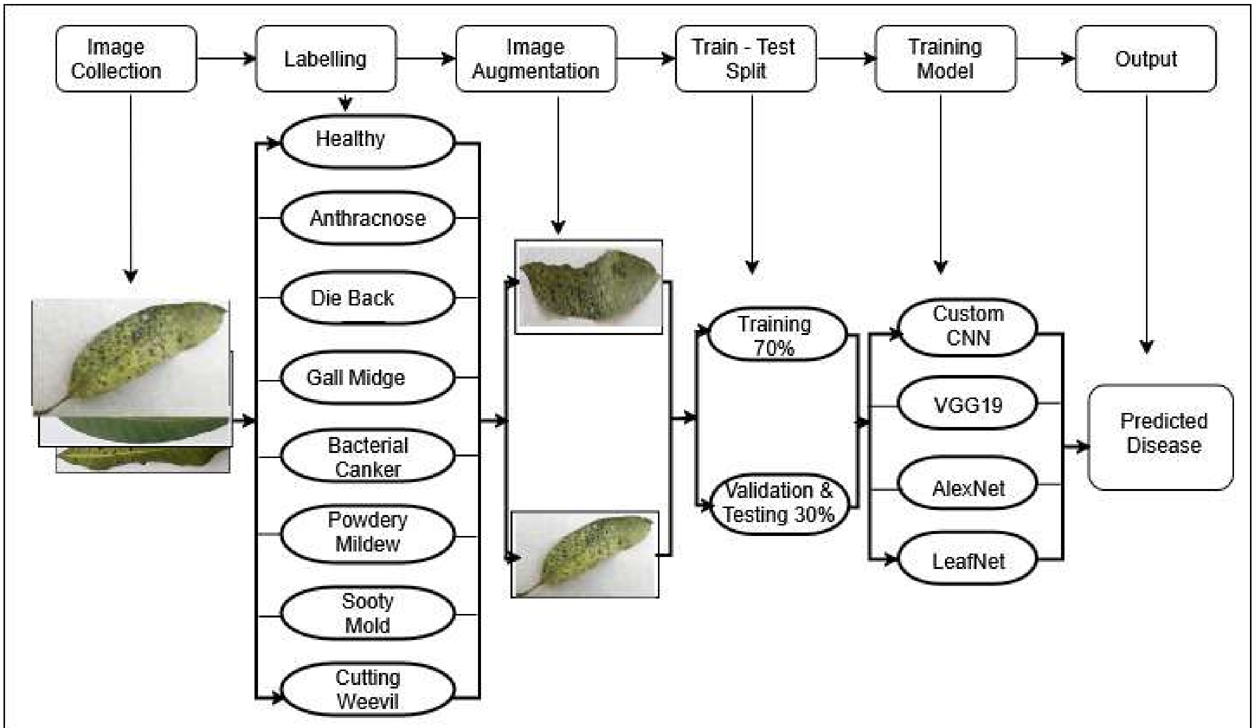


Figure 3.

The State-Of-The-Art Architecture

This is three State-of-the-Art Architecture (algorithms) AlexNet, VGGNet19, LeafNet and the Custom CNN based.

A Custom Convolutional Neural Network (CNN) is a deep learning model specifically designed for a particular task (e.g., image classification, object detection) by manually configuring its architecture, layers, and hyperparameters. Unlike pre-trained models (e.g., VGG, AlexNET, LeafNET), a custom CNN is built from scratch or modified to suit unique dataset requirements.

AlexNet Architecture

The architecture of AlexNet is presented to properly understand the layers, feature maps, activation functions, and parameters. At first, the architecture expands the number of channels, then it gradually shrinks the number of channels or filters. There are mainly five convolutional blocks and two fully connected dense layers.

VGGNet Architecture (VGG19)

The architecture of VGG19 is described to understand its parameters and flow of information in. VGG19 belongs to the category of generic VGG architectures and is known for its depth and complexity in terms of layers and parameters. Here, instead of a single convolution, multiple convolution layers are used one after another, and then the resultant feature map is passed through a max pooling layer (Max Pool) before sending to the following set of convolutional layers (CONV).

LeafNet Architecture

LeafNet is a specialized Convolutional Neural Network (CNN) designed for plant leaf disease detection, including mango leaf diseases. It is optimized to extract discriminative features from leaf images while maintaining computational efficiency.

4. Results and Discussion

Theseven classes are represented in the four models. Figures 4 to 15 comprising the models showcasing its result as confusion

Matrix then Validation and testing graph. Prediction and training time are in histogram format.

Confusion matrix of Custom CNN Model

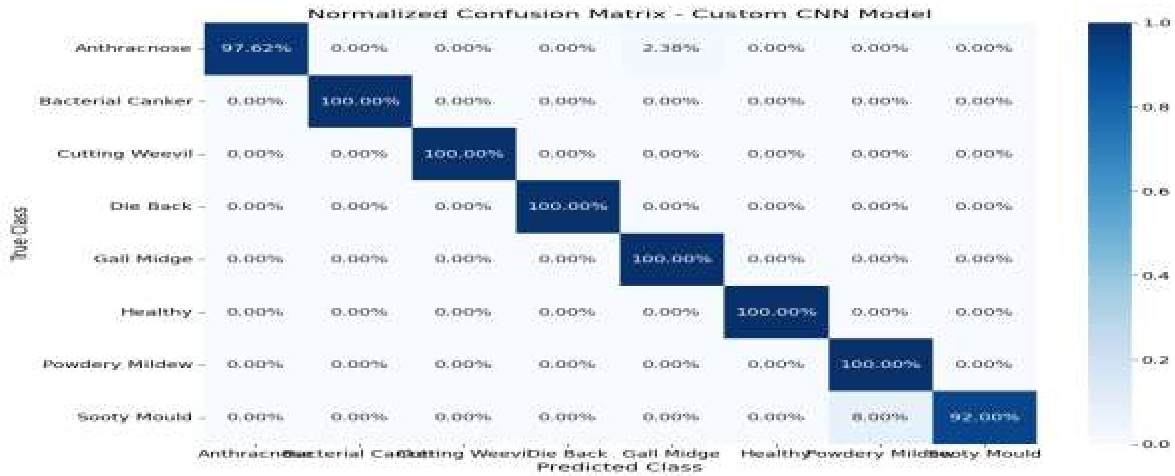


Figure 4.

Training and Validation graph of Custom CNN Model

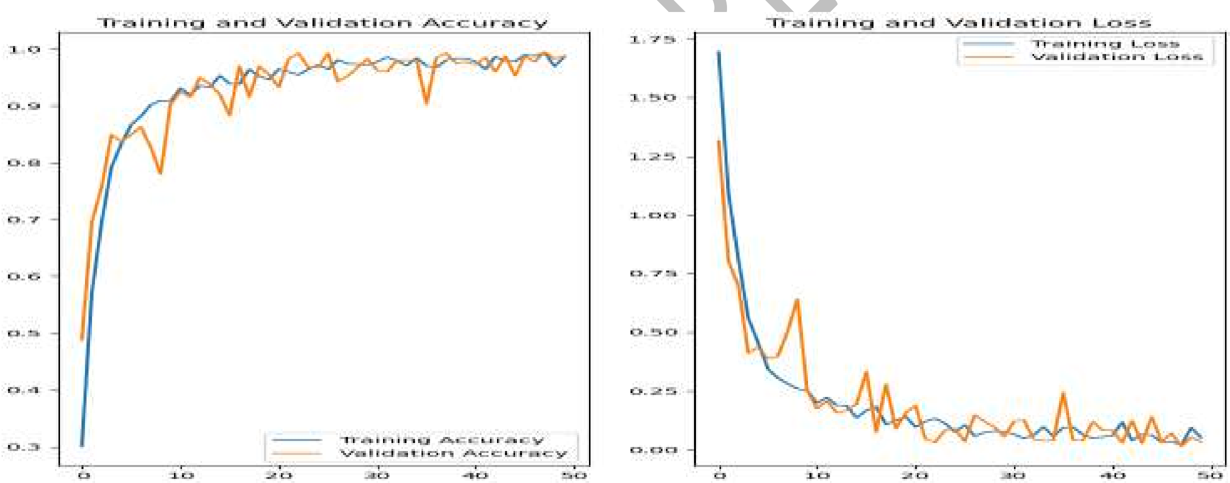


Figure 5.

Confusion matrix of AlexNet Model

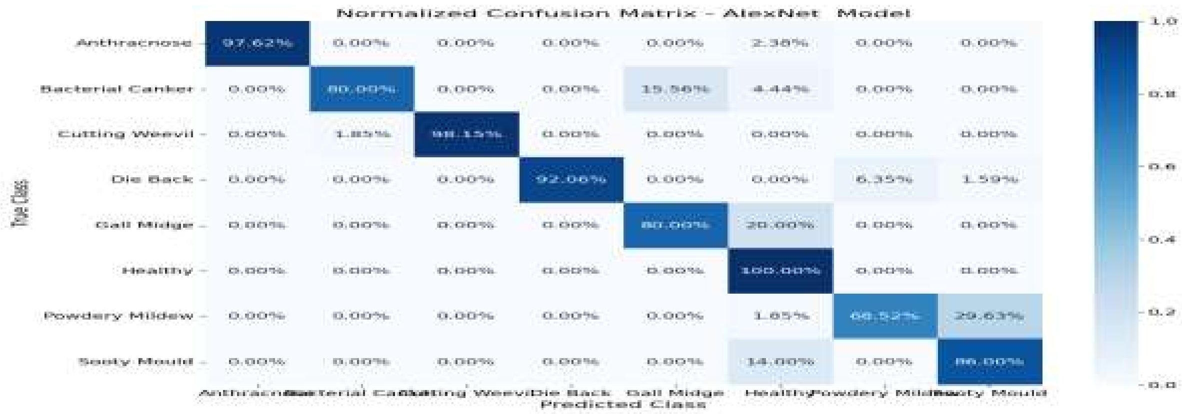


Figure 6.

Training and Validation graph of Alex Net Model

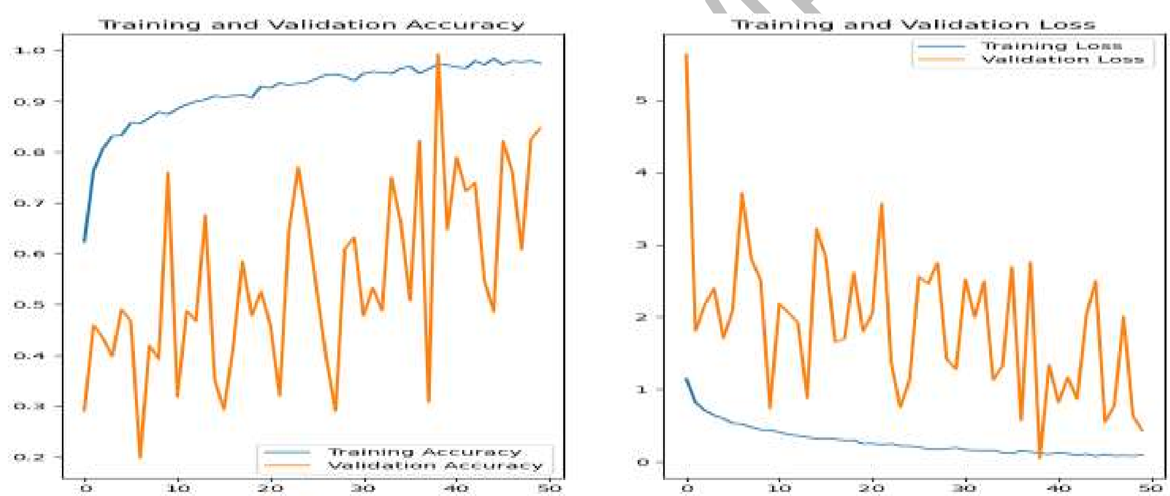
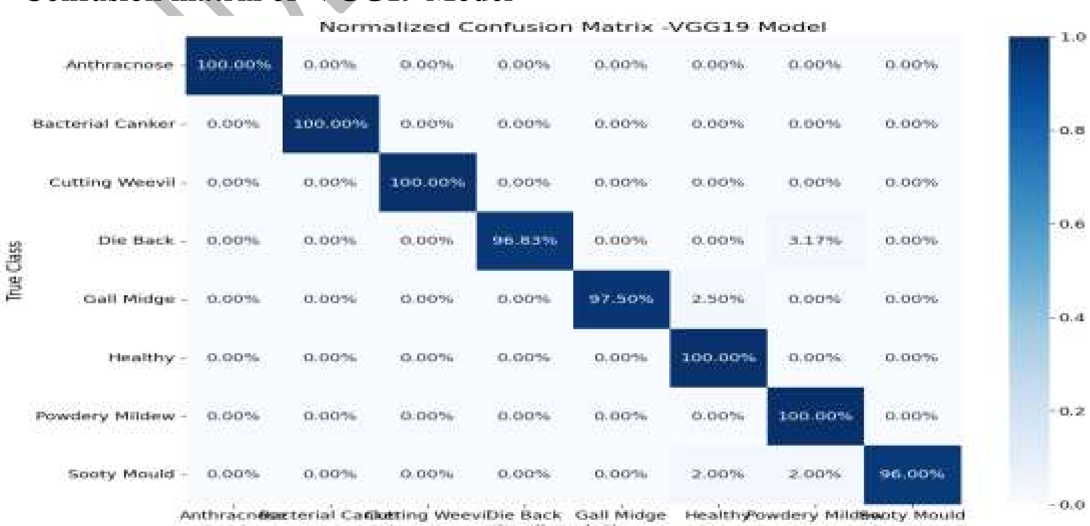


Figure 7.

Confusion matrix of VGG19 Model



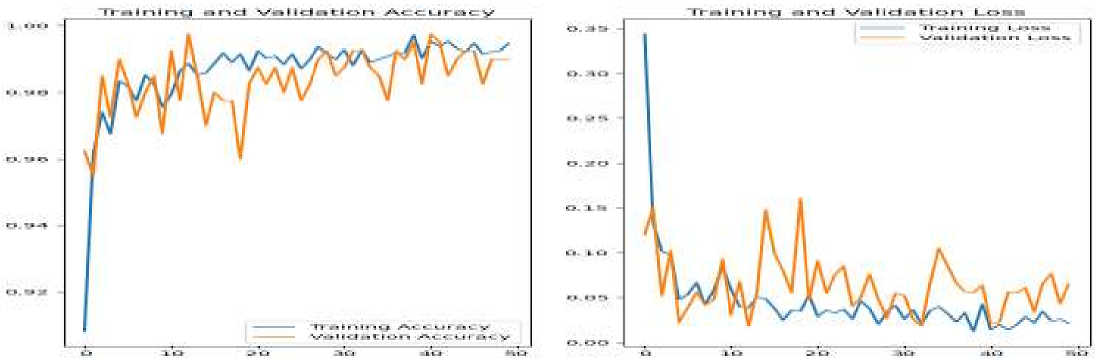


Figure 8

Training and Validation graph of Custom VGG19 Model

Figure 9

Confusion matrix of LeafNet Model

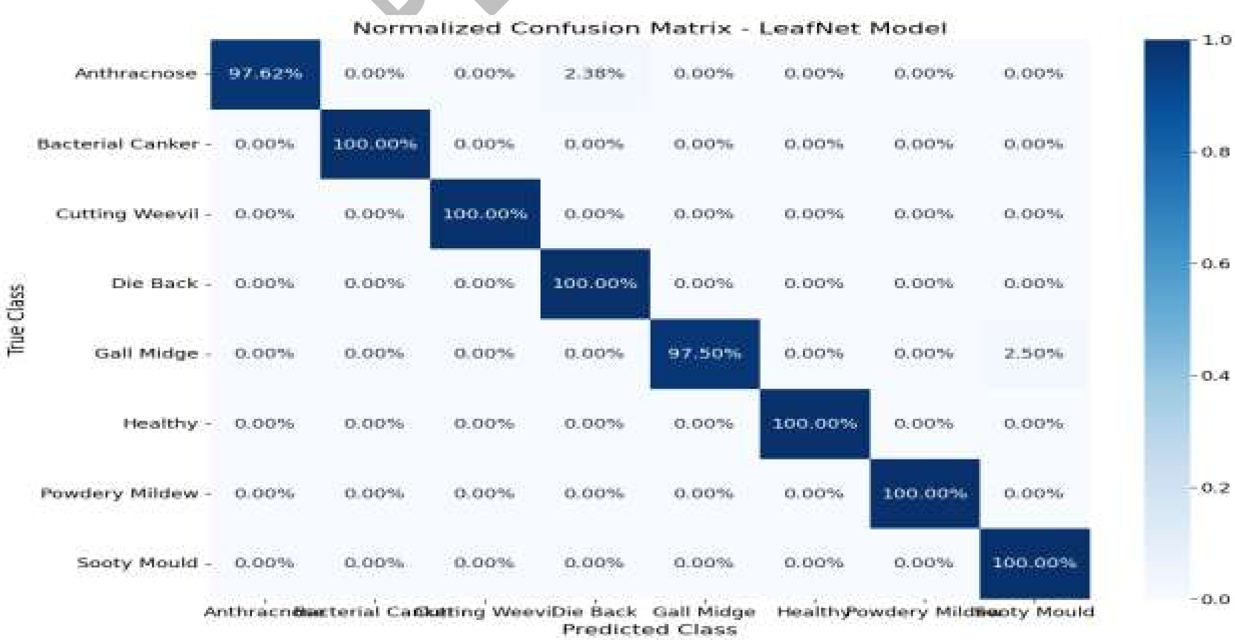


Figure 10.

Training and Validation graph of Custom LeafNet Model

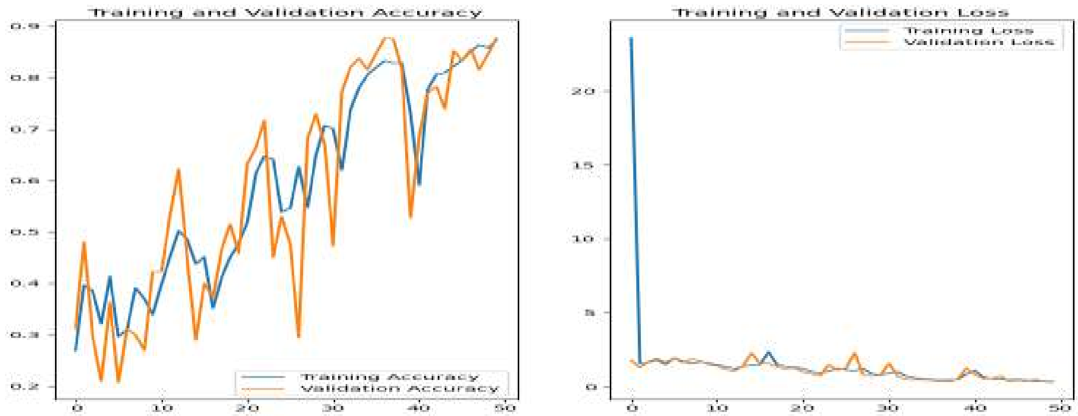
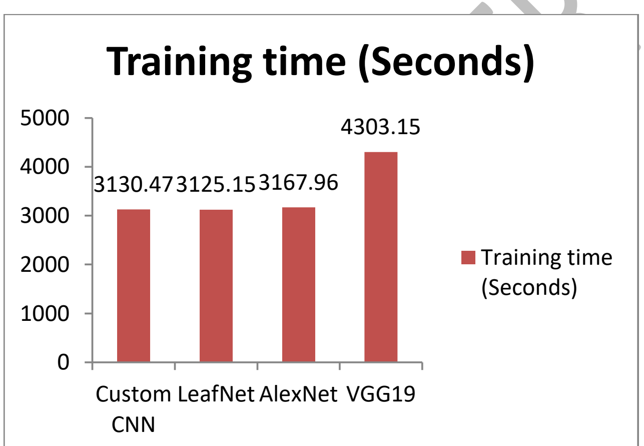


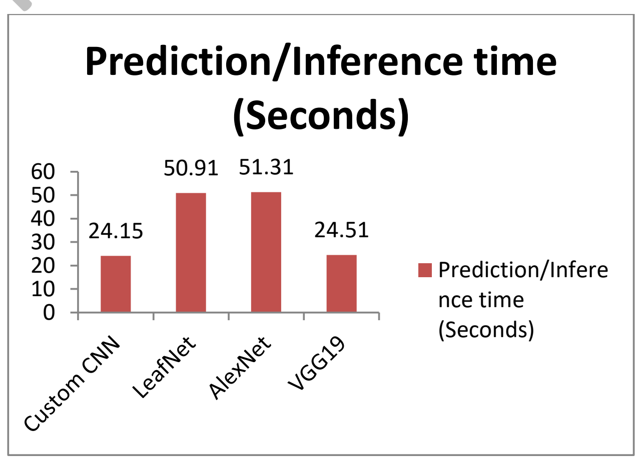
Figure 11.

Comparative Training and Prediction Time of the used Models Represented on Bar Chart

Table 1: Model's Training and prediction time

S/No	Model	Training time (Seconds)	Prediction/Inference time (Seconds)
1	Custom CNN	3130.47	24.15
2	LeafNet	3125.15	50.91
3	AlexNet	3167.96	51.31
4	VGG19	4303.15	24.51





Comparative Time as represented of the used Models Represented in Color Bar Chart

Figure 12.

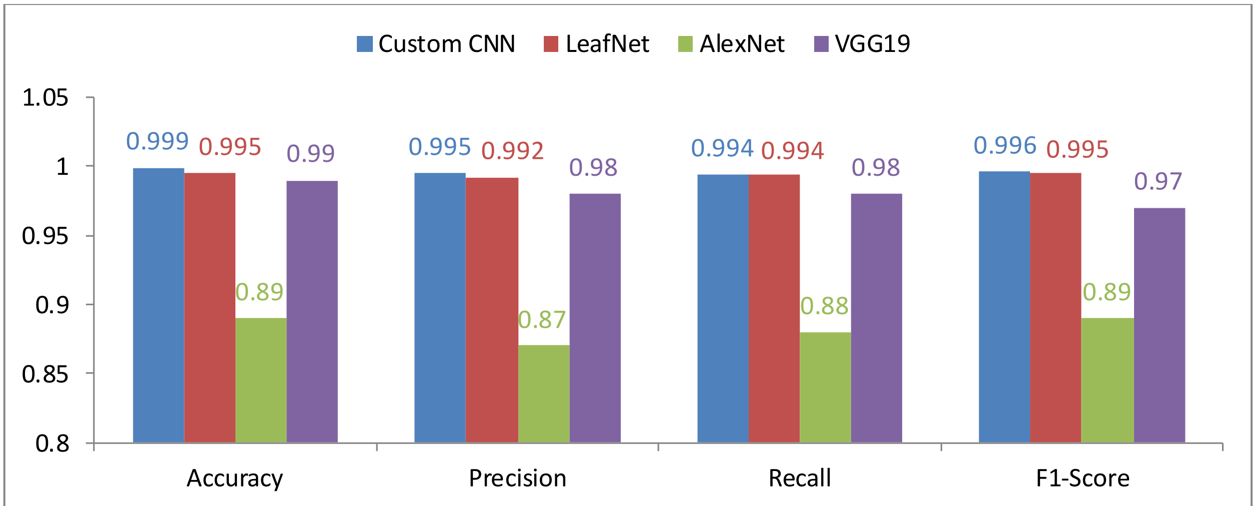


Figure 13.

Comparative Prediction Time of the used Models Represented on Bar Chart

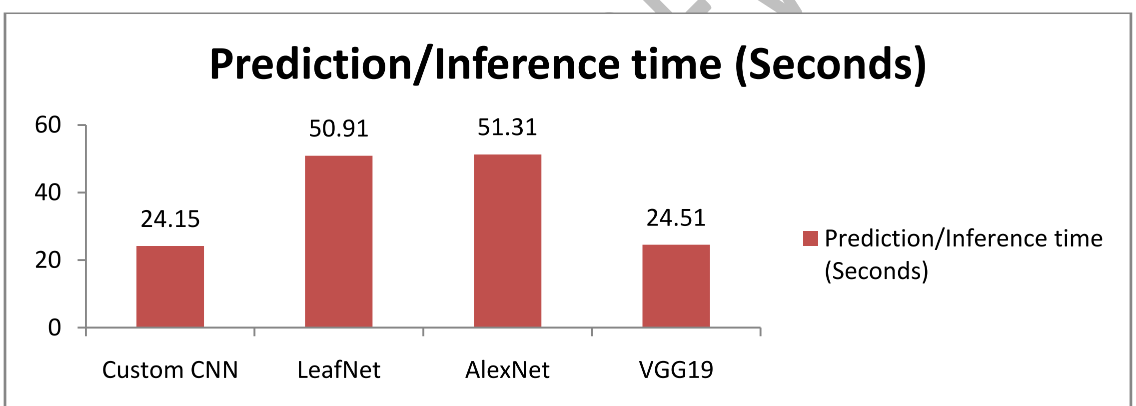


Figure 14

Comparative training Time of the used Models Represented on Bar Chart

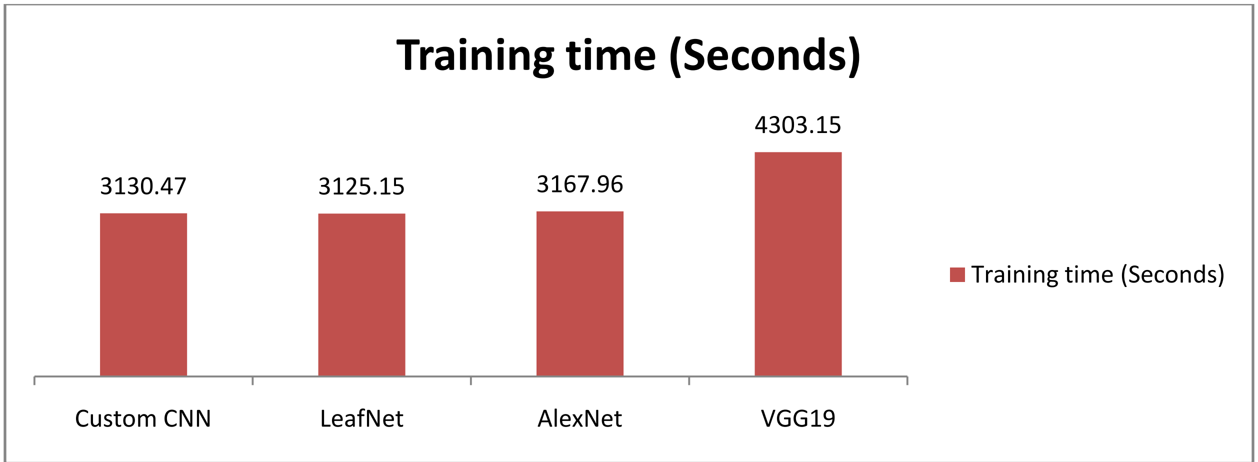


Figure 15.

4.5 Comparison with State-of-the-Art Models

Table 2 Compares the performance of the proposed models with selected state-of-the-art approaches reported by [13]. The proposed Custom CNN outperformed all models, achieving 99.9% test accuracy. LeafNet and VGG19 also delivered strong results, whereas AlexNet remained the weakest.

Table 2: Models General Comparison

Metric	LeafNet [13]	**AlexNet** [13]	VGG16 [13]	PROPOSED Custom CNN	PROPOSED LeafNet	PROPOSED AlexNet	PROPOSED VGG19
Test Accuracy	0.9955	0.9925	0.784	0.999	0.995	0.89	0.99
Macro Avg Precision	0.9950	0.9925	0.8084	0.995	0.992	0.87	0.98
Macro Avg Recall	0.9945	0.9908	0.8068	0.994	0.994	0.88	0.98
Macro Avg F1-	0.9947	0.9905	0.8046	0.996	0.995	0.89	0.97

Score							

5Discussion

The outcomes of the experiment validate deep learning's efficacy in detecting mango leaf disease. LeafNet and the suggested Custom CNN both performed better (0.995–0.999), matching or exceeding cutting-edge benchmarks like VGG16, AlexNet, and LeafNet [13]. These results demonstrate CNN architectures' ability to capture intricate spatial characteristics in images of mango leaves.

Custom CNN's improved performance shows that a task-specific architecture can match or surpass pretrained models while retaining computational efficiency if it is designed with the right depth and feature extraction capabilities. Despite being lightweight, LeafNet had higher prediction times, indicating a trade-off between deployment viability and efficiency. Despite its excellent accuracy, VGG19 had the longest training period, which made it impractical for real-time or large-scale applications. The limits of previous designs for fine-grained classification tasks are highlighted by AlexNet's noticeably poor.

Time complexity analysis further emphasizes the importance of balancing accuracy with efficiency in agricultural applications. Custom CNN offered the most favorable balance, achieving high accuracy with reduced inference time, making it a strong candidate for real-time field deployment.

Overall, the results validate deep learning as a reliable approach to mango disease detection. By combining accuracy, generalization, and efficiency, the Custom CNN developed in this study addresses gaps identified in the literature: limited disease coverage, lack of vein-pattern-based segmentation, and poor generalizability of earlier models. These contributions reinforce the role of deep learning in advancing precision agriculture and provide a foundation for future work on real-time mobile and IoT-based disease detection systems.

6.0 Conclusions

This study set out to develop and evaluate deep learning models for the detection and classification of mango leaf diseases, addressing the limitations of existing approaches that often focused on a narrow set of diseases or computationally heavy architectures. A balanced dataset of 4,000 images spanning eight classes, including healthy and diseased leaves, was preprocessed and used to train and evaluate four models: Custom CNN, LeafNet, VGG19, and AlexNet.

The results demonstrated that both Custom CNN and LeafNet achieved outstanding performance, with overall accuracy, precision, recall, and F1-scores of 99.5%–99.9%. VGG19 also performed strongly, though at the cost of higher training time, while AlexNet lagged significantly behind with 88% accuracy. Importantly, the Custom CNN provided the best trade-off between accuracy and inference speed, making it suitable for real-time deployment in agricultural contexts.

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