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LeafNet: Enhanced Deep Learning and Ensemble Models for High-Accuracy Classification of Mango Leaf Diseases

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Abstract: Plantation disease surveillance is still a major problem for the agriculture industry, especially for expensive products like mangos. Crop yield, quality, and farmer profitability can all be significantly increased by early and precise detection of mango leaf diseases. However, due to high expert expenses, a shortage of specialists, and inconsistent visual symptoms, manual diagnosis is frequently incorrect. This study presents an improved deep learning-based framework for automated categorisation of mango leaf diseases to overcome these drawbacks. Several cutting-edge deep learning architectures, such as VGG16, DenseNet201, MobileNet, MobileNetV2, and two recently released ensemble models, LeafNet1 (MobileNetV2 + DenseNet201) and LeafNet2 (VGG16 + DenseNet201), are used in this study. These models were chosen for their exceptional feature extraction and their ability to handle intricate spatial patterns in photos of damaged leaves. The models that performed well were VGG16 (98%), DenseNet201 (89%), MobileNet (98%), MobileNetV2 (88%), LeafNet1 (95%), LeafNet2 (99%), and VGG22 (79%). Notably, LeafNet2 outperformed all individual architectures, achieving a maximum accuracy of 99%, highlighting the value of ensemble approaches in enhancing classification resilience. For the early diagnosis of mango leaf disease, the suggested approach provides a quick, precise, and scalable solution. Our solution outperforms current deep learning-based detection techniques and greatly decreases reliance on human expertise by automating disease diagnosis. This approach enhances farmers' and stakeholders' decision-making capacity and provides a reliable tool for managing contemporary agricultural diseases.

Keywords: Mango Fruit; Deep Learning; Leaf Disease and Plantation Disease; Agriculture Industry; Deep Learning Architectures; Visual Symptoms; Ensemble Approaches; Detection Techniques; Disease Diagnosis.

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1. Introduction

The mango (Mangifera indica L.), a fruit of significant global economic and nutritional value, is persistently threatened by phytopathogenic diseases such as anthracnose, powdery mildew, and bacterial canker, which manifest as visible leaf lesions

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[1]. Mango trees are vulnerable to a variety of insect pests and pathogenic viruses, which can result in large crop losses and lower farmer profits [3]. Mango leaf diseases pose a significant risk to global agriculture, requiring swift and precise identification to prevent devastating consequences [4]. Leaf diseases significantly reduce mango productivity, thereby affecting food security and the economy [5]. Mango leaf diseases hurt mango quality and yield [6]. It can be challenging to make a precise diagnosis of mango leaf disease solely by visual inspection [7]. Mango is among the most widely cultivated tropical fruits worldwide [8]. Mangoes are an important tropical fruit that supports the livelihoods of over 20 million farmers worldwide and generates over USD 30 billion annually [9].

The mango fruit comprises both macronutrients and micronutrients [11]. Mango, known for its wonderful flavour, is experiencing unprecedented popularity worldwide, and Bangladesh is no exception [12]. Remarkably, Bangladesh has become the world's seventh-largest mango producer [13]. Research by the Food and Agriculture Organisation (FAO) indicates that a substantial number of mangoes are shipped to the global market each year. In 2021, the regional distribution of mango exports was as follows: South America — 620,745 tonnes; Central America and the Caribbean — 545,428 tonnes; Africa — 202,010 tonnes; Asia — 912,510 tonnes; Oceania — 4,254 tonnes [2]. The traditional diagnostic method, relying on manual inspection by human experts, is fundamentally limited by its subjectivity, high labour costs, and inability to scale, frequently leading to delayed or inaccurate interventions that compromise crop yield [6]. To surmount these challenges, the field has turned to computer vision, where Deep Learning (DL)—and specifically Convolutional Neural Networks (CNNs)—has provided a powerful new paradigm for automated, accurate disease detection by autonomously extracting complex hierarchical features from imagery [14]. Within this domain, two advanced architectural philosophies are being explored to achieve even greater robustness and precision. The first is ensemble deep learning, a methodology that aggregates predictions from multiple diverse models [10].

By leveraging the "wisdom of the crowd," this approach mitigates the errors of individual models and enhances overall generalisation. The second philosophy favours a singular, exceptionally deep network, such as a VGG22, which is theoretically designed to learn a highly intricate feature space capable of capturing the granular and abstract features necessary to distinguish between subtle, visually similar disease symptoms. Despite the promise of each strategy, a critical research gap exists in the direct, empirical comparison between them for this specific application [25]. This study addresses that gap by presenting a rigorous comparative analysis of custom-designed ensemble architectures against a VGG22 model, using a curated dataset of mango leaf images and evaluating performance through key metrics like accuracy, precision, recall, and F1-score to provide definitive insights into the architectural trade-offs and guide the development of next-generation diagnostic tools for plant pathology. To address this gap, this paper presents a rigorous comparative analysis of custom-designed ensemble deep learning architectures against a VGG22 model for robust mango leaf disease classification [1]. Researchers make the following contributions:

- Researchers design and implement several ensemble deep learning models that combine diverse CNN architectures to maximise predictive synergy.
- Researchers construct and train a VGG22 model, serving as a benchmark for single-model deep architectures.
- Researchers conduct a comprehensive performance evaluation of a curated dataset of mango leaf images, using key metrics such as accuracy, precision, recall, and F1-score to assess the robustness and efficacy of each approach quantitatively.

The results of this study aim to provide definitive insights into the architectural trade-offs between ensemble methods and single deep networks, guiding the development of next-generation, high-fidelity diagnostic tools for plant pathology.

2. Literature Review

Recent years have witnessed substantial progress in the classification of plant diseases via the utilisation of deep learning (DL) techniques. Convolutional Neural Networks (CNNs) have demonstrated exceptional efficacy, as multiple studies have confirmed their precision in diagnosing plant diseases from leaf imagery. Machine learning has been used throughout the literature to address real-world problems across a range of agricultural domains. Various studies have been conducted to identify and overcome methodological barriers. Ligi and Arivazhagan [15] employed a Convolutional Neural Network (CNN) to detect five distinct leaf diseases. Convolutional Neural Networks (CNNs) are specifically engineered to process pixel-based data and are widely utilised in image recognition applications. These networks comprise numerous interconnected layers, with each subsequent layer extracting and enhancing the properties acquired by its predecessors.

The proposed CNN model achieved 96.67% accuracy, demonstrating significant potential for real-time disease detection applications. Prabu et al. [20] employed the MobileNetV2 pre-trained model in conjunction with a crossover-based Lévy flight algorithm for efficient feature selection. MobileNetV2 is designed for efficiency on mobile platforms, enabling lightweight, rapid deployment. Using this methodology, the model achieved 94.5% accuracy in identifying three specific forms of mango leaf illness. Matrouk et al. [16] introduced a MapReduce-based system that combines sequential association rule mining with deep learning methodologies for user classification in retail contexts. The method achieved a precision of 0.88, accompanied by significant performance improvements. This study emphasises MapReduce's efficacy in managing and processing large-scale data, indicating its potential application in agriculture, specifically in managing massive plant disease datasets to enhance classification accuracy and disease detection performance.

Mohanty et al. [17] illustrated the capacity of deep learning (DL) to enhance agricultural research. Their research employed sophisticated deep neural networks (DNNs) to surpass conventional machine learning (ML) methods in diagnosing plant diseases. The proposed deep learning models achieved greater diagnostic accuracy and robustness by extracting intricate and distinguishing disease characteristics from large leaf image datasets, surpassing traditional methods. Pre-trained deep learning models are indispensable for plant disease classification, providing exceptional accuracy and reliability. Architectures such as VGGNet, ResNet, AlexNet, and InceptionV3 have repeatedly demonstrated exceptional performance on image-related tasks, particularly in plant pathology. In a thorough study, Ferentinos [18] assessed the efficacy of deep learning models across diverse crops, revealing that models such as VGGNet and ResNet can precisely identify plant illnesses. The research emphasised the versatility of these models, demonstrating their potential to generalise across various plant diseases and agricultural contexts. Rao et al. [19] introduced an automated approach for classifying mango leaf diseases using deep learning (DL) and transfer learning. Their method achieved 89% accuracy in diagnosing illnesses on mango leaves using the pre-trained AlexNet model (Table 1).

Table 1: Comparison

Reference	Model	Dataset	Contribution	Challenges
Prabhu and Chelliah [6]	TWDO-SAM + DCNN	Frequent Itemset Mining Dataset	A MapReduce framework was established to combine sequential association rule mining with deep learning for user classification.	Effectively processing large datasets while preserving model accuracy in real-time applications remains a significant challenge.
Mia et al. [7]	AlexNet, GoogLeNet (Transfer Learning)	PlantVillage dataset	Utilised deep learning for precise identification of plant diseases from leaf photos, facilitating smartphone-based diagnostics.	The reliance on observable symptoms, the lack of real-time diagnostic tools, and the vulnerability to overfitting due to constrained sample sizes continue to pose significant hurdles. Furthermore, the integration of multimodal data remains a significant research gap.
Faye et al. [8]	VGG (highest accuracy), AlexNet(OWTBn)	Open database of 87,848 images.	Engineered convolutional neural network-based deep learning models for the classification of plant diseases.	Performance declines with the introduction of new data sources, compounded by restricted testing in actual settings.
Tengsetasak et al. [9]	Transfer Learning (VGG16, ResNet50)	Custom grape and mango datasets	This study aims to identify diseases in mango and grape leaves using transfer learning within deep learning frameworks, thereby enhancing precision farming methodologies.	The model's efficacy diminishes in photos with inadequate illumination or when foliage overlaps significantly.
Chen et al. [21]	ResNet50, DenseNet121, InceptionV3, EfficientNet-B0, VGG19, ViT-B-16, ConvNeXt, DeiT	To enable accurate model evaluation, a dataset of photos of mango leaves (Mangifera indica) was used, split into training, validation, and test sets,	To improve transparency and confidence in model predictions, the study integrates Explainable AI approaches, such as Grad-CAM and LIME, into an AI-driven, scalable framework for automated	The study addresses the need for precise, comprehensible, and early-stage disease detection in sustainable mango farming while simultaneously addressing the drawbacks of traditional manual disease diagnosis,

		and classified into several disease classes.	mango leaf disease diagnosis. It also demonstrates higher classification performance.	such as time-consuming procedures, reliance on expert knowledge, and human error.
Attri et al. [22]	Multi-scale and multi-pooling convolutional neural network (MSMP-CNN)	Real-world mango leaf photos collected in field settings are used to train and assess the model, which is intended to represent real-world scenarios influenced by environmental factors.	To greatly improve the accuracy of mango leaf disease classification, the study presents a robust deep learning framework that integrates multi-scale feature extraction, transfer learning, and fine-tuning. Visualisation techniques including t-SNE and CAM heatmaps bolster this framework.	To ensure accurate and reliable disease identification in real-world settings, the study addresses key challenges, including environmental interference in field photos and the difficulty of collecting high-quality mango leaf data.
Ahammad [23]	ResNet-50, VGGNet-16, and AlexNet.	To facilitate real-time classification in real-world agricultural settings, the model is trained and evaluated on image datasets of apple and mango leaves, including both healthy and diseased samples.	To promote sustainable crop management, this research presents a lightweight, effective AI solution for real-time plant disease diagnosis, achieving 93.1% accuracy and deployable in remote, resource-constrained environments.	While preserving dependable classification performance for agricultural applications, the work addresses challenges of real-time disease detection, constrained processing resources, and energy limitations in edge sensors.
The Proposed Study	DenseNet201, VGG22, VGG16, MobileNet, MobileNetV2	Kaggle + Own Dataset	LeafNet2 achieved the highest accuracy of 99%, while other algorithms performed less effectively. By comparing the performance of these deep learning models with results from related studies, the research provides a comprehensive perspective and contextual understanding of the model's effectiveness. Future improvements could involve using alternative datasets, augmenting data, and exploring additional algorithms to further enhance performance.	A significant challenge is effectively processing large-scale datasets while maintaining high model accuracy in real-time applications.

The research emphasised the feasibility of implementing an economical, smartphone-based disease-detection system that could mitigate financial losses for farmers. Nonetheless, the research identified several limitations, including dataset diversity, difficulty in early-stage detection, and the influence of real-time environmental conditions, underscoring the need for future exploration and advancement in this domain.

3. Proposed Methodology

The goal of this study was to assess various transfer learning architectures for leaf detection using the mango leaf disease dataset. Here are the specifics of the several experiments carried out, including CNN model construction, training, augmentation, data preparation, and dataset description. VGG16, DenseNet201, MobileNet, MobileNetV2, LeafNet1 (Ensemble of MobileNetV2 and DenseNet201), LeafNet2(Ensemble of VGG16 and DenseNet201), were among the models researchers used. A new architecture, VGG22, designed by researchers, was also used. The practice of adding fresh and enhanced photos to an existing dataset is known as image data augmentation. For computers, images are just collections of two-dimensional data. These numbers represent pixel values, which can be adjusted in various ways to produce new and better visuals. Augmented data may be produced by cropping, flipping, and scaling data. Next is the training data. The training data was then used to train each model, and the testing data was used to assess each model. The characteristics of the deep learning models and their layers are shown in Table 2.

Performance metrics were used to evaluate the models, and LeafNet2 performed the best. Here is a theoretical explanation of why LeafNet2 (VGG16 + DenseNet201 ensemble) performs better, emphasising learning behaviour and processes rather than merely empirical performance. VGG16 and DenseNet201, which learn essentially distinct but complementary representations of leaf pictures, are integrated into LeafNet2. VGG16 employs deep, sequential convolutional layers with uniform 3x3 kernels. It acquires robust local edge patterns and texture. It is also extremely good at catching the spots, lesions, edges, and colour changes typical of leaf diseases. With dense connections, every layer in DenseNet201 gets inputs from every layer before it. It learns sophisticated, high-level semantic characteristics. It also maintains venation distortions, subtle indicators of illness, and spatial connections.

Table 2: Model with layer number and details

Model name	Number of Layers	Layer description
DenseNet201	204	Input Layer Base Model layer Pooling layer Dense Layer Dropout layer Output Layer
VGG22	31	Input layer Flatten Layer Dense Layer Dropout Layer Output Layer
VGG16	22	Input layer Flatten Layer Dense Layer Dropout Layer Output Layer
MobileNet	32	Input Layer Base Model layer Dense Layer Output Layer
MobileNetV2	33	Input Layer Base Model layer Pooling layer Dense Layer Dropout layer Output Layer

VGG-16 is a 16-layer deep convolutional neural network. A pretrained network trained on over a million images can be loaded from the ImageNet database. The pretrained network can classify images into 1000 categories, including many animals, keyboards, mice, and pencils. 201 layers make up the deep convolutional neural network known as DenseNet-201, or Densely Connected Convolutional Network. DenseNet201 adds dense connections, in which every layer in a block gets inputs from every layer before it and sends its output to every layer after it. This promotes feature reuse, lessens redundancy, and enhances network information flow. MobileNetV2 is a quick and effective deep learning model designed for devices with limited power or memory. It is perfect for real-time applications because it strikes a good mix between speed, size, and precision. Figure 1 shows the full procedure. To achieve a more reliable, accurate result, an ensemble integrates predictions from several models. Table 4 compares five deep learning models in terms of the number of layers and the layer arrangement. DenseNet201 is a deep network with the maximum number of layers (204), including an input, base model, pooling, dense, dropout and output layers. VGG22 and VGG16 have 31 and 22 layers, respectively, with comparable flatten, dense, dropout and output layer architectures. MobileNet has 32 layers, while MobileNetV2 has 33 levels plus a pooling layer on top of the base, dense, and dropout layers. Table 2 generally shows structural differences of the analysed models.

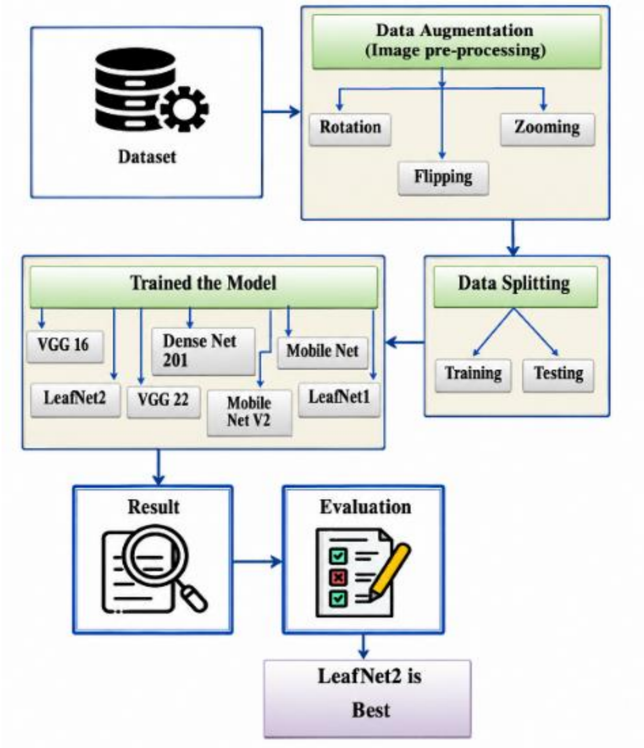

Figure 1: Proposed approach

The ensemble combines the "opinions" of each model to arrive at a more intelligent conclusion. LeafNet1 is an ensemble deep learning model that combines the strengths of two powerful CNN architectures.

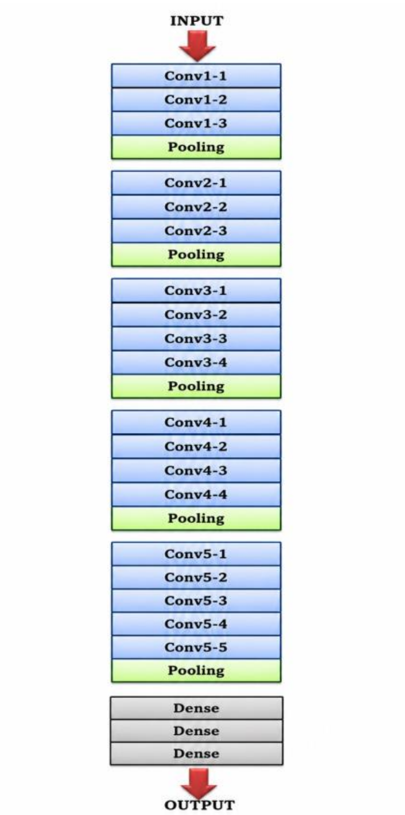

Figure 2: VGG22 architecture

A key strength of MobileNetV2 is that it is lightweight, fast and well-suited for real-time or mobile deployment. DenseNet201 is deep and accurate, excelling at feature reuse and complex pattern recognition. So, the ensemble can perform better than either model alone. LeafNet2 is an ensemble deep learning model combining VGG16 and DenseNet201 for accurate and explainable leaf disease detection. VGG16's simplicity, robustness, and high accuracy make it a popular choice for image classification, feature extraction, and transfer learning. It has already been trained on the ImageNet dataset and may be readily adjusted for specific uses, including item identification, medical imaging, and plant disease diagnosis. DenseNet201 is deep and accurate, excellent at feature reuse and complex pattern recognition. So, the ensemble can perform better than either model alone. Inspired by the original VGG16/VGG19 designs created by Oxford's Visual Geometry Group, VGG22 is a deep convolutional neural network (CNN). This system comprises 22 weighted layers (19 convolutional and 3 fully connected). Usually employed for transfer learning applications such as medical imaging or leaf disease detection, feature extraction, and picture classification. Figure 2 shows the full architecture of VGG22.

3.1. Dataset Description

The dataset comprises 8,000 photos across 8 classifications. The dataset has been collected from the Kaggle trustworthy repository [24].

Figure 3: Represents some samples of our captured images

For our healthy leaf dataset, researchers took 1046 pictures of mango leaves from various mango plants. A cell phone camera was used to capture images of healthy mango leaves attached to the plant in a field setting (Figure 4).

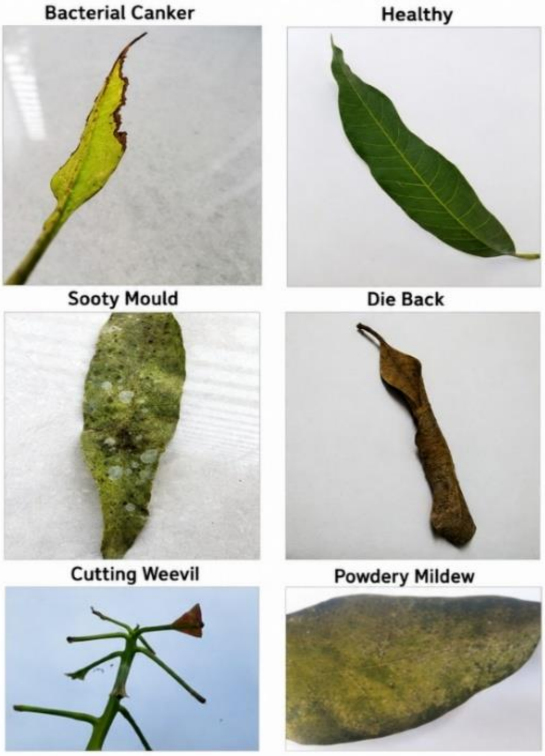

Figure 4: Sample dataset

To improve dataset variety and generalisation capacity, images were captured multiple times of day to incorporate differences in lighting, orientation, and backdrop. Researchers have used 7360 images for training and 640 images for testing. Figure 3 represents some samples of the dataset.

Table 3: Number of images in each class

Class Name	Number of Images
Anthracnose	1048
Bacterial Canker	1154
Cutting Weevil	956
Die Back	1052
Gall Midge	944
Healthy	1046
Powdery Mildew	1056
Sooty Mould	744
	Total - 8000 images

The classes in the dataset, along with the number of images in each class, are shown in Table 3. The total number of images in the dataset is 8000. The dataset is split into test, training and validation sets. For testing purposes, almost 20% of the images are used. The remaining dataset is used for training the model.

3.2. Exploratory data analysis (EDA) and Data Pre- Processing (Data Augmentation)

To guide the implementation of preprocessing techniques, researchers used exploratory data analysis. Before preprocessing and model training, the dataset was split into mutually exclusive training, validation, and test sets to ensure objective evaluation. Only the training set was augmented, and duplicates or near-duplicates were removed before splitting. Without calculating statistics from the test data, image normalisation was carried out using predefined constants. Only the training set was used to refine the pretrained VGG16 and DenseNet201 models, while the test set was only utilised for the final performance assessment. These metrics verify that real model generalisation, not data leakage, is responsible for the observed high accuracy. A horizontal bar plot is presented in Figure 5. When validation_split=0.2 is set in machine learning, 80% of the data is used for training, and 20% is reserved for evaluation. For instance, when the dataset you have is a single array or tensor, Keras uses validation_split=0.2 with methods like model.fit() rather than generators (such as ImageDataGenerator). Instead, it's necessary to design distinct instruction and verification generators. The framework becomes more resilient when horizontal_flip = True, making it invariant to image orientation.

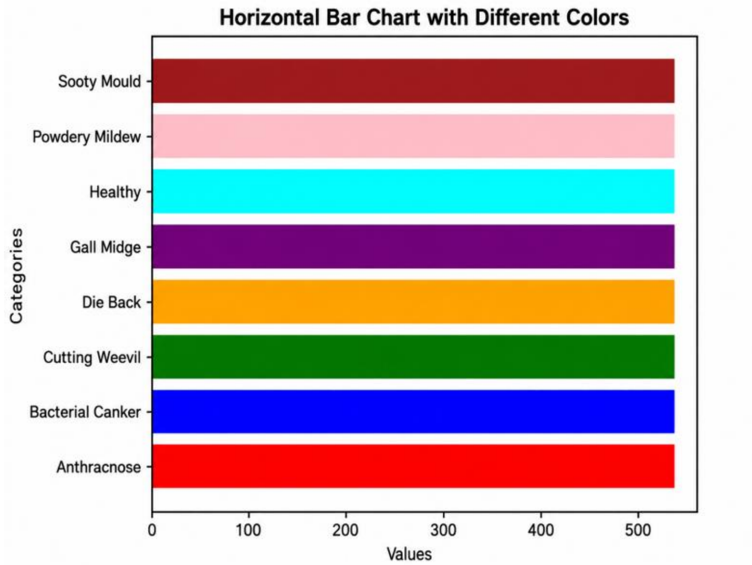

Figure 5: Horizontal bar plot

For instance, rotating a picture horizontally can help the model generalise better to changes in input by simulating various viewpoints during the identification of mango leaf diseases. The range for randomly modifying an image's brightness during data augmentation is specified by the brightness_range option in an ImageDataGenerator in Keras/TensorFlow. The minimum and maximum brightness scaling factors are 0.75 and 1.3, respectively. Researchers also used Random Height (0.2), which denotes a stage of data processing in which image heights are randomly changed. When Random Height (0.2) is applied to an image that has a height of 100 pixels, the height adjustment may range from 80 to 120 pixels. The height may differ by 20% from its initial value due to the scaling factor (0.2). Furthermore, a fraction (or percentage) of the total allowed rotation (0.2) is used in the Random Rotation (0.2) approach. The maximum rotation angle is 0.2, meaning each image will typically be rotated at random by an angle between -0.2 and +0.2 times this maximum. The Randomised Flip ("horizontal") enhancement technique can be used to randomly flip images horizontally during training. It implies that there is a certain likelihood that an image will be horizontally duplicated or reversed.

3.3. Model Evaluation

The performance of our suggested model was examined visually. In our study, researchers assessed our proposed model using accuracy as described below:

Accuracy = (Number of correct predictions) / (Total number of predictions) (1)

This is an important milestone towards the conclusion of the modelling process. By computing many metrics, including classification accuracy, F1-score, and the confusion matrix shown in Figure 6, as well as equations 1, 2, 3, and 4, researchers meticulously evaluate the accuracy of our forecasts.

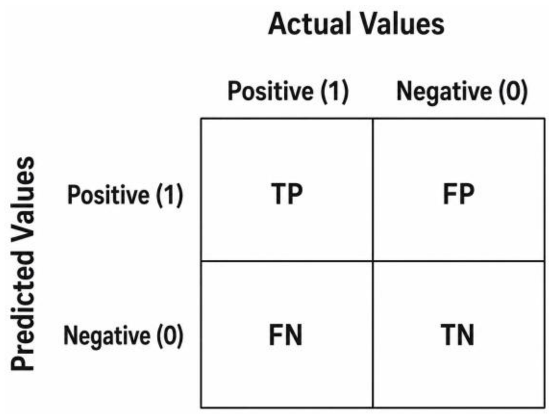

Figure 6: Confusion matrix

where TP: True Positive, FP: False Positive, FN: False Negative, TN: True Negative:

Accuracy= (TP + TN) / (TP + TN + FP + FN) (2)

Precision= TP / (TP + FP) (3)

F1 score = 2 × (Precision × Recall) / (Precision + Recall) (4)

Recall = TP / (TP + FN) (5)

4. Result and Discussions

The research was implemented in Python using the Google Colaboratory Environment; F1 score, precision, recall and accuracy have been considered. VGG16, DenseNet201, MobileNetV2, LeafNet1 (Ensemble of MobileNetV2 and DenseNet201), LeafNet2(Ensemble of VGG16 and DenseNet201), VGG22 (A new architecture) models have been examined in this work. Table 4 shows the results for different models.

Table 4: Accuracy comparison

Model Name	Train accuracy	Train loss	Test accuracy	Test loss
MobileNetV2	0.8459	0.4557	0.9007	0.3858

VGG22	0.7703	0.2756	0.9072	0.2153
VGG16	0.9378	0.1834	0.9667	0.0406
DenseNet201	0.8477	0.4321	0.9758	0.0323
LeafNet1 (Ensemble of MobileNetV2 and DenseNet201)	0.9799	0.0846	0.8943	0.1813
LeafNet2 (Ensemble of VGG16 and DenseNet201)	0.9843	0.0291	0.9881	0.0114

For the ADAM optimiser, the LeafNet2 model achieved the best accuracy of 98.81%, with a test loss of 0.0114%. Figure 7 shows some prediction results.

Table 5: Performance analysis of the models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 score (%)
LeafNet2	98	98	98	98
VGG22	90	91	90	90
MobileNetV2	90	90	90	90
VGG16	96	97	96	96
DenseNet201	97	98	97	97
LeafNet1	89	91	89	89

LeafNet1 has provided the lowest F1 score (91%), precision (89%), recall (89%), and accuracy (89%). Gradually, LeafNet1, VGG22, MobileNetV2, VGG16, DenseNet201and LeafNet2 have improved their performance.

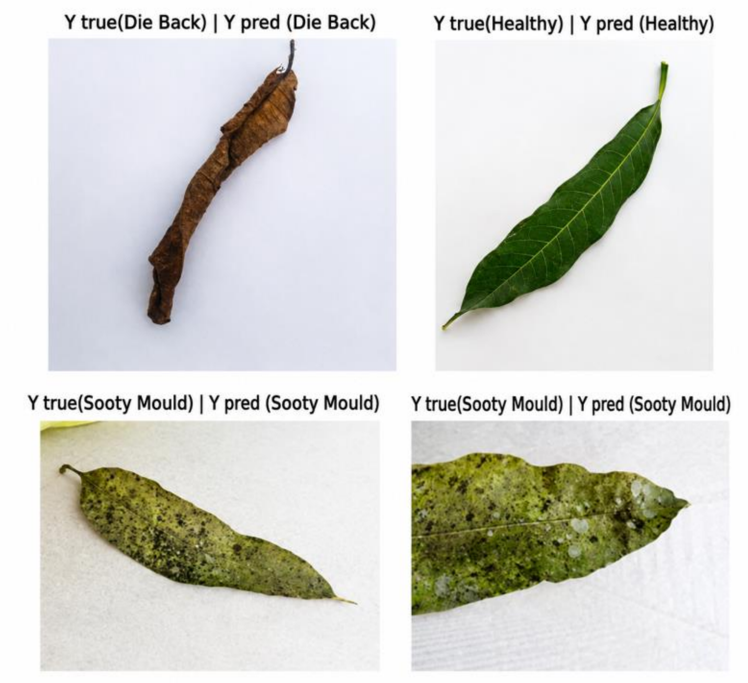

Figure 7: Prediction result

Among them, LeafNet2 has achieved the highest accuracy (98%), F1 score (98%), precision (98%), and recall (98%). It was our desired model. The model's performance results are listed in Table 5. The confusion matrix provided predictions of true and false values as shown in Figures 7 and 8. True labels are indicated vertically, and predicted labels are indicated horizontally, from which False Negatives (FN), False Positives (FP), True Positives (TP), and True Negatives (TN) can be calculated. Figure 9 shows a "confusion matrix of an ensemble classification model" for detection of different plant diseases. The matrix consists of 8 classes: Anthracnose, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Healthy, Powdery Mildew and Sooty Mould.

The large diagonal values indicate that most samples are correctly assigned to their corresponding categories, and the few lighter off-diagonal cells indicate minor misclassifications. Figure 7 presents four sample leaf images along with their true and predicted labels from the classification model. The first sample represents a Die Back leaf, which is correctly predicted as Die

Back, while the second sample is a Healthy leaf and is correctly classified as Healthy. The third and fourth samples represent Sooty Mould, and the model correctly predicts both as Sooty Mould. The agreement between the true and predicted labels demonstrates that the model successfully identifies the three leaf conditions shown in Figure 7. Overall, these examples indicate accurate classification performance for Die Back, Healthy, and Sooty Mould categories.

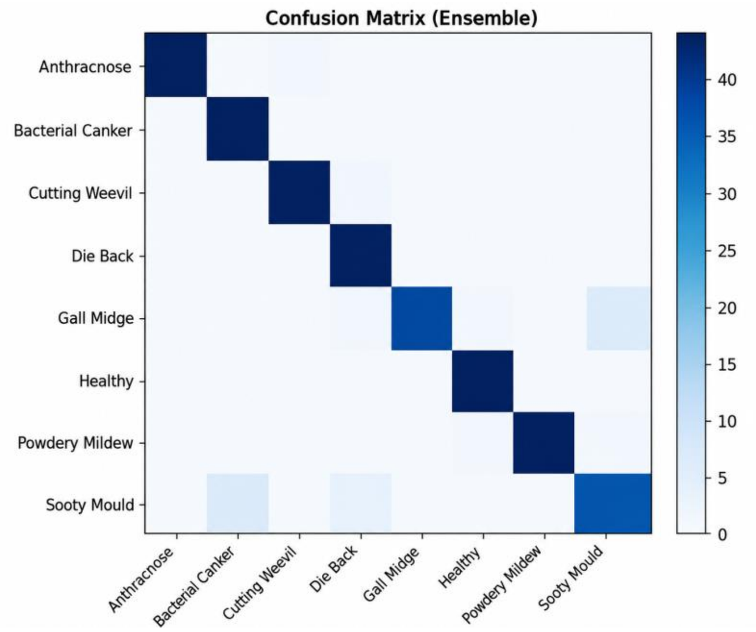

Figure 8: Confusion matrix of LeafNet1

In general, the matrix indicates that the ensemble model has “a good classification performance with relatively low confusion between disease classes”.

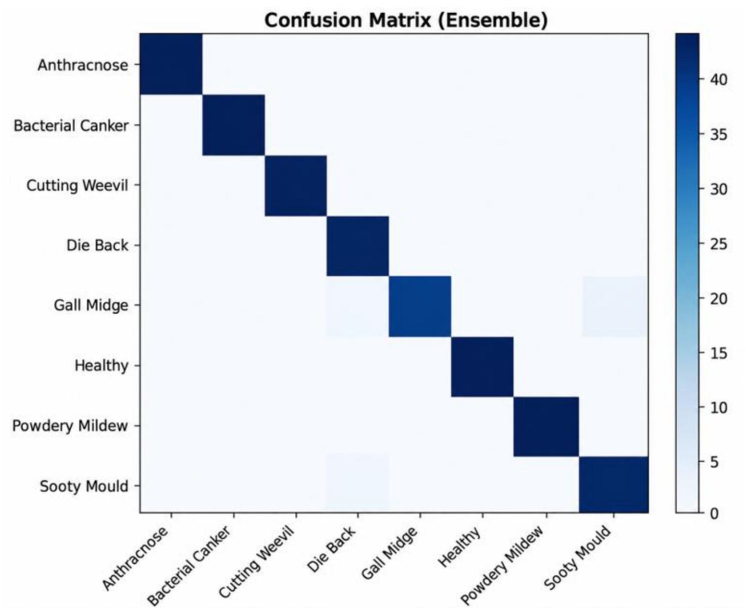

Figure 9: Confusion matrix of LeafNet2

Figure 10 presents the confusion matrix of the VGG22 classification model for eight classes of plant diseases. As shown by the darker diagonal cells, most samples are correctly classified into their respective classes. Limited misclassification occurs in a few lighter off-diagonal cells (particularly for “Die Back, Gall Midge and Sooty Mould”). Overall, Figure 10 shows that the VGG22 model is “performing well for classification,” as most of the predictions are along the main diagonal. Overall, these results show that LeafNet2 performs well. It has the highest accuracy.

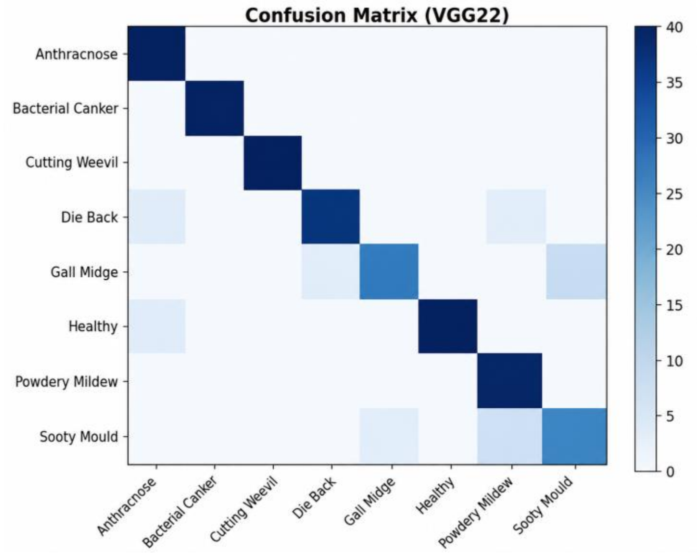

Figure 10: Confusion matrix of VGG22

5. Conclusion and Future Work

In this study, the selected dataset is used to evaluate in detail several deep learning algorithms, assessing their effectiveness and predictive accuracy. The experimental results show that the LeafNet2 method achieves the best performance, with an accuracy of 98%, indicating its strong capacity to learn significant patterns and features from the dataset. The other assessed algorithms yield lower results, indicating differences in their capacity to handle the dataset's peculiarities and complexity. These results show the effectiveness of LeafNet2 and its likely applicability to the considered application. Moreover, the performance of the presented deep learning method is compared with results from related research. These comparisons provide broader context for the results and help define the model's performance relative to the current research. This comparison also provides important insights into the benefits of applying deep learning techniques to the selected problem. It underscores the importance of choosing an appropriate algorithm to achieve robust predictive performance. While LeafNet2 demonstrates promising performance, there are still openings for future research. Researchers can test the technique on other datasets from other sources and environments to assess its generalisation capabilities. Larger, more diverse data sets can further increase the model's reliability and resilience. Further studies can explore other deep learning algorithms, hybrid approaches and optimisation techniques to determine whether there is room for further gains in accuracy and overall performance. Such extensions could validate the results and give a more complete review of the proposed approach.

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Ethics and Consent Statement: This research adheres to ethical guidelines and obtains informed consent from all participants. Confidentiality measures were implemented to safeguard participant privacy.

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