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| RESEARCH ARTICLE

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

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| 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.

| KEYWORDS

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

|ARTICLE INFORMATION

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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.

Introduction:-

The mango is one of the most important tropical fruits in the world, valued for both its substantial economic potential and nutritional worth [1]. Mango cultivation promotes international trade, rural livelihoods, and food security in many tropical and subtropical countries.The minerals nitrogen, potassium, phosphorus, iron, sodium, calcium, magnesium, and vitamins A, B, E, and C may be found in mango leaves (MLs). Protein is one of the main bio-acromolecules found in mango leaves. In underdeveloped nations, MLs can be used as a substitute source of animal feed to help alleviate the livestock food deficit. Diabetes, bronchitis, diarrhea, asthma, renal disease, scabies, respiratory issues, syphilis, and urinary illnesses have all been treated with ML extracts in traditional medicine. Monoterpenes, sesquiterpenes, trace amounts of oxygenated and non-terpenoid hydrocarbons, and small amounts of other analogues are all present in MLs Oil (MLO). The literature on mango seeds, leaves, and bark is dispersed, but regardless of the mango's involvement, it begins with the leaf. Because the mango tree's positive economic significance is determined by the health of its leaves [2]. However, it contains various oil extracts and protein in its nutritional content. In impoverished nations, it can be used as a substitute source of feed for animals to help alleviate the scarcity of food.

As a result, foliar diseases pose a major threat to mango crops, resulting in annual output losses of 30 to 40%. Due to the difficulty of identifying symptoms with the naked eye, many diseases frequently go undiagnosed in their early stages. The symptoms differ greatly: some generate powdery fungal growth, some produce white or black patches on leaves and immature fruits, and some diseases only affect young shoots and developing leaves. These disorders spread quickly and inflict serious harm if they are not identified early, which emphasizes the critical need for prompt and precise diagnosis.The majority of traditional disease detection methods rely on continuous visual inspections by farmers or agricultural specialists. Large farms or commercial orchards cannot use this method since it is slow, labor-intensive, and requires specialized knowledge. However, it works effectively in small-scale settings. Furthermore, accurate diagnosis often requires costly resources and frequent monitoring, which can be challenging for smallholder farmers [3]. Mango leaves frequently develop spots, blights, anthracnose, scabs, and oily patches. Accurate identification of these illnesses is crucial for effective management strategies and maintaining output, even if the most popular diagnostic method, professional eye examination, still requires a lot of time and resources [4].

Recent advances in digital photography and artificial intelligence (AI) have opened up new ways to identify plant diseases. Applications of computer vision and deep learning (DL) have transformed agricultural diagnosis. DL models, particularly Convolutional Neural Networks (CNNs), which have demonstrated the ability to automatically extract complex information from leaf images, including as textures, edges, and vein patterns, enable high-accuracy sickness categorization. These technologies offer opportunities to enhance sustainable agricultural practices, reduce the requirement for human expertise, and scale disease surveillance [1].In addition to their economic importance, mangos offer nutritional value; they are utilized as a supplementary source of animal feed in impoverished countries and supply proteins and oil extracts. This highlights even more how important it is to protect mango crops against disease-related losses. Recent studies have demonstrated the feasibility of using DL-based models for the early identification and categorization of mango leaf diseases such as powdery mildew, anthracnose, dieback, and bacterial canker [5]. Nevertheless, the majorities of systems rely on generic segmentation techniques and frequently overlook structural indicators that could enhance the localization of sick areas, such as leaf vein patterns.

This paper suggests a deep learning method for precise mango leaf disease identification and classification based on these discoveries. We examine the performance of four models: a Custom CNN, LeafNet, AlexNet, and VGG19, using a dataset of photos covering seven disease classes. Additionally, the work investigates an improved CNN training strategy that uses an optimized gradient approach and an exponential moving average function with temporal limitations. This study attempts to determine the best architecture for detecting mango leaf disease and contribute to workable, scalable solutions for early crop protection by methodically comparing model performance.

Review of Related Works:-

Crop monitoring and plant disease identification have advanced significantly in recent years because to the use of computer vision in agriculture. Traditional machine learning techniques were the mainstay of early research on mango leaf diseases. [6] employed a Convolutional Neural Network (CNN), pointing out that the majority of earlier studies used traditional algorithms like Support Vector Machines (SVM) and K-Nearest Neighbors (KNN), with little detection of diseases unique to mangos. In a similar vein, [7] used KNN and Artificial Neural Networks (ANN) on a dataset of 4,000 images, emphasizing the need of upkeep and care in preventing sickness but only attaining mediocre results. For complicated, multi-class classification issues, these early attempts exposed the shortcomings of manually created features and conventional models.

The field was greatly advanced by the development of deep learning (DL). [5] used the SKUAST-J dataset to classify three mango leaf diseases with 90.36% accuracy, demonstrating the potential of CNNs. [8] expanded on this work by comparing CNN, VGG16, and InceptionV3 using a bigger dataset of 4,000 images from seven illness classifications. According to their findings, VGG16 outperformed CNN and InceptionV3 with an accuracy of 96.87%. In order to achieve high accuracy across a variety of illnesses, including anthracnose, bacterial canker, gall midge, powdery mildew, and sooty mold, [1] suggested a DL-based automated inspection system that integrated transfer learning with models including VGG16, MobileNet, GoogleNet, YOLOv8, and EfficientNet. Together, these experiments show how effective CNN-based architectures and transfer learning are at identifying intricate visual patterns in mango leaves.

To further enhance performance, improved and hybrid deep learning techniques have been investigated in addition to traditional CNNs. In order to achieve better accuracy than state-of-the-art techniques, [9] proposed a CNN architecture optimized using a crossover-based linear flight distribution algorithm, incorporating MobileNetV2 for feature extraction and SVM for classification. [10] also examined hybrid models, which reported 97.7% accuracy by fusing deep learning with ensemble techniques like SVGD. In order to achieve 98.57% accuracy, [11] developed an ensemble stacking DL architecture that combined many deep neural networks with a machine learning model. [12] classified eight mango leaf diseases, including red rust, using a hybrid deep learning approach on a dataset of 4,873 photos, achieving 93.01% accuracy and proving scalability for real-time applications. These works demonstrate how ensemble and hybrid approaches can strike a compromise between generalization and accuracy, but frequently at the expense of higher computing complexity.

Lightweight and effective architectures for real-world implementation have been another area of study. [13] presentedLeafNet, a small CNN created especially for detecting mango leaf disease. LeafNet is more effective and less prone to overfitting than AlexNet and VGG16, achieving 98.55% accuracy with fewer parameters. In a similar vein, [14] demonstrated how lightweight pretrained models may maintain good accuracy with lower training costs by utilizing the Fast.ai framework with ResNet18 for transfer learning. When real-time deployment is required in contexts with limited resources, these works are especially pertinent.

Since high-quality picture data is the cornerstone of dependable DL performance, efforts have also been focused on segmentation and dataset generation. [15] used a fully convolutional network to separate diseases, whereas [16] presented a unique vein-pattern-based segmentation method that was verified using SVM to improve recognition accuracy. In order to implement CNN-based models like VGG16, Unet, and MobileNet in mobile applications for field diagnostics, [17] presented a dataset from Sahelian mango plantations in Senegal.

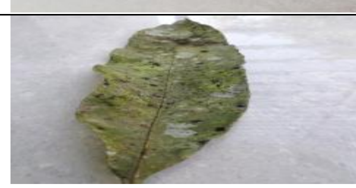
The first public dataset of Bangladeshi mango leaves, MangoLeafBD, was created by [18], highlighting the significance of standardized datasets for reproducibility. Several pretrained models, including VGG19, InceptionV3, ResNet152V2, DenseNet121, and Xception, were systematically analyzed by [19], with InceptionV3 attaining the best accuracy of 99.87%. These studies highlight the need for reliable datasets and sophisticated segmentation methods in order to produce results that are broadly applicable.

Non-visual techniques have also been investigated in addition to image-based ones. [20] presented a 90% accurate ultrasonic sensor-based method for identifying phoma blight and bacterial canker. Despite being novel, these techniques are still not as scalable as image-based DL techniques.

When considered collectively, the examined literature shows notable advancements in the detection of mango leaf disease, with CNNs and transfer learning emerging as leading methods. While dataset generation and segmentation advancements offer crucial assistance for model generalization, hybrid models and lightweight networks further expand the applicability of DL to real-time agricultural contexts. There are still significant research gaps, nevertheless. The practical usefulness of many studies is limited since they concentrate on only three or four illness types. Although they are getting better, segmentation techniques especially those that use vein pattern structures have not always been incorporated into classification processes. Additionally, there is a trade-off between economy and precision: lightweight models compromise performance, whereas certain models attain extremely high accuracy but are computationally demanding.By comparing four models—Custom CNN, LeafNet, AlexNet, and VGG19—on a balanced dataset of 4,000 pictures covering seven illness classifications, our study fills in these gaps. To improve illness localization, it also presents a segmentation method based on leaf vein patterns. This work advances the creation of scalable, precise, and effective frameworks for early mango disease diagnosis in precision agriculture by fusing comparative benchmarking with domain-specific improvements.

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**

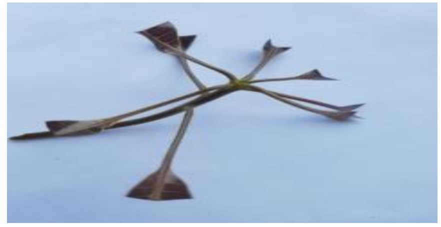
7			**Cutting Weavil leaves**

Figure 1

System Workflow:-

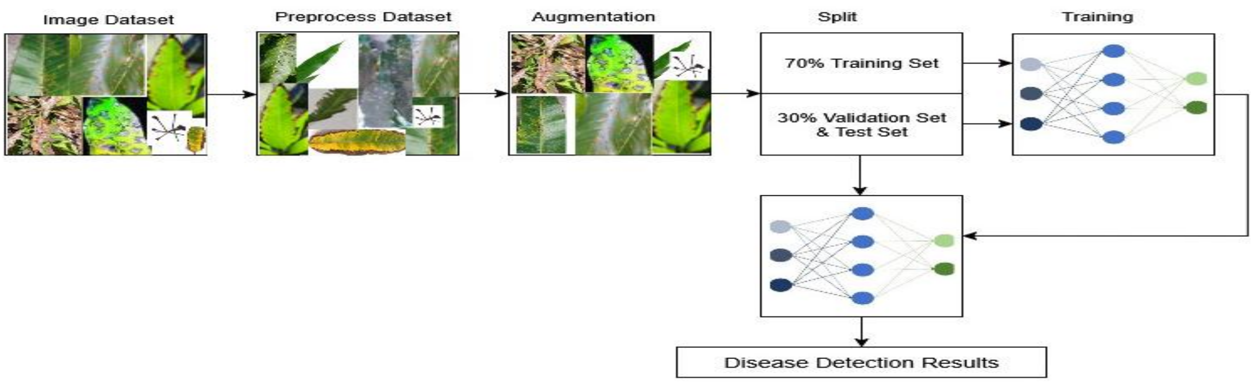


Figure 2

Methodology:-

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). Type of data: 240 x 320 mango leaf images, Data format: JPG. Number of images: 4000 images. Of these, around 1800 are of distinct leaves, and the rest are prepared by zooming and rotating where deemed necessary. Diseases considered: Seven diseases, namely Anthracnose, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Powdery Mildew, and Sooty Mould. Number of classes: Eight (including the healthy category). Distribution of instances: Each of the eight categories contains 500 images. How data are acquired: Captured from mango trees through the mobile phone camera. Data source locations: Four mango orchards of Bangladesh, namely Sher-e-Bangla Agricultural University orchard, Jahangir Nagar University orchard, Udaypur village mango orchard, and Itakhola village mango orchard [21]. The dataset was selected for its balance across categories, which supports robust model training and reduces bias during classification.

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

1. Image collection from the Kaggle dataset.
2. Data preprocessing and augmentation to enhance dataset consistency and diversity. Geometric Transformation method of augmentation was applied on the dataset. Preprocessing was conducted to enhance image quality, standardize inputs, and improve model performance. All images were originally sized at 240×320 pixels and were resized to 224×224 pixels to conform to the input requirements of convolutional neural networks (CNNs). This dimension is widely adopted in deep learning applications due to its computational efficiency while retaining essential features.
3. Dataset splitting into training and testing subsets, 70% of the data was set aside for training subset and 30% was set aside for testing subset.
4. Model training using Custom CNN, VGG19, AlexNet, and LeafNet.
5. Performance evaluation using classification metrics and confusion matrices.
6. Prediction output, representing the identified disease class for each test image.

Methodology Process:-

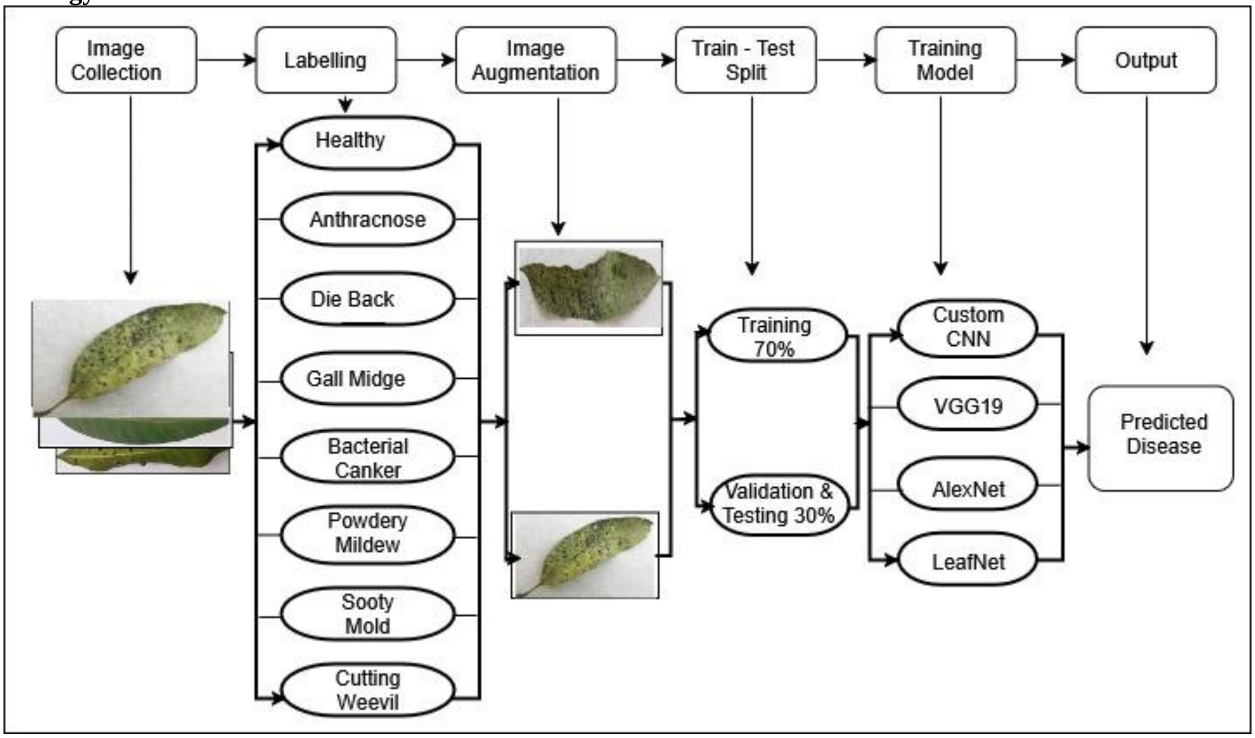


Figure 3

The State-Of-The-Art Architecture:-

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

Custom CNN Architecture:-

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. In this study, we present a unique CNN architecture for the classification of illnesses affecting mango leaves. Table 1 displays the simulation parameters of the suggested CNN architecture, and Table 2 displays the parameters along with their adjusted values. Four max-pooling layers, one dense layer with Softmax activation, and seven convolutional layers with RELU activation make up the model. A hidden layer called flatten is used to increase deep CNN efficiency. It uses the image as input to create a 1D array, which makes handling massive quantities of input easier. Multiple hierarchical levels in the model's API design are used to extract and process features from the input image. Eight convolution layers make up the first layer, which comes after RELU activation. The second layer, the max pooling layer, reduces the size of the image supplied in it by having a pool dimension of 2x2. The third and fourth levels use convolution layers with 16 and 32 filters, followed by RELU functions. Another maximum pooling layer with a comparable pool size is the one that follows. Another layer named flatten is added, as illustrated in Figure 4, and it returns features from each input it gets while flattening the results of the preceding levels. The layer's output, the class label, is used to evaluate the overall accuracy of the proposed model.

Table 1: Parameter details of the proposed Custom CNN architecture.

Layer(type)	OutputShape	Param#	KernelSize/Stride
InputLayer	(224,224, 3)	0	-
Rescaling(1/255)	(224,224, 3)	0	-
Conv2D	(222,222, 8)	224	3×3/1
MaxPooling2D	(111,111,8)	0	2×2/2
Conv2D	(109,109, 16)	1,168	3×3/1
Conv2D	(107,107, 32)	4,640	3×3/1

MaxPooling2D	(53,53,32)	0	2×2/2
Conv2D	(51,51,64)	18,496	3×3/1
Conv2D	(49,49,32)	18,464	3×3/1
MaxPooling2D	(24,24,32)	0	2×2/2
Conv2D	(22,22,16)	4,624	3×3/1
Conv2D	(20,20,8)	1,160	3×3/1
MaxPooling2D	(10,10,8)	0	2×2/2
Flatten	(800)	0	-
Dropout(0.5)	(800)	0	-
Dense	(8)	6,408	-
Total		55,184	

Table 2: Parameters and their tuned values.

Parameters	Values
Convolutional layer	7 (3*3)
Pooling layer	4 (2*2)
Optimizer	RootMeanSquarePropagation(rmsprop)
Epochs	50
Batchsize	32
Learningrate	0.001

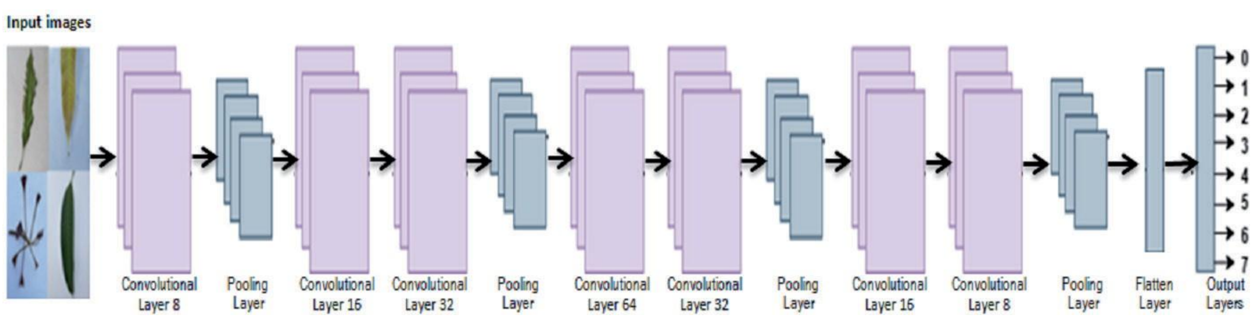


Figure 4 The proposed Custom CNN architecture.

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.

VGG 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.

Results and Discussion:-

Theseven classes are represented in the four models. Figures 5 to 16 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

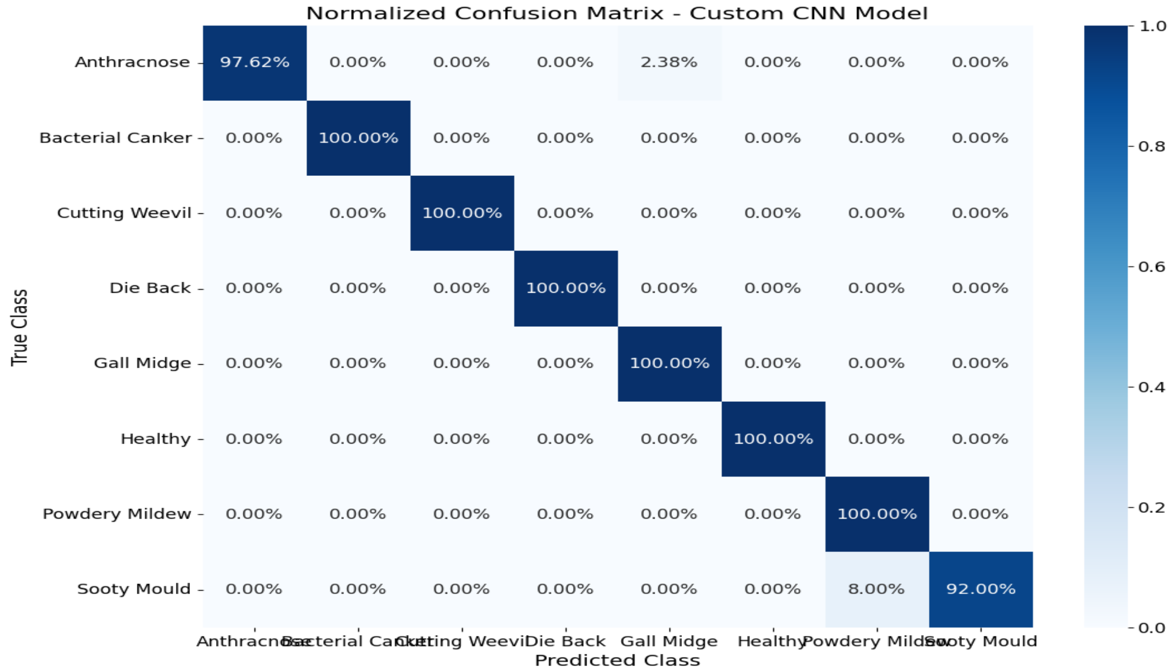
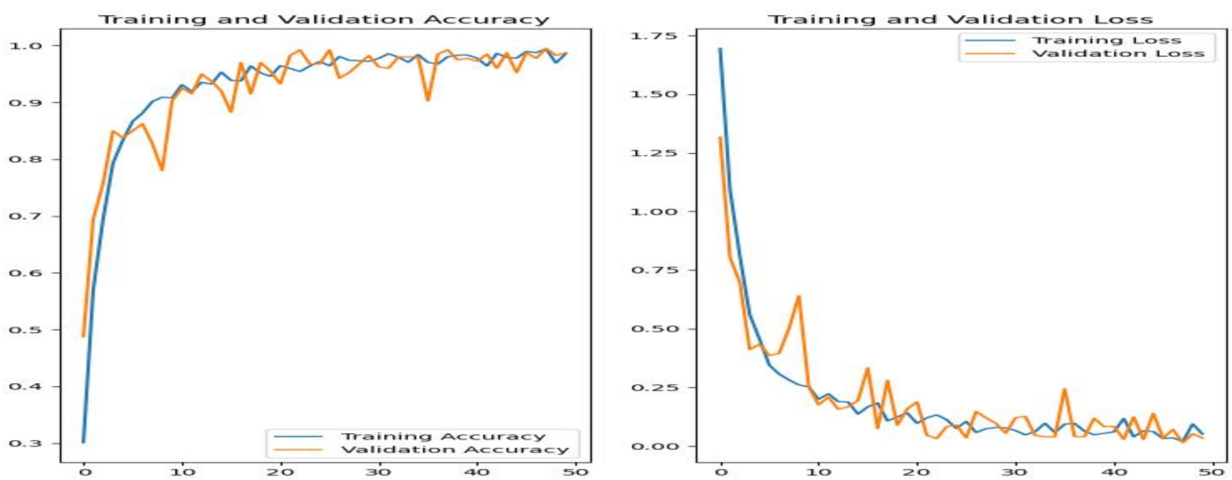


Figure 5



Training and Validation graph of Custom CNN Model Figure 6

Confusion matrix of AlexNet Model

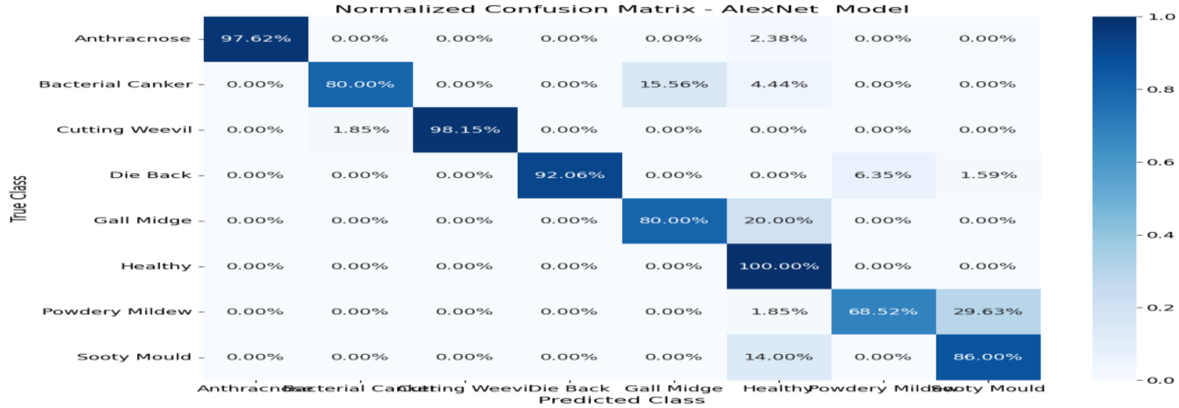


Figure 7

Training and Validation graph of Alex Net Model

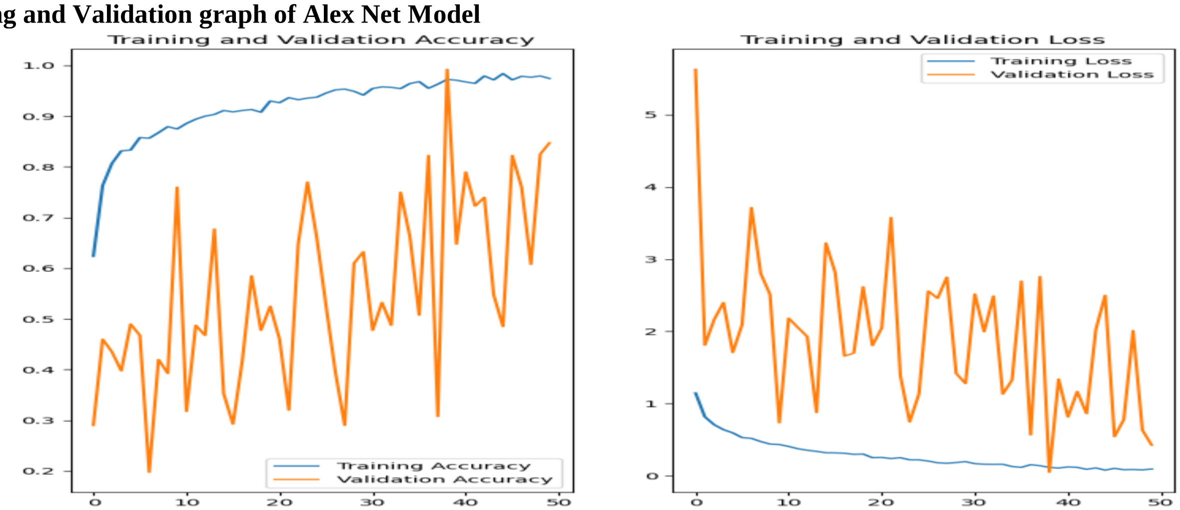


Figure 8

Confusion matrix of VGG19 Model

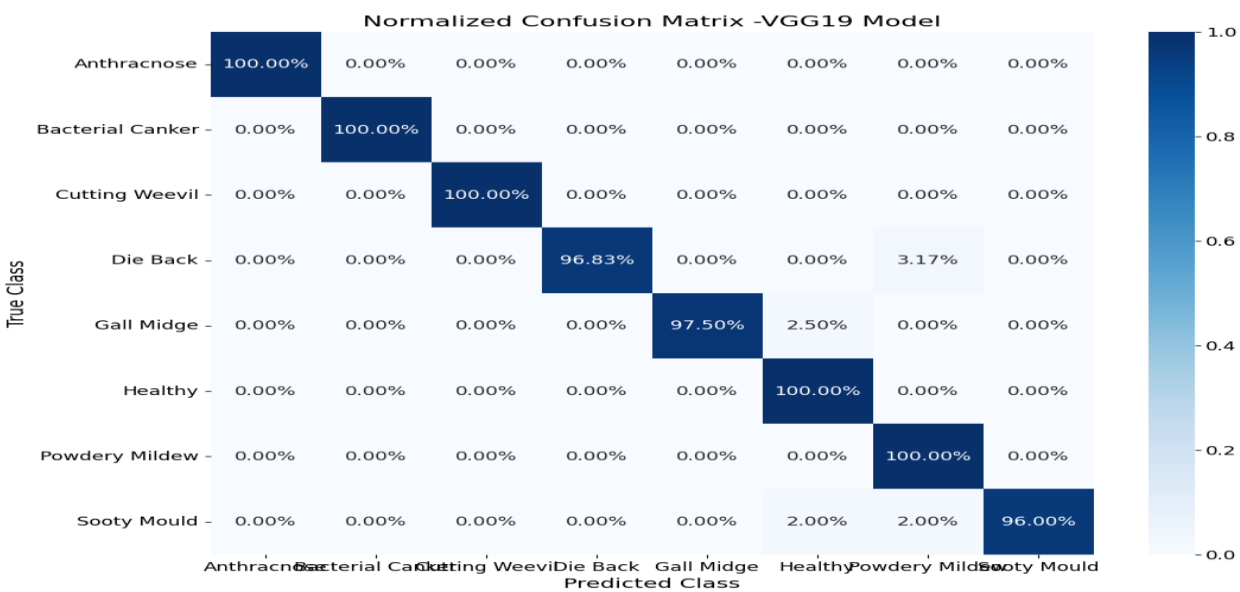
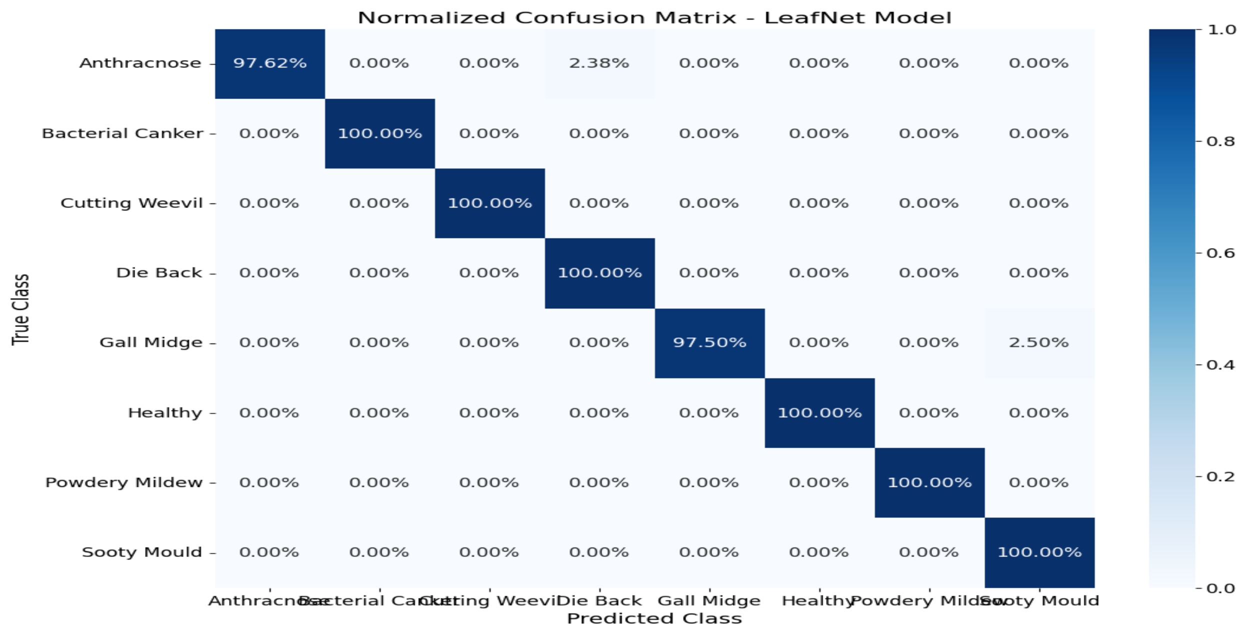


Figure 9



Training and Validation graph of Custom VGG19 Model
Figure 10

Confusion matrix of LeafNet Model

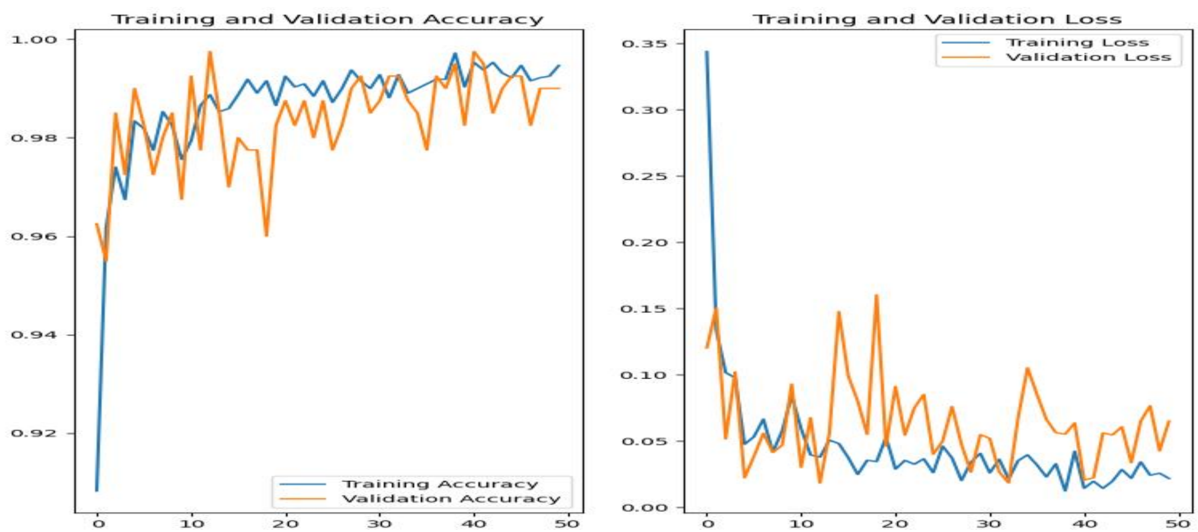


Figure 11
Training and Validation graph of Custom LeafNet Model

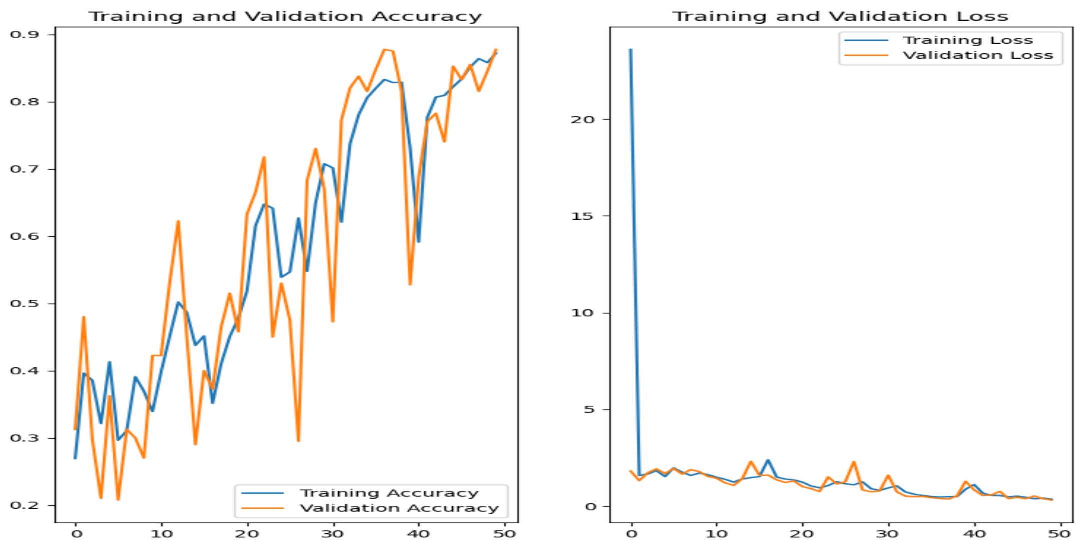
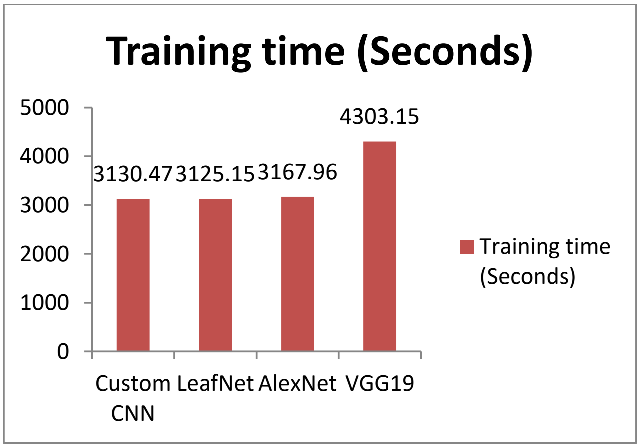


Figure 12

The experimental results demonstrate that the proposed Custom CNN and LeafNet models outperform AlexNet and VGG19 in terms of classification accuracy, precision, recall, and F1-score. This superior performance can be attributed to several architectural and dataset-related factors. First, the Custom CNN achieved the highest performance due to its task-specific design. Unlike generic pre-trained models, the Custom CNN was carefully optimized for mango leaf disease characteristics, enabling it to learn highly discriminative features such as lesion texture, color variation, and vein distortions. Its relatively shallow yet efficient architecture reduces unnecessary parameter complexity, thereby minimizing overfitting while maintaining strong feature extraction capability. The inclusion of dropout regularization further improved generalization by preventing co-adaptation of neurons. Second, LeafNet performed comparably well because it is specifically designed for plant leaf classification tasks. Its architecture focuses on extracting fine-grained features relevant to plant pathology, such as edge irregularities and spot distributions. Additionally, its lightweight design reduces over-parameterization, making it less prone to overfitting despite the relatively small dataset size. In contrast, VGG19, although deep and powerful, showed slightly lower performance due to its high computational complexity and large number of parameters. While deep architectures can capture complex hierarchical features, they require significantly larger datasets to generalize effectively. In this study, the dataset size (4,000 images) may not have been sufficient to fully exploit VGG19's depth, leading to marginal overfitting and reduced efficiency.

Similarly, AlexNet recorded the lowest performance among the evaluated models. This can be attributed to its relatively shallow architecture and larger convolutional kernels, which limit its ability to capture fine-grained features such as small lesions and subtle discolorations on mango leaves. As a result, AlexNet struggles with distinguishing visually similar disease classes. Another key factor contributing to the high performance of the proposed approach is the balanced dataset distribution. Each class contains an equal number of images, which prevents class imbalance and ensures that the models learn uniformly across all disease categories. This significantly improves recall and precision across classes. Furthermore, the image preprocessing and augmentation techniques played a crucial role in enhancing model robustness. Resizing images to a uniform dimension (224×224) ensured compatibility with CNN architectures, while augmentation techniques such as rotation and zoom improved generalization by exposing the models to diverse variations of leaf patterns. The introduction of a vein-pattern-based segmentation approach also contributed to improved performance. By emphasizing structural features of the leaf, this method enhances the localization of disease-affected regions, allowing the models to focus on relevant areas rather than background noise. From a computational perspective, the Custom CNN achieved the best balance between accuracy and efficiency, with relatively low prediction time compared to deeper models like VGG19. This makes it more suitable for real-time agricultural applications, particularly in resource-constrained environments. Overall, the results suggest that model performance is strongly influenced by the alignment between architecture design and task requirements. Lightweight, task-specific models outperform deeper generic architectures when trained on moderately sized datasets, especially in domain-specific applications such as plant disease detection.

Figure 13
Comparative Training and Prediction Time of the used Models Represented on Bar Chart



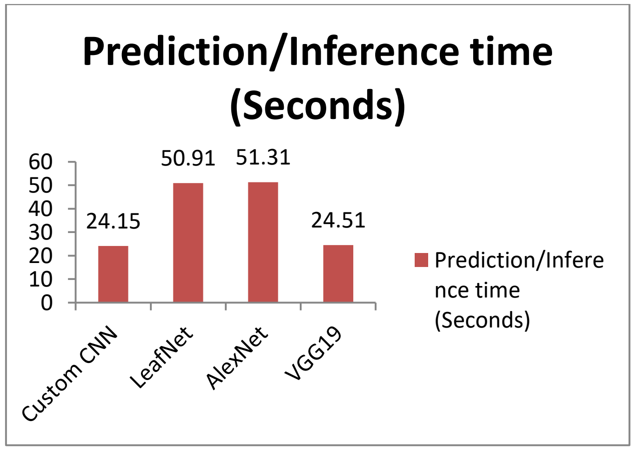


Table 3: Model's Training and prediction time

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

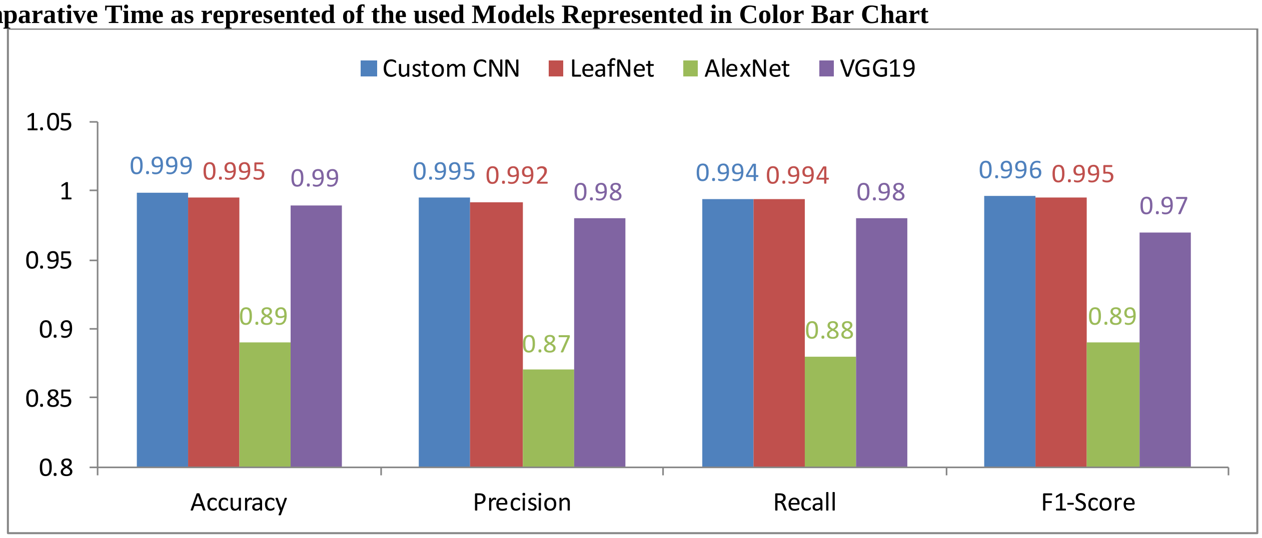


Figure 14
Comparative Prediction Time of the used Models Represented on Bar Chart

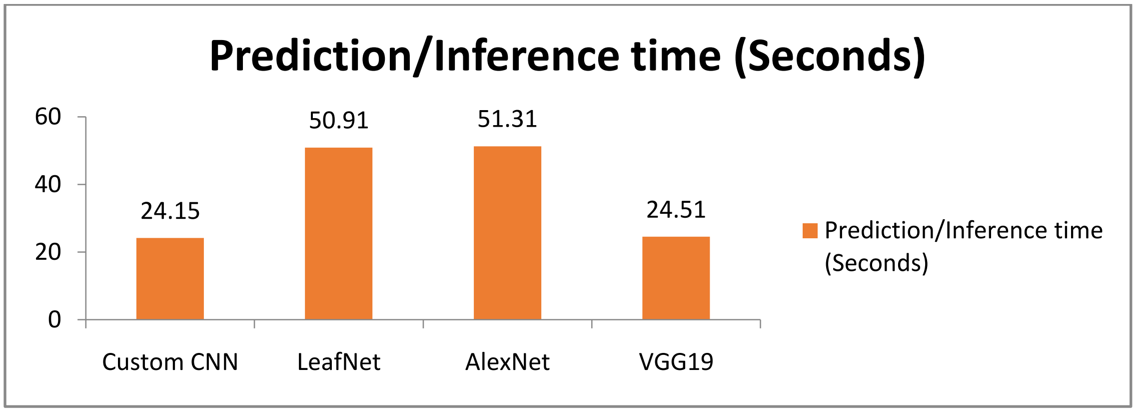


Figure 15
Comparative training Time of the used Models Represented on Bar Chart

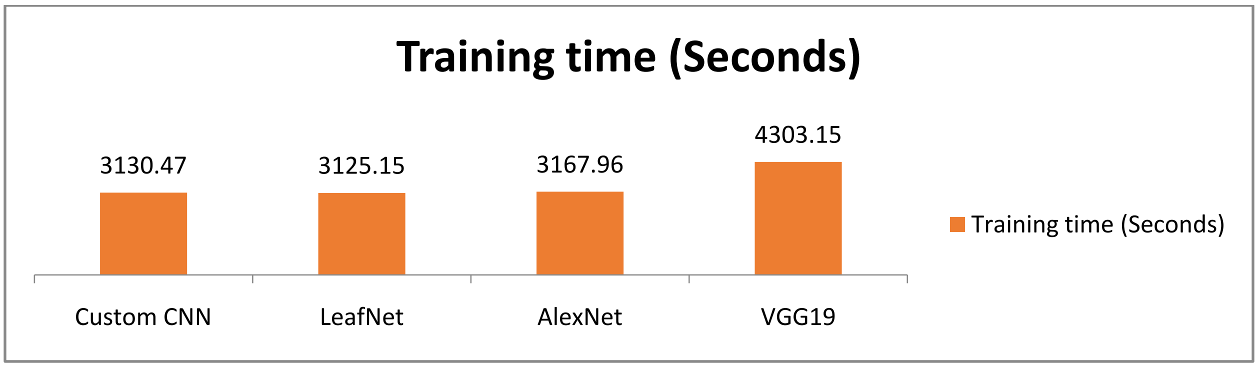


Figure 16

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 4: Models General Comparison

Metric	LeafNet [13]	AlexNet [13]	VGG16 [13]	PROPOSED Custom CNN	PROPOSED LeafNet	PROPOSE D 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-Score	0.9947	0.9905	0.8046	0.996	0.995	0.89	0.97

Discussion:-
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.

Conclusion:-

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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