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Revolutionizing Mango Leaf Disease Detection: Leveraging Segmentation and Hybrid Deep Learning for Enhanced Accuracy and Sustainability

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Abstract*:* The time and effort saved by farmers thanks to automatic plant disease diagnosis is substantial. In agriculture, identifying plant diseases is crucial for increasing both the quality and quantity of harvests. Due to their importance as a plant's food source, spotting leaf illnesses as soon as possible is crucial. The implementation of automation in the detection and management of plant diseases has proven to be advantageous, as it minimizes the need for extensive monitoring efforts in vast agricultural settings. So far, the research was done on single class or maximum of 4 classes of same location. The present study employs an Hybrid Deep learning methodology to automate the detection of eight different leaf diseases in mango trees. A dataset comprising 4873 images collected from mendley and local locations of India. The Images of healthy and ailing mango leaves has been analyzed, revealing the presence of eight distinct leaf diseases, namely Anthracnose, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Powdery Mildew, Red rust, and Sooty Mould. The hybrid model presented in this study demonstrates a 93.01% accuracy rate in recognizing leaf diseases in mango plants, indicating its potential for practical implementation in real-time applications.

Keywords: *Mango leaf, leaf disease detection, deep learning, image segmentation, crops.*

1. Introduction

Indian farmers are responsible for 40 per cent of the world's mango crop [1, 2]. Pests and diseases can cut yields by as much as 30–40 per cent. Flaws in the plant's anatomy cause diseases in plants, and they can have devastating effects on the parent plant or its offspring [3]. Many environmental factors have a role in how plants mature. Plant pathology is an academic discipline that focuses on the scientific study of diseases that affect plants [4] and the development of strategies to combat them in agriculture. Plant pathology's overarching goals can be broken down into four categories: aetiology, pathogenesis, epidemiology, and management.

Disease detection in mango plants is less reliable when performed visually. The low mango harvest is mostly attributable to farmers' lack of knowledge about the various diseases that might affect mango trees. Infectious diseases can severely impact the mango harvest. The sickness will cause the skin to develop strange black patches. Leaves and newly ripened fruit may have these markings. Small at first, these spots can quickly spread across an entire fruit or leaf, killing it. Most of the time, deformities and diseases are to blame for a plant's deformed leaves. Pathogenic microorganisms such as fungi, bacteria, algae, and viruses, among others, are responsible for the onset of diseases, whereas non-living factors, such as temperature, moisture, inadequate nutrition, and the like, contribute to the development of disorders. Negative effects on the harvest from these factors' interference with the tree's metabolic pathway, blocking the photosynthetic process from spreading from the leaves to the rest of the tree, promoting the growth of infuriates on the foliage, lowering leaf area index (LAI), lowering carbohydrate concentrations, persistently disturbing the host by up taking resources, and so on. Time is of the essence in the early diagnosis and treatment of many diseases. Eliminating these pests is critical because they pose a threat to the health of mango crops by interfering with photosynthesis, transpiration, pollination, fertilization, germination, and other vital processes [5]. The etiology of these diseases can be attributed to fungal organisms, microorganisms, and viruses.

Back in the day, agricultural specialists would keep a tight eye on crops to detect any potential diseases. When it comes to early disease detection and prevention measures, small farms have the upper hand. This creates a significant amount of extra work and costs for businesses. Consequently, it is essential to create a mechanized, accurate, quick-to-use, and user-friendly system for identifying plant diseases. The most common method for identifying and classifying plant diseases is based on the use of AI and computer vision.

Currently, there is a prevalent utilization of automated systems that employ artificial intelligence to diagnose a diverse range of diseases [6]. Over the past ten years, numerous conventional machine-learning and deep learning approaches have been suggested for detecting and categorization of plant

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ailments [7-11].

The main contributions of this study are described below.

a) We introduced a mango leave disease dataset containing 4873 pictures of mango leaves that are either healthy or diseased has identified the existence of eight distinct types of leaf diseases, which are Anthracnose, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Powdery Mildew, Red rust, and Sooty Mould [12].

b) The Fast Fourier Transform (FFT) technique was used to extract significant features from the image dataset.

c) We employed a hybrid deep learning method to automatize the identification of leaf ailments in mango trees. This model is a combination of EfficientNetB4 and a cuztomized convlutional neural network (CNN).

d) The study's proposed hybrid model exhibits a recognition accuracy rate of 93.01% for identifying leaf diseases in mango plants, suggesting its viability for practical utilization in real-time applications.

2. Literature Review

The identification of leaf diseases has been a focus of study for years. Scholars have investigated several machine learning and pattern recognition strategies to boost the accuracy of leaf disease detection. Mango is one example of a plant or tree that has benefited from the widespread application of segmentation, feature fusion, and image classification-based methods for detecting leaf diseases [13]. Enhancing the display of symptoms of disease and segmenting the diseased region for categorization are two common applications of ML approaches used to optimize the performance of computer-based plant disease detection systems.

The Convolutional Neural Network is capable of autonomously performing both feature extraction and categorization. Alternative techniques for feature extraction include the Color Co-occurrence matrix [14], Angle Code Histogram [15], Zooming algorithm [16], Canny edge detector [17], and several other approaches. Numerous research endeavours have been conducted to categorize a singular ailment across various plant cultivars or multiple maladies within a solitary plant species. Therefore, several crops are subjected to these proficient methods. When compared to other methods, CNN requires minimal to no preprocessing of pictures.

Iqbal and colleagues conducted a survey exploring various methodologies for detecting and classifying diseases present in the leaves of citrus plants [18]. Various techniques pertaining to the preprocessing of images, the segmentation of images, the extraction of image features, the selection of features, and the classification of images were investigated in the course of the study. It was seen that the majority of the techniques under investigation are currently in a nascent stage.

In the study conducted by Shin *et al.*, speeded-up robust features (SURF) were mined in order to construct an automated system for detecting powdery mildew (PM) on strawberry leaves, using both support vector machine (SVM) and artificial neural network (ANN) algorithms [19]. The results indicate that the utilization of a joint approach involving ANN and SURF algorithms yielded the highest classification accuracy of 94.34% for PM detection. Regarding the duration required for real-time processing, the research findings indicate that HOG exhibits the shortest extraction time.

The findings of Lin *et al.* demonstrated a statistically significant improvement in accuracy, measuring at 3.15% higher compared to the conventional approach employed in the analysis of pumpkin leaves. Principal Component Analysis (PCA) was utilized to attain a precision of 97.3% [20]. The study of Pham *et al.* aimed to identify disease symptoms in the initial stages on plant foliage that entailed minute disease patches, discernable merely via higher resolution images, through an ANN method [21]. The outcomes obtained exhibit superior performance compared to those achieved by convolutional neural networks utilizing a less complex architectural design. The proposed approach is amenable to low-end devices, including smartphones, which would be substantially valuable to farmers engaged in fieldwork.

Mia *et al.* presented in their study a neural network ensemble aimed at facilitating the recognition of diseases that afflict mango leaves [22]. The present study has established the successful ability of the proposed system to detect and categorize four distinct types of diseases with an average degree of accuracy reaching 80%. In the proposed study conducted by Srunitha *et al.*, the utilization of a multi-class Support Vector Machine (SVM) model was implemented in the classification and segmentation of diseases via the use of k-means clustering. The study identified regions with poor health conditions for mango leaves, characterized by the prevalence of red rust, anthracnose, powdery mildew, and sooty mould [23].

3. Problem Definition and Objective

3.1. Problem Definition

The complexity in finding diseases present in the mango leaves are:

- The images can be blurry, low-quality, low resolution.
- Images in the dataset can be taken from far away distances.
- Background and leaves' colour can end up being the same.
- The structure of the diseases is difficult to classify at first glance.
- The affected region is hard to detect, and region coefficients are not available directly.
- Each leaf angle in the images can vary.
- Image sizes are different in each instance.
- All the images present in the dataset are not captured using the same camera.
- Segmentation is required to differentiate between the affected and non-affected regions of the leaves.
- The other state-of-the-art models are designed in such a way that they yield a high disease-predicting model accuracy up to 5 classes, but there are more distinct mango leaf diseases to explore.

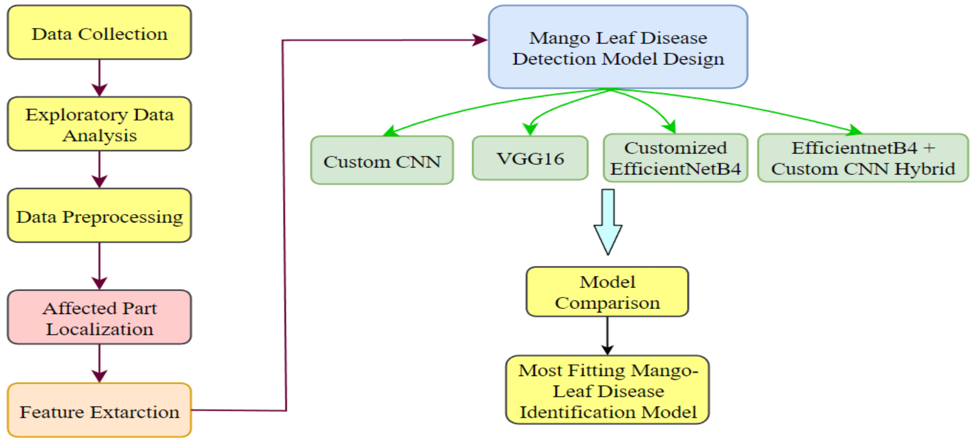


Fig.1. The Workflow of this Research

3.2. Objective

- Exploration of mango leaves images and understanding the different diseases to develop a compact and balanced dataset containing various categories of disease images.
- To develop the mango leaves disease detection model using deep learning approaches.
- Build a localization of the mango disease model to segment the healthy and unhealthy regions in mango leaf images.
- Develop a combination of deep learning models to build a novel approach for predicting more than 4 mango leaves diseases.

4. Methodology

4.1. Research Workflow Overview

The methodology employed in this study is depicted in the graphical representation illustrated in Figure 1. Our main goal is to predict different mango leaf disease classes. We collected the image data from various sources to form a more enriched dataset with a large number of images. Exploratory data analysis was conducted on the dataset in order to obtain comprehensive statistical information. Subsequently, the examination is exhibited through the means of a graphical representation of information. Preprocessing techniques and image segmentation were employed on the images. Afterwards, the dataset was partitioned into distinct subsets for training and validation purposes. Subsequently, the dataset underwent data augmentation to mitigate the issue of data imbalance. Then, various models were developed for the purpose of forecasting mango leaf disease. Four distinct models were utilized to evaluate the dataset. The models under consideration are Custom CNN, VGG-16, EfficientNetB4, and a hybrid model. After this stage, we compared different model performances to find the best-fitting one for predicting the affected leaf disease categories.

4.2. Data Collection

This paper employs an image dataset compiled from three different data sources. One is focused on Anthracnose and Powdery Mildew and comes from the University of Mysore's Department of Horticulture. Another source photographed sooty mould in an agricultural landscape in the Mysore region using a 128-megapixel HD mobile phone camera setup. The next example comes from the publicly accessible Mendeley dataset.

Table 1. The image data count present in each class of the dataset.

Mango Leaf Condition			Number of Images
With Disease	1.	Anthracnose	743
	2.	Bacterial Canker	500
	3.	Cutting Weevil	500
	4.	Die Back	500
	5.	Gall Midge	500
	6.	Powdery Mildew	500
	7.	Red Rust	163
	8.	Sooty Mould	797
Healthy	9	Without disease	670

There are eight different types of mango-leaf diseases included in the dataset. These eight categories are Anthracnose (743 images), Bacterial Canker (500 images), Cutting Weevil (500 images), Die Back (500 images), Gall Midge (500 images), Powdery Mildew (500 images), Red rust (163 images), and Sooty Mould (797 images). This collection includes 670 pictures of mango leaves that are in good health. Table 1 depicts all these count data in a tabular manner.

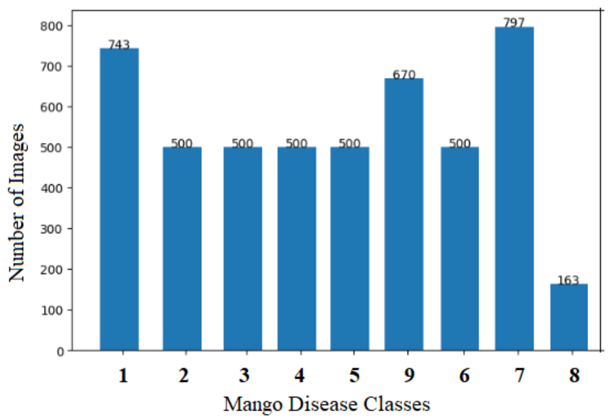


Fig. 2. The distribution of images in 9 distinct classes in the dataset. The numbers in the X-axis represents different classes in this dataset as mentioned in Table 1

4.3. Data Visualization & Preprocessing

An exploratory data analysis was performed to ascertain the image conditions utilized in the dataset under consideration. We plotted the bar plot to get the count of pictures present in individual classes in the dataset. Figure 2 represents the distributions of images of various mango leaf conditions across distinct classes.

The data distribution visualization shows that there is a data imbalance among different classes. The Sooty Mould class has the lowest number of images (163), whereas the 'Red rust' class have 797 images. This data imbalance can lead to less accurate predictions. Therefore, we implemented a data augmentation approach to solve this issue. The 'shear_range' function, which uses stretching the picture while one axis is fixed, has been created to enable us to tilt the image data. Using zoom_range, we were able to produce many randomly-zoomed representations of the original data. Images were also rotated using the rotating function. To further diversify the images in the collection, a brightness range from 0.3 to 1 was included.

Table 2. Parameters Applied for Data Augmentation

Parameters	Values
Rescale	1./255
Shear Range	0.05
Zoom Range	0.05
Rotation Range	20
Brightness range	[0.3,1]
Fill Mode	"nearest"
Horizontal Flip	True
Vertical Flip	True

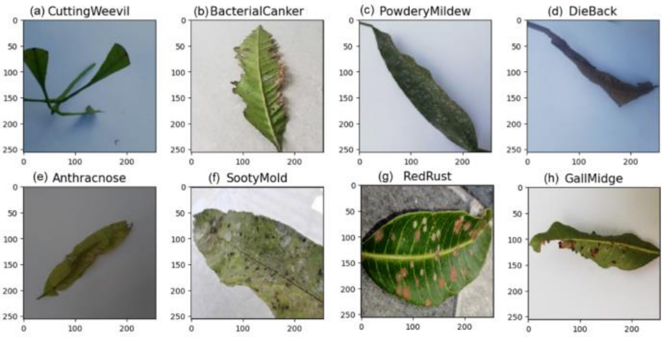


Fig. 3. Sample images of different mango leaf disease classes: (a) Cutting Weevil, (b) Bacterial Canker, (c) Powdery Mildew, (d) Die Back, (f)Anthracnose, (g) Sooty Mould, and (h) Gall Midge.

The whole dataset was separated into a training and a validation subset. The validation split is kept at 0.2. So, the training dataset contains 80% of the main dataset (3900 images). Subsequently, the validation dataset contains 20% of the original dataset (973 images).

The conversion of the images into a NumPy array was performed to facilitate their utilization in the training of the model. The dataset comprised images of varying sizes. All images were resized to a dimension of 256 × 256. The infrared images are formatted in 'RGB', thereby comprising three distinct colour channels. The dimensions of each input image in the dataset are 256 × 256 × 3.

4.4. Segmentation and Feature Extraction

The Fast Fourier Transform (FFT) is a widely employed technique for converting an image from the spatial domain to the frequency domain and vice versa. The FFT is a computational procedure that efficiently computes the Discrete Fourier Transform of a given input, surpassing the speed of direct computation.

The following equation is the mathematical representation of discreet Fourier transform.

$$f[l] = \sum_{m=0}^{M-1} f[m] e^{\frac{-j2\pi lm}{M}} \qquad (1)$$

Here, *f[l]* is the Fourier transform of a M-element function *f[m]*.

The FFT algorithm is capable of reducing the computational complexity required to solve the issue of size *P* from $O(P^2)$ to *O(PlogP)*. This big *'O'* notation indicates the order of the time complexity here. An effective technique for attenuating unrelated noise is to implement a mask. Here, the mask is generated by using a filter matrix.

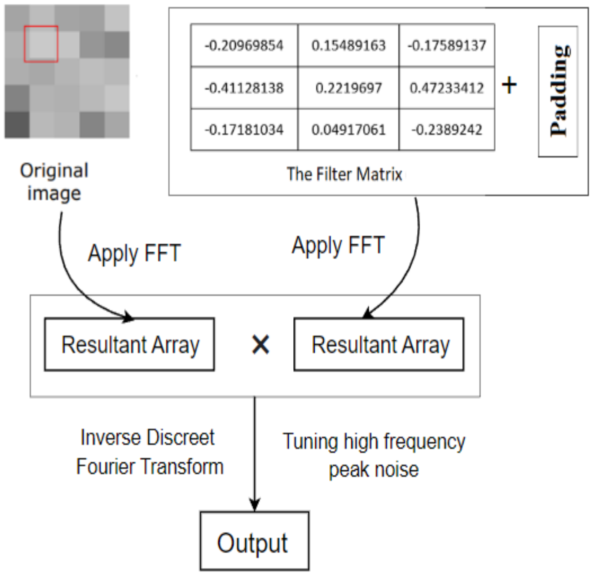


Fig. 4. The application of FFT to a sample image in this case study.

Figure 4 depicts how the customized FFT filter is applied to an original image.

This approach maintains the entirety of the initial data. Moreover, the FFT completely converts images into the frequency domain, in contrast to time-frequency or wavelet transforms. The Fast Fourier Transform (FFT) algorithm is utilized to break down an image into sinusoidal and co-sinusoidal functions that have distinct amplitudes and phases. This process enables the identification of repetitive patterns present within the image.

4.5. Detection Model Design

4.5.1. Custom CNN

Convolutional Neural Networks (CNNs) are a sort of advanced machine learning methodology employed for the purpose of analyzing data that is arranged in a grid-like structure. Temporal or spatial deep learning approaches are employed for the purpose of analyzing information. The utilization of a stack of convolutional layers confers an additional level of intricacy to convolutional neural networks in contrast to alternative neural network architectures. The CNN architecture comprises three primary categories of layers. The three layers in question are the convolutional layer, the pooling layer, and the fully connected layer [24]. Convolutional layers utilize a sequence of filters perform image processing [25]. Upon the application of filters to the input image at this layer, a feature map is generated. As the complexity of the framework increases, it becomes capable of acquiring more comprehensive characteristics from the images it is presented with. This is achieved through the utilization of stacked convolutional layers. The study showcases a Convolutional Neural Network (CNN) model that comprises 25 layers. The model comprises of 10 convolutional layers. The 'relu' activation function has been utilized in the implementation of each of these layers. Batch Normalization was done in the third layer. Five ‘max pooling’ layers were introduced in this CNN model to extract the highest values from the convolution stage feature maps.

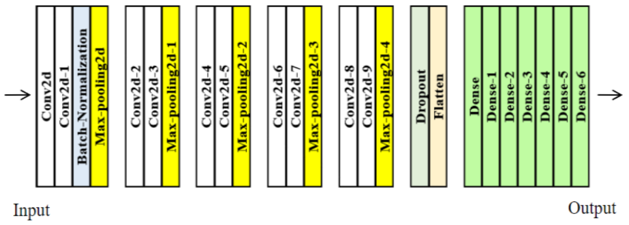


Fig. 5. Architecture of Custom CNN

4.5.2. VGG16

The frequently utilized multi-layer deep CNN framework known as Visual Geometry Group, denoted as VGG, is the object of discussion herein. The VGG16 model is characterized as a model comprising 16 layers. The aforementioned set of layers is comprised solely of Convolutional Layers and Fully Connected Dense Layers. Advanced object recognition models are developed utilizing the VGG framework. The VGGNet, which was trained by means of a deep neural network, exhibits superior performance as compared to the benchmark across various tasks and datasets beyond mere ImageNet. The VGG network is constructed using diminutive convolutional filters as fundamental elements. The architectural composition of the model comprises thirteen convolutional layers tailed by three fully connected layers. This configuration serves as the foundation for the computational framework. Regarding VGG19, it can be observed that it entails a total of sixteen layers dedicated to the convolutional processing task. Due to its straightforward implementation, the VGGNet exhibits considerable utility as an architectural foundation suitable for educational purposes.

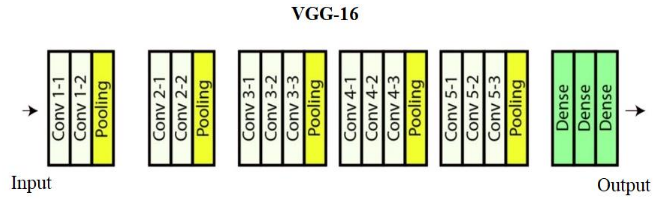


Fig. 6. Architecture of VGG-16

4.5.3. EfficientNet

The EfficientNet model may be understood as an amalgamation of many convolutional neural network architectures. This ImageNet classification problem incorporates 66 million parameters. The EfficientNet group includes eight models ranging from B0 to B7. As the model number increases, the number of computed parameters exhibits only modest growth, whereas the accuracy demonstrates a discernible improvement. EfficientNet diverges from conventional CNN models by incorporating a novel activation function, Swish, as opposed to the frequently employed Rectifier Linear Unit (ReLU) activation function [26].

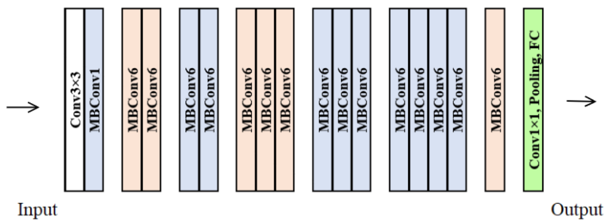
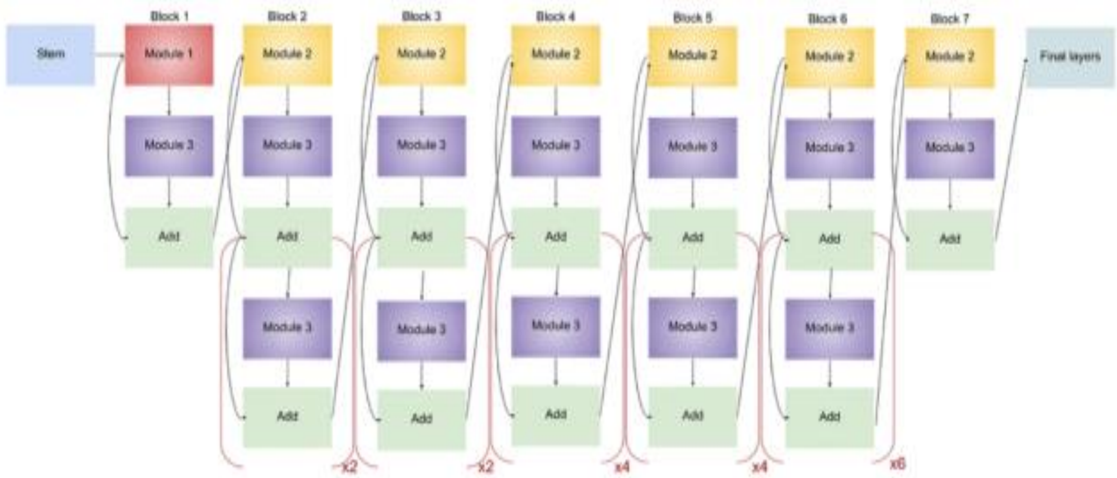


Fig. 7. Schematic Diagram of EfficientNetB4 where MBConv is a type of building block.

Fig. 8. Fundamental Architecture of EfficientNetB4



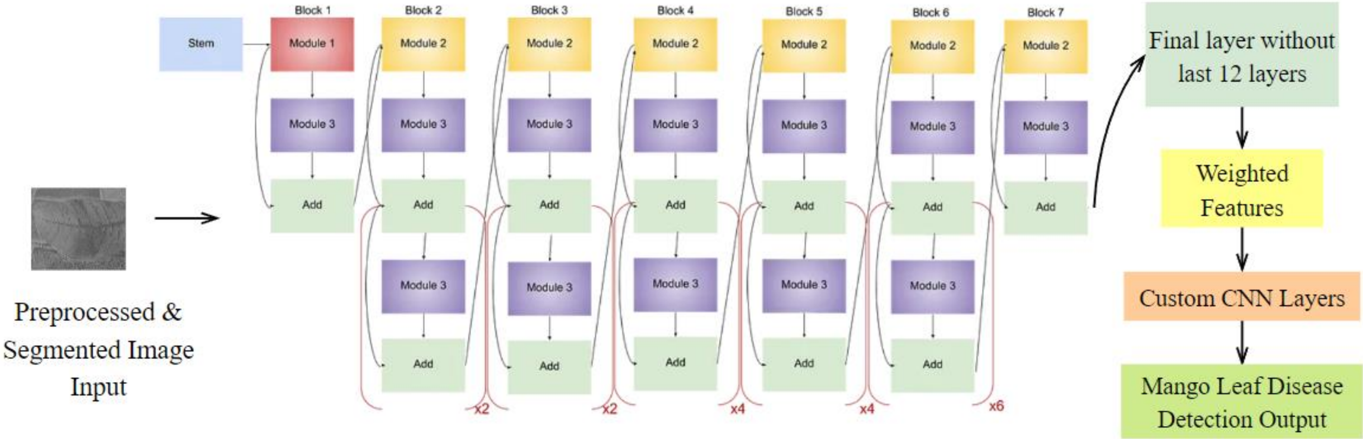


Fig. 9. The EfficientNetB4 + Custom CNN Hybrid Model for Mango Leaf Disease Detection

The fundamental unit utilized in the construction of EfficientNet is the upside-down bottleneck. MBConv, an abbreviation for Mobile Inverted Residual Bottleneck Convolutional blocks, is a type of building block frequently used in state-of-the-art convolutional neural networks (CNNs). In the MBConv architecture, each block is characterized by a two-stage transformation approach (Figure 6). This involves an initial expansion of channel dimensions followed by a subsequent compression of these dimensions. Direct links are constructed between bottleneck points that possess relatively lesser channels compared to those present in expanding layers to facilitate the optimal transmission of data across the network. The current architectural design integrates separable convolutions that are characterized by a comprehensive depth, resulting in a noteworthy decrease in computations by approximately k^2, in contrast to conventional layers. The variable k denotes the dimension of the kernel, which pertains to the length and breadth of the 2D convolutional frame.

We utilized Keras's EfficientNetB4 as a building block of our classifier system for detecting distinct mango leaf disease class detecting. Originally, the EfficientNetB4 model had 478 layers in it. It comes with 19 million parameters. In our case, we modified the network. So, the model used here in this study has 344 layers ion it along with 13 million parameters.

The compound scaling method used in the structure of Efficient Net models involves the utilization of a compound coefficient, denoted as φ, to systematically scale the network's width, depth, and resolution uniformly. This approach is based on sound principles, which are presented in Equation 1. EfficientNetB4 has a φ value of 4.

- $(\alpha)^{\varphi}$ = depth
- $(\beta)^{\varphi}$ = width
- $(\gamma)^{\varphi}$ = resolution

Then, $FLOPS = (\alpha.\beta^2.\gamma^2)^{\phi}$ (2)

4.5.4. The Hybrid Model

In machine learning, the term "transfer learning" refers to the practice of using the abilities and knowledge acquired while training on one issue to train for a different one. The first few "deep learning" layers are taught to determine the task's properties. For transfer learning, the top few layers of a previously trained network can be discarded and replaced by layers specific to the current job at hand. When opposed to building a model from scratch, the transfer learning method's use of a network that has already been trained on a significant quantity of visual data is very favourable in terms of saving time and obtaining high accuracy.

Here, we employed EfficientNetB4 as the first training model in our designed hybrid model. We trained this model using the preprocessed and segmented images as input. After the training, we removed the last 12 layers in the EfficientNetB4 structure. Then, we added our custom CNN network layers above it and retrained the system to get better outputs than the cases when EfficientNet or CNN was used as single models. The final dense layer helps to predict the nine classes of mango leaf disease dataset. We tuned various hyperparameters to get better precision and accuracy.

5. Results and Discussion

5.1. The Dataset

One of the foremost challenges encountered in developing solutions for mango pest and disease identification pertains to the dearth of adequately sized and accurately annotated databases. The efficacy of deep learning (DL) models is constrained by the scarcity of available training data. In order to circumvent overfitting, minimize errors and enhance the model's potential for generalization, DL models require sufficiently large training datasets. Recently, researchers have employed a multitude of computer-aided and machine-learning procedures to categorize various mango leaf diseases. Notwithstanding, these methodologies have exhibited certain constraints in their efficacy, which may be attributable to issues arising from augmented feature dimensionality, overfitting, elevated computational complexity, extended time consumption, reduced feature considerations, inadequate feature quality, and lower segmentation outcomes. Therefore, we gathered a novel dataset that consists of 4873 images distributed in nine classes. Even though this dataset has an ample amount of data, the whole dataset requires preprocessing as the images come in different shapes and sizes.

5.2. Experimental Setup

In this experiment, we only utilized models that could be constructed with GPU support. All experiments were executed with Google's Collaboratory Pro environment, which was operating on a 64-bit Windows machine with 25.5 GB of RAM and a Graphics processing unit with 15 gigabytes of system memory. A maximum of 166.8 GB of storage space was available. The Keras framework, a free and open-source Python toolkit for deep neural networks, is used to implement all of the scripts. Figure 9 shows a sample of the hardware system specification running in the backend.

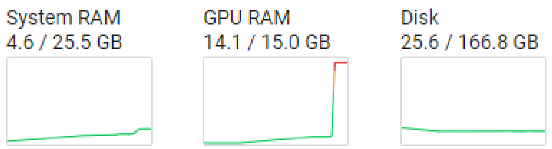


Fig. 10. Hardware System Specifications in the Backend.

5.3. Segmentation Output

The images present in the dataset here required some preprocessing and segmentation of the disease-affected area. This procedure can make the model implementation easier. We used convolution for image segmentation.

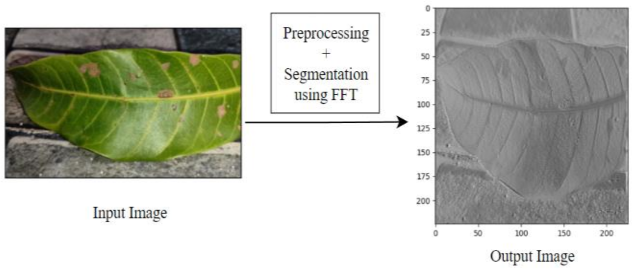


Fig. 11. Output images after preprocessing and segmenting the raw input images

The term ‘kernel’ can be alternatively referred to as a ‘mask’ or a ‘convolutional matrix’, as it is obtained by masking a convolution. Image kernels can be utilized to achieve various effects such as image blurring, image sharpening, contrast enhancement, and other similar effects. Here, in this case, study, the implementation of the convolution matrix resulted in a generation of such an image which helped to avoid the issues generated due to too much light or shadow effects on the target leaves. This problem initially was a hindrance as the human eye or machine was not able to recognize if there was any affected region where the light or shadow effects were blocking the leaf condition.

5.4. Evaluation Metrics

Multiple metrics were employed to evaluate the various models that were presented in this study. The confusion matrix is a matrix that is specifically designed to evaluate the performance of a given technique in the context of classification tasks within the domains of pattern recognition and machine learning. The output of the classifier generates multiple parameters. The aforementioned categories encompass both positive and negative outcomes, which may either be accurate or inaccurate. Multiple evaluation metrics can be derived from these. Precision, recall, F1-score, and accuracy metrics are widely recognized as highly esteemed.

The statistical concept of precision involves the computation of the ratio of accurate predictions produced by an algorithm to the total number of predictions made. The recall rate can be determined through the division of the aggregate number of true positives and false negatives by solely the number of true positives. The utilization of precision and recall metrics can be advantageous in obtaining a deeper understanding of the effectiveness of a particular methodology, as well as in guaranteeing that the output aligns with predetermined specifications. However, the task of selecting the most suitable approach for the data while simultaneously assessing multiple methods trained on the same information sets presents a challenge when relying solely on these metrics for comparison. The significance of the F1 score is paramount. The F1 score is a metric that represents the harmonic mean of the precision and recall measures. The ensuing expressions, denoted as equations (3-6), represent the mathematical formulations of precision, recall, F1-score, and accuracy.

$$precision = \frac{TP}{TP + FP} \quad (3)$$

$$recall = \frac{TP}{TP + FN} \quad (4)$$

$$F1 - score = \frac{2 \times precision \times recall}{precision + recall} \quad (5)$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (6)$$

5.5. Model Tuning and Classifier Outputs

The EfficientNet model stands out among contemporaneous models owing to its ability to realize enhanced efficiency through the uniform scaling of depth, width, and resolution while at the same time reducing overall model size. The initial phase of the compound scaling technique involves the quest for a grid that elucidates the correlation between diverse scaling dimensions of the underlying network, subject to a consistent limitation of resources. The present methodology enables the determination of a suitable scaling factor for depth, width, and resolution dimensions. Subsequently, these coefficients are employed to adjust the magnitude of the foundational network in order to attain the intended target network [26].

Table 3. Number of total parameters on each model implemented in the experimental study

Model Name	Total Number of Layers
Custom CNN	25
VGG-16	23
EfficientNetB4	344
EfficientNetB4 + Custom CNN Hybrid	357

The normalization process involved dividing each pixel value of the images in both the original and augmented datasets by

255, as per the methodology employed in this study. Subsequently, the images were resized to the standard dimensions that were compatible with the respective models. The custom CNN was configured to process images of size 256 × 256, while the VGG16 and EfficientNetB4 models were designed to handle images of size 224 × 224 pixels in our case study.

The models require hyperparameter tuning to get better outputs. One of those parameters is the learning rate. The utilization of an adaptable learning rate has the potential to enhance the performance of a model. The Keras callback ReduceLROnPlateau was used for this purpose. The monitoring of the cost function value for cross-validation data was implemented, and in the event of a lack of improvement after a predetermined number of epochs, the learning rate was decreased. Because early stopping was employed, the training duration was calculated as the time up to the epoch at which the models' loss values began to grow. By dividing the overall training time by the overall amount of epochs, we were able to determine how long each epoch takes to train the model.

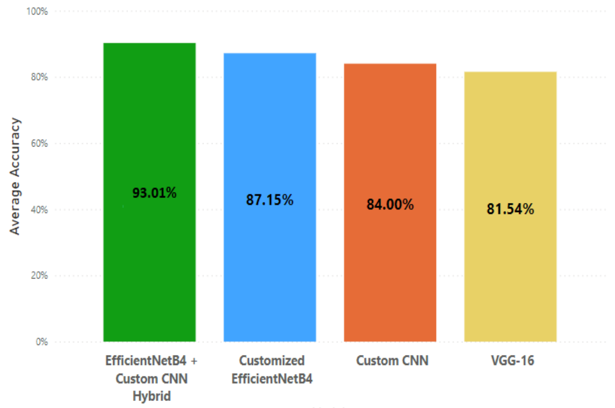


Fig. 12. The comparison of average prediction accuracy of different models.

Figure 12 depicts the comparison of different model accuracies obtained during the experimental study. The custom CNN model reached an average accuracy of 84.00%. VGG-16 obtained an accuracy of 81.54% after 50 epochs. Then we employed the Customized EfficientNetB4 model to the intended dataset. It gave us 3.15% higher accuracy than the previous two models. Then we tuned this model using a hybrid structure, and at this time, the model reached an average accuracy of 93.01% in detecting 9 different mango leaf disease classes. Table 4 illustrates the average outcomes from each of the four models we implemented to the dataset.

Table 4. Average Results Of Different Models

No.	Model Name	Avg. Accuracy (%)	Avg. Precision (%)	Avg. Recall (%)	Avg. F1-Score (%)
1.	Custom CNN	84.27	86.23	85.78	86.67
2.	VGG-16	81.54	86.40	85.11	85.45
3.	Customized EfficientNetB4	87.15	97.22	89.00	88.10
4.	EfficientNetB4 + Custom CNN Hybrid	93.01	93.23	94.00	93.07

Initially, we tried the custom CNN prediction model. After employing the model in the dataset, we noticed that it predicted three classes really well. They are: ‘Sooty Mould’, ‘CuttingWeevil’, and ‘Die Back’. The lowest precision found in this case was the ‘Healthy’ leaves. So, basically, this model could not accurately predict healthy leaves as well as it identified disease-affected leaves.

We tried with the VGG16 model to get a more efficient model, but VGG16 output accuracy dropped to 81.54%, which is lower than that of the custom CNN one. Therefore, we tried working with EfficientNet. After some trial-and-error processes, we found that EddicientNetB4 was a fitting model in this case. So, we modified the model a bit, reducing the number of layers to 344. In return, in reduces the number of total parameters in his framework. This model reached an average accuracy of 87.15%. After this step, we designed a hybrid model to get a more proficient mango leaf disease-identifying model. We designed a transfer learning model using the EfficientNetB4 and the custom CNN models. After the implementation of this hybrid model, it was seen that the overall accuracy increased to 5.86% than that of the EfficientNetB4 model.

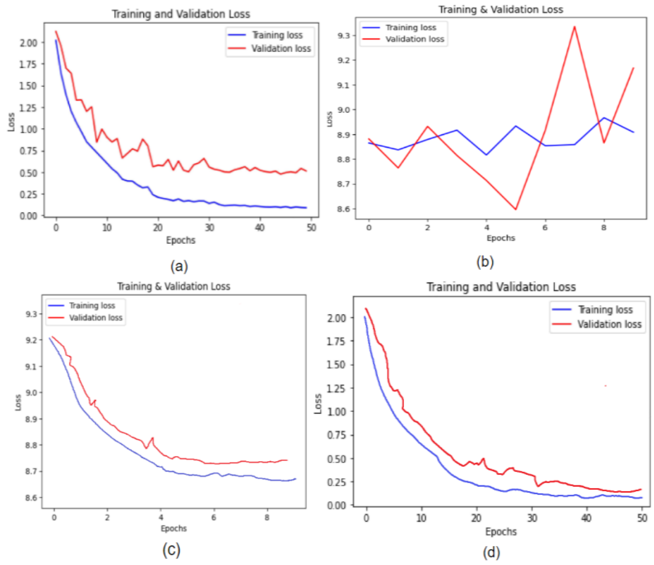


Fig. 13. The training and validation loss in different models- (a) Custom CNN, (b) VGG-16, (c) EfficientNetB4, (d) Hybrid Model.

Due to the hybrid model implementation, the precision of the ‘Gall Midge’ and ‘Healthy’ classes increased to 88%. This is a far better result than the other three models. Similarly, the precision for ‘Red rust’ and ‘Sooty Mould’ increased too. Although, the overall time taken to execute this whole model was a bit higher than others. The recall of the ‘Cutting Weevil’ and the ‘Gall Midge’ categories reached the highest value in case of the hybrid model output. Figure 13 visually compares the training v/s validation loss plot in different models. In the case of the VGG-16 model, this plot is unstable. The other three models show a gradual increase in stability from customized CNN to the Hybrid model, respectively. Figure 14 illustrates the confusion matrices generated due to the outputs of these four distinct models.

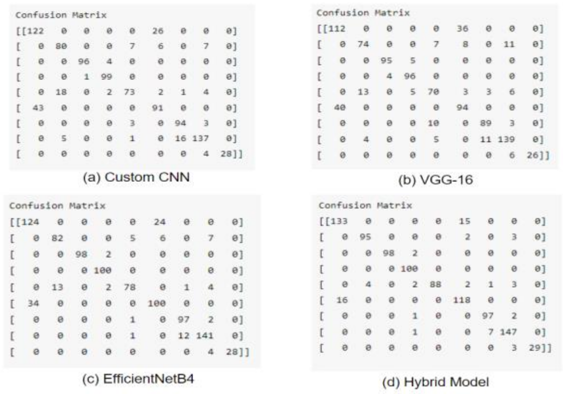


Fig.14. Confusion Matrix for different models utilized in this study.

Figure 15 depicts some of the sample output images and their predicted classes. This is the output of prediction done by the proposed hybrid model. It accurately identifies almost all the nine categories of mango leaf conditions.

Fig. 15. The Sample Images and the Disease Label Prediction Using the Hybrid Model.

Table 5. Various Model comparisons in terms of mango disease classes and disease detection accuracies.

Paper	Class	Model	Average Accuracy
Trongtorkid *et al.* [27]	3	Rule-based	89.92%
Tuman *et al.* [28]	3	SVM + GLCM	85%
Gulavani *et al.* [29]	5	CNN-ResNet50	91%
Proposed Model	9	EfficientNetB4 + Custom CNN Hybrid	93.01%

One of the primary difficulties in assessing the efficiency of a deep learning model is in its comparison to other cutting-edge predictive models that are appropriate to the given task. Conducting a comprehensive and methodical evaluation can effectively illustrate the merits and limitations of various methodologies while also pinpointing optimal strategies and viable avenues for further scholarly investigation. Hence, a comparison was conducted between our findings and pertinent studies for the suggested predictive model, as presented in Table V. It has been noted that despite the existence of numerous models in this domain that exhibit high levels of predictive accuracy, these models are found to be deficient in a specific aspect. This issue pertains to the quantification of unique categories of mango leaf diseases. Previous models have primarily focused on up to five distinct classes, with one of them being the category associated with good health. Presented here is our suggested model, which demonstrates the capability to accurately predict nine distinct types of mango leaves with a precision of 93.01%.

6. Conclusion and Future Directions

The efficiency gains resulting from the implementation of automated plant disease diagnosis in agriculture are significant. The identification of plant diseases is a critical aspect of agriculture as it plays a pivotal role in enhancing the quality and quantity of crop yields. The timely identification of leaf diseases is of utmost significance owing to their critical role as a primary source of nourishment for plants. The utilization of automation in identifying and controlling plant diseases has demonstrated its benefits, as it reduces the necessity for extensive surveillance endeavours in large-scale agricultural environments. The current research utilizes a deep learning approach for the purpose of automating the identification of leaf ailments in mango trees. The analysis of a dataset consisting of 4873 images of mango leaves that are either healthy or diseased has identified the existence of eight distinct types of leaf diseases. These diseases include anthracnose, bacterial cellulase, Cutting Weevil, Die Back, Gall Midge, Powdery Mildew, Red Rust, and Sooty Mould. The study presents a hybrid model that exhibits a recognition accuracy rate of 93.01% for identifying leaf diseases in mango plants.

Other state-of-the-art models have predominantly concentrated on 3-5 discrete categories, one of which belongs to the field of healthy leaves without any disease. The model proposed in this study exhibits the capacity to effectively predict 9 different categories of mango leaves with an average accuracy rate of 93.01%. This finding suggests that the model has the potential to be implemented in real-time applications.

Identifying diseases that might affect mango leaves is essential in maintaining the high quality and production of mango harvesting. Various points can be considered for improvement in future study cases. More images can be collected in the case of the 'Red rust' category to avoid a huge scale data imbalance and bias in predictive modelling outputs.

One potential possibility for further investigation involves the examination of the efficacy of multispectral and hyperspectral imaging in detecting instances of mango leaf disease. Through the utilization of multispectral and hyperspectral imaging techniques, scholars can acquire more comprehensive and precise data regarding the condition of mango leaves, encompassing factors such as chlorophyll concentration, water scarcity, and nutrient insufficiency. This information can aid in identifying the type and severity of diseases affecting mango leaves, as well as in monitoring disease progression and recovery over time.

The methodology of deep learning necessitates substantial computational resources and power to facilitate the training and operation of models, which may not be readily accessible or economically feasible for a significant number of farmers or researchers. Hence, it is imperative for researchers to investigate the uncomplicated and resilient implementations of a deep learning-driven system for detecting mango leaf diseases in real time. Another aspect pertains to assessing and verifying deep learning models in practical contexts and situations. It encompasses diverse environmental conditions, camera perspectives, lighting fluctuations, and so forth.

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