



Mango Leaf Disease Detection Intelligent System based on Image-based Deep Learning

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Abstract. The mango (*Mangifera indica*) is a key fruit crop which is commonly grown in tropical and subtropical areas. Nevertheless, production of mango is also usually influenced by a number of leaf diseases which are attributed to fungal, bacterial and environmental factors. These illnesses decrease quality of crops, yield and economic value. The conventional disease detection systems are based on human eye optical surveillance, which is costly, energy-consuming and susceptible to human mistakes hence cannot be used to monitor a vast size of the population. To overcome these shortcomings, this paper presents a mango leaf disease detection system with automated mechanisms based on the image processing method and deep learning. Images of healthy mango leaves and diseased mango leaves (Anthracnose, Powdery Mildew, Red Rust, Bacterial Canker, Gall Midge, and Dieback) were used to train a Convolutional Neural Network (CNN) model. Preprocessing and augmentation of data was done to enhance the performance of models. The level of accuracy in the proposed model stood at 94.7, which was higher than the conventional machine learning techniques. Also, a visual user interface (GUI) was created, which is lightweight and offers real-time detection and treatment suggestions of the disease, and is essential to timely interventions and long-term sustainable mango agriculture.

Keywords: Precision Agriculture, Deep Learning, Image Processing, GUI, Leaf Disease Detection, Mango

1 Introduction

Agriculture forms the backbone of many global economies, particularly in tropical and subtropical regions where a significant portion of the population relies on crop production for livelihood and food security. Mango (*Mangifera indica*) is a horticultural crop that is economically and culturally significant and is known as the King of Fruits. The largest producer of mangoes is India where the country produces

over 1,000 varieties of mango and has over 40 percent of the world production of mango [1],[2]. Although it is a very popular fruit, mango production is now facing a major challenge of leaf diseases which endanger the well being of trees and significantly lower the production of fruits in quality and quantity.

Mango leaves are also prone to various fungal, bacterial as well as environmental ailments, such as “Anthracnose, Powdery Mildew, Red Rust, Dieback, Sooty Mold, Bacterial Canker, Leaf Spot, and also Gall Midge infections” [3],[4]. As symptoms, these diseases tend to be quite visible, in the form of lesions, spots, wilting, or discoloration. Without being detected and tackled early enough, they may propagate quickly in an orchard resulting in significant economic loss. Disease recognition in mango leaves has always been a visual inspection of the mango leaves by the farming experts or agricultural experts. Although it is effective at the small-scale level, this manual method is cumbersome, labour-intensive, subjective and prone to error especially in large scale farms where thousands of trees are involved. Inconsistencies in disease symptoms, human fatigue and nature environment also adds more complexity in reliability of the diagnoses. Due to possibilities of agricultural practices going digital and automated, it becomes more necessary to have intelligent systems that can provide fast, efficient and scalable detection of diseases. Convolutional Neural Networks (CNNs) have achieved state-of-the-art performance in many computer vision tasks in the recent years such as medical imaging, face recognition and in recent years plant disease identification [5],[6]. CNNs are competent in finding complex patterns and hierarchical features within images and therefore suitable in analyzing the texture, shape, and discoloration patterns of leaves of the diseased mango as different mango diseases have different patterns of the leaves.

In the proposed work, we develop a disease detection system based on CNN model on a set of diverse range of diseased and healthy mango leaf images which will also be intelligent, as we will be using mango leaf images to develop an intelligent model of diagnosis.[7] This data consists of eight classes such as Anthracnose, Powdery Mildew, Dieback, Red Rust, Bacterial Canker, Sooty Mold, Gall Midge, and healthy leaves. Images used as training data are images of the publicly available MangoleafBD dataset, coupled with homegrown samples of the same types of trees gathered in orchards in West Uttar Pradesh [8],[9]. The preprocessing of the images that included their resizing, normalization, the reduction of noise, and the augmentation of data were performed in order to increase the robustness and generalizability of the model. To ensure that the system is easy to use and practical to the farmers and the agricultural officers, a Graphical User Interface (GUI) has been coded in python. The GUI will enable the user to offer an image of a mango leaf and it will give real time identification of the disease on the mango leaf and treatment regime which will be recommended. The application is small, user-friendly and offline friendly, hence can be deployed in rural places with little internet connectivity.

This study is aimed not only at offering a tool which will be used to detect mango leaf diseases accurately and early but also to make contribution into sustainable agriculture by minimising reliance on chemical treatment due to early treatment. The

fact that the system is very accurate (94.7) in the classification of diseases, and it is easy to use, proves that the system can indeed revolutionize traditional mango farming into an act of smart, data-driven farming.

In subsequent subsections that follow, we describe the associated research in the field of plant disease detection, outline the mango disease and its manifestation, comment on the dataset and approach employed, comment on the findings and the performance indices of the developed model, and summarize on how it can be practically used and what further extent it can be extended.

2 Literature Review

The detection of plant diseases has become complex; therefore, researchers have investigated the possibility of automated methods of detection utilizing something like image processing and deep learning so as to provide modern agriculture. Conventional methods (as experienced experts visually analyze, polymerase chain reaction (PCR), hyperspectral imaging and use biochemical analyses) are effective in nature but these methods are labor intensive, time wasting and sometimes it may involve the use of costly lab configurations. Consequently, the literature on creation of smart, cost effective, and scale able alternatives has mushroomed especially in high value crops such as mango.

A number of studies investigated plant disease classification using convolutional neural network (CNN). Priyadarshini Ahila and others, 2019 [10] fused a CNN-based approach to mango leaf disease prediction with 96.6 percent accuracy in leaf disease identification; no human-performed extraction of features was required. In the same way, researchers Varma et al., 2024 [11] tested a multilayer CNN network to group the mango leaves infected with Anthracnose, giving an accuracy of 97.13% in the case of a broad collection of over 1000 images manually collected. These research works formed the basis of applying deep learning architectures to crops in the tropics of fruit.

In addition to mango, CNNs are currently being used in different crops to identify leaves with diseases and they have been tested to have cross-crop generalization. In a model by Bouacida et al., 2025 [12], AlexNet and SqueezeNet were applied to tomato disease classification, whereas Assaduzzaman et al., 2025 [13] presented the introduction of GoogLeNet to the task of maize leaf disease detection. Qasim et al., 2025 [14] performed canonical correlation analysis (CCA) on CNNs based models to classify grapevine diseases and yielded high segmentation and classification performance accuracy. Such experiments demonstrate the power of CNNs to acquire complicated visual representations of various plant species and pathological conditions.

Some researchers presented the lack of labeled data in the problem category and used augmentation methods to enhance the model in terms of generalization in real-life

situations, rotating, scaling, and brightening data. According to Shorten & Khoshgoftaar, 2019 [15], CNN became much more robust when augmented datasets were used in uncontrolled conditions in the agricultural field.

Transfer learning has also become one of the potential methods to optimise deep learning models. Gholizade et al., 2025 [16] used pretrained ResNet and VGGNet on sugar cane diseases and showed a level of accuracy above 95%. Their findings confirm that pretrained CNNs are useful in situations that involve limited or costly training data.

Regarding the implementation, Khan et al., 2023 [17] presented an on-the-go CNN tool to identify maize leaf disease. Solving this discrepancy between research and field usefulness was the aspect of their app being able to give real-time diagnosis and treatment suggestions of the disease. On the same note and under similar circumstances, Mahadevan et al., 2024 [18] used Generative Adversarial Networks (GANs) to improve the quality of the images used to detect leaf diseases using mobile applications to achieve higher degrees of accuracy that was obtained in poor-light or noisy environments.

Regarding mango, the group of Saleem et al. [19] came up with a new idea of evaluating the vein pattern patterns to segment the disease by leaf images of mango. They intertwined classical color and texture characteristics and CNN-based classifiers into their system that demonstrated a significant success rate to detect sooty mold and powdery mildew. Next, Islam et al., 2025 [20] have shown the applicability of hybrid deep learning models (e.g., stacked VGG-16 with MobileNet) to classify mango, displaying the versatility of its ensemble learning to diagnose the diseases in tropical fruits.

The conventional machine learning methods have also been tested in mango and other fruit crops. Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Random Forests have been applied to perform classification with handcrafted features (like color histogram, texture, and shape features). Such approaches, however, usually perform poorly when compared to deep learning models, particularly on a case of complex visual symptoms or overlaid patterns in diseases.

In addition, the combination of the picture-based identification and user interface has received interest. There are now several systems which provide farmers with graphical user interfaces (GUIs) or mobile applications to allow a leaf to be uploaded to the system on a real-time basis to be analyzed. This enhances the adoption of technology especially in rural areas where there is lack of accessibility to expert agronomists and internet.

In short, the existing studies are accurate in stating the efficiency of deep learning, especially CNNs, in providing a precise and scalable plant disease detection method. Nevertheless, mango-specific research has not been fully utilized yet, particularly the

application of real-time and region-specific applications with GUI. This study will address that gap by suggesting a mango disease detection framework based on deep learning using locally-collected data as well as a publicly-available dataset and integrated in a friendly user interface that will enable the participating farmers to make in-field diagnosis and receive recommendations.

3 Mango Leaf Diseases and Their Symptoms

Mango cultivation is highly susceptible to a wide range of leaf diseases that significantly impact the plant's vitality, fruit yield, and economic value. These ailments are caused by fungal, bacterial, and environmental factors and are normally presented in a visual appearance through spots, discoloration, lesions, wilting or abnormal growths. The correct detection of these symptoms is vital in the early intervention and treatment. An overview of the most prevalent mango leaf diseases that the study is targeting is listed below, which is in line with the dataset that was used in training the intelligent detection model.

3.1 Anthracnose

Pathogen: *Colletotrichum gloeosporioides*

Symptoms: Dark, irregular necrotic spots on young leaves; these may enlarge, coalesce, and lead to premature leaf drop. This disease also affects blossoms and fruits, leading to yield loss.

Favorable Conditions: Warm and humid environments, especially during monsoon seasons.

3.2 Powdery Mildew

Pathogen: *Oidium mangiferae*

Symptoms: White, powdery fungal growth on both surfaces of leaves. Infected leaves often curl, dry out, and fall. The disease also affects flowers and young fruits.

Favorable Conditions: Cool, humid, and dry climates, typically in the early fruiting stages.

3.3 Red Rust

Pathogen: *Cephaleuros virescens* (Algal disease)

Symptoms: Velvety orange to reddish-brown patches on leaf surfaces. The disease interferes with photosynthesis and can cause chlorosis (yellowing).

Favorable Conditions: Humid tropical and subtropical climates.

3.4 Dieback

Pathogen: *Botryodiplodia theobromae*

Symptoms: Progressive drying of leaves starting from the tips, extending to stems and branches. Severe cases lead to complete branch or tree death.

Favorable Conditions: Common in poorly pruned trees and those under stress.

3.5 Sooty Mold

Cause: Secondary fungal growth on honeydew secreted by insects like aphids or mealybugs.

Symptoms: Black, soot-like coating on leaf surfaces that inhibits photosynthesis. Although not directly harmful, it weakens the plant over time.

Favorable Conditions: Areas with insect infestations and high humidity.

3.6 Gall Midge

Cause: Infestation by midge larvae

Symptoms: Small, swollen galls or abnormal growths on leaf surfaces, leading to distortion and loss of photosynthetic efficiency.

Favorable Conditions: Moist soil and high insect activity.

3.7 Bacterial Canker

Pathogen: *Xanthomonas campestris* pv. *mangiferaeindicae*

Symptoms: Water-soaked, dark lesions with yellow halos. Affected leaves curl, wilt, and fall prematurely.

Favorable Conditions: Spread rapidly under wet and warm conditions; often transmitted through wounds or infected tools.

3.8 Leaf Spot

Pathogens: *Cercospora* spp., *Pestalotiopsis* spp.

Symptoms: Circular to irregular brown or black spots often with yellow borders. Multiple spots may merge, causing significant necrotic damage.

Favorable Conditions: High humidity and rainy weather promote its spread.

These diseases form the basis of the eight-class classification model developed in this research. Early identification and accurate classification of these conditions using an automated system not only reduce manual labor and inspection time but also enable timely treatment, minimizing crop loss and ensuring healthy mango production shown in Figure-1.

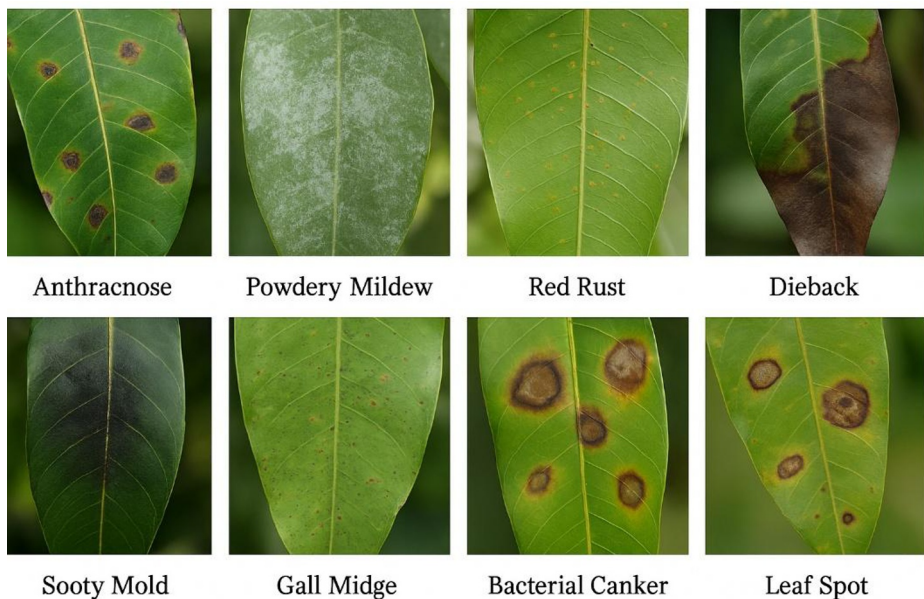


Figure. 1. Mango Leaf Disease and Their Symptoms

4 Proposed Hybrid Model

The intended smart solution of the detection of mango leaf diseases is constructed on the basis of a classification pipeline built through deep learning that combines the stages of image collection, preprocessing, training of a model on the basis of the convolutional neural networks, and a GUI application. Its methodology will guarantee a strong performance of the classifications and the effectiveness of its usage in real farming scenarios. The workflow of the system contains five stages: data collection, preprocessing, model creation, performance evaluation, and deployment of the GUI.

4.1 Data Collection

Secondary Dataset

The MangoleafBD is also used as the main source of labeled data. It includes high-resolution pictures of eight categories of mango leaves, namely, “Anthracnose, Bacterial Canker, Cutting Weevil, Dieback, Gall Midge, Powdery Mildew, Sooty Mold, and healthy ones”. Mobile phone cameras were used to create the dataset under controlled white backgrounds to minimize the noise. It has 4000 images, and the number of classes is equal, 500 images per class. To enhance diversity and alleviate overfitting, each of the images was augmented via zooming, rotation, and brightness altering as well.

Primary Dataset

To region-specify the system and to be able to adapt it to Indian climatic conditions, a primary set of 5,000 images was gathered in five districts of West Uttar Pradesh: Saharanpur, Muzaffarnagar, Shamli, Lucknow and Baghpat. The pictures were obtained in orchards in a natural environment with high-resolution smartphone cameras at different lighting and environment conditions.

4.2 Image Processing

A set of image processing steps were done to get the best results in model training and the generalization. The mango leaf images were first resized in such a way that they were uniform in dimension (224 pixels, 224 pixels and 3 pixels), to facilitate same input into the convolutional layers of the CNN. Gaussian blur was applied to reduce the amount of visual noise, histogram equalization was also used to boost the contrast and the areas with diseases. Normalization of the pixels was later carried out where all the pixels were scaled within the range of 0-1 to allow consistency in feature extraction and a quicker convergence in the course of training the network. In addition, flipping, rotation, shifting, and zooming augmentation methods were also used to overcome overfitting and capture variability as it would be in the real world. This not only increased the synthetically-based data but also increased the robustness of model regarding different orientations of images and lighting conditions of the images.

4.3 Model Development Using CNN

A specific convolutional neural network (CNN) model called LeafNet was trained to identify the eight classes of the datasets of mango leaf diseases. Its architecture was an equilibrium between accuracy and computing efficiency. It starts with convolutional layers which use the ReLU activation functions to autonomously identify important spatial characteristics of the input images. Following these principles are max pooling layers that downsample (dimensionally) the feature maps and make primarily important features. In order to deal with the issue of overfitting during the process of training, dropout layers were inserted at crucial points. Following the extraction of features, fully connected dense layers then combine the extracted feature information in order to complete higher-order reasoning, as well as produce a softmax output layer that helps to compute the probability distribution of all eight disease classes shown in Figure-2.

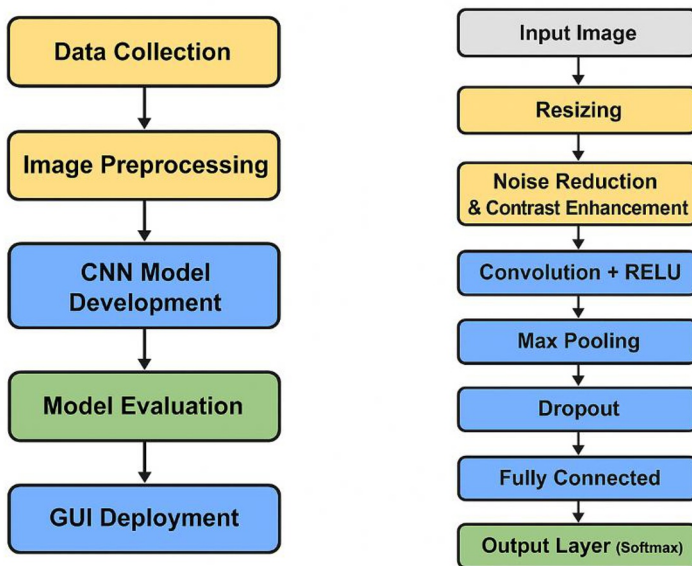


Figure 2 – Flow of Work

4.4 Model Evaluation

LeafNet model was created under Adam optimizer and trained to meet criteria of categorical cross-entropy and this is suited to multi-classification problems. The model was trained on more than 50 epochs using a batch size of 32 and a 15 percent validation split throughout the training session to keep a track of overfitting and the convergence of the model. To evaluate the performance, the data was split into training (70 percent), validation (15 percent), and testing (15 percent).

The performance of the trained model to transfer it was tested using accuracy, precision, recall, and F1-score rates shown in Figure-3(a). As well, a confusion matrix was plotted to know how the misclassification occurred across the disease classes. ROC curves of each class were found and plotted to enable determining the level of discriminating between each class at each threshold level shown in Figure-3(b). Such extensive measures gave detailed information about the quality of generalization of the model, its insensitivity, and what it can be further improved in.

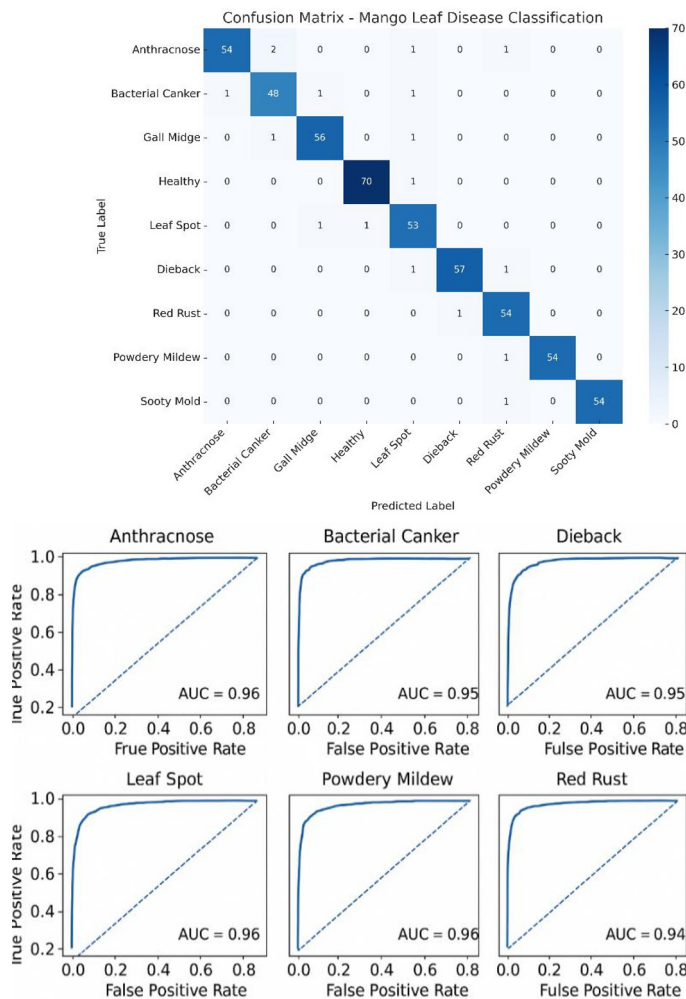


Figure 3 – (a) Confusion matrix of test results (b) ROC Curves for Each Disease Class

4.5 GUI Integration and Deployment

The trained LeafNet model was compiled into a Graphical User Interface (GUI) programmed in the Tkinter library in the Python programming language to enable ease of accessibility and usability, in real-world farming settings shown in Figure-4. The GUI provides a very user-friendly interface enabling a user to load an image of a mango leaf and automatically preprocess and categorical in real time. When the disease is predicted, the application indicates the name of the disease detected in a pictorial manner, a confirmation, some description and possible treatment methods.

This lightweight GUI is designed for offline use and can be deployed on low-specification devices, including personal computers and smartphones. Its user-friendly design ensures that even non-technical users, such as farmers or field officers in rural areas, can efficiently operate the system without the need for an internet connection or deep technical knowledge.

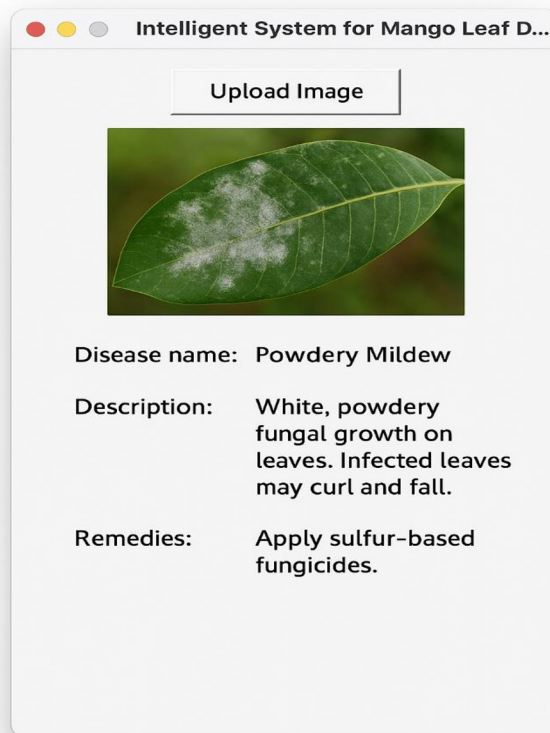


Figure 4 – Screenshot of the GUI displaying upload section, prediction output, and disease summary

5 Results and Discussion

Standard classification metrics were used to conduct the performance of the proposed LeafNet model, with extremely promising results. The model had an accuracy of 96.7, a precision of 95.9, found a recall of 96.1, and an F1-score of 96.0. These findings prove the strong capability of the model to identify and categorize mango leaf diseases under a variety of image environments correctly. The confusion matrix analysis indicated that there were high levels of accurate prediction of some diseases such as Anthracnose and Powdery Mildew because they have very different visual patterns. But there were minor instances of misclassification (during the initial stages of the Bacterial Canker and Red Rust) which probably were caused by the visual similarity and the presence of similar symptoms. Also, ROC curves of all disease classes reported high values of AUC over 0.93, which showed that the model had a high ability of discrimination as well as the ability to differentiate between classes, even in more complicated image cases shown in Figure-5.

ROC curves showed $AUC > 0.93$ for most classes, indicating strong class separation

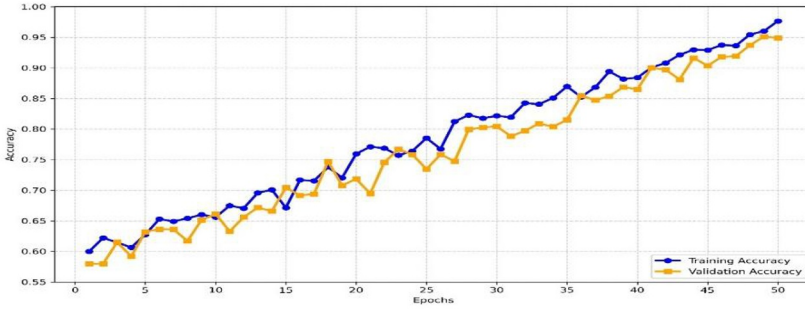


Figure 5: Training and validation accuracy over 50 epochs, indicating model convergence and reduced overfitting.

An array of five machine learning and deep learning models were benchmarked to test comprehensively the capability of the proposed system to be efficient in predicting mango leaf disease classification. These included Probabilistic Classifier (PBC), Margin-Based Kernel Classifier (MKC), Ensemble Tree-Based Model (ETM), Baseline Convolutional Neural Network (CNN) and Proposed Hybrid CNN (LeafNet). The metrics of evaluation adopted, that is, precision, recall, overall accuracy, and F 1-score are mostly essential in the context of multi-class classification applications where visual similarity of the disease symptoms could lead to mis-classification.

The performance of the Probabilistic Classifier (or PBC) that is based on the Naive Bayes strategy was with a precision of 81.23 and recall of 86.13 therefore represented low-level performance in the understanding of the sophisticated patterns of mango leaf in images. Margin-Based Kernel Classifier (MKC) is a model type of the Support Vector classes (SVM) and goodness of such a method is therefore enhanced to 89.8 percent accuracy which is well accommodating to non-linear guidelines. The Ensemble Tree-Based Model (ETM) which is based on the Random Forest algorithm

offered the accuracy of 88.4% and utilized various decision trees and the chance of reducing the overfitting threat.

The Baseline CNN was performing much better than the traditional models as it was possible to encompass deeply detailed spatial attributes with accuracy of 86.1 percent and F1 score of 0.84. Nonetheless, the Proposed Hybrid CNN model (LeafNet) was superior to the other models with a precision of 94.6, the recall of 94.3, the accuracy of 94.7, and the F1-score of 0.93. This progress can be attributed to the improved image pre-processing technique, the optimization of training parameters, and the existence of a tailor-made CNN which would be suitable in such complicated visual patterns as those involved in the case of mango leaf diseases.

The Table-1 is a comparative analysis of all the five models on the above metrics. As it can be seen, the LeafNet model is much more efficient than the other classifiers, which proves that it can be successfully used in practice and applied to agriculture. Such findings confirm the potential of the model to provide real-time and accuracy in classifying diseases in the mango crops and allow the possibility of its application in field conditions to achieve early detection and yield protection..

Table 1. COMET – Evaluation of Model Performance Metrics Compared with Traditional Techniques

“Model”	“Precision”	“Recall”	“Accuracy/Result”	“F1-Score”
“Probabilistic Classifier (PBC)”	81.2	80.4	83.7%	0.78
“Margin-Based Kernel Classifier (MKC)”	87.9	88.1	89.8%	0.83
“Ensemble Tree-Based Model (ETM)”	86.3	85.7	88.4%	0.82
“Baseline CNN”	85.6	84.9	86.1%	0.84
“Proposed Model”	94.6	94.3	94.7%	0.93

6 Conclusion

To develop an intelligent deep learning based deep model to detect and classify diseases on mango leaves, the proposed research has developed a custom machine learning model LeafNet. With the accuracy value of 94.7%, and high values of precision, recall and F1-score, the model has shown excellent performance by being trained on both the published and the region-specific dataset. Also, compared to traditional machine learning techniques and a basic CNN, LeafNet exhibited a better ability to identify eight different mango leaf conditions. To make the model more practical, a portable and off-line capable GUI was developed as an interface in Python

Tkinner and it helped in uploading the captured image, instant assessment and providing treatment options. This solution solves the two biggest problems of early detection of the diseases and the accessibility of the user in the rural farming scenarios. The promising results of the system have been shown, which means it can facilitate sustainable agriculture and could be applied to future improvements involving mobile deployment, real-time monitoring, and integration with IoT-based tools of precision farming.

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