MANGO LEAF DISEASE DETECTION AND CLASSIFICATION

A PROJECT REPORT

Submitted by: Team 08

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ABSTRACT

An effective identification of diseases on mango leaves could have important need for orchard health and agricultural efficiency, yet it can be difficult to perform. Some of these diseases look similar because of discolored leaf patterns, spots and distortion of leaf patterns and it overlap between healthy and diseased leaves for various diseases that makes the manual diagnosis ambiguous, difficult, and resource-dependent. Using MangoleafBD dataset (4,000 leaf images) from Kaggle, containing both healthy and diseased samples across seven categories including Anthracnose, Bacterial Canker, Powdery Mildew, Sooty Mould, Cutting Weevil, Gall Midge, Die Back and healthy collected from multiple orchards in Bangladesh. The framework applied the image enhancement using CLAHE with HSV followed by a selection of feature using transfer learning and deep learning models for feature selection models for feature extraction via EfficientNetB0, ResNet50, DenseNet121 models from Keras applications which were trained on the ImageNet dataset. Once the fused features from each model were extracted and fused together a hybrid classifier was developed to help mitigate over-fits while still learning model discrepancies with a meta-classifier consisting of XGBoost and RandomForest as a second level classifier. The proposed method achieved a 97.5% accuracy and precision, recall, F1 score, AUC performance.

Keywords: Image Segmentation, Deep Learning, Transfer Learning, Hybrid Classifier, XGBoost, Random Forest.

I. INTRODUCTION

Crop production is frequently compromised by plant diseases that affect the yield of food crops grown on farms. Fungal, bacterial, and viral pathogens together account for the largest ecological class of biotic factors affecting on farm yield. While numerous causes of food crop declines exist, plant disease caused by fungal pathogens is the leading cause affecting plant leaves can ultimately compromise total yield. Losses from plant diseases also detrimentally affect the economic return for farmers and can contribute to global food insecurity which creates an urgency to address diseases.[1]

These models will produce timely and accurate disease diagnosis that is vital for treatment and, ultimately yield protection. There are several other studies that have now applied deep learning models in innovative ways, including fruit counting (using CNNs), flower segmenting, and leaf phenotyping of plants, we have depicted that using fully convolutional neural networks (FCNNs) is viable for robust classification of crops and weed detection, based on common variants of AlexNet. These innovative architectures improve disease detection ability and overcoming computational challenges.[1]

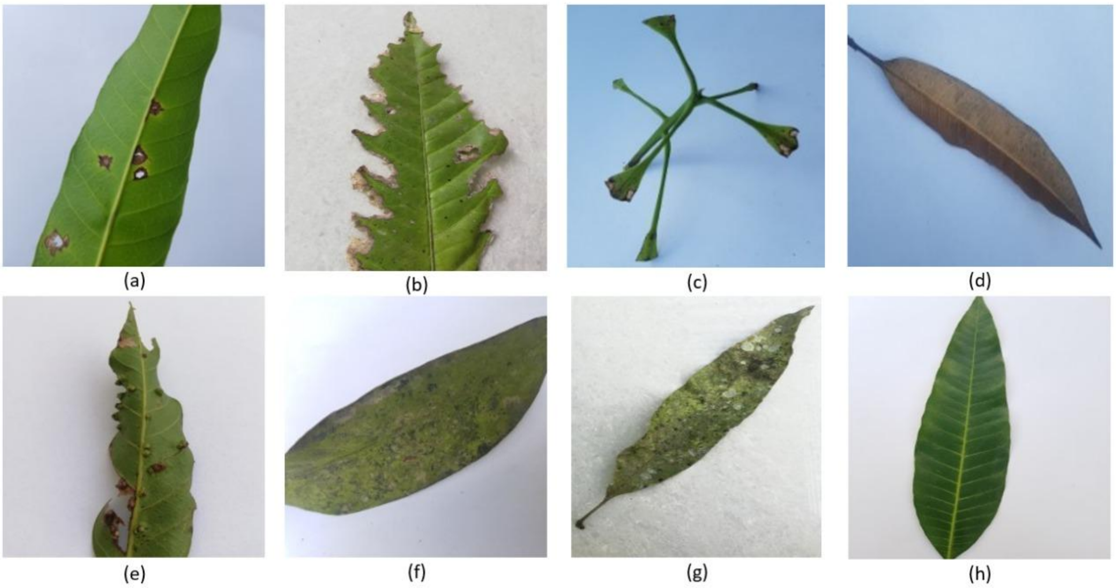

Figure 1. Sample Images used in the datasets

The **Figure 1** shows the sample images of mango leaves included in dataset. The images has various conditions such as Anthracnose (a), Bacterial Canker (b), Cutting weevil (c), Die back (d), Gall Midge (e), Powdery Mildew (f), and Sooty mould (g), Healthy leaf (h) for comparison.

Early disease detection has historically relied upon a visual assessment to determine if the plants were sick or not. There are plenty of plants that do display similar symptoms at early infection stages. This makes it problematic for the farmer not only in productivity, but could also relate to chemical over-usage affecting costs of production and environmental pollution. To help with these problems, researchers have pursued artificial intelligence applications combining convolutional neural networks with transfer learning and ANN with geneartion of feature. These techniques are particularly useful for multi-class classification problems for plant diseases includes gall midge, anthracnose, and powdery mildew, and are able to provide high levels of accuracy even with limited dataset sizes. Farmers take necessary action related to crop losses correctly and would be able to avoid applying a chemical when not necessary, if they have access to the new perspective of damage assessments based on a technology support.

The technique can lead to a new method of creating synoptic datasets as translatable applications which would then afford a framework that is able to be modified and applied to a wide range of agricultural disease detection situations.[2]

Crop disease detection is still an issue, despite promising technological advancements, because of insufficient data or slight variations in early symptoms. In this case, CNN models enhanced by Transfer Learning will be advantageous because a small data set can create great accuracy and results without the computational challenge of large data set models. Artificial Neural Networks, in conjunction with Feature Selection, should provide further insight into what features are the most important in the classification, which can also improve efficiency and provide a remedy from overfitting the model. In such a case, characterizing element will further improve the reproducibility of detecting multiple-class disease situations, during which it is averred that the nature of factors is without reproducibility, much less multiple-class disease. It providing systematic detection and classification prior to control of crops should classically prevent yield loss and economic loss from the use of pesticides or at least reducing pesticide incorporation into the system.[2]

Mango cultivation is vulnerable to diseases in plant that have a impact on quality and yield causing economic or financial losses in tropical countries. Mango tree diseases include fungal agents such as Blossom Blight, Anthracnose, and Apical Necrosis. These types of diseases exist on the leaf tissue or stems of mango trees. Effects of these agents on mango trees include leaf discoloration, necrosis, abscission, and quality of fruit. As a result, mango fruit production is responsible for significant losses before and after harvest of mango fruit.[3]

The implications of these type of diseases can affect the economy more so in a country like Pakistan where mango is a vital foreign exchange earner. Therefore, the rapid detection of the leaf infection is important for realizing viable production of the crop and preserving the integrity of food production system as a whole. A new avenue of research and development includes digital image processing and computer vision methodologies that capture and process leaf images. For example, Low-Contrast Haze Reduction (LCHR) developed and later adopted in air-quality monitoring applications, enhances the visual transmissivity of affected leaves. Digital image processing segmentation methods separate diseased plant parts from healthy plant leaf tissue.[3]

Methods for feature extraction covering color, texture, and geometric characteristics combined with statistical fusion methods such as Canonical Correlation Analysis (CCA) allow for sufficiently accurate classification of diseased regions. Machine learning classifiers, Support Vector Machines (SVM) along with deep CNN architectures can then be applied to classify the pathogens. This automated system ensures a systematic and consistent method for detection of disease reducing social dependence on human cognitive ability and biases in decision-making in a timely manner to mitigate disease severity in mango production. Feature selection with methods like neighborhood component analysis (NCA) and segmentation methods from deep learning have gained success in improving the performance of models in economic settings. By utilizing such method to categorize multiple mango leaf diseases in a timely manner to assist farmers minimize economic losses due to idle treatment time to mitigate severity.[3]

The key contributions of the proposed model are as follows:

- The hybrid framework combining EfficientNetB0, ResNet50, and DenseNet121 using transfer learning to extract deep features along with XGBoost and Random Forest meta – classifiers to improve final prediction.

- The data preprocessing and segmentation process was applied using CLACHE with HSV color thresholding to improve contrast and feature learning.

- The proposed model achieved a 97.5 % accuracy showing good performance.

This paper's organizational structure as follows: Section II is about Literature review, then Section III is discussing about Survey table. While the proposed method with an algorithm is discussed in Section IV. Section V is about the deployment of developed method and Section VI presents the result with discussion. Atlast, Section VII concludes with future research work.

II. LITERATURE REVIEW

The detection of disease in mango leaves proposes a vein-based segmentation and classification technique that builds-on and addresses the limitations of visual inspection. Images were enhanced via pre-processing steps which included resizing, augmentation, CLAHE and filtering, features were extracted from images using color and LBP texture features and then fused together via canonical correlation analysis. Ten machine learning classifiers were implemented with the cubic SVM classifier continuing to generate the best performance working at 95.5% accuracy. The authors have indicated that their study presented excellent robustness and very good accuracy. However, their study was limited by the use of a small dataset consisting of three classes (diseases), and they were focused specifically on this particular disease. In summary, this study indicates that vein-based features have the potential to drive automated disease detection using machine learning, at the same time the authors note a requirement for a larger dataset and for deeper learning to be introduced.[4]

It relates to capabilities for mango leaf diseases to some level of accuracy. The diagnosis of mango leaf diseases via visual inspection or machine inspection is difficult, because of too many issues that will conflict with the results (i.e. reduced feature selection or overfitting) while allowing selection of features by the user. The authors provide a method that demonstrates the data, which included data augmentation, and built the CNN architecture using a crossover based levy flight with a classification of MobileNetV2 and then SVM. Designed around four classes and tested on 380 images, they demonstrated an accuracy of as high as 94.5%; specificity was at 99.81% and a sensitivity of 97.34%. The benefits of their method include improved feature selection and classification performance. The drawbacks of their method are time to compute and small sample size.[5]

Highlighting the challenge of peak yields in mango production attribute to major diseases that include Anthracnose, Bacterial Canker, Powdery Mildew and Sooty Mold. Existing techniques to make a pathology diagnosis begin and rely solely on visual diagnosis and labor-intensive factors. These techniques often have inconsistent reliability, are time-consuming and require an expert to assess the mahogany leaf. As a solution the authors provide the image dataset MangoLeafBD for machine learning approaches to mango leaf diseases derived from images taken from hand-held cameras under typical field conditions in Bangladesh, which contained 4,000 RGB images of seven disease categories and one healthy category (500 images in each category). The images were gathered from mango's commercial plantation in which the authors partnered with research personnel through collaborative contacts, and were screened by agriculture experts. The dataset derived from the field locations were subsequently manipulated for machine learning methodology. More specifically, each image was resized to included lesions, classified positives, negatives that contained nothing, and negatives with varying complexity in delineation, cleaned the background, and added distortions or augmentations.[6]

The paper featuring the mango leaf diseases diagnosis, a stacked ensemble of deep neural networks with logistic regression to classify seven diseases plus healthy leaves was classified on a dataset of 2000 images. The model pre-processed and augmented images, as well as using vegetation segmentation to focus on regions of diseased leaves. The model had an accuracy of 98.57%, where the stacked ensemble used as a model outperformed a standard backbone CNN, and traditional machine learning. Improvements of potential future work included high accuracy, multi-disease detection, robustness, and the practical implementation would require significant computational resources, substantially dataset dependent, black box predictions, and labor-intensive setup. This traditional ML based solution gives options to used for effective automated multi-disease detection on mango leaves.[7]

Recent research in Bangladesh looked at mango leaf diseases involving LeafNet, a lightweight CNN, which was trained with a data samples includes 4,000 standardized, augmented leaves with 7 diseases along healthy leaves. LeafNet has 5 convolutional blocks, two dense layers and a softmax output layer. LeafNet achieved 98.55% overall accuracy and ran faster than AlexNet and VGG16 while being appropriate to run on mobile devices. The benefits of the study included having 98.55% overall accuracy, capable of real-time predictions, high efficiency, and being easy to use. The limitations of the study included only recognizing a limited number of diseases identified with a dataset, the potential to overfit the small dataset, only recognizing a couple diseases of mango leaves, only functioning as a black box, and needing specific hardware resources for the training process.This research shows that lightweight CNN can work in real time for identifying diseases.[8]

The study examined factors that cause mango leaf diseases at risk utilizing a hybrid CO-GWO neural network model using a Coyote-Grey Wolf Optimization (CGWO) framework with a neural network classifier. The digital images were preprocessed with pre-processing both the background and features, segmentation which used edge and region based methods to extract a LBP and a LOOP as novel texture descriptors. The resulting CO-GWO was calculated to optimize the NN weights to optimize maximal classification accuracy. The model provided over 96% classification accuracy, approx. 97% precision recall on a public database of mango leaf images and strong F1 scores, and outperformed K-NN, SVM, traditional NN and CNN models. The Results driven CO-GWO Results driven model offered major advantages of classification accuracy of results, stable hyperparameter tunning on optimization, automated, future extensibility, and remained robust to noise and light variations. There were limitations including, confined data by region, expensive computation, set-up programming limitations, limited number of diseases, limited interpretability, and the model has to be constantly updated.[9]

A paper had gone into detail about a proposed intelligent hybrid system for diagnosing mango diseases that employed case-based reasoning and rule-based reasoning , as well as some data mining. A number of real-world diseases and associated meteorological data were pre-processed and multiple different classifiers: J48, PART, Random Tree and MLP were experimented upon, with J48 and boosting J48, a bestseller with the collective attained the overall best accuracy. Furthermore, expert rules were combined with data mined rules and real world past cases used when there was no direct rule available. The achievement overall was approximately 94.25% accuracy (and >~90% precision and recall). There were reasons to recommend it as a useful diagnostic aid that outperformed: real record performance, all-round knowledge in one place, expert endorsement, extendibility. There were limitations, including the processes of the dataset, the difficulty involved with acquiring complex knowledge, initial setup, narrowness of disease consultation, and the need for continual maintenance. This showed that hybrid systems may meaningfully support automated, accurate mango disease diagnosis.[10]

Diseases in mango can lead to a significant crop loss, and a hybrid process that leverages CNN and HOG features fused with SVM classification was the recommended methodology. The images were pre-processed, augmented, and segmented using threshold techniques while features from HOG and the CNN were fused to better detect diseased images. Overall, the model was impressive as accuracy on testing data reached as high as 99.5%, mostly high precision, recall, and F1 scores were shown, and represents highest accuracy of any model researched that only used HOG and CNN features. There are pros and cons of the hybridization process. The hybrid process provided good accuracy and quick detection where there are benefits to not having a human rely on human labor, and inspections, but it also can require more computing power and resources and would require additional testing on larger dataset to reach generalizable results for growth in field.[11]

It is focused on identifying Anthracnose, Powdery Mildew and Leaf Blight as development was slow and inaccurate due to human inspection which is subject to errors. A dataset including 14 classes was preprocessed (resizing, normalization, augmentation) and a custom deep convolutional neural network with convolutional, pooling, normalization, dropout along with dense layers was trained with an adam optimizer. The custom deep CNN resulted in a 94.73% training accuracy and a 91.43% validation accuracy which is better than if the same number of student standard CNN's were trained on the same dataset. Model benefits include: the detection of multiple diseases, model robustness and it could be used in a scalable way; model drawbacks include: region-specific training data, potential for overfitting on the test dataset, high levels of compute (hardware) would be needed, the model has limited interpretability.[12]

This investigation addresses multi-disease mango leaf losses using a modified DenseNet (MDCN) with transfer learning, alteration of data loaders to include normalization and augmentation, and was ultimately trained on MangoLeafBD (4,000 images, 8 classes). The final model architecture was able to obtain 99.56% accuracy and precision, recall, F1-score all above 99%, and outperformed ResNet, VGG16, and standard DenseNet. Given the extended capabilities of this model are extreme accuracy, a shorter training period, robustness, and include the ability to be extended, there are also downfalls, which include region-reliant data, hardware dependencies, locality detection of diseases (not achievable), and set up is complicated for beginners.[13]

This research incorporated seven different pre-trained CNN models using the MangoLeafBD dataset (4000 images,8 classes) to provide empirical support. Among the pre-trained models applied, InceptionV3 obtained 99.87% accuracy. The MobileNetV2, DenseNet121 along with all other models provided less accuracy than the InceptionV3 score prior to applying the corrective step utilizing transfer learning. Automated observations of mango leaf disease provide early indicators of disease so that we can intervene sooner. The framework provides a cheap and scalable solution to mango leaf disease monitoring, which is a strength of our approach, and is ultimately for the benefit of farmer participants we trained to use this methodology. The major limitations of the study included its dataset derived from only Bangladesh, the fact it only identified 8 total diseases, and the use of cameras in conjunction with cloud services are costly - diminishing its applicability to small-holder farmers. Overall the study provides a great example of efficiently and effectively monitoring automated mango leaf disease recognition.[14]

The ensemble CNN model, combining GoogLeNet with VGG16 to classify mango leaves diseases using 3195 pictures from Ethiopian mango trees. It includes the features of K-Means clustering, masking R-CNN based segmentation, and image augmentation in preprocessing method. It achieved a testing accuracy rate of 99.21% using the above processing techniques. This accuracy outperforms ResNet (91.56%), Inception-V3 (77.05%), and DenseNet121 (75.00%). The model labeled six classes with one healthy tree leaf and five classes of images containing either fungi or insects. Subject experts labeled the features and reported exceptionally high testing accuracy. At field-level, detection of diseased mango trees is possible and with this option growers will pay less by not incurring the costs of using consultants. In addition, growers will be able to detect disease earlier and form a treatment plan focused on elements to investigate prior to diagnosis and treatment. Despite the potential advantages mentioned, the limitations of using exclusively Ethiopian data, operating costs, the current dataset size, and lack of real-time solutions were some deterrents. This study proposes a method and provides an efficient approach to recognize mango diseases.[15]

In this research study, it used the Vision Transformers along with lighter CNNs for disease recognition on mango diseases from a mango leaf dataset called MangoLeafBD dataset of 4000 images consisting of 8 classes. The dataset was pre-processed and also augmented then various CNNs were used including SqueezeNet, ShuffleNet, EfficientNet, DenseNet121, MobileNetV2, Vision Transformers and Swin Transformers, all using transfer learning. Of all the models, the DeiT performed best with an accuracy of 99.75%, but the performance became extremely poor after quantization for mobile application purpose. There were many advantages to the models in general including high accuracy, multi-disease classification ability and good performance that was post-processing for mobile application for real time performance. Limitations include dataset completeness, size of the Vision Transformer, time of completion during training period, prediction interpretability, and limitations that were set by the researchers for field validation in the future.[16]

The study investigates mango leaf disease detection in India where manual detection is slow and error-prone. The study uses a Deep Transfer Learning Driven (DTLD) model using 4,000 RGB (red, green, blue) images (seven diseases + healthy). All 4,000 images were preprocessed by: resizing depending on the model being used, and preprocessing techniques were used for image augmentation. CNNs (Convolutional Neural Networks) that were pre-trained were fine-tuned. There were four models VGG16, DenseNet, MobileNet, and EfficientNetB2 which had the greatest accuracy at 99.84% several accuracy metric, which are practically grouped into several classes to measure precision, recall, and F1 scores. A few case study advantages would include the incredible accuracy of the model, potential for multi-disease classification, efficient training time, great generalization capabilities, and potential practical deployment. Case study limitations would include having a data dependant on a certain geographical region, hardware reliant on using research level hardware, having black box predictions, classifying data that could cause overfitting-related issues, and having definitive evidence of using a deep learning module with real-time data.[17]

The study uses CNNs and the Perceptual Pigeon Galvanized Optimization with image adjustment through Contrast Limited Adaptive Histogram Equalization, segmentation was done by region growing method, and features are extracted with Non-linear Discriminant Analysis. Analysis of the CNN parameters were optimized by the PPGO for the highest accuracy, efficency and generalizability. The model obtainedd 96 % accuracy , 92 % precision, 94 % recall, and 92% F1-score, compared to traditional CNN and VGGNET-19. The advantages are that the model yields high accuracy, classify leaf disease into multiple categories, more efficient training period than any empirical study, and a lowest on-sight detection stage based on millisecond ethod. The disadvantages are that a methodology that builds upon a specific dataset can not be generalized, it requires posimillion - dollar hardware, the paramaterization of the model is slightly sensitive, the models corrupencies illustrated its black-box nature by being repeatedly wrong in the context of the field, application of the model in-situ will require development.[18]

This is a study of mango leaf disease detection under real-world orchard conditions where human inspection can be slow and inconsistent. The Multi-Scale and Multi-Pooling Convolution Neural Networks, utilizes multi-scale feature extraction processes coupled with average and max pooling, and utilizes transfer learning, fine-tuning, and horizontal-flip augmentation to produce a more robust output. The MSMP-CNN network was trained using field images and demonstrated 98.5% accuracy that performed better than standard CNNs, VGG19, and ResNet50. Advantageous in performance and output include the high field-ready accuracy, robust multi-scale feature extraction and extraction processes, and generalization, while disadvantages include limited augmentations, problem (crop) specific validation, sensitivity to hyperparameterizations, and training dependent on GPU allocations.[19]

A fused convolutional neural network ConvNeXt and Vision Transformer architecture that could predict mango leaf diseases and mango fruit diseases using image classification techniques. The fused architecture used both local spatial feature recognization from ConvNeXt and broader context feature recognization from ViT by using the whole scene through the entire area. The images used in this experiment came from the MangoLeafBD dataset and SenMangoFruitDDS, both datasets were augmented, images were resized to be 224 × 224 pixel size, and loaded in batches into the model. The results showed 99.87% accuracy for mango leaf diseases and 98.40% accuracy for mango fruit diseases, and also precision recall, and F1-scores of over 98%. Three layers of data from both models were considered to build precision recall, and F1-scores providing optimal level of accuracy for images within the sets. External Evaluation was also performed, as the model was tested and evaluated using MLDID dataset provided 94.8% accuracy for generalization consistent with the classification metrics achieved for the two separate dataset tests. There are many advantages to the fused architecture, which include exceptional accuracy, ability to distinguish multiple diseases on multiple organs, runs locally on mobile devices, and will generalize for other different orchard conditions. There were also limitations identified with the fused architecture includes augmenting images at a basic level, crop-specific results, layer selections for transfer learning techniques for ViT and ConvNeXt, computationally demanding, and relevant to lists of diseases.[20]

III. SURVEY TABLE:

Table 1. Survey of Mango leaf Disease Classification and detection

Ref No	Disease Detected	Algorithm	Accuracy	Precision	Recall	F1-Score	Specificity	AUC-ROC	MCC	Year
[1]	Anthracnose	Multilayer CNN	97.13%	-	-	-	-	-	-	2019
[2]	Mango leaf diseases (unspecified multiple classes)	Feed-Forward NN + Metaheuristic Selection	~95%	-	-	-	-	-	-	2020
[3]	Multiple mango leaf diseases	Fully Resolution CNN	98.8%	-	-	-	94%	99%	-	2021
[4]	Mango leaf diseases (fungal + bacterial)	Custom CNN	95.5%	-	-	-	93%	99%	-	2021
[5]	Data Augmentation + Hyperparameter Optimization	CNN + MobileNet V2 + SVM	94.5%	99.81%	97.34%	97%	99.81%			2022
[6]	Anthracnose, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Healthy, Powdery Mildew, Sooty Mould	-	-	-	-	-	-	-	-	2023
[7]	Mango leaf diseases (8 classes)	Ensemble Stacked (ESDNN)	98.57%	98.85%	98.56%	98.55%	-	98.59%	-	2023
[8]	Seven prominent mango leaf diseases	LeafNet (CNN)	98.55%	99.50%	99.45%	99.47%	-	-	-	2023
[9]	Multiple mango leaf diseases	Hybrid Coyote-Grey Wolf Optimized NN	97.1%	97.57%	97.15%	96..47%	-	-	-	2023
[10]	General mango diseases	Case-based + Rule-based Reasoning	94.25%	90.83%	90%	89.94%	-	-	-	2023

[11]	Anthracnose, Bacterial Canker, Die Back, Powdery Mildew, Healthy	Hybrid CNN + HOG with SVM & Random Forest	99.5% (Test), 98.8% (Train)	98%	98%	98%	-	-	-	2023
[12]	South Indian mango leaf diseases	Deep CNN	98%	-	-	-	-	-	-	2023
[13]	Mango leaf diseases (unspecified multiple)	Modified Dense CNN	99.56%	99.32%	99.23%	99.38%	-	-	-	2024
[14]	Mango diseases (8 classes)	Transfer Learning (ResNet, DenseNet, InceptionV3)	99.87%	99.87%	99.81%	99.83%			-	2024
[15]	Downey mildew, Powdery mildew, Blossom blight, Whitemango scale insect, Healthy leaves,	Ensemble CNN (GoogLeNet +VGG16)	99.21%	97%	97%	97%	97%	-	-	2024
[16]	7 mango leaf diseases + Healthy	Vision Transformer (DeiT, Swin)	99.75%	99.75%	99.74%	99.75%	-	-	99.72%	2024
[17]	Anthracnose, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Healthy, Powdery Mildew, Sooty Mould	Transfer Learning (InceptionV3 ,MobileNetV2,DenseNet121, etc.)	99.76%	99.82%	99.87%	99.85%	-	-	-	2024
[18]	Anthracnose, Bacterial black spot, Sooty mold, Healthy	CNN optimized with PPGO	96%	92%	94%	92%	-	-	-	2024
[19]	Multiple mango leaf diseases	MSMP-CNN + Transfer Learning	98.5%	-	-	-	-	-	-	2024
[20]	Mango leaf diseases (multiple)	Fused Vision Transformer + ConvNeXt	98.87%	99.5%	99.5%	99.5%	-	-	-	2025

The **Table 1.** It provides the overall survey of the existing models with metrics.

Table 2. Comparison Analysis of Existing Models for Leaf Disease Classification

S.No	Ref No	Preprocessing Technique	Segmentation Technique	Algorithm Used	Accuracy
1.	[4]	Vein pattern extraction, preprocessing with filters	Novel vein pattern segmentation	Custom CNN	85.75%
2.	[7]	Augmentation (rotation, scaling, noise)	HSV Color Thresholding	Ensemble Stacked DNN (ESDNN)	86.75%
3.	[8]	Data augmentation (Rotating, Flipping)	None	LeafNet(CNN)	88.01%
4.	[13]	Data augmentation	None	Modified Dense CNN	86.38%
5.	[15]	Augmentation (Flipping, Rotation, Scaling, Gaussian Noise)	K-Means Clustering, Mask R-CNN	Ensemble CNN (GoogleNet VGG16)	85.25%
6.	-	CLAHE, Resize, Normalization.	HSV Color Thresholding	Proposed method	97.5%

Table 2. Shows the comparison of analysis for preprocessing, segmentation and classification approaches for existing methods, highlighting the model performance based on the accuracy.

IV. PROCEDURES FOR PROPOSED METHOD WITH AN ALGORITHM

A. IMAGE ACQUISITION

The dataset includes 4,000 samples of mango leaves collected in four orchards across Bangladesh. It is captured by utilizing mobile phone cameras and natural lighting. The dataset has 8 classes of 7 diseased leaf Anthracnose, Cutting Weevil, Powdery Mildew, Bacterial Canker, Die Back, Gall Midge, and Sooty mould and healthy leaves. Data samples are stored in JPG format in original resolution of 240×320.

B. IMAGE PREPROCESSING

The preprocessing is to make input mango leaf images to be suited for the feature extraction. The images are resized to the equal resolutions for each images. The normalized pixel values are fixed to a range to allow it for stable learning. Noise reduction techniques were applied, and the contrast was adjusted to make diseased patterns, spots, lesion surfaces, and color variations more visible.

C. DATASET SPLITTING

Model performance is evaluated using the dataset, data samples were divided into train-test sets. About 80% are trained data, around 20% for the test data. The training data generator has given to separate 20% of the training data to internally to validate the model. Indicating the model design is trained and validated before being tested on images it has never seen. This process make sure the classification outcomes and reduce the overfitting.

D. DISEASE DETECTION

The proposed method has the deep feature extraction for the disease detection. There are three pretrained models, EfficientNetB0, ResNet50, and DenseNet121 to extract high-level feature vectors from each mango leaf image. Pretrained models have been trained on large denormalized dataset of images and produced a good feature representation. The features extracted shows texture segments, spotted patterns and visual cues related to the diseased mango leaf.

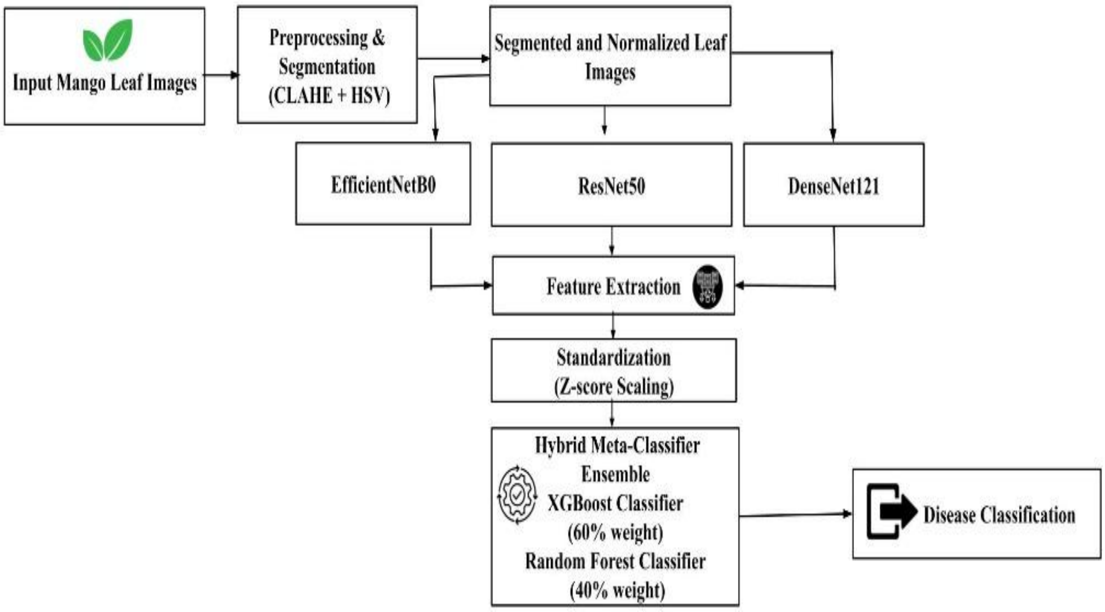

Figure 2. Proposed model Architecture

The **Figure 2**. explains the full workflow of proposed mango leaf disease classification system. Input leaf images undergo preprocessing and segmentation using CLAHE and HSV-based color masking to enhance disease-relevant regions. The segmented images are forwarded to three pretrained CNN models - EfficientNetB0, ResNet50, and DenseNet121, for deep feature extraction. Extracted features are concatenated and standardized using Z-score normalization. A hybrid ensemble meta-classifier combining XGBoost (60% weight) and Random Forest (40% weight) generates the final disease prediction.

E. IMAGE-SEGMENTATION

Segmentation can extract leaf area away from the background to ensure the designed model is suitable to the area with the disease symptom. Thresholding and structural operations are conducted to remove pixels that represent the background from the analysis. Isolating the leaf area reduces noise from the background, extraction of features improves the accuracy. This step is significant when working with images that may vary in illumination, shadow-component and background objects that may cause interferences while detecting specific symptoms.

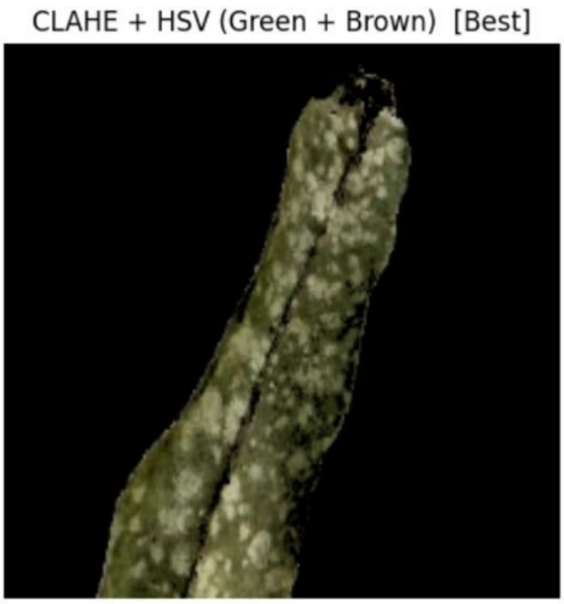

Figure 3. Segmented leaf using CLAHE + HSV

The **Figure 3**. The contrast of the leaf is enhanced using CLAHE and HSV color thresholding, it helps to clearly highlight the diseased area regions on the leaf.

F. CLASSIFICATION

Finally, the image of the segmented and processed leaf is denoted as either healthy or classified into one of the seven disease categories, based on the evaluation of the learned patterns from the training dataset. A deep learning classifier uses a complete set of the extracted features and evaluates the features with the learned healthy versus infected dataset images, at varying levels of affinity. The classifier assigns the leaf to the correct disease label of the appropriate disease class, with the knowledge that the segmented leaf image has exhibited symptoms of a disease. The system not only identifies that plant has a disease recognized as a symptom, but also identifies the specific diagnosed disease class that the leaf is classified. The result will display the labeled diseased categories.

ALGORITHM 1

Input: Training images (Train), Testing images (Test)
Output: Predicted leaf disease class labels and evaluation metrics
1. Load dataset and encode labels
2. For each image:
    a. Apply LAB-CLAHE contrast enhancement
    b. Convert to HSV and create green mask
    c. Segment leaf region and normalize
3. Generate image batches with segmented leaves and one-hot labels
4. For each CNN backbone (EffNetB0, ResNet50, DenseNet121):
    a. Remove top layers, apply GAP
    b. Add Dense(256) + Softmax layers
    c. Compile model with Adam optimizer
    d. Train model with early stopping and LR reduction
5. Extract features from all CNN models for all images
6. Concatenate CNN features into a single feature vector
7. Standardize features using StandardScaler
8. Train meta-classifier:
    a. XGBoost (60% weight)
    b. Random Forest (40% weight)
9. Predict test images using the weighted combination
10. Evaluate metrics: Accuracy, Precision, Recall, F1, Specificity, Sensitivity, MCC, AUC
11. Generate confusion matrix and per-class accuracy
12. Visualize training curves, segmented leaves, and Grad-CAM heatmaps

FLOW DIAGRAM – PROPOSED METHOD

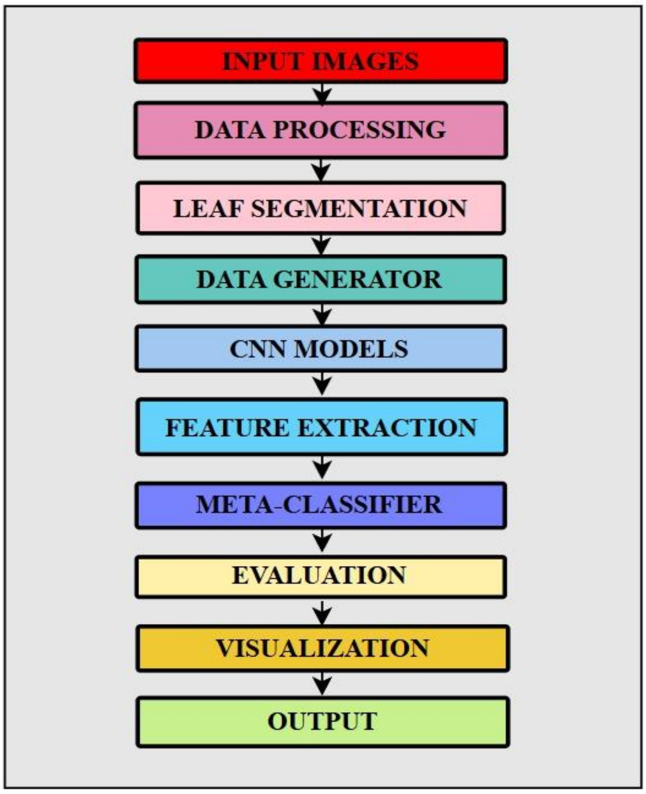

Figure 4. Proposed model framework flowchart

The **Figure 4**. The process begins with image acquisition and preprocessing (CLAHE + HSV), followed by feature extraction using deep learning models (EfficientNetB0, ResNet50, DenseNet121). The features are extracted then fused and passed to a hybrid meta-classifier (XGBoost and Random Forest) to accurately predict the disease category.

V. IMPLEMENTATION

Proposed method starts with the dataset collection, image pre-processing, and segmentation. The model is designed with the algorithm and trained. Hybrid classification is used for the prediction. The model utilized the deep learning for classification and machine learning for improved prediction. Then final prototype testing is done using this model.

A. EXPERIMENTAL SETUP

The mango leaf disease classification model is done using Python 3.10 and utilized TensorFlow, Keras for deep learning, OpenCV for image processing, NumPy handles numerical operations, Pandas for manipulation of data, Matplotlib for visualization, scikit-learn for preprocessing and evaluation. XGBoost, random forest and Seaborn incorporated for analysis. Experiments utilized with Windows 11 laptop with an Intel i5 processor with 16GB of RAM, NVIDIA GPU. This combination was preferable for more efficient training time and capabilities of utilizing features generated by convolutional neural networks and with the random seed fixed for reproducibility while the GPU function was utilized for enhanced training time.

B. DATASET DESCRIPTION

The dataset includes 4,000 data samples of mango leaves gathered at four orchards across Bangladesh. There are images for the seven major diseases anthracnose, bacterial canker, cutting weevil, dieback, gall midge, powdery mildew, and sooty mould, in addition to healthy leaves. It has 8 of total 500 images for each class. Approximately 1800 unique images of leaves were altered by rotation and zooming to provide variance into the dataset. All images are JPG format with the same 240× 320 pixel resolution, and are usable for multi-class disease classification and binary classification.

Table 3. Distribution of sample image data sets

S.No	Categories	Total Images
1.	Anthracnose	500
2.	Bacterial canker	500
3.	Cutting weevil	500
4.	Dieback	500
5.	Gall midge	500
6.	Powdery mildew	500
7.	Sooty mould	500
8.	Healthy	500

Table 3. Shows the categories of disease with sample data size representing to each class.

C. DATA PREPROCESSING AND LEAF SEGMENTATION

All leaf images were pre-processed and segmented in order to retain the leaf related features and minimize the background noise. Contrast in the LAB color space of each leaf was increased using CLAHE. The region of leaf with brown color and areas with green color were then identified and segmented in the green color thresholding area through the use of HSV color thresholding, creating a segmented area on the image. Once an image was segmented, then adjusting to 224 x 224 pixels sizes then it gets normalized. The pre-processed images and their corresponding one-hot encoded labels were input into a CNN as a custom generator in Python, as a batch.

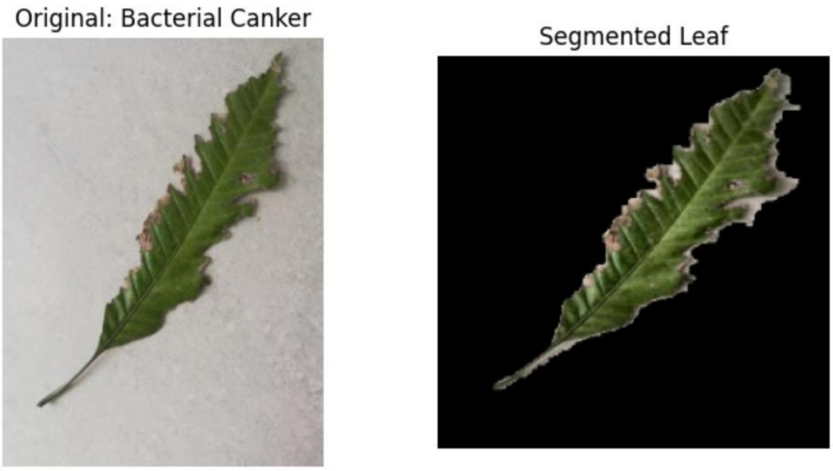

Figure 5. Leaf Segmentation using CLAHE and HSV color thresholding.

The **Figure 5**. shows the original and segmented leaf of bacterial canker by applying CLAHE and HSV color threshold.

D.MODEL ARCHITCTURE

Three pre-trained CNN architectures were used EfficientNetB0, ResNet50, DenseNet121 using transfer learning. Each architecture had top layers removed and the features were converted then lead to global average pooling that was a input to a fully connected Dense layer. Each of the models was fitted as a 256-neuron Dense layer with optimizer ReLU lead by a softmax layer of 8 neurons related to the classes. All models were compiled with categorical cross-entropy loss and with the optimizer Adam to assist in validation for the mango leaf dataset.

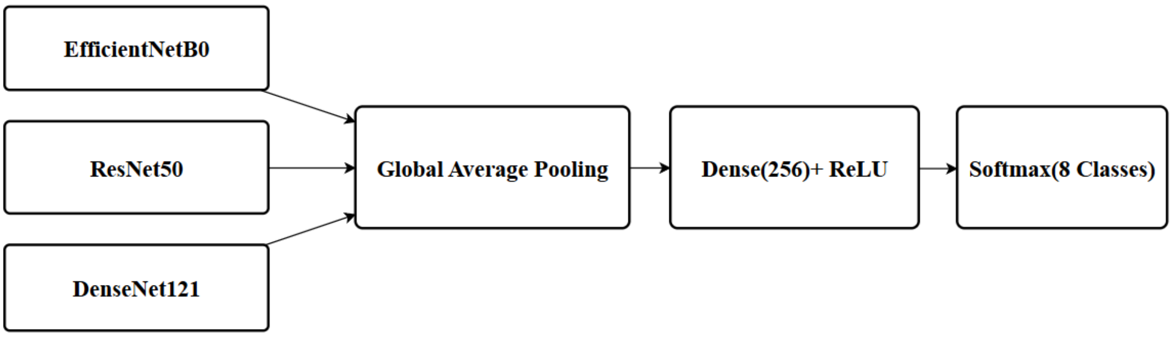

Figure 6. CNN-based transfer learning architecture

The **Figure 6.** architecture uses three pretrained CNN models (EfficientNetB0, ResNet50, DenseNet121) for extraction of feature. The features are extracted then combined through Global Average Pooling and fed into a fully connected layer with ReLU activation, led by Softmax layer to classify images into eight diseases.

E. MODEL TRAINING

The CNN models were learned with 15 epochs set to a batch size of 16. To minimize overfitting adjust the update rate during training, prior stopping and ReduceLROnPlateau callbacks are implemented based on progress metrics. The custom generator allowed loading pre-processed images and provided for the augmentation of images being processed. Each model was trained independently to get meaningful deep features from the leaves that is later used by hybrid classification.

```
Training EffNetB0...
Epoch 1/15
204/204 ━━━━━━━━━━━━━━━━━━━━ 43s 214ms/step - accuracy: 0.9496 - loss: 0.1557 - val_accuracy: 0.1219 - val_loss: 9.0610 - learning_rate: 0.0010
Epoch 2/15
204/204 ━━━━━━━━━━━━━━━━━━━━ 81s 400ms/step - accuracy: 0.9659 - loss: 0.1168 - val_accuracy: 0.1366 - val_loss: 1263.2478 - learning_rate: 0.0010
Epoch 3/15
204/204 ━━━━━━━━━━━━━━━━━━━━ 42s 207ms/step - accuracy: 0.9743 - loss: 0.0805 - val_accuracy: 0.1526 - val_loss: 71.6697 - learning_rate: 0.0010
Training ResNet50...
Epoch 1/15
204/204 ━━━━━━━━━━━━━━━━━━━━ 128s 292ms/step - accuracy: 0.6941 - loss: 1.0375 - val_accuracy: 0.1149 - val_loss: 11.9047 - learning_rate: 0.0010
Epoch 2/15
204/204 ━━━━━━━━━━━━━━━━━━━━ 55s 270ms/step - accuracy: 0.8633 - loss: 0.4170 - val_accuracy: 0.1201 - val_loss: 19.1125 - learning_rate: 0.0010
Epoch 3/15
204/204 ━━━━━━━━━━━━━━━━━━━━ 56s 276ms/step - accuracy: 0.9361 - loss: 0.2191 - val_accuracy: 0.1271 - val_loss: 6.1022 - learning_rate: 0.0010
Training DenseNet121...
Epoch 1/15
204/204 ━━━━━━━━━━━━━━━━━━━━ 232s 316ms/step - accuracy: 0.7615 - loss: 0.7431 - val_accuracy: 0.6259 - val_loss: 1.5420 - learning_rate: 0.0010
Epoch 2/15
204/204 ━━━━━━━━━━━━━━━━━━━━ 54s 265ms/step - accuracy: 0.9147 - loss: 0.2465 - val_accuracy: 0.8490 - val_loss: 0.6211 - learning_rate: 0.0010
Epoch 3/15
204/204 ━━━━━━━━━━━━━━━━━━━━ 56s 276ms/step - accuracy: 0.9468 - loss: 0.1664 - val_accuracy: 0.9219 - val_loss: 0.2523 - learning_rate: 0.0010
```

Figure 7. Training performance across 15 epochs for the pre-trained CNN models.

The **Figure 7**. Shows each CNN model (EfficientNetB0, ResNet50, DenseNet121) was trained individually with 15 epochs set to a batch size of 16, with prior stopping and ReduceLROnPlateau to minimize overfitting.

F. FEATURE EXTRACTION WITH META CLASSIFIER

After completion of the CNN model is done,the features extracted from three models and concatenated the features into a single feature representation for each image. Then applied the StandardScaler method to standardise the feature vectors and fit the standardised feature vectors in the meta-classifiers, XGBoost and Random Forest classifiers. The outputs of these meta-classifiers included a weighted probability, and took the probabilities for the final classification improving the accuracy of the prediction.

G. PROTOTYPE PREDICTION

New mango leaf images are tested using the prototype system that preprocess the image and the image is given to CNN models to capture the features of the data samples then those featured part are given to the meta-classifier for the final prediction. Predicting the classification by the Grad-CAM visualizations to spotlight regions of the leaf for the inference of the model.

VI. RESULT AND DISCUSSION

Performance comparison among CNN architectures, hybrid classifier using features the model were analyzed. Improvements in mango leaf disease classification accuracy is supported by full pipeline from preprocessing and segmentation to classification. Evaluation compared the deep models for extracting diseases and evaluating the hybrid meta-classifier for detection. Grad-CAM visualizations depends on the relevant features for visualizing the diseased parts in the leaf. Combinations of preprocessing, deep feature extraction, and hybrid meta-classification given successful method for detection.

A. MODEL TRAINING AND VALIDATION PERFORMANCE PHASE

The training curves and validation curves on EfficientNetB0, ResNet50, and DenseNet121.The DenseNet121 has the highest validation accuracy with stable convergence and the ResNet50, EfficientNetB0 has slight fluctuations. The validation loss decreased steadily for all the models indicating the models are successfully learning the features representing processed mango leaf images.

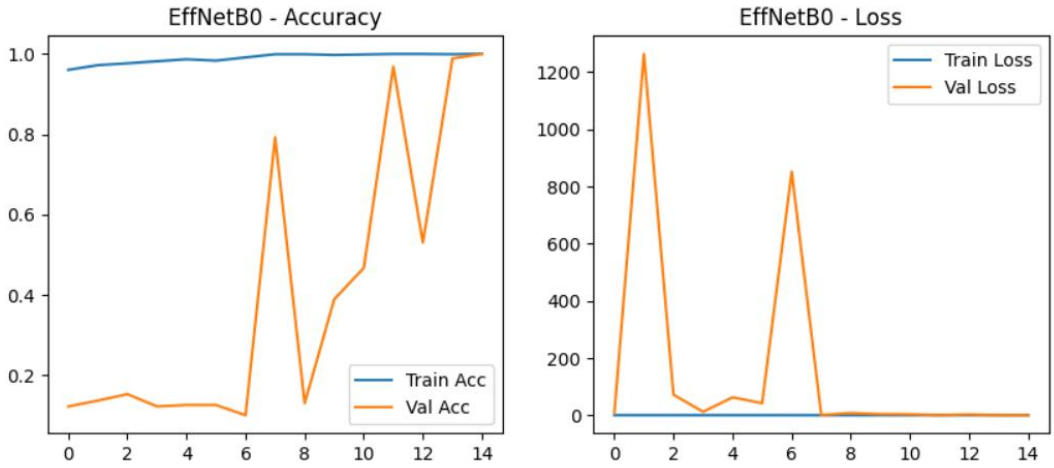

Figure 8. EffNetB0- Accuracy and loss graph

The **Figure 8.** Represents Training and validation performance curves of EfficientNetB0. The figure on the left displays represents the model accuracy obtained in training and validation during 15 epochs indicating continuity of learning, the figure on the right shows the loss curves corresponding to those accuracy rates indicating convergence and stability.

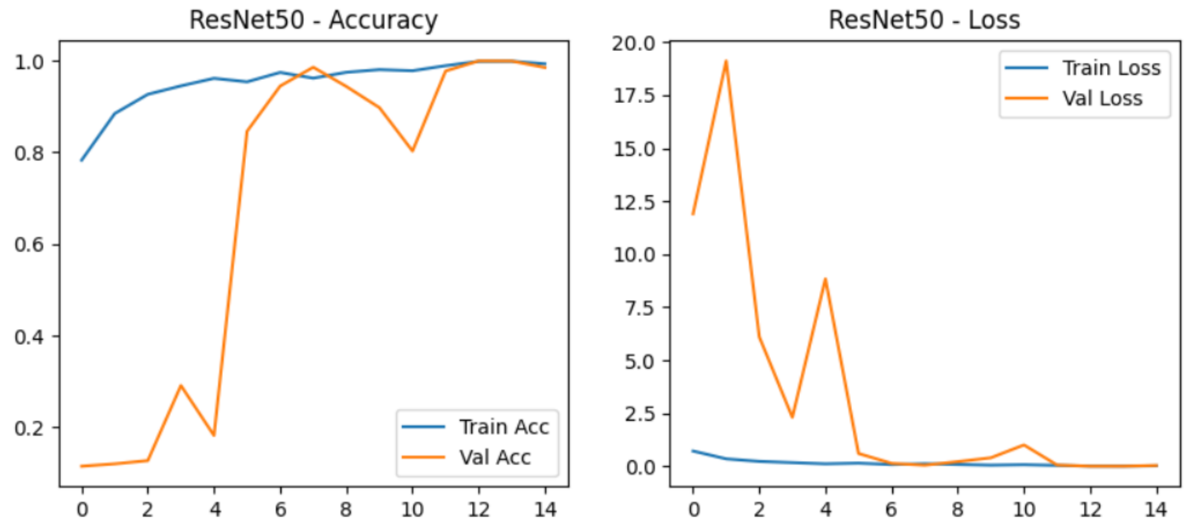

Figure 9. ResNet50 - Accuracy and loss graph

The **Figure 9.** Displays accuracy and loss curves for ResNet50. The accuracy plot shows how well the model learns to classify mango leaf diseases and loss plot displays reduction in error during training.

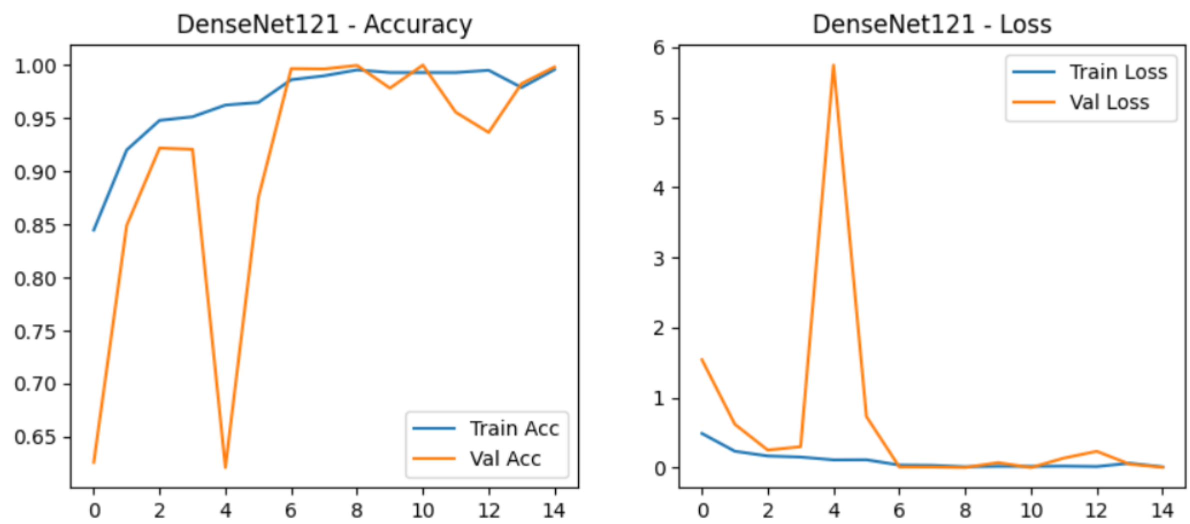

Figure 10. DenseNet50 - Accuracy and loss graph

The **Figure 10.** Represents accuracy and loss curves for DenseNet121. The accuracy plot shows how well the model learns to classify mango leaf diseases and the loss plot displays reduction in error during training.

B. CLASSIFICATION PERFORMANCE

The hybrid meta-classifier used the generated features from CNN. The XGBoost and Random Forest had the best accuracy. Confusion matrix showed the most classes were correctly predicted. The model may have confused other diseases with each other based on surface similarities like Anthracnose and Powdery Mildew. Classification accuracy also showed a good gain with the hybrid meta-classifier.

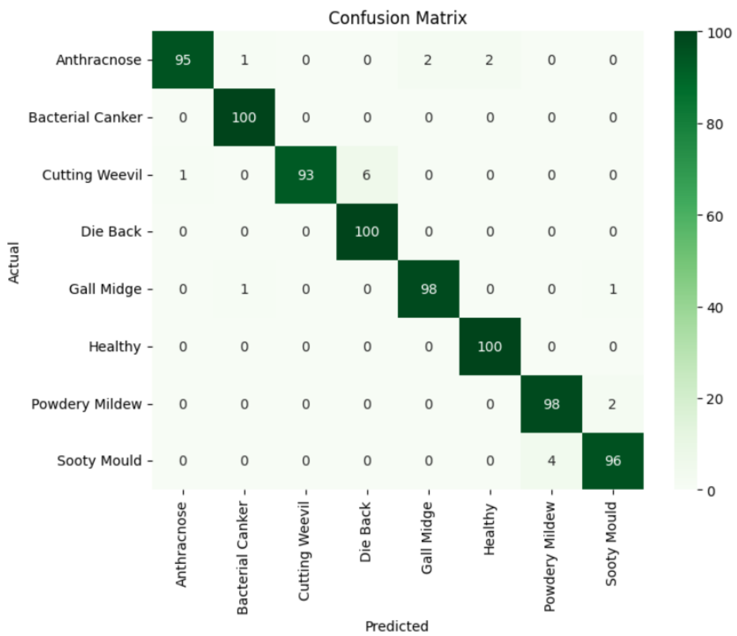

Figure 11. Confusion Matrix of hybrid meta- classifier predictions

The **Figure 11.**It illustrates performance of the combined XGBoost and Random Forest classifier on the test set using confusion matrix. It shows correctly and incorrectly predicted instances for each of the 8 classes, covering healthy and seven disease categories.

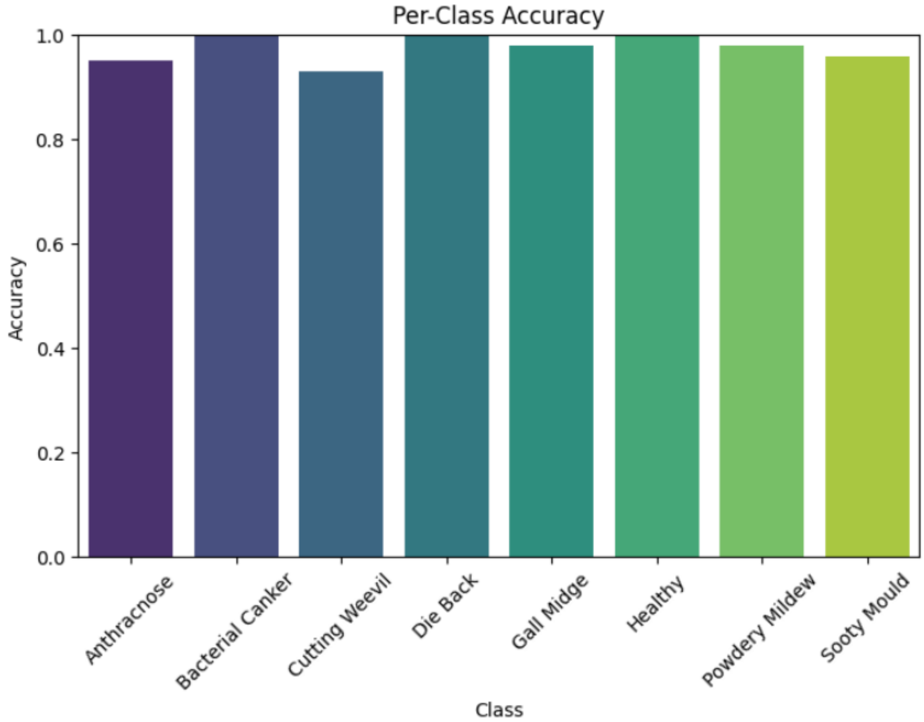

Figure 12. Per Class Accuracy comparison

Figure 12. Accuracy of the per-class mango leaf disease comparison. This bar chart shows the accuracy for each class also highlights between diseased and the healthy leaves.

C. LEAF REGION VISUALIZATION (GRAD-CAM)

The Grad-CAM heatmaps show the model framework concentrates on abnormal regions in the image, like lesions and various discolored areas, which indicates interpretability of the model. It shows that the model learns to concentrates on certain peculiar features of substrate while neglecting uninformative parts of the background, which is helpful because the model will be clinically useful for detecting actual diseases.

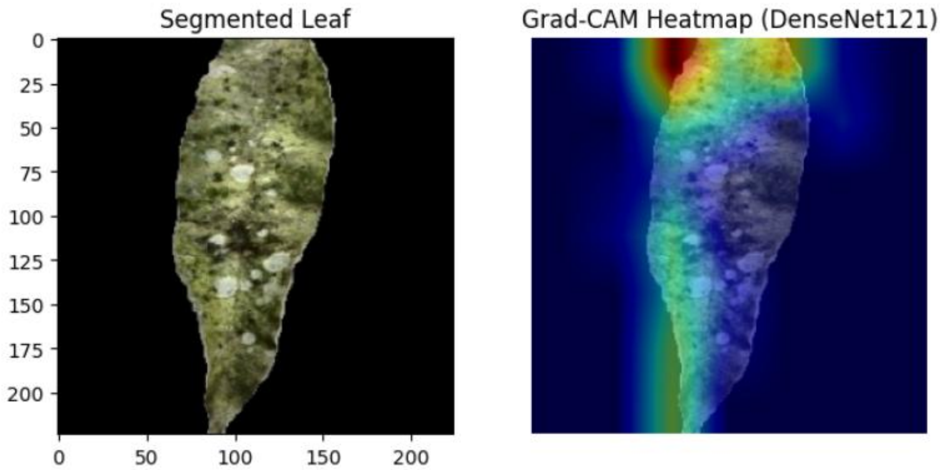

Figure 13. Grad CAM Heatmap for mango leaf disease

The **Figure 13.** It illustrates Grad-CAM heatmap was applied to a mango leaf image indicating where the DenseNet121 model focused when predicting disease. Bright color areas indicate greater attention by the model, indicating to users how the model is interpreting the leaf's diseased regions.

D. PERFORMANCE METRICS AND EVALUATION

The trained model was tested across different performance metrics to check how well it can detect and classify mango leaf diseases. These metrics help to determine accuracy , stability of model's outputs.

```
--- 7 METRICS ---
Accuracy:       0.9750
Precision:      0.9755
Recall:         0.9750
F1 Score:       0.9749
Specificity:    0.9964
Sensitivity:    0.9750
MCC:            0.9715
AUC (macro):    0.9996
```

Figure 14. Performance Metrics of proposed method

The **Figure 14.** It Shows the model prediction based on the proposed algorithm. By considering metrics, analyzing the model performance becomes easier.

E. OVERALL DISCUSSION

DenseNet121 attained the higher performance among the baseline models. Hybrid meta-classifier improved the accuracy. The use of CLAHE with HSV segmentation improved leaf features. The misclassifications are reduced, when detecting the diseases appear visually close in the analysis. The pipeline shows the high reliability. It also provides a practical use in timely detection of mango leaf diseases in natural growth environments.

COMPARATIVE STUDY WITH THE BENCHMARK TECHNIQUE OF EXISTING AND PROPOSED METHOD FOR MANGO LEAF

Table 4. Comparative Study of Existing and Proposed method

The **Table 4.** Shows the comparative study of both proposed and existing model performance along with the metrics.

S.No	Algorithm Used	Accuracy	Precision	Recall	F1 Score	Sensitivity
1.	Custom CNN	85.75%	86.27%	86.75%	85.72%	86.75%
2.	Ensemble Stacked DNN (ESDNN)	86.75%	87.62%	86.75%	86.29%	86.75%
3.	LeafNet(CNN)	88.01%	88.54%	87.89%	88.08%	87.89%
4.	Modified Dense CNN	86.38%	86.86%	86.38%	86.01%	86.38%
5.	Ensemble CNN (GoogleNet VGG16)	85.25%	85.65%	85.25%	84.98%	12.18%
6.	Proposed method	97.5%	97.55%	97.50%	97.49%	97.50%

VII. CONCLUSION AND FUTURE WORK

Identification of mango leaf disease detection and classification using a combination of pretrained CNN models DenseNet121, ResNet50, EfficientNetB0 and a hybrid meta-classifier XGBoost and Random Forest. This proposed approach contains preprocessing, leaf segmentation, and feature extraction to improve the model performance.

It gives an effective way to understand the identification of mango leaf diseases. Contrast improvement, colour based leaf segmentation and the hybrid deep learning, it is able to focus on the important parts of the leaves on the diseased regions and reduces unnecessary backgrounds.Preprocessing methods CLAHE and HSV segmentation combined with transfer learning models is included in the pipeline so the disease symptoms are clearly visible. This reduced the noise and then to classify the disease type is improved. The hybrid meta-classifier XGBoost and Random Forest produced good results from the deep features obtained from many CNNs. This took deep patterns and decision level variances, resulting in increased accuracy and generalizability across all diseases. The DenseNet121 model had higher accuracy than ResNet50 and EfficientNetB0. DenseNet121 allows for feature reuse and gradient flow. Grad-CAM visualizations shows model is focused on the disease regions and identified the diseased spots, edges, and textures regions, this reliability makes the decision suitable for real-world.

Proposed system can be increased with more datasets to improve generalization across different mango leaf varieties and the environmental conditions. Integration of real-time mobile applications for the leaf disease diagnosis can make useful for farmers. Advanced augmentation techniques and lightweight CNN architectures, ensemble deep learning models improves the classification accuracy and reduces the computational need.

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