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Synergistic Use of Convolutional Neural Networks and Support Vector Machines for Mango Leaf Disease Diagnosis

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ABSTRACT

Even in the age of digitalisation and capitalism, agriculture still plays a significant role in many economies, such as in certain Asian countries where mangoes have become an important export commodity. However, plant diseases put serious constraints on both productivity and quality. Existing methods for identifying disease typically rely on the experience of farmers and are time-consuming and error-prone. In this study, we propose a new hybrid framework consisting of a custom Convolutional Neural Network (CNN) and a Support Vector Machine (SVM) classifier to classify eight mango leaf conditions: Anthracnose, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Powdery Mildew, Healthy, and Sooty Mould. The model uses a dataset of 4000 images collected from mango orchards throughout Bangladesh and incorporates rigorous pre-processing and data augmentation to help improve model robustness and generalisability. The results indicate that the hybrid CNN-SVM model performs best, outperforming state-of-the-art models with an accuracy of 99.75%. The research thus emphasises the role of deep learning and machine learning in enabling more accurate disease detection in agriculture, benefitting farms and the environment via sustainable practices and higher crop yields.

KEYWORDS
Classification, custom CNN model, deep learning, disease detection, feature extraction, machine learning

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1. Introduction

Agriculture is a central part of the economy for many states; therefore, the well-being of plants is vital for high-performance production. Despite advancements, the agricultural sector continues to face challenges due to various diseases affecting plants, as well as pests and weeds, resulting in significant losses (Nayef and Al-Barhawee, 2025). This is particularly true for mangoes, which are significant for several Asian nations that cultivate and transport large quantities of them (Gautam and Rani, 2022). Mango trees have known diseases such as anthracnose, bacterial canker, leaf-cutting weevils, dieback, gall midges, powdery mildew, and sooty mould that reduce productivity, as well as the quality of the fruit. Given that mangoes are a vital product for many regions, particularly India, which contributes over 40% of global production (Rao *et al.*, 2021), it is imperative that farmers adopt sustainable agricultural practices to enhance both the quantity and quality of the fruits they produce. In the past, the identification of diseases in plants was done by examining the plants through the eyes of a qualified farmer, which is very slow, ineffective for screening large amounts of plants, and may involve some level of error. Additionally, damage caused by incorrect disease identification and pesticide misuse reduces soil fertility and harms the natural environment. Existing research has demonstrated the effectiveness of image recognition in the detection of plant diseases in apples, maize (Nishat and Faisal, 2018; Ullagaddi and Raju, 2017), and other healthy and diseased crops (Parashar *et al.*, 2023). Successful outcomes have been observed in the evaluation of diagnoses in mango leaves through the application of automatic image detection and feature extraction (Salma *et al.*, 2024). In this context, the world needs to adopt several measures, including accurate and automated methods for detecting diseases. New trends such as computer vision, machine learning (Kaur *et al.*, 2023), and deep learning (Jain and Jaidka, 2023) present the possibility of establishing efficient tools for the identification of diseases that affect plant life. Additionally, convolutional neural networks are known to achieve high accuracy in image recognition, which makes them fit for use in disease detection on plant leaves through assessing visual characteristics.

Gautam *et al.* (2023) proposed a layered assembling DL model using a traditional ML framework for categorising mango leaf diseases across eight distinct classes. This article demonstrated superior performance matrix outcomes compared with state-of-the-art (SOTA) DL and ML techniques. In an associated research article, Prabu and Chelliah (2022) proposed a CROLFD algorithm for classifying mango leaf diseases using a custom dataset collected from Andhra Pradesh that includes four different datasets. Their algorithm outperformed the existing approach, accomplishing efficient extraction with optimal outcomes. For agricultural precision, Rao *et al.* (2021) presented a distinct algorithm for the classification of mango leaf disease using a DL model. They used the pre-trained DL model AlexNet and achieved satisfactory classification accuracies for grape and mango leaves of 99% and 89.89%, respectively. The authors stated the following: 'This research demonstrates how even cutting-edge computer models can be combined with agriculture and used to solve problems with food production and quality control.' Saleem *et al.* (2021) introduced a novel approach by considering the vein pattern, canonical correlation analysis, and a cubic support vector machine for the detection and classification of mango leaf diseases. The approach achieved a 95.5% accuracy for a self-collected dataset from the various regions of Pakistan. Pratap and Kumar (2024) demonstrated a combination of an advanced DL model, YOLOv8, with African buffalo optimisation, achieving an impressive classification accuracy of 94.5% for detecting and classifying mango leaf diseases. These advances highlight enhanced disease management in agriculture. Pham *et al.*, (2020) employed wrapper-based feature extraction with adaptive particle-grey wolf optimisation (APGWO) and a multiple-layer perceptron (MLP). They highlighted the usefulness of an artificial neural network (ANN) over CNNs like AlexNet, VGG16, and ResNet-50 for the accurate classification of mango leaf disease, demonstrating an accuracy of 89.41%. Mathur *et al.*, (2024) proposed novel research with the aim of classifying disease in mango leaves. The methodology highlights the robustness and accuracy that can be achieved through suitable pre-processing and the critical fine-tuning of pre-trained models, including the Inception V3 model, the

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MobileNet V3 (small and large) models, and ResNet50. This unprecedented accuracy for an early-stage model, validated by k-fold cross-validation in the study, highlights its promise for large-scale field deployment in agriculture; it could serve as a major push in developing new protocols for accurate disease detection, which are essential to ensuring sustainable growth and maximized crop yields. Mohapatra *et al.* (2022) proposed a new algorithm that exploits texture, colour, and pixel-based features extracted from segmented images. The Cat Swarm and Black Widow Optimizer Algorithm (CSUBWO) showed better accuracy (91.2%) when pre-trained models were fine-tuned. This development is set to help mango growers achieve better detection of mango leaf diseases, and the improvement within the feature extraction and optimisation technique can catalyse the improvement of disease detection in agricultural environments. Designed for automated plant disease diagnosis and introduced by Ahmed *et al.* (2023), LeafNet is a customised DL CNN model that recognises seven types of mango leaf diseases for developing countries like Bangladesh. Using 4000 manually classified images as the dataset, LeafNet achieves a record average accuracy of 98.55% over other SOTA models and, at the same time, has less computational complexity. With a portable, lightweight design that enables the sensor to be integrated with smartphones, the device is accessible to farmers, and further improvement and optimisation can be made for more accuracy and efficiency in plant disease diagnosis.

Adopting transfer learning approaches, Rajbongshi *et al.* (2021) applied various CNN models, namely DenseNet201, InceptionResNetV2, and Xception. The DenseNet201 model resulted in a 98% accuracy rate. According to this study, the CNN is more effective at classifying mango leaf diseases, which could have substantial effects on agricultural techniques. The aim of the proposed work is to expand the scope to include additional diseases and address the flaws of the existing approaches, which could improve the accuracy of disease classification.

Recent advancements in computer vision in ML (Mia *et al.*, 2020) and DL (Jain and Jaidka, 2023) have demonstrated significant potential in automated plant disease detection. Several studies that applied DL models targeting mango leaf diseases employed pre-trained DL models like AlexNet (Rao *et al.*, 2021), YOLOv8 (Hossain *et al.*, 2024), and DenseNet201 (Rajbongshi *et al.*, 2021), as well as hybrid approaches integrating feature extraction algorithms (Saleem *et al.*, 2021; Pham *et al.*, 2020; Mohapatra *et al.*, 2022). However, existing techniques still face the following challenges:

- Many images in existing datasets suffer from blurriness, low resolution, and poor quality, which can inhibit accurate feature extraction.
- Extracting detailed features from images taken from far away can be challenging.
- The low contrast between the leaf colour and background elements can reduce the ability to classify different types of mango leaf disease.
- The structural characteristics of different mango leaf diseases may overlap, making classification challenging, especially when symptoms appear similar.
- Images in existing datasets have various resolutions and dimensions, requiring additional pre-processing to standardise input sizes for DL models.
- Most existing models can accurately classify only a few common diseases, but we need a more comprehensive classification of mango leaf diseases.

Traditional detection is not as efficient because it requires more time, and also, the farmer might fail to notice some disease symptoms, failing to address the disease in time. In this research, we focus on developing an efficient hybrid model that combines a custom CNN and a support vector machine (SVM) classifier to classify eight classes of mango leaf conditions, which include plant pests and diseases: anthracnose, bacterial canker, leaf-cutting weevils, dieback, gall midges, powdery mildew, healthy, and sooty mould. The dataset consists of 4000 images from various areas, and it was augmented with additional data to diversify the trained model. Altogether, our suggested framework has the potential to help farmers utilise a reliable method for early disease identification and facilitate the timely management of diseases so that significant crop yield losses will not be incurred. The proposed model has been optimised to maximise the benefits of CNNs and SVMs while also ensuring that it is not too complex to run in a short amount of time, requires as few resources as possible, and still achieves acceptable accuracy in the classification of disease. Not only does this framework facilitate the conservation of agricultural land and environmentally friendly farming practices, but also it helps the economy of areas that are entirely reliant on mango cultivation. Several challenges, including high computational complexity, overfitting, higher process times, restricted feature variables, poor feature quality, inferior segmentation results, and larger feature dimensionality, lead to the erroneous identification of mango leaf diseases.

To address these challenges, this study proposes a hybrid approach combining a custom CNN with an SVM classifier for classifying mango leaf diseases. The key findings of our work are as follows:

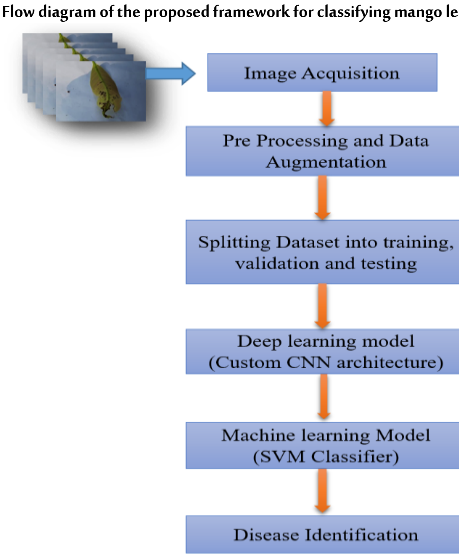
- Various image augmentation techniques are applied to resize input images of different sizes to 256 × 256 pixels to enhance dataset diversity and robustness.
- A unique DL model for the detection of mango leaf disease is designed.
- DL and ML algorithms are integrated to create an effective approach for predicting more than four mango leaf diseases.
- The proposed method demonstrates superior performance in terms of evaluation metrics such as the average accuracy, precision, recall, F1-score, and specificity.

We have structured this study as follows: Section 1 presents the introduction and a review of previous studies that used ML and DL techniques to detect plant diseases. Section 2 provides a description of the proposed work and a detailed discussion of the dataset and pre-processing techniques. Section 3 explains the structure of the hybrid model, including the customised architecture of the CNN and its integration with the SVM classifier. Section 4 contains experimentation and performance measures for the proposed work. Lastly, Section 5 summarises the study and suggests possible future research.

2. Proposed Work

The proposed work presents a classification of mango leaf diseases using an integrated custom CNN architecture with an SVM classifier. This model consists of a CNN that extracts fine-grained features from leaf images, followed by an SVM for classification. The model predicts eight classes of leaf conditions: anthracnose, bacterial canker, leaf-cutting weevils, dieback, gall midges, powdery mildew, healthy, and sooty mould. The flow diagram of the proposed work is illustrated in Figure 1.

Figure 1: Flow diagram of the proposed framework for classifying mango leaf diseases

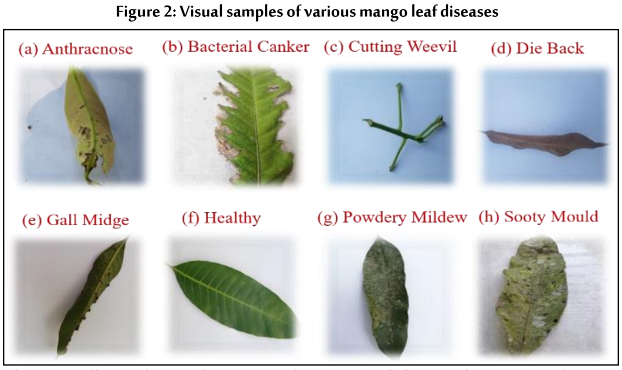


2.1. Dataset:

The images adopted in the present investigation were obtained from MangoleafDB, and each image in the studied cohort was collected from mango trees propagated mainly in Bangladesh. It includes eight distinct classes. One healthy mango leaf is included, and the following seven different diseases are depicted in the model: anthracnose, bacterial canker, leaf-cutting weevils, dieback, gall midges, powdery mildew, and sooty mould. Figure 2 visualises some of the dataset. The backgrounds of all the training and validation images were set to white to emphasise important features and eliminate bias and errors caused by backdrop variance. Random flips over the X- and Y-axes, random rotation limited to the intervals [-30, 30] and [-60, 60], and random scaling between 0.8 and 1.2 were applied to enhance dataset diversity. There are 500 images in each class, for a total of 4000 well-balanced images in the collection. These images were taken with a mobile phone camera at four mango orchards in Bangladesh: the Itakhola village orchard, the Sher-e-Bangla Agricultural University orchard, the Jahangir Nagar University orchard, and the Udaipur village orchard. The images are in the JPG format and have a size of 240 × 320 pixels. This enormous quantity of data is provided as a versatile and complete set of images that is necessary for the training and validation of the model.

The dataset used in this study, 'Mango Leaf Disease Dataset', is publicly available on Kaggle. It can be accessed at https://www.kaggle.com/datasets/aryashah2k/mango-leaf-disease-dataset.

Figure 2: Visual samples of various mango leaf diseases



Almost all traditional ML and DL models perform poorly on classification tasks with more than four classes. The random copy technique has been employed to increase the diversity of the image dataset; the image augmentation technique is deployed for the custom CNN architecture to overcome these challenges and prevent overfitting.

The CNN, a DL tool, has been discussed for applications in image processing, computer vision, and healthcare since the network can extract features from input datasets entirely on-premises while the network is being trained. The deep neural network, a specific type of CNN, has proven effective in image processing by accurately detecting and classifying objects through virtual pre-processing techniques.

2.2. Pre-Processing:

The CNN (Salma *et al.*, 2024) classifier receives the raw image dataset and pre-processes it to eliminate noise. This process plays a crucial role in enhancing the quality of the data prior to training the model. Extracting appropriate features from images is crucial in enhancing reliability. Although RGB images contain rich colour information, many symptoms of mango leaf disease are expressed through texture and structural features rather than colour differences. Converting to greyscale enhances edge detection and simplifies the feature space, which reduces the computational load without significantly compromising the classification accuracy. It also mitigates colour variation across lighting conditions, making the model more robust. This stage analyses the architecture of the framework and dataset for the generation of a better outcome. However, the images in this study had a coherent white background; real-world circumstances may introduce concerns like extensive backgrounds, interference, jitter, or deviations in brightness. Pre-processing plays a critical role in improving data quality before model training. In the pre-processing stage, first, the images are converted to greyscale format, and then all the images are normalised to pixels and standardised using Z-score normalisation to improve convergence.

2.2.1. Conversion

Initially, images in datasets undergo greyscale format conversion to achieve efficient outcomes. A greyscale image has a single channel representing brightness and intensity information across the entire spectrum of the image (Karthik *et al.*, 2020). This initial transformation plays a vital role in enhancing specific aspects of image-processing tasks:

$$\text{RGB to Gray:} = 0.299R + 0.587G + 0.114B. \quad (1)$$

Equation 1 illustrates the conversion of an RGB image into a greyscale image, where R, G, and B represent the red, green, and blue colour channels.

2.2.2. Normalisation

The study utilised normalization techniques to enhance the data. To ensure that the input features are consistently scaled and centred, this procedure comprises standardising a tensor image using the mean and standard deviation (std) (Gupta and Mukhopadhyay, 2022). This process often improves convergence during the training process. Enhanced convergence decreases the length of the training period, concurrently rendering the model training process more effective and efficient. The Z-score of the data is estimated per channel through the use of optimal values for the mean and standard deviation, respectively, which represent the first- and second-order statistics per channel. We refer to this procedure as standardisation. To improve the model's applicability across multiple image types, standardisation through normalisation is crucial. The following equation illustrates the normalising method:

$$Output = \frac{Input-Mean}{Standard\ deviation}. \quad (2)$$

2.2.3. Data Augmentation

We aim to confirm the precision and suitability of our method in classifying mango leaf diseases across various situations. We implement extensive data augmentation strategies on the training and validation datasets to enhance model generalisation. We adopted a train-test split approach, splitting the dataset into training, validation, and testing sets at a ratio of 70:10:20, respectively. The network is trained with a mini-batch size of 64, leveraging the Adam optimiser (Kumar *et al.*, 2021), at a learning rate of 0.001 across 30 epochs. Every 15 iterations, we assess the framework. Furthermore, several augmentation techniques, such as horizontal flip, vertical flip, and zooming in and out, combining shifts in brightness and rotation, have been employed to enhance the model's robustness and generalisability, as well as to reduce overfitting issues. In particular, the proposed work used techniques such as X-Y reflections (random), rotations ([-30, 30] and [-60, 60]), and scaling (0.8—1.2), and it resized the original input image from 512 × 512 pixels to 256 × 256 pixels for further processing purposes. The list below displays the data augmentation techniques employed (Table 1).

Table 1: Data augmentation techniques employed

Technique	Parameters
Horizontal flip	Random
Vertical flip	Random
Rotation	[-30°, 30°] and [-60°, 60°]
Scaling	0.8 to 1.2
Brightness shift	Applied

By enhancing the diversity of the training set, this technique helps the model predict invariant features. This makes our model more robust when it is used to classify mango leaf diseases under different conditions.

3. Classification

3.1. Custom CNN Model:

Over the years, artificial intelligence (AI) has considerably developed, diminishing the chasm between human performance and machine capabilities (Jiang *et al.*, 2022). At the heart of this evolution is the ANN, the mathematical model of the brain that includes neurons, synapses, and their connections. An ANN is employed to replicate the way the human brain works, and it learns from experience, which makes it able to recognise the patterns and structure of data in a way that is similar to human brain activity, particularly in image analysis and classification. When the model is retrained by replacing reinforced learning with supervised learning, this improves its data processing power, making it learn in the way that humans do. CNNs represent a significant advancement over traditional ANNs because they perform image selection and sorting much more effectively. Another important characteristic of CNNs is that they reduce the number of required neurons relative to earlier ANN architectures, adding efficiency to the computation. CNNs (Sharma *et al.*, 2023) can also run on GPUs like most Deep Neural Networks (DNNs) and obtain phenomenal computational speeds. CNNs are an advanced class of ML algorithms built explicitly to analyse grid-structured data. The information processing utilises temporal and spatial DL. CNNs also involve a more in-depth level of complexity than other neural network architectures due to the use of multiple convolutional layers. Convolutional layers, pooling layers, and fully connected layers constitute the majority of the CNN architecture. Convolution layers use a filter that slides over the input image, multiplying the values in the input image and the filter at each placement; then, they output the result as a feature map. Finally, more stacked convolutional layers can extract deeper and more detailed features from the images as the sophistication of the model improves.

Here is a detailed explanation of the custom architecture of the algorithm:

- **Input Layer:** 256 × 256 × 3 RGB images
- **First Convolutional Block:**
  - 16 filters, 3 × 3, padding = 'same'
  - Batch normalisation
  - ReLU activation
  - MaxPooling (2 × 2)
- **Second Convolutional Block:**
  - 32 filters, 3 × 3, padding = 'same'
  - Batch normalisation
  - ReLU activation
  - MaxPooling (2 × 2)
- **Third Convolutional Block:**
  - 64 filters, 3 × 3, padding = 'same'
  - Fully connected layer (125 units)
  - ReLU activation
  - Fully connected layer (256 units)
  - ReLU activation
  - Fully connected layer (125 units)
  - ReLU activation
  - Fully connected layer (8 units)
- **Output Layer:**
  - Softmax activation for eight-class classification

The proposed work utilises state-of-the-art performance to classify the images. The input consists of features extracted from the custom CNN approach; the model is trained on these features. The image dataset passes through a series of layers, each containing many filters. Figure 3 shows the overall CNN structure (Salma and Madhuri, 2024), consisting of ten convolutional layers, one batch normalisation layer, four fully connected layers, one softmax layer, and one classification layer. Table 2 illustrates the hyperparameters employed to configure the custom CNN architecture.

Figure 3: The architecture of the proposed custom CNN classifier

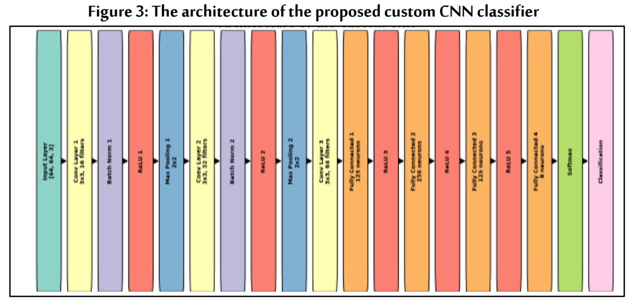


Table 2: Tuning parameters for the custom CNN model.

Parameter	Description
Convolution layer	3, 3, 3 (3 layers with filter size 3 × 3)
Max pooling layer	2 × 2, stride 2
Dropout rate	Not explicitly used
Net weight assigned	Uniform distribution
Activation function	ReLU
Number of filters	16, 32, 64
Stride	(1, 1)
Optimiser	Adam
Learning rate	0.001
Batch size	64
Epochs	30
Experimental setup	MATLAB with GPU and graphics

Researchers across the world have used various CNN architectures, namely ResNet50, VGG16, VGG19, AlexNet, Inception V3, and others. While these models are similar to one another, they are adapted in terms of the number of layers and other parameters, especially the depth, weights, learning rate, non-linear functions, etc. We update these parameters to achieve the desired outcomes. The dataset utilised in the proposed research was previously employed with CNN models, and the successful outcome prompted a paradigm shift in the application of DL architectures. DL subsequently created applications for speech detection, object detection, pattern recognition, and image classification. The model utilises a sequence-to-sequence architecture, taking the input image and processing it through a set of layers. The input image layer will take images of size 256 × 256 with three colour channels (RGB), and the input layer of the model will concatenate the image with noise to create the generated input image. We illustrate the detailed architecture of the custom CNN model as follows.

3.1.1. First Convolutional Block

- The first layer is a convolutional layer with 16 filters with a size of 3 × 3 and 'same' padding.
- Batch normalisation is done in the second layer to normalise the output from the previous layer to make mean = 0 and std = 1.
- The ReLU activation function is utilised for non-linearity in layer 3.
- The fourth layer, a MaxPooling layer with a pool size of 2 × 2 and a stride of 2, reduces the feature map's size.

3.1.2. Second Convolutional Block

- The fifth layer is a convolutional layer with 32 filters of size 3 × 3 and 'same' padding.
- The sixth and seventh layers are batch normalisation followed by the ReLU activation function.
- The eighth layer is a MaxPooling layer with a pool size of 2 × 2 and a stride of 2.

3.1.3. Third Convolutional Block

- The ninth layer is a convolution layer with 64 filters of size 3 × 3 and 'same' padding.
- The tenth layer consists of a fully connected layer with 125 units.
- The 11th and 12th layers are the ReLU activation function followed by a fully connected layer with 256 units.
- The 13th and14th layers are the ReLU activation function followed by a fully connected layer with 125 units.
- Layers 15 and 16 are the ReLU activation function followed by a fully connected layer with 8 units.

3.1.4. Output Layer

The final layer employed is the output layer; it includes a softmax activation layer that returns the class potential and the final classification layer with eight classes.

3.2. SVM Classifier:

The SVM classifier extracts features from a given CNN layer after training. We reshape the output of this layer and then feed it to the SVM, training it to correctly classify the extracted features. SVMs (Patel *et al.,* 2023) and various other supervised learning algorithms are illustrations of effective approaches to classification. An SVM model depicts multiple classes in the hyperplane in multi-layered dimensions. To lower inaccuracy, the SVM generates the hyperplane recursively. SVMs enjoy widespread use due to their ability to operate with both categorical and continuous variables. SVMs classify datasets, aiming to identify the massive marginal hyperplane. A proprietary CNN is combined with an SVM to accurately evaluate the performance in classifying diseases in mango leaves. The SVM efficiently separates multi-class outputs using hyperplanes, enhancing the classification performance.

3.3. Performance Measurements:

We evaluate the model using the F1 score, accuracy, precision, and recall metrics. The confusion matrix helps in identifying the misclassifications of the model and providing a basis for improvement. It is a popular metric for evaluating the performance of classification models in ML. The confusion matrix is a standard configuration used to represent the prediction accuracy. It is an N × N matrix with the actual dataset classes in each column and the predicted classes in each row (Rao *et al.*, 2021). The depicted matrices can be used to determine the true positive (TP), true negative (TN), false positive (FP), and false negative (FN) results.

Accuracy is one of the most prominent metrics for assessing the classification model. The ratio of accurately classified classes to all datasets is illustrated in Equation 4:

$$A_{CCURACY} = \frac{T_P+T_N}{T_P+T_N+F_P+F_N}. \quad (4)$$

Precision — the most important metric — indicates if there are more FPs than FNs, and it measures how reliably the model will return a TP result:

$$P_{RECISION} = \frac{T_P}{T_P+F_P}. \quad (5)$$

Recall evaluates the model's accuracy in forecasting TP cases; it becomes more useful when we are trying to minimise N:

$$R_{ECALL} = \frac{T_P}{T_P+F_N}. \quad (6)$$

The F1-score, the harmonic mean of the precision and recall, gives a more balanced view of these two metrics while still measuring the model performance:

$$F1_{SCORE} = 2 \times \frac{P_{RECISION} \times R_{ECALL}}{P_{RECISION}+R_{ECALL}}. \quad (7)$$

4. Result Analysis and Discussion

We measure the performance of the mango leaf disease classification model using a confusion matrix and a held-out test dataset. The predicted class labels are illustrated along the X-axis of the matrix, and the authentic (true) class labels are shown along the Y-axis. The proposed model's accuracy and loss curves for the training and validation sets demonstrate a 99.75% accuracy result. A graph illustrating the model training, the validation set accuracy, and the validation set loss over 30 epochs are shown in Figure 4. This plot reveals precious intuition about the learning curve of the model and shows how the accuracy improves as the loss drops after each iteration. These plots help us contemplate how the learning proceeded and how the model fit itself to the data. Figure 5 illustrates the confusion matrix of the proposed algorithm.

Figure 4: Training and validation accuracy and loss curves over 30 epochs.

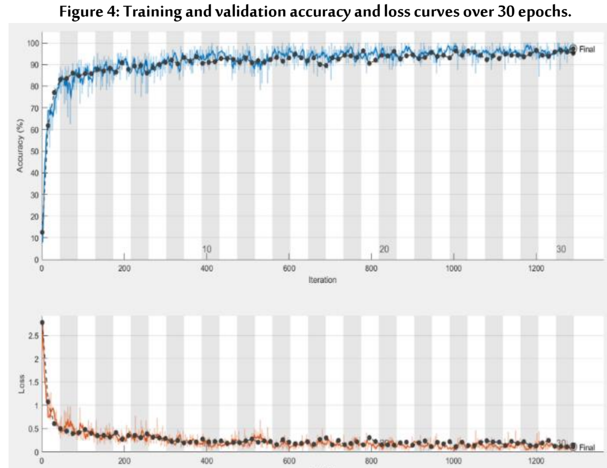


Figure 5: Multiclass confusion matrix.

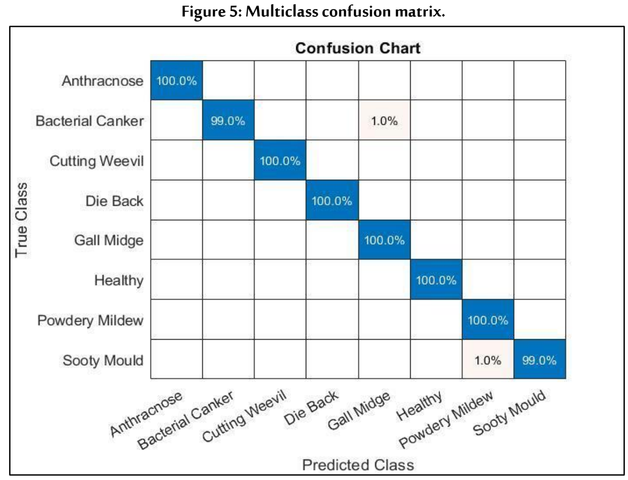
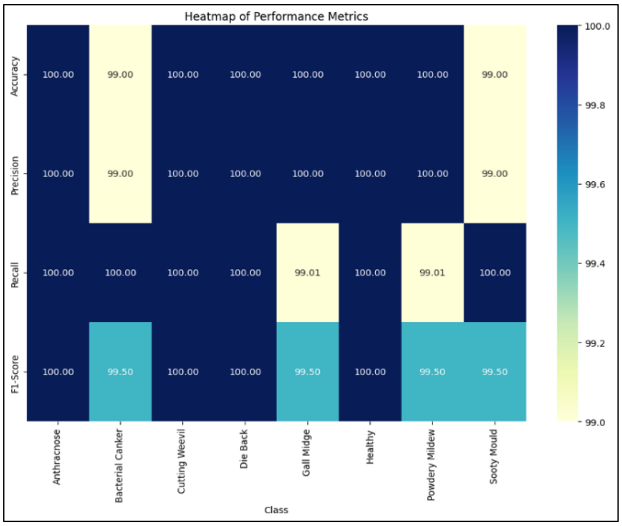


Table 3: Numerical confusion matrix and class-wise performance metrics.

Performance Measure	Different Classes							
	Anthracnose	Bacterial canker	Leaf-cutting weevils	Dieback	Gall midges	Healthy	Powdery mildew	Sooty mould
Accuracy	100	99	100	100	100	100	100	99.00
Precision	100	99	100	100	100	100	100	99.00
Recall	100	100	100	100	99.01	100	99.01	100
F1-score	100	99.50	100	100	99.50	100	99.50	99.50

Figure 6 and Table 3 illustrate the confusion matrix and heat map, showcasing the performance measurements of the proposed technique across eight distinct classes.

Figure 6: Heat map that represents the classification performance.



An evaluation of the predicted models in comparison to other models offers evidence that supports the presented research. We have conducted a comparative exploration of multiple SOTA techniques in the proposed approach to strengthen our proposal. Here, the proposed model is compared with other classification algorithms, including AdaBoost, naive Bayes, VGG16, ResNet50V2, SVM, ResNet50, VGG19, ResNet101V2, and ESDNN (Gautam *et al.*, 2023), which were applied to the mango leaf disease dataset with eight classes. The comparison demonstrates that the proposed method provides a higher classification accuracy.

Table 4: Comparative exploration of the accuracy of different proposed methods and SOTA techniques.

Deep Learning Model	Accuracy (%)
AdaBoost (Koushik *et al.*, 2020)	70.0
Naive Bayes (Limsripraphan *et al.*, 2024)	75.0
VGG16 (Pratap and Kumar , 2024)	83.20
ResNet50V2 (Porna *et al.*, 2024)	91.6
SVM (Maheshwari *et al.*, 2021)	93.12
ResNet50 (Patil *et al.*, 2022)	93.99
VGG19 (Saleem *et al.*, 2021)	94.83
ResNet101V2 (Yuliansyah *et al.*, 2021)	96.79
ESDNN (Gautam *et al.*, 2023)	98.57
Proposed method	99.75

Table 4 illustrates outcomes from the comparison of previous models and the proposed approach. Checkpoints were employed to preserve the weights of the proposed technique, and the algorithms were initially trained using a dataset of mango leaf diseases. This graphical representation validates the algorithm's high performance, as well as its clear visual representation compared with SOTA techniques. The results highlight that the proposed algorithm carries out the classification of mango leaf disease for eight distinct classes, and its efficiency and reliability are validated.

4.1. **Computational Complexity**:

The proposed architecture maintains computational efficiency due to its lightweight design. The training time was approximately 1 hour and 47 minutes on a standard GPU (NVIDIA RTX 3060), and the model required a minimal memory footprint during inference. Such a performance makes it suitable for deployment in agricultural environments with limited computational infrastructure.

4.2. **Discussion**:

The experimental results confirm that the hybrid approach effectively balances a high classification accuracy with computational simplicity. Our model not only excels at detecting multiple mango leaf diseases with high precision but also shows strong generalisation capabilities due to robust augmentation strategies. Despite excellent results, the model's performance under extreme real-world variability requires further exploration. Additional testing on cross-seasonal datasets and mobile deployment can extend its practical utility.

5. Conclusion

The present study performed a comparative evaluation of deep learning and machine learning algorithms for mango leaf disease classification, reinforcing the significance of multilevel feature fusion with adaptive channel, spatial, and pixel attention mechanisms. The proposed algorithms are evaluated and analysed through a comparison with various binary classification approaches, such as AdaBoost, naive Bayes, VGG16, ResNet50V2, SVM, ResNet50, VGG19, and ResNet101V2, which were applied to the mango leaf dataset. The evaluation indicated that the proposed model was more accurate. The algorithms were initially tested using a dataset of mango images, and checkpoints were implemented to store the parameter values of the trained model. The model was evaluated based on the accuracy, precision, recall, and F1-score metrics. Considering the integration of deep learning and machine learning, the present model is effective in detecting and enhancing the classification of different plant diseases. The present research highlights the potential of hybrid models to enhance agricultural diagnostics and enable farmers and agronomists to apply useful tools for advanced plant health. Conducting future research is important for exploring advanced algorithms featuring additional data sources, such as environmental and genetic variables, which could strengthen the classification accuracy and expand disease detection.

Data Availability Statement

The dataset used in this study, 'Mango Leaf Disease Dataset', is publicly available on Kaggle. It can be accessed at https://www.kaggle.com/datasets/aryashah2k/mango-leaf-disease-dataset.

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Conflicts of Interest

No conflicts of interest exist.

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