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Research Article

Mango Leaf Disease Detection Using Deep Feature Extraction and Machine Learning Methods: A Comparative Survey

Yavuz Ünal[1a], Muammer Türkoğlu[2b]
[1]Computer Enginerring Department, Amasya University, Amasya, Türkiye
[2]Software Engineering Department, Faculty of Engineering and Natural Science, Samsun University, Samsun, Türkiye
yavuz.unal@amasya.edu.tr

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ORCID: [a]0000-0002-3007-679X; [b] 0000-0002-2377-4979.

Abstract : Plant diseases pose a significant threat to the quality and quantity of agricultural production, with leaf diseases being particularly detrimental to plant growth and yield. In the near future, ensuring access to affordable and safe food will become one of the most pressing global challenges. As a result, the early detection of plant diseases is crucial for both economic stability and food security. Detecting and monitoring diseases in mango leaves, however, is a complex task when relying solely on visual inspection. This study seeks to address this challenge by utilizing image processing and deep learning techniques to detect mango leaf diseases. We extracted deep features from mango leaf images using several prominent architectures, including Darknet19, Xception, SqueezeNet, MobileNetv2, DenseNet201, GoogLeNet, ResNet18, VGG16, and AlexNet. These features were then classified using machine learning algorithms such as decision tree, linear discriminant analysis, naive Bayes, support vector machine, k-nearest neighbors, and ensemble classifiers. Our findings demonstrate an improvement over existing results in the literature, with detailed experimental results presented within the article.

Keywords : Deep Feature Extraction, Mango Leaf Disease, Transfer Learning, Deep Learning.

1 Introduction

Agricultural products are one of the most effective ways of feeding the world's growing population. Protecting plants from disease and detecting disease at an early stage are key to producing high-quality agricultural food. Many factors, such as climate change, are increasing the incidence of plant diseases. Each year, around 40% of the world's food crops are destroyed by pests and diseases. Minimising plant diseases is also important to ensure global food security [1], Plant diseases, weeds and pests are responsible for low crop yields. Known as the "king of fruits", the mango is one of the most important fruit crops grown in various countries around the world. The mango plant is one of the leading agricultural products and plays an important role in the economies of some Asian countries. Millions of people depend on mango cultivation for their livelihoods [2]. Plant diseases are one of the major constraints to the growth of mango plants. The major diseases are anthracnose, bacterial blossom blight, golmachi, moricha disease, shuttling, bacterial black spot, apical bud necrosis, red rust, lichen, powdery mildew, root rot, dumping off and ganoderma root rot. Powdery mildew and anthracnose are the two diseases that cause the most damage to mango trees [3].

In recent years, with the rapid development of deep learning technologies, people have begun to experiment with various artificial intelligence (AI) methods for plant disease detection. Traditional machine vision algorithms need to consider the task and prior knowledge when selecting the right features. These features often include the colour, shape and texture of the image. The manual design is the basis of the feature extractors. This process is tedious and challenging. In addition, the feature extractors are not able to generalise. On the other hand, deep learning techniques can modify the weight parameters and create a suitable feature extractor. The process is quite convenient and effective. In addition, feature extractors have greater generalisation capabilities and can successfully overcome the drawbacks of traditional image processing techniques [4]. As technological methods such as machine learning, deep learning, and image processing are applied in the field of agriculture, yield loss will decrease and production will increase [5]. In this study, features were extracted from mango leaves using deep feature extraction and disease classification was performed on mango leaves using different machine learning algorithms.

In this paper, deep feature extraction and various machine learning algorithms were used to detect mango leaf diseases. Previous studies have demonstrated the effectiveness of deep learning and image processing techniques in the field of disease detection. Among these studies, Manoharan et al. [6] divided mango leaf images, consisting of a total of 440 images, into two classes, sick and healthy, and classified them with AlexNet, VGG16, and the method they suggested. They achieved a classification accuracy of 61% with AlexNet, 62% with VGG16, and 98% with the model they suggested. In their study, Mia et al. [3] classified the features extracted from mango leaf images using neural networks and support vector machines (SVMs). They classified 4 diseased mango leaf varieties and 1 healthy mango leaf variety with 80% accuracy. Saleem et al. [7] proposed a new segmentation approach to segment diseased parts by considering vein patterns in mango leaves. For this purpose, they performed canonical correlation analysis (CCA)-based feature extraction. These authors classified these features with cubic SVM and obtained a classification accuracy of 95.5%. Rao et al. [1] classified grape leaves and mango leaves in the PlantVillage dataset with AlexNet, the pre-trained CNN model. These models achieved classification accuracies of 99% and 89%, respectively. By using Faster R-CNN, Merchant et al. [8] detected the stems and leaves of mango plants with 74% accuracy. A mobile application has been developed for this purpose. Venkatesh et al. [9] developed a network named V2IncepNet based on the VGGNet model to detect anthracnose disease on mango leaf images, and they achieved 92% classification accuracy with this network. Kumar et al. [10] classified anthracnose disease in mango leaves by deep learning. They proposed a new CNN architecture and achieved 96.16% classification accuracy with this proposed network. Singh et al. [11] classified a dataset consisting of 1070 mango leaf images with a multilayer convolution neural network (MCNN) and compared them with PSO, SVM, and RBFNN, which they used as other classifiers. These authors achieved 97% accuracy with MCNN and obtained better results than the others. Arya et al. [12] applied CNN and AlexNet to mango and potato leaf images consisting of 4004 images. They obtained a classification accuracy of 90.85% with the CNN and 98.33% with the AlexNet. Pham et al. [13] studied a dataset consisting of 450 mango leaf images. This dataset included anthracnose, Gall Medge, powdery mildew, and healthy classes. They classified the leaf images by feature selection with AlexNet, VGG16 ResNet50, and ANN. The best result was obtained from the ANN (89.41%). Trang et al. [14] studied a dataset consisting of 394 mango leaf images and anthracnose, gall midge, powdery mildew, and healthy classes. They classified this dataset with InceptionV3, AlexNet, MobilnetV2, and their proposed residual network. They obtained the most successful classification with their own proposed residual network. With this model, they achieved 88.46% classification accuracy. Mohona et al. [15] analyzed a dataset consisting of corn, grape, mango, and pepper plant leaves with VGG16, VGG19, GoogLeNet, and the network model they proposed. They achieved the most successful results with their proposed network model. Tumang et al. [16]first performed contract enhancement, to determine pests and diseases on mango leaves and subsequently performed image segmentation via K-means. The authors extracted gray level and GLCM features and classified them with Multi SVM. They achieved 85% classification accuracy. Rajbongshi et al. [17] used a dataset of 1500 mango leaf images in their study. This dataset included anthracnose, gall machi, healthy leaf, powdery mildew, and red rust classes. DenseNet201, InceptionResNetV2, InceptionV3, ResNet50, ResNet152V2, and Xception transfer learning techniques from pre-trained networks were applied to this dataset. They achieved 98% classification accuracy with DensNet201. Gulavnai and Patil (2019) applied the transfer learning models ResNet18, ResNet34, and ResNet50 to a dataset consisting of mango leaf images in their study. These leaf images contained the following diseases: powdery mildew, anthracnose, red rust, and Golich. With this dataset consisting of a total of 8853 images, the best classification accuracy was obtained with ResNet50 (91.50%). Ahmed et al. [18] created a dataset of 4000 mango leaf images. This dataset contains 1800 manually captured images and 2200 augmented images in the following classes: bacterial canker, cutting weevil, dieback, gall midge, powdery mildew, sooty mold, and healthy. The authors achieved 87% precision in their classification with CNN, 79% precision with ResNet50, and 91% precision with CNN-SVM.

In this study, deep learning and machine learning techniques were used for early detection of mango leaf diseases. Deep features were extracted from mango leaf images using various deep learning models (Darknet19, Xception, SqueezeNet, MobileNetv2, DenseNet201, GoogLeNet, ResNet18, VGG16 and AlexNet) and these features were classified using decision tree, linear discriminant analysis, naive bayes, support vector machines, k-nearest neighbour and ensemble classifiers. As a result of the experimental studies, the existing results in the literature have been improved and detailed results are presented in this paper.

2 Materials and Method

2.1 Dataset

The mangoleafbd dataset was used in this study [19]. There are 4000 images of mango leaves in this dataset. A total of 1800 plants were obtained by photographing different leaves. The remaining 2200 images were prepared by zooming and rotating where necessary. There are seven disease classes of mango leaves and one healthy leaf class in this dataset. These diseases include anthracnose, bacterial canker, cutting weevil, dieback, gall midge, powdery mildew and sooty mould. The images have a size of 240x320 pixels and are three-channel (RGB) coloured in JPG format. There are 500 images in each category. The photos were taken with a mobile phone camera. Details of the dataset are given in Table 1.

The dataset includes 500 images for each of the mango leaf disease classes, with conditions such as anthracnose, bacterial canker, cutting weevil damage, die-back, powdery mildew, and sooty mold. Anthracnose, caused by Colletotrichum gloeosporioides, manifests as black spots on leaves, affecting young branches and reducing fruit production. Bacterial canker,

Table 1: Classes in the mangoleafbd dataset.

Label	Class	Number of Images
1	Anthracnose	500
2	Bacterial Canker	500
3	Cutting Weevil	500
4	Die Back	500
5	Gall Midge	500
6	Powdery Mildew	500
7	Sooty Mould	500
8	Healty	500

from Xanthomonas axonopodis, appears as yellow to brown spots with a white halo. Cutting weevil damage is represented by insect-eaten leaves. Die-back, due to Liaiodiplodia theobromae, impacts leaves, flowers, and fruits. Powdery mildew, caused by Oidium mangiferae, produces a white fungus layer, leading to leaf yellowing and death in severe cases. Sooty mold, associated with insect feeding, blocks sunlight and hinders photosynthesis [18], [20]. Sample images in the data set used in the study are given in Figure 1.

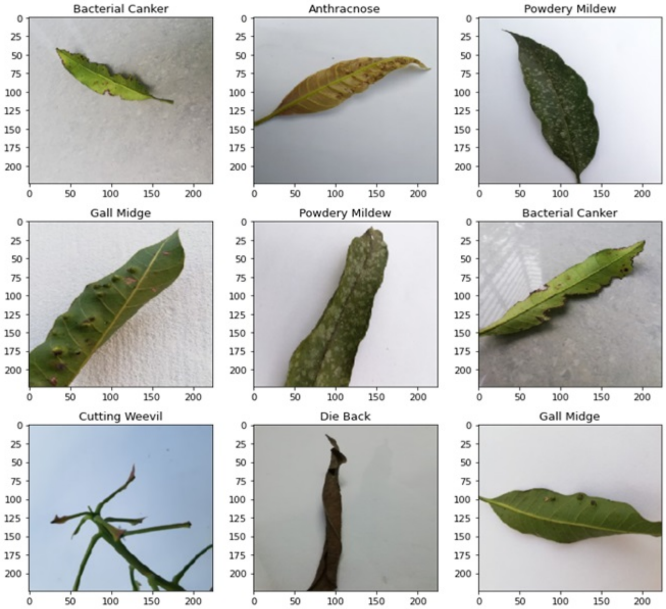

Figure 1: Data samples from the dataset used in this study

2.2 Proposed Method

In this paper, we present deep convolutional neural networks (CNNs) and machine learning classifiers for mango leaf disease detection. In this method, 9 powerful pre-trained deep architectures based on a transfer learning approach such as DenseNet201, AlexNet, VGG16 and ResNet18 are used. These architectures are used to extract deep features from mango leaf images. These deep features are then fed into six machine learning classifier methods, such as decision tree, SVM and KNN, and the training process is carried out. A general representation of the developed system is shown in Figure 2.

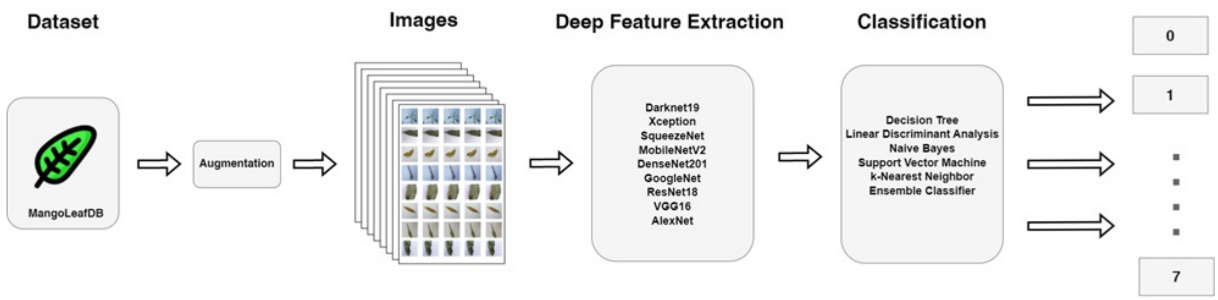

Figure 2: Summary of proposed methods in this study

As shown in Figure 2, extensive experimental studies based on pre-trained deep models and classifiers have been carried out for mango leaf disease detection. The theoretical background of these algorithms is given in the subheadings below.

2.3 Deep Learning and Pretrained CNN Models

Hinton proposed a new approach to artificial neural networks in the article he published with his studies. This approach is called the deep convolution neural network. Convolutional neural networks are known as multilayer neural networks. Important studies have been carried out with these neural network systems, and high-performance results have been obtained. Deep convolutional neural networks have achieved important success by increasing these achievements to higher levels [21]. With the training of deep learning models, especially convolutional networks, on large datasets such as ImageNet, very successful models have been developed. Training such models on relatively small datasets quickly causes the model to diverge or overfit. Therefore, the use of such models with pre-trained weight parameters on big data can produce successful test results on data of similar content and small size. Pretrained models with fine-tuning are frequently used for solving image processing problems [22], [23]. In this study, the pre-trained models Darknet19, Xception, SqueezeNet, MobileNetV2, DenseNet201, GoogLeNet, ResNet18, VGG16, and AlexNet were used. Features are extracted by using the weight parameters of these pre-trained models, and then classification is performed with various methods consisting of comprehensive classification methods. The feature extractor layers and feature sizes of the deep learning models used in the current study are given in Table 2.

Table 2: Feature extractor layers of the pre-trained CNN models used in this study

Pretrained Deep Models	Feature Extractor Layer	Feature Count	Image Size
DarkNet19	avg1	1000	256x256
AlexNet	fc6	4096	227x227
Xception	predictions	1000	299x299
SqueezeNet	pool10	1000	227x227
MobileNetv2	Logits	1000	224x224
DenseNet201	fc1000	1000	224x224
GoogLeNet	loss3-classifier	1000	224x224
ResNet18	fc1000	100	224x224
VGG16	fc6	4096	224x224

The deep learning architectures listed in Table 2 are known for their high performance in object classification. Among them, MobileNetV1 [24]. is a model developed by Google in 2017 for mobile devices with low computational power, which significantly reduces network complexity and model size by using deeply separable convolutions. MobileNetV2 improves on this structure and provides more efficient performance. Another model, the Xception network [25], is based on InceptionV3 and performs more efficient operations on multidimensional data by treating the convolutional layers as separate operations. ResNet [26] overcomes the 'vanishing gradient' problem by adding residual blocks and provides better learning by preventing information loss in the deeper layers of the network. DenseNet [27] is a model that facilitates network training by connecting each layer to all subsequent layers and optimises loss of function in multi-layer networks. VGG16 [28] is a model developed by Simonyan and Zisserman in 2014 that includes 5 block convolutional layers of 3x3 size and was successful in the ImageNet Visual Recognition Competition. SqueezeNet [29] is an architecture developed in 2016 with the aim of achieving AlexNet-level accuracy with fewer parameters, reducing the computational load of the network by using efficient layers and enabling it to work fast. Finally, AlexNet [21] is a model developed by Krizhevsky, Sutskever and Hinton in 2012, which won the ImageNet competition and gained worldwide recognition for deep learning. AlexNet is considered one of the models that started the deep learning revolution with its sequential convolution and fusion layers.

2.4 Classifiers

In this study, various machine learning classifiers, including decision trees, linear discriminant analysis (LDA), naive Bayes, support vector machines (SVM), k-nearest neighbors (KNN), and ensemble methods, are employed to classify the deep features extracted from specific layers of pre-trained deep learning models. These classification techniques can be summarized as follows:

- *Decision Tree:* Decision trees are structured similarly to real trees, consisting of roots, branches and leaves. The process begins at the root node, where the data set is progressively divided into smaller subsets based on specific feature values, creating branches. Each internal node represents a decision or condition, while the final nodes, known as leaves, represent the class labels or results. The classification process involves two main stages: the training (learning) phase and the testing phase. During the training phase, the model is built by examining the training data and generating classification rules based on patterns in the data. These rules are used to build the decision tree. In the classification phase, test data is applied to the model to verify its accuracy in predicting the correct classes by following the decision paths established in the learning phase [30] .
- *Linear Discriminant Analysis (LDA):* Dimensionality reduction is one of the most widely used techniques in machine learning applications and its main purpose is to reduce the dimensionality of the feature space by removing redundant features. LDA, one of the most commonly used methods in this process, optimises class separation by maximising the ratio of between-class variance to within-class variance. By transforming the data into a lower dimensional space, this technique performs the projection of features in a way that provides the highest separation between classes [31].

Table 3: Parameters of the classifiers used in this study

Preset	Max. number of splits	Split Criterion		
		Decision Tree		
Fine Tree	100	Gini's diversity index		
Medium Tree	20	Gini's diversity index		
Coarse Tree	4	Gini's diversity index		
		SVM		
Kernel Function	Kernel Scale	Box constraint level	Multicalss method	
Linear	Automatic	1	One-vs-One	
Quadratic	Automatic	1	One-vs-One	
Cubic	Automatic	1	One-vs-One	
Gaussian	32	1	One-vs-One	
Gaussian	100	1	One-vs-One	
		KNN		
Preset	Number of neighbors	Distance metric	Distance weight	
Fine	1	Euclidean	Equal	
Medium	10	Euclidean	Equal	
Coarse	10	Euclidean	Equal	
Cosine	10	Cosine	Equal	
Cubic	10	Minkowski	Equal	
Weighted	10	Euclidean	Squared Inverse	
		Ensemble		
Preset	Ensemble method	Learner Type	Max. number of splits	Subspace dimensions
Boosted Trees	AdaBoost	Decision tree	20	-
Bagged Trees	Bag	Decision tree	3199	-
Subspace Disc.	Subspace	Discriminant	-	500
Subspace KNN	Subspace	Nearest neigh.	-	500

- *Naive Bayes:* The Naive Bayes classifier is an algorithm commonly used in supervised learning and is widely used in areas such as data mining, machine learning and sentiment analysis. It uses Bayes' theorem to estimate the probability that a feature belongs to a particular class. Naive Bayes assumes that the features in the classification are independent of each other and performs class prediction by calculating the probability of each feature independently of the others. Simple probability calculations are used to estimate the probability of events occurring [32].
- *Support Vector Machine (SVM):* Support Vector Machines are a powerful classification method that works by creating an n-dimensional hyperplane that optimally separates the data into two classes. SVMs use a sigmoid kernel function and a two-layer feed-forward neural network, and are closely related to artificial neural networks. The interesting aspect of SVMs is that they use structural risk minimisation rather than the traditional empirical risk minimisation based on minimising the mean of the error squares. SVMs can be used in regression and classification tasks and have the ability to solve non-linear cases with kernel functions [33].
- *K-Nearest Neighbours (KNN):* KNN is a simple and adaptive multi-class classifier based on neighbourhood. The parameter 'k' indicates how many nearest neighbours should be considered when determining the class of a new sample. Small values of k can make the classification more sensitive to noise, while large values of k become computationally expensive. When k=1, a new sample is classified by nearest neighbour. When k>1, the classification can be influenced by more than one neighbor [34].
- *Ensemble Classifier:* Ensemble learning techniques, which combine the results of several algorithms, outperform individual algorithms. By combining the votes of different classifiers, it makes more accurate predictions based on features derived from different data projections. The first examples of ensemble learning date back to the early part of the last century, and this method often produces stronger results by combining weak classifiers [35].

  The hyperparameters for the classifier algorithms used in the present study are given in Table 3.

2.5 Performance Metrics

In this study, accuracy, derived from the confusion matrix, is used as the primary metric to evaluate performance. The confusion matrix is a widely used tool in classification tasks and consists of a table with rows and columns representing the predicted and actual classes. Each cell in the matrix contains values corresponding to the number of correctly or incorrectly classified instances. Additional performance metrics such as accuracy, precision, recall and F1 score can also be calculated from the confusion matrix.

The confusion matrix contains four essential parameters: true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN). True positives (TP) are the number of correctly predicted positive cases, while true negatives (TN) are the number of correctly predicted negative cases. False positives (FP) are the number of negative cases incorrectly predicted as positive, and false negatives (FN) are the number of positive cases incorrectly predicted as negative. The accuracy formula is given below.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FN + FP} \tag{1}$$

3 Results and Discussion

The experiments were performed using a computer with an Intel Core i7-10875H-2.30 GHz CPU, 32 GB of RAM, and an NVIDIA GeForce RTX 2080 super. In addition, we used 10-fold cross-validation to calculate the performance of the proposed model in all the experimental studies.

In the experimental phase, the first step was to evaluate the performance of different pre-trained deep learning models using a transfer learning approach. The results of these evaluations are shown in Figure 4. The transfer learning method used in this study involved modifying the original deep learning architectures by replacing the last three layers with four newly designed layers: fully connected, softmax and classification layers. This adjustment allowed the models to better adapt to the specific dataset used for mango leaf disease detection. The experimental setup included key deep learning hyperparameters, with each model trained for 50 epochs, a batch size of 8, and using the Adam optimizer. The choice of Adam was driven by its ability to adjust learning rates for different parameters, ensuring faster convergence and improved performance. This configuration was designed to optimize the balance between computational efficiency and model accuracy, allowing effective fine-tuning of the pre-trained models on the new dataset.

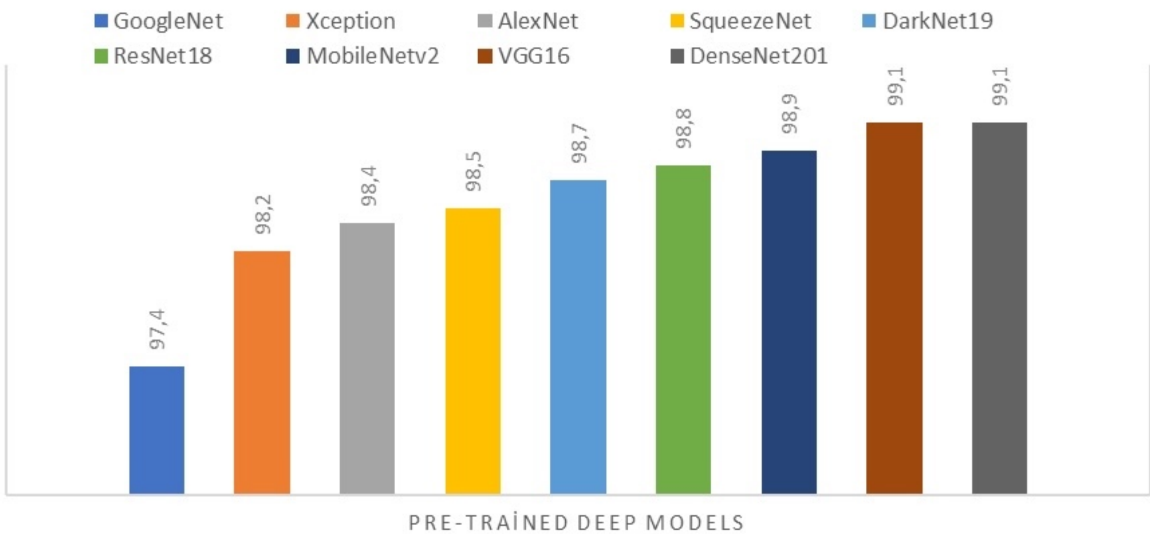

Figure 3: Accuracy scores of pre-trained deep models based on transfer learning approach

As shown in Figure 3, the highest accuracy was achieved with the DenseNet201 and VGG16 architectures, both reaching an impressive 99.1%. In contrast, the GoogLeNet architecture produced the lowest accuracy of the models evaluated. However, the remaining deep learning models showed strong performance, with accuracy scores ranging from around 98% to 99%, highlighting their overall effectiveness in the classification task.

In the second phase of the experimental study, pre-trained deep learning models were used as feature extractors. The deep features from the mango leaf images were extracted using each of the pre-trained architectures. These extracted features were then used to train different machine learning classifier algorithms. First, the performance of the decision tree classifier was evaluated using the parameters outlined in Table 3, and the corresponding results are presented in Table 4.

As shown in Table 4, the highest accuracy of 87.9% was achieved by combining the fine kernel-based decision tree with the Darknet19 model. In addition, the medium tree classifier gave the best performance when combined with the ResNet18 model. In contrast, the coarse tree classifier showed significantly lower accuracy compared to the other approaches, indicating relatively poor performance.

The performance results were then calculated using the parameters given in Table 3 based on the SVM classifier and are shown in Table 5.

As shown in Table 5, the highest accuracy achieved was 99.8%, resulting from several combinations of deep learning models, including Quadratic SVM-DenseNet201, Quadratic SVM-ResNet18, Quadratic SVM-VGG16, Cubic SVM-DenseNet201 and Cubic SVM-VGG16. In addition, five different kernel-based SVM classifiers consistently produced an average accuracy of 99% or higher.

Table 4: The accuracy scores % based on the combination of a deep feature extractor and a decision tree classifier

	Tree		
	Fine	**Medium**	**Coarse**
DarkNet19	87.9	81.5	48.4
Xception	86.5	72.4	45.2
Squeezenet	86.1	73.2	46.7
Mobilenetv2	76.9	73.2	42
Densenet201	87.8	79.9	47.9
GoogleNet	82.1	71.9	45.3
Resnet18	87.5	82.4	46.7
Vgg16	86	76.3	45.1
AlexNet	81.7	75.8	45.6

Table 5: The accuracy scores % based on the combination of the deep feature extractor and SVM classifier

	SVM				
	Linear	Quadratic	Cubic	Medium Gaussian	Coarse Gaussian
DarkNet19	99.3	99.7	99.6	99.5	98.6
Xception	98.7	99.4	99.3	98.9	97.7
Squeezenet	99.2	99.4	99.5	98.8	98
Mobilenetv2	99.5	99.7	99.7	99.4	98.9
Densenet201	99.6	99.8	99.8	99.5	98.9
GoogleNet	98.2	98.7	98.9	98.2	96.7
Resnet18	99.6	99.8	99.7	99.4	98.9
Vgg16	99.7	99.8	99.8	99.5	98.9
AlexNet	99	99.4	99.4	99	97.7

The performance results using the k-nearest neighbours (KNN) classifier were then evaluated using the parameters given in Table 3, with the results summarised in Table 6.

As shown in Table 5, the highest acc98uracy achieved was 99.8%, resulting from several combinations of deep learning models, including Quadratic SVM-DenseNet201, Quadratic SVM-ResNet18, Quadratic SVM-VGG16, Cubic SVM-DenseNet201 and Cubic SVM-VGG16. In addition, five different kernel-based SVM classifiers consistently produced an average accuracy of 99% or higher.

The performance results using the k-nearest neighbours (KNN) classifier were then evaluated using the parameters given in Table 3, with the results summarised in Table 6.

As shown in Table 7, the highest accuracy, 100%, was achieved by combining the ensemble subspace discriminant classifier with the DenseNet201 model. In addition, all other pre-trained deep models also showed strong performance when using the ensemble subspace discriminant classifier, achieving accuracies of 99%. Furthermore, the ensemble subspace KNN classifier outperformed both the boosted trees and bagged trees methods.

Table 6: The accuracy scores % based on the combination of the deep feature extractor and KNN classifier

	KNN					
	Fine	Medium	Coarse	Cosine	Cubic	Weighted
DarkNet19	99	97.3	91.5	97.5	97.3	97.7
Xception	98.7	97.1	91.9	98	97.3	97.7
Squeezenet	98.2	97.1	90.3	95.9	97	97.4
Mobilenetv2	99.1	98.3	94.2	98.4	98.3	98.6
Densenet201	99.2	98.4	92.2	98.5	98.2	98.7
GoogleNet	96.9	95.3	89.5	95.5	95.4	96
Resnet18	99.1	98	94.8	98.3	98.1	98.3
Vgg16	98.9	96.6	88.1	97.7	96.5	97.2
AlexNet	96.9	93.8	84.8	94.9	93.8	95

Table 7: The accuracy scores % based on the combination of a deep feature extractor and an ensemble classifier

	Ensemble			
	Boosted Trees	Bagged Trees	Subspace Discriminant	Subspace KNN
DarkNet19	88.4	95.9	99.8	99
Xception	91.6	94.8	99.2	98.9
Squeezenet	89.7	94.9	99.6	98.2
Mobilenetv2	89.1	95	99.6	98.2
Densenet201	91.6	96.5	100	99.2
GoogleNet	83.9	93.7	99	96.7
Resnet18	92.1	95.9	99.9	99
Vgg16	92.8	96.2	99.7	99
AlexNet	90.4	93.2	99.2	96.8

Table 8: The accuracy scores % based on the combination of a deep feature extractor and machine learning classifiers

Ensemble Classifier Models Accuracy Comparison						
MODELS	Transfer Learning Approach	Linear Discriminant	KNN (Fine)	Decision Tree (Fine)	SVM (Quadratic)	Ensemble Subspace Discriminant
DarkNet19	98.7	99.8	99	87.9	99.7	99.8
Xception	98.2	99.4	98.7	86.5	99.4	99.8
Squeezenet	98.5	99.7	98.2	86.1	99.4	99.6
Mobilenetv2	98.9	99.7	99.1	76.9	99.7	99.6
Densenet201	99.1	100	99.2	87.8	99.8	100
GoogleNet	97.4	99.1	96.9	82.1	98.7	99
Resnet18	98.8	99.8	99.1	87.5	99.8	99.7
Vgg16	99.1	99.8	98.9	86	99.8	99.7
AlexNet	98.4	99.2	96.9	81.7	99.4	99.2

Finally, Table 8 provides a comprehensive comparison of the results of the deep learning models using the transfer learning approach and the deep feature extraction approach combined with different machine learning classifiers.

As shown in Table 8, the best performing classifiers on average were the Linear Discriminant Analysis (LDA) and the Ensemble Subspace Discriminant methods. When combined with the DenseNet201 model, these classifiers achieved perfect accuracy of 100%. In addition, DenseNet201 proved to be the best deep feature extractor overall. In comparison, the other deep learning models using the transfer learning approach delivered lower performance than the models where deep feature extraction was paired with machine learning classifiers.

4 Conclusion

In this paper, the features extracted by deep feature extraction from the data of seven diseased plants and one healthy class of mango plant leaves were classified by different machine learning algorithms and the results were compared. In this study, both features were extracted by deep learning and these extracted features were classified by seven different classifiers. We extracted deep features from the fully connected layers of these deep models (DarkNet19, Xception, SqueezeNet, MobenetV2, DenseNet201, GoogLeNet and ResNet18). The features obtained were classified by decision tree, linear discriminant, naive Bayes, support vector machine, k-nearest neighbour, ensemble and MLP methods. Several of the classifiers were tested with different kernels. Fine, medium and coarse kernels are used for the decision tree, and linear, quadratic, cubic, fine Gaussian, medium Gaussian and coarse Gaussian kernels are used for the SVMMs. Fine, medium, coarse, cosine, cubic and weighted kernels were used for k-nearest neighbours. For ensembles, boosted trees, bagged trees, subspace discriminants, subspace KNNs and rusboosted tree kernels were used. In future studies, different approaches and analyses can be applied to this dataset. This study provides insight into the evaluation of architectures run on this particular dataset, the possibility of automatic diagnosis of mango leaf diseases, and performance parameters. This study has made a unique contribution to the literature by applying the proposed methodology to a mango leaf image dataset. The methodology fulfilled the task of automatically diagnosing mango leaf diseases with an accuracy rate of more than 99%.

Authors' Contributions

Methodology, Y.U.; software, M.T.; validation, M.T.; formal analysis, M.T.; investigation, Y.U.; resources, Y.U.; data curation, M.T.; writing-original draft preparation, Y.U.; writing-review and editing, M.T.

Competing Interests

The authors declare that they have no conflict of interest.

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