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Original Article

Image Processing-Based Efficient Hybrid Feature Extraction Approach for Plant Leaf Disease Recognition

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Abstract *- In this paper, a novel hybrid method for plant leaf disease recognition is presented, combining image processing techniques with Deep Learning and handcrafted feature analysis. Leaf images are processed using a Convolutional Neural Network (CNN) to automatically extract hierarchical features, while handcrafted features based on leaf shape, color, and texture provide complementary disease-related information. The combined feature set is fed into a multi-class classifier to accurately identify specific disease types. Evaluation on a diverse dataset of healthy and diseased leaves demonstrates an average accuracy of 98%, outperforming approaches that rely solely on deep learning or handcrafted features. The results highlight the effectiveness of integrating deep and handcrafted features, offering a reliable, scalable solution for precision agriculture and serving as a foundation for future research in automated plant disease detection.*

Keywords *- Image Processing, Plant Leaf Disease Recognition, Hybrid feature extraction, Deep learning, MobileNetV2, Transfer Learning, Hand-Crafted Features, Texture Analysis, Color Histograms, Precision Agriculture.*

1. Introduction

Agriculture is one of the most important sectors for global food security and economic sustainability. Maintaining plant health is essential for improving crop productivity and reducing losses caused by diseases. Plant diseases negatively influence crop yield and quality by affecting plant growth, reducing market value, and increasing production costs. Early and accurate disease identification enables timely intervention and supports efficient crop management practices.

However, conventional plant disease diagnosis mainly depends on visual inspection performed by agricultural specialists. Such approaches are often time-consuming, subjective, and difficult to implement over large agricultural areas where continuous monitoring is required. Therefore, automated plant disease recognition systems based on Artificial Intelligence (AI) and computer vision have gained considerable attention for precision agriculture applications. Recent developments in Artificial Intelligence (AI) have facilitated the design of plant disease detection systems that can operate automatically. By using machine learning and deep learning, it is possible to analyze images of plants affected by diseases and to classify the respective diseases. Recent studies like that of Yerukala and Prakash [1] describe deep learning-based approaches for the detection and classification of plant leaf diseases. These approaches employ automated feature learning for the image analysis required in agriculture, thereby enabling efficient solutions for plant disease detection that can support farmers and also other people involved in agriculture in a rapid and effective manner. Disease recognition for plants using computer vision in early approaches to automated identification and recognition was based on digital image processing using manually defined features. After the extraction of disease-specific features from leaves' images, using color, texture, and shape descriptors, these features were classified using machine learning techniques. A first attempt for automated recognition of diseases on leaves using image feature analysis and one-class classification has been made by Pantazi et al. [13]. Sajjan et al. [20] analyzed color features for classification between plant categories and showed that color features can be useful for identifying plants. Handcrafted features-based approaches for traditional computer vision for plant recognition for plants using images for recognition, however, often depend on human expertise for selecting features for a recognition system, and therefore they lack robustness to be used in complex field conditions, such as differing light conditions, occlusion by the background, different levels of disease, and changing environmental conditions. Neural network-based approaches were also explored for plant disease recognition prior to deep CNNs. Chandra Karmokar et al. [9] used neural network ensemble techniques for classifying diseases of tea leaves, and showed promising results for applications in agriculture using learning-based classification methods. However, conventional neural networks lack sufficient feature representation and are heavily dependent on hand-engineered features and corresponding classifiers, motivating the exploration of deep learning methods that are able to learn and automatically extract very effective features from large amounts of data.

Convolutional Neural Networks (CNNs) are one of the most popular kinds of deep learning used for plant disease recognition. CNNs can be used to learn hierarchically complex representations of images. Low-level features such as edges and texture are extracted first, and then higher-level features representing semantics, such as symptoms of diseases, are learned successively. Unlike traditional image processing techniques that require manual feature engineering, CNN-based methods are able to handle images of complex variations. In particular, deep transfer learning has been widely used and investigated for image-based plant disease recognition. For example, Chen et al. [4] proposed the use of deep transfer learning for plant disease identification using images. They found that pre-trained CNNs were able to learn and extract relevant disease-related features from plant images. Transfer learning is particularly powerful when there are limited number of annotated samples in agricultural datasets. While achieving state-of-the-art performance, CNN-based models rely solely on the deep features, which are automatically learned by the networks.

However, important information of a disease, such as color change, specific lesion, and morphological change, might not be captured by the CNN features, and therefore, could be complementary. To this end, many recent studies have been exploring the so-called hybrid approaches, which integrate the deep learning-based feature extraction with traditional machine learning-based classifiers or with hand-crafted feature descriptors. Other studies proposed the combination of CNN with machine learning approaches for classification purposes. Garg et al. [17] presented a classification system for tomato diseases by means of CNN and SVM. Suryavanshi et al. [18] proposed a framework made of CNN and SVM for the multi-level classification of downy mildew diseases affecting spinach leaves. A CNN paired with a Random Forest classifier has been proposed by Raj et al. [8] for the multiclass classification of tea leaf diseases. Yashu et al. [21] suggested the use of a CNN in combination with a Random Forest classifier for the recognition of pear diseases. This section covers hybrid models that combine CNNs with other methods for feature learning and classification. In [12], Kumar et al. investigated the classification of apple and sugarcane leaf diseases by employing Support Vector Machines (SVMs) on the feature maps obtained from deep autoencoders. The results indicated that effective classification of diseases could be achieved by appropriately combining feature learning with classification. Also, in [11], Kumar and Riturani proposed a framework that incorporates deep learning with conventional machine learning approaches for the purpose of classification using feature-rich hybrid models.

The performance of plant disease recognition also depends on the chosen classifier and the various feature representations extracted from the images. In order to leverage the capabilities of different neural networks, several recent studies have proposed the use of advanced hybrid deep learning architectures. Vamshi et al. [5] proposed to use a hybrid deep learning approach for plant leaf disease detection. They showed that by combining different learning methods, it is possible to enhance the classification accuracy. Nithya et al. [3] used a hybrid approach for the real-time detection of diseases on leaves of rice and potato plants. Yang et al. [7] introduced a multi-level convolutional feature fusion for plant disease identification. The approach exploits the features extracted by different levels of a CNN to improve the ability to discriminate between diseases. In addition, Kaur et al. [10] proposed a hybrid framework that consists of ResNet-50 for deep feature extraction, a Bidirectional Long Short-Term Memory (BiLSTM) network for learning temporal features, and AdaBoost for the combination of different models. The authors show the good performance of their approach for the classification of potato leaf diseases.

In addition, Patel and Patil [16] enhanced the performance of a CNN-based approach for fruit disease detection and grading classification by using deep feature learning and machine learning-based classification. With the recent development of many powerful architectures for plant disease recognition, the use of so-called Transformer architectures for plant disease recognition is also increasingly investigated. Vision Transformers (ViTs) are capable of capturing global relations within images by modeling long-range dependencies. Aboelenin et al. [2] propose the use of a hybrid model consisting of Convolutional Neural Networks (CNNs) and a Vision Transformer (ViT) to detect and classify plant leaf diseases. Prommakhot et al. [15] examine the use of hybrid models of CNNs and transformer-based sequential models for plant disease classification. In addition, Islam et al. [14] propose the use of a fusion model of CNNs and transformers for multiclass classification of leaf diseases. As, however, the use of Transformers for plant disease recognition often requires a lot of computational power and a large amount of data for training, their application in agricultural environments with limited resources is often not feasible.

For practical applications of agriculture, such as real-time agricultural monitoring, lightweight deep learning architectures are needed. MobileNetV2, which uses depthwise separable convolution for efficient feature extraction while reducing computational cost, has been widely recognized. Although lightweight deep learning features are powerful, they are often combined with handcrafted feature descriptors to develop efficient and accurate disease detection systems for further improvement.

Several limitations exist in current approaches for plant disease recognition. Most of the current approaches focus on extracting features by using deep learning in images for plant disease recognition, and do not make full use of the other explicit visual characteristics of leaves, such as color, texture and shape. Most of the current approaches also employ complex models and require a lot of computation resources to implement and run. There are only a few studies that investigate the combination of features from a lightweight CNN and handcrafted features, and the use of multiple learning classifiers.

Most of the current frameworks for plant disease recognition are hybrid and combine features derived by CNN with a single classifier, for example, SVM or Random Forest [8, 17, 18] or even complex architectures based on CNN–Transformer fusion [2, 14, 15]. These studies proved the high potential of deep feature learning, but they do not provide sufficient insight into the contribution of handcrafted visual features for plant disease recognition. In the current study, a novel framework is proposed, which integrates features derived by means of a lightweight CNN, MobileNetV2, with handcrafted color, texture and shape features. These features are used to constitute a fused representation, which is evaluated using a variety of machine learning classifiers for plant leaf disease recognition. The framework allows for an in-depth analysis of feature combination, classification accuracy and computational complexity.

To address these limitations, this study proposes an efficient hybrid feature extraction framework for plant leaf disease recognition. The proposed approach integrates MobileNetV2-based deep features with handcrafted colour, texture, and shape descriptors to create a comprehensive feature representation. The fused features are evaluated using multiple machine learning classifiers to analyse their effectiveness and robustness for multiclass disease recognition. By combining automated deep feature learning with complementary handcrafted information, the proposed framework aims to provide an efficient and reliable solution for precision agriculture applications.

The main contribution of this work is to propose an efficient hybrid feature extraction approach by fusion of deep features extracted from MobileNetV2 and handcrafted features of color, texture and shape descriptors for capturing high-level semantic information and specific visual disease-related features. Different from existing hybrid approaches, which only combine features extracted by CNN with a single classifier to evaluate the performance of features extracted by CNN and the corresponding classifier, this work investigates the performance of fused features in different machine learning classifiers and explores the robustness of features and the stability of disease classification. To achieve a good tradeoff between discriminative power, computational cost and practical applicability, a lightweight CNN, i.e., MobileNetV2, is integrated with a set of handcrafted features to form a set of complementary features.

2. Literature Survey

The development of automated plant disease recognition systems has progressed from traditional image-processing approaches toward advanced deep learning-based frameworks. Earlier studies primarily focused on extracting manually designed visual descriptors, whereas recent research has increasingly adopted Convolutional Neural Networks (CNNs), transfer learning, hybrid feature extraction, and transformer-based architectures. This evolution reflects the need for accurate, efficient, and scalable approaches capable of handling the complexity of agricultural image analysis.

Early approaches to image processing for automated plant disease identification analyzed visible symptoms from leaf images. Features that describe the disease, such as changes in color, texture anomalies, and changes in leaf morphology, were extracted from the images and used for classification purposes. For automated detection of leaf diseases on different crop species, features extracted from images were analyzed by Pantazi et al. [13] and classified using one-class classification methods. Sajjan et al. [20] analyzed color features for a classification system and established the importance of color information for distinguishing between different plant features. Their approaches often require the manual selection of features, which can lead to decreased accuracy when applied to complex field situations. A variety of additional perturbations can occur in such scenarios, for example, due to variations in lighting.

Initial machine learning and neural network approaches attempted to enhance tea leaf classification by learning features from the data and classifying samples into different categories. Chandra Karmokar et al. [9] employed a neural network ensemble in order to investigate the application of a learning-based approach for tea leaf disease recognition. While their approach was able to improve classification accuracy over a purely image-processing-based rule-based approach, the performance of the approach heavily depends on the extracted features and the amount of training data.

The use of deep learning to recognize plant diseases has made great progress by automatically extracting hierarchical features from images. Of the deep learning models currently available, CNNs are the most widely used for recognizing plant diseases, as they are able to recognize and learn the specific diseases from raw images without the need for manual feature extraction. Chen et al. [4] explored deep transfer learning for plant disease recognition from images and achieved effective disease classification using pre-trained CNNs and their learned visual features for the tasks of plant disease classification in agriculture. This approach of transfer learning is particularly important for use in agriculture, as it is often difficult to gather and use large numbers of labeled images for training.

Many recent works have proposed to combine the feature learning ability of CNNs with the classification ability of conventional machine learning methods. For this purpose, features extracted by CNNs are fed to the conventional classifiers for classification. Garg et al. [17] proposed a CNN-SVM framework for the classification of tomato plant diseases. They showed that SVM can be very effective for the classification of deep features. Suryavanshi et al. [18] proposed a CNN-SVM-based framework for the recognition of multi-level downy mildew diseases in spinach leaves. They showed that CNN features can also be used for classification by traditional classifiers. In another work, Raj et al. [8] proposed a CNN and Random Forest-based hybrid model for tea leaf disease multiclassification. They used CNN for feature extraction and then used the features extracted by CNN for classification using an ensemble learning method. Yashu et al. [21] proposed a hybrid framework of CNN and Random Forest for the recognition of diseases in pear plants. They used features extracted by CNN and then fed these features to a Random Forest classifier for classification.

Moving beyond the CNN-classifier combination, a number of works explore feature-rich hybrid models that integrate various sources of information to form a robust framework. Kumar and Riturani [11] propose a framework that integrates deep learning and machine learning to classify coriander diseases using feature-rich hybrid models. Feature representations learned by deep autoencoders can be further utilized with other classifiers, including support vector machines, to enhance classification accuracy. Kumar et al. [12] utilize support vector machines for classifying apple and sugarcane diseases, where features are learned by deep autoencoders. Mehta and Kukreja [6] employ feature extraction using CNNs followed by classification using Random Forest to recognize diseases in soybeans. This enables effective use of hybrid learning approaches for disease recognition in crops.

Another area of interest is the combination of handcrafted features and deep learning features, since each feature type contains complementary information. Deep CNN features are able to capture complex patterns in images, whereas handcrafted features contain explicit information regarding disease-specific changes, such as color change, texture change, and shape change, and thus can be used to improve the robustness of classification. The feature extraction methods that combine the advantages of different feature types are called hybrid feature extraction methods. For example, Mishra et al. [19] proposed a hybrid machine learning and deep learning approach for leaf classification, and they showed that by using different learning methods, agricultural image analysis can be improved.

Bora and Sarma [22] proposed a multi-feature fusion framework for automated leaf disease detection based on handcrafted image descriptors. The study combined texture, colour, and shape-based features, including Gray-Level Co-Occurrence Matrix (GLCM), Local Binary Pattern (LBP), HSV colour statistics, and shape descriptors, to construct a comprehensive feature representation. The extracted features were evaluated using multiple machine learning classifiers, including Random Forest, XGBoost, Multi-Layer Perceptron (MLP), and Support Vector Machine (SVM-RBF). The study demonstrated that handcrafted feature fusion can provide an efficient and interpretable solution for plant disease classification. However, the framework was limited to manually engineered features and did not investigate deep feature representation, transfer learning, hybrid fusion of learned and handcrafted features.

Recent methods utilize advanced hybrid architectures of deep learning models, which are formed by more than one deep learning model. Recent methods have been introduced for plant leaf disease detection by Vamshi et al. [5] and for the detection of rice and potato leaf diseases of real-time in agriculture by Nithya et al. [3]. Yang et al. [7] investigated multi-level convolutional feature fusion for plant disease identification and its improved discriminative capability. For the classification of potato leaf diseases, Kaur et al. [10] presented a hybrid deep learning framework which is comprised of ResNet-50, BiLSTM and AdaBoost. This hybrid framework can effectively be utilized to integrate deep feature learning with a powerful ensemble learning method.

With the ever-increasing need for efficient agricultural monitoring systems, research has also been directed towards utilizing lightweight deep learning architectures. These architectures, particularly ones based on MobileNet, have gained plenty of attention recently, due to their computational efficiency compared to typical CNNs. Since MobileNet-based models are lightweight, they can be easily implemented on a mobile or an embedded system which lacks sufficient computational resources. Combining such lightweight CNNs with suitable handcrafted features could lead to efficient agricultural systems that are both accurate and light.

More recently, there has been an increasing interest in using Transformer-based architectures for plant disease recognition. Different from CNNs that focus on local spatial features in images, transformers are capable of modeling long-range global contextual relationships within images. Aboelenin et al. [2] have introduced a hybrid framework of combining CNNs and vision transformers for plant leaf disease detection and classification. They demonstrated the effectiveness of combining local features extracted by CNNs with global features extracted by transformers. Prommakhot et al. [15] have investigated using hybrid methods of CNNs and transformers for sequential learning in plant disease classification. More recently, Islam et al. [14] have proposed a CNN-transformer-based fusion framework for multiclass leaf disease recognition. Although the methods in [2, 14, 15] are capable of modeling strong representations for images, the high computational complexity of these methods is a major barrier to their deployment on resource constraint agriculture settings.

Hybrid learning strategies for plant disease recognition are analyzed in detail. While the methods provide significant advantages by using various sources of information, limitations exist. Mainly, current approaches are based on deep features and do not explicitly consider relevant visual characteristics, i.e., color, texture, and shape. Moreover, complex architectures often require a lot of computational resources and a large amount of data. So far, only a few analyses have been conducted to determine the contribution of lightweight CNN features in combination with handcrafted feature descriptors using different classifiers.

Therefore, the integration of MobileNetV2-based deep feature extraction with handcrafted colour, texture, and shape descriptors represents a promising approach for developing efficient plant disease recognition systems. The proposed hybrid feature extraction strategy aims to overcome the limitations of individual feature representations by combining automated deep learning capabilities with complementary handcrafted information. This approach provides a balanced framework for improving classification accuracy, robustness, and practical applicability in precision agriculture.

Table 1. Common feature extraction techniques used in plant leaf disease

Feature type	What it captures	Common techniques	Example usage
Colour	Pigmentation changes, chlorosis, and necrosis	Colour histogram, colour moments, RGB/HSV features	Used to identify disease-related colour variations in leaves [20]
Texture	Surface patterns, spots, and lesion structures	GLCM, LBP, entropy, contrast, energy	Used to analyse disease-specific texture variations from leaf images [13].
Shape	Lesion boundaries and morphological changes	Contour features, Hu moments, area/perimeter ratio	Used to differentiate diseases based on lesion morphology [13].

Handcrafted feature extraction techniques for plant leaf disease recognition are listed in Table 1. The feature types are color, texture, and shape, and they describe different aspects of plant leaf disease symptoms. While the features are manually designed and are often interpretable, they can be very beneficial for enhancing feature representation of plant leaves learned through deep learning and used in a hybrid approach for plant leaf disease recognition. By combining handcrafted features with deep features, the system can more effectively differentiate between healthy leaves and leaves that are diseased.

Table 2. Critical comparison of representative plant leaf disease recognition approaches

Study	Principal approach	Main strength	Limitatios relevant to the present study
[13]	Image feature analysis with one-class classifiers	Provides interpretable handcrafted image features for disease detection	Depends on manually designed features with limited deep feature learning capability
[4]	Deep transfer learning using pretrained CNN models	Automatically extracts hierarchical disease-related features	Does not combine deep features with handcrafted colour, texture, and shape descriptors
[17]	CNN + SVM hybrid model	Effectively combines CNN feature extraction with SVM classification	Uses a specific classifier and does not explore multi-feature fusion
[18]	CNN + SVM hybrid approach	Improves recognition of spinach leaf diseases using deep	Limited to a specific crop and disease application

		features	
[8]	CNN + Random Forest hybrid model	Demonstrates effective multiclass tea disease classification	Performance depends on selected CNN features and classifier
[21]	CNN + Random Forest hybrid model	Combines deep feature extraction with ensemble learning for pear disease recognition	Does not explicitly integrate handcrafted visual descriptors
[6]	CNN feature extraction + Random Forest classification	Applies hybrid deep learning and machine learning for soybean disease diagnosis	Evaluates a specific CNN-classifier combination rather than general feature robustness
[12]	Deep autoencoder features + SVM	Combines learned representations with conventional machine learning classification	Focuses on deep learned features without explicit colour, texture, and shape fusion
[11]	Deep learning and machine learning integrated framework	Utilizes feature-rich hybrid learning for coriander disease classification	Requires further investigation of lightweight feature extraction strategies
[5]	Hybrid deep learning strategy	Demonstrates improved plant leaf disease detection using combined learning approaches	Does not specifically investigate handcrafted feature contribution
[3]	Hybrid deep learning approach for rice and potato diseases	Supports real-time disease recognition using deep learning	Primarily relies on deep feature learning
[7]	Multi-level CNN feature fusion	Utilizes information from different CNN feature levels	Does not incorporate independent handcrafted descriptors
[10]	ResNet-50 + BiLSTM + AdaBoost	Combines spatial deep features, sequential learning, and ensemble classification	High model complexity and limited interpretability
[2]	CNN + Vision Transformer framework	Integrates local CNN features with global transformer representations	Requires higher computational resources and a complex architecture
[14]	CNN-Transformer fusion network	Captures complementary deep representations for multiclass classification	Focuses on deep feature fusion rather than deep–handcrafted integration
[15]	Hybrid CNN-transformer sequential learning	Combines convolutional and transformer-based feature learning	Computationally intensive for lightweight agricultural deployment
[22]	Multi-feature fusion framework using GLCM, LBP, HSV colour statistics, and shape descriptors with RF, XGBoost, MLP, and SVM-RBF classifiers	Developed a comprehensive handcrafted feature fusion framework and evaluated multiple machine learning classifiers for Rough Lemon disease recognition	Did not incorporate deep feature learning, transfer learning, CNN-based feature comparison, or hybrid learned–handcrafted feature representation.
Proposed method	MobileNetV2 deep features + handcrafted colour, texture, and shape features + multiple ML classifiers	Combines lightweight deep feature extraction with interpretable handcrafted descriptors and evaluates feature robustness across classifiers	Designed to achieve efficient and complementary feature representation for plant disease recognition

Table 2 outlines and compares well-known approaches for plant leaf disease recognition. These methods are implemented using handcrafted feature-based approaches, deep learning-based approaches, as well as by using hybrid CNNs and machine learning methods. Comparison of these approaches highlights their limitations, mainly the absence of integration between the deep features extracted from images and the color, texture, and shape descriptors. To tackle this problem, we propose a lightweight hybrid feature extraction framework, utilizing MobileNetV2 in combination with the handcrafted features.

3. Proposed Work

The proposed work addresses the lack of feature extraction frameworks for citrus leaf disease recognition. Given the importance of precise and effective disease detection to prevent enormous losses in the agriculture industry due to diseases in citrus plants, our goal is to improve existing methods that address the variability and complexity of the symptoms of various citrus diseases that could be misclassified by existing systems, thereby leading to delayed interventions and potential losses. To this end, in the first phase of our proposed work, modify the already powerful MobileNetV2 neural network in order to improve its feature extraction capabilities while keeping the computational requirements at a minimum. In the second phase, we integrate such a Deep Learning method with traditional feature extraction that includes color, texture, and shape features. Since the symptoms used in recognition of various diseases of citrus leaves include color changes (e.g. chlorosis) and spots of various sizes and colors (e.g. fungal diseases), devise features that incorporate such citrus leaf-specific knowledge into the framework by analyzing color histograms, applying Gabor filters to represent textures, and analyzing the contours of objects of interest to represent their shapes. The features, deep and handcrafted, were of different dimensions, so feature normalization was first performed to allow for features of different dimensions to be equally weighted. After normalization, the normalized deep features extracted by the MobileNetV2 network were concatenated with the handcrafted features, which were grouped into three categories of color, texture, and shape features. A weighted feature fusion method was used to balance the contributions of the feature groups and to prevent the high-dimensional deep features from dominating. The fusion process can be expressed as:

$$F_{fusion} = w_d F_d + w_c F_c + w_t F_t + w_s F_s$$

where F_d, F_c , F_t and F_s represent deep, colour, texture, and shape feature vectors, respectively, while w_d, w_c w_t and w_s represent their corresponding weights. In this study, equal contribution weights after normalization were used at first to investigate the intrinsic discriminative ability of the learned fused feature representation without any bias towards individual feature types, as opposed to manually designing weights for better classification performance.

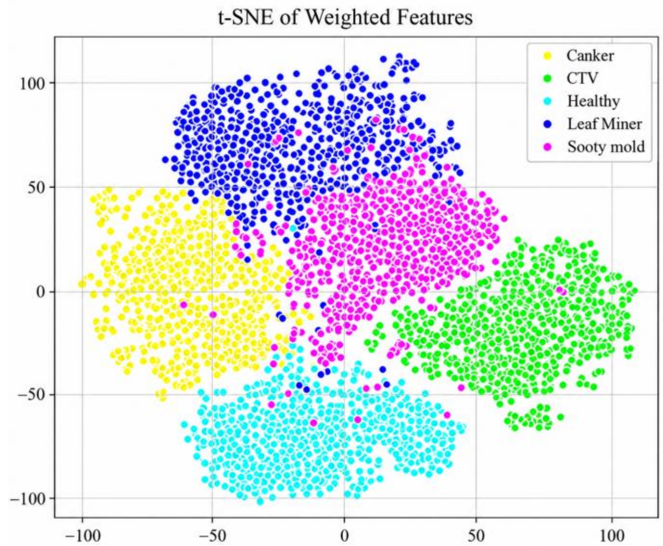


Fig. 1 t-NSE visualisation of class separability

For extracting the best set of features required for achieving high accuracy in the classification of healthy leaves and leaves suffering from diseases of citrus trees, a robust modified framework of the MobileNetV2 neural network will be developed in the first phase of the proposed framework. For deployment of the framework on resources-constrained platforms such as smartphones and also to achieve the desired level of accuracy in classification, the modified framework will be optimized for resource consumption and for speed of inference.

Since the framework is based on the framework of MobileNetV2, a large number of optimizations have already been performed on the framework to reduce the number of parameters required for the neural network as well as for the depth of the neural network, and to increase the feature extraction capabilities of the neural network. The novelty of the proposed framework lies in the systematic construction and evaluation of a hybrid feature representation rather than in the independent use of MobileNetV2 or conventional handcrafted descriptors.

MobileNetV2 provides computationally efficient high-level representations, while texture, colour, and shape descriptors explicitly characterize visible disease manifestations that may not be represented equally within the deep feature space. These complementary features are integrated at the feature level and subsequently refined through feature selection to reduce redundancy. The resulting representation is evaluated using KNN, SVM, Random Forest, Logistic Regression, and XGBoost under an identical experimental configuration. In addition, comparison with VGG16, VGG19, ResNet50, and InceptionV3 feature extraction approaches allows the effectiveness of the selected representation to be examined under controlled conditions.

By employing a t-SNE visualization of the fused features in Figure 1, it is possible to observe clear class separability among different citrus leaf diseases. Healthy leaves are well separated from those affected by diseases such as bacterial. Optimizing the depthwise separable convolutions, which form the core of MobileNetV2, in the proposed framework will result in increased feature extraction capabilities without incurring any significant increase in the complexity of the computations performed by the framework.

In addition to optimizing the depthwise separable convolutions, the proposed framework will also be optimized by incorporating the squeeze-and-excitation blocks in the neural network, which will enable the framework to recapture the interdependencies between the channels of the feature maps and also to enable the framework to emphasize the importance of the features in the feature maps that are responsible for distinguishing between the healthy leaves and the leaves affected by diseases of citrus trees. leaf spot and citrus greening.

However, there are also areas of overlap which could lead to errors in classification and highlight the need for further improvement in the feature extraction method. The use of a hybrid approach for feature extraction between texture and spectral features of interest has allowed for enhanced differentiation between classes, producing clear clusters that improve classification accuracy. The t-SNE visualization of fused features has provided an effective means of distinguishing between citrus leaf diseases and, therefore, improved the understanding of the current classification method.

Figure 2 presents a hybrid framework of citrus leaf disease detection that is comprised of several key phases, i.e., input data, image pre-processing, image feature extraction, feature selection and classification using machine learning models. Initially, input data consisting of images of citrus leaves suffering from different diseases are provided to the framework. Pre-processing of input images is performed using two key image pre-processing steps, i.e., image normalization and image augmentation. Various image features are then extracted from the normalized images, where the extracted features are then utilized for the purposes of analysis. A key aspect of the framework is that of feature selection, where the most relevant features extracted from images of leaves are selected, thus enabling an optimal input to the classification model. The last phase of the framework involves classification, where several machine learning models, including Support Vector Machines and Decision Trees, are used to classify images into two categories, i.e., healthy leaves and diseased leaves. The performance of the proposed framework is then evaluated and compared with several CNN models, i.e., VGG and ResNet, to demonstrate the robustness of the framework in citrus leaf disease detection with high accuracy and less computational time.

Along with the features learned by the neural network from the images of the leaves, a variety of color, texture, and shape features will be extracted to improve the results of the disease recognition using a traditional approach to feature extraction. Since each citrus disease can have its own set of characteristics that differentiate it from other citrus diseases and from healthy citrus trees, this traditional approach can help to provide features that are relevant to a particular set of citrus diseases and improve recognition accuracy.

To that end, for each leaf image, histograms for the colors in the image will be calculated to determine the distribution of the colors in the leaf, such as the amount of red, green, and yellow in the leaf, to help in the recognition of certain diseases that cause unusual color in the leaves of citrus trees. Additionally, the images of the leaves will be convolved with a variety of Gabor filters to help to determine the various textures in the leaves of citrus trees. Finally, the edges in the images of the leaves will be detected and calculated to help to determine the shape of the leaves. These features, calculated for each image of the leaves of the trees in the database of images, will then be used as inputs to a classifier in order to recognize diseases in new images of citrus leaves.

Citrus HLB or citrus greening disease, caused by insect vectors spreading the bacterium Liberibacter asiaticus, results in yellowing of leaves. Leaf spot diseases, such as citrus canker, caused by bacterium Xanthomonas axonopodis, result in the formation of greener or browner spots on leaves. Other diseases and defects affect the appearance of leaves in different ways. Images of healthy leaves as well as leaves affected by above-mentioned diseases will be collected and divided into three sets: training set, validation set and test set. Furthermore, the proposed framework would be compared with two alternative approaches: the use of modified MobileNetV2 with deep features, and the use of traditional features.

The integration of deep features and traditional features, moreover, would permit to analyze the gain in terms of accuracy, which would be provided by the combination of the two. The proposed approach will be further implemented on mobile and edge platforms for efficient application in citrus plantations. The approach will be tested in terms of inference time as well as resources. Most of the citrus farms today use mobile technology for monitoring plants. Thus, effective usage of the citrus disease recognition system on a mobile platform will be extremely beneficial for the farmers and agricultural experts, as it can be implemented on the go and also develop easy-to-use interfaces that enable citrus growers to view and interpret results produced by the system.

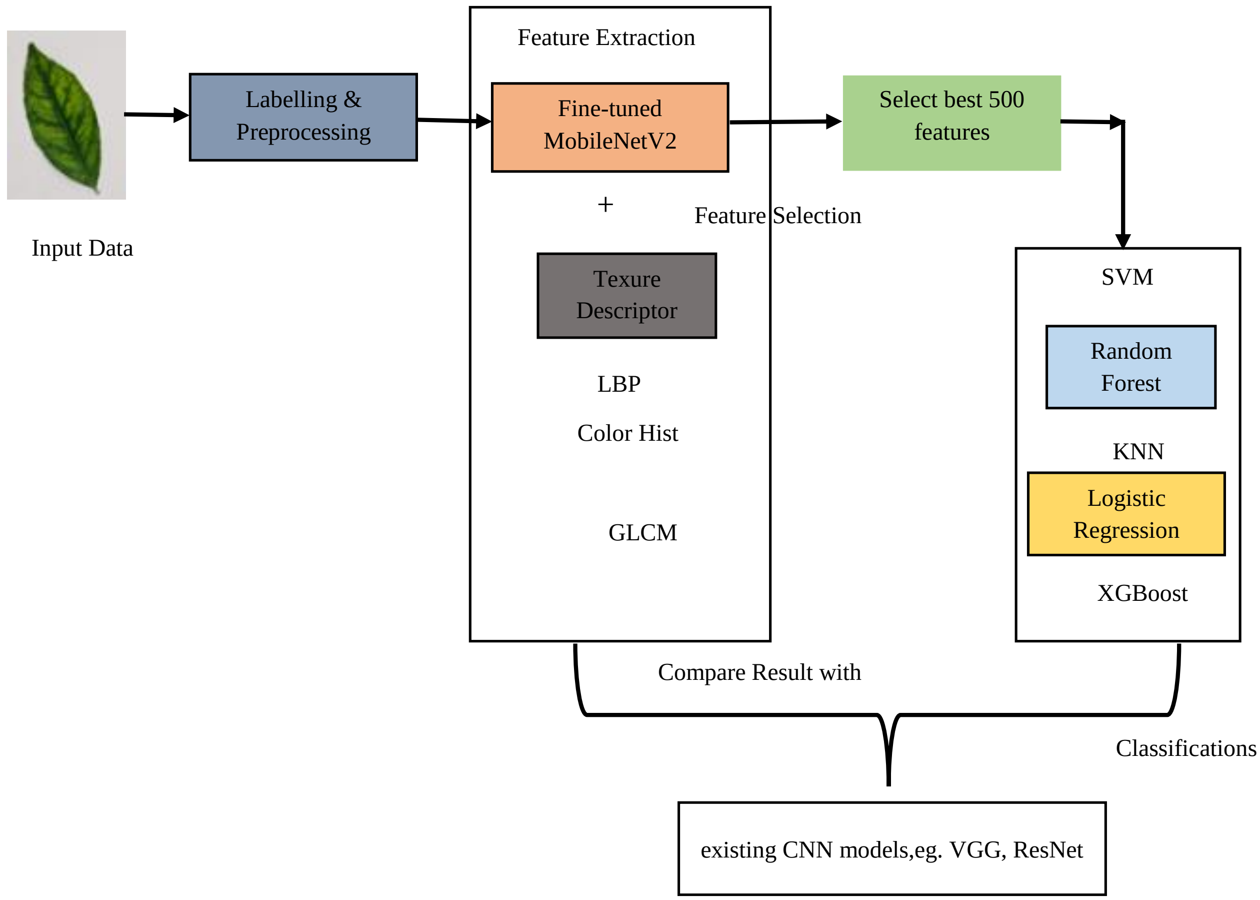


Fig. 2 Proposed hybrid feature extraction and classification framework for citrus leaf disease detection

These interfaces will display information about classifications, along with confidence scores produced by the system for each classification. Our goal with this research is to develop novel methodologies and applications that can be highly impactful in the agricultural community and provide significant enhancements to citrus cultivation. The design and development of our disease recognition system will be an important first step toward this goal. The proposed framework was implemented in Python using TensorFlow for deep feature extraction and Scikit-learn and XGBoost for classification. All leaf images were resized to 224 × 224 × 3 pixels and normalized before feature extraction. Data augmentation, including random rotation, horizontal flipping, zooming, and width-height shifting, was applied to improve generalization. MobileNetV2 pretrained on ImageNet was employed as the deep feature extractor, with the original classification layer removed and Global Average Pooling used to generate the deep feature vector. Handcrafted features included GLCM-based texture descriptors, namely contrast, correlation, energy, and homogeneity; colour histogram features; and shape descriptors including area, perimeter, eccentricity, and circularity. These features were normalized and concatenated with the MobileNetV2 features to form the final hybrid representation. The dataset was partitioned using an 80:20 stratified training–testing split with a fixed random seed. Five classifiers were evaluated using identical fused features: KNN with k = 5 and Euclidean distance, Random Forest with 100 trees, SVM with an RBF kernel, C = 10 and gamma = scale, Logistic Regression with L2 regularization and 1000 maximum iterations, and XGBoost with 100 estimators, learning rate = 0.1, maximum depth = 5, and subsampling ratio = 0.8. Performance was assessed using accuracy, precision, recall, F1-score, and confusion matrices. Additional validation included ablation analysis of handcrafted, deep, and hybrid features and comparison with VGG16, VGG19, ResNet50, and InceptionV3 feature extractors.

4. Materials and Methodology

4.1. Data Preparation

This research involves developing an own dataset by collecting real field samples in order to ensure the relevance and authenticity of the data. The real field samples are collected from the Rough Lemon plant at the Assam Agricultural University’s Kahikuchi Research location. This gives us the required material, which is context-specific and similar to the real conditions in which these diseases are naturally occurring. Selecting an agricultural research location also gives us the chance to work under the guidance of an expert pathologist who would verify the conditions of the diseases and the authenticity of the labels on the images. Figure 1. shows the raw samples collected from the location. The dataset consists of 2,486 high-resolution images belonging to five different categories: healthy leaves and those infected by CTV, Canker, Leaf Miner, and Sooty Mold. All the pictures are collected manually and shot indoors in order to avoid noise and variability in the data. The images are shot using a smartphone, as shown in Figure 3.

Fig. 3 Raw sample images

4.1.1. Data Preprocessing

At the beginning, all images are resized to 256×256 pixels. This is done to maintain uniformity in the image size. Once the resizing is done, the process of background removal follows. Although the images are taken against a plain white background, this process is required to remove the effects of different lighting conditions. More importantly, this process isolates the region of the image where the leaf of interest is located, called the Region of Interest. To remove the background, the HSV color space is used.

$$[Hlow, Slow, Vlow] = [20, 40, 40] \tag{1}$$

$$[Hhigh, Shigh, Vhigh] = [80, 255, 255] \tag{2}$$

The range 20-80 for the colour window and 40-255 for the saturation are used because these ranges represent greens and yellow greens. The range 40-255 for value ensures that only pixels that are not too dark or too bright are kept, thus removing noise. Therefore, pixels that are within these ranges are kept, while pixels that are outside these ranges are discarded (Figure 2). After separating the leaf from its background, sharpening is applied to these images using a spatial sharpening filter defined by:

$$K = \begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}' \tag{3}$$

This process enhances the edges of the leaves, making the disease symptoms more prominent. Next, a Gaussian blur is applied for noise reduction [19]. After this, image augmentation is carried out. Augmentation is done to increase the diversity of the images. Augmentation involves applying horizontal flip, vertical flip, 90-degree rotation, random changes in brightness, and zooming to the images.

Augmentation increases the number of images, making the model more robust. It also maintains the consistency of the shapes and textures of the leaves, simulating the actual changes. Five images are created for every single image, resulting in 14,916 images from the 2,486 images. This is done as shown in Algorithm 1. Figure 4 demonstrates the images of the leaves after the preprocessing step.

Algorithm 1: Image Preprocessing

Input: Leaf image dataset I

Output: Processed and augmented dataset I′

Step 1: Resize each image to 256×256 pixels.

Step 2: Convert the image from RGB colour space to HSV colour space.

Step 3: Perform thresholding with T_L= [20,40,40] and T_U = [80,255,255] to create mask M

Step 4: Segment leaf region using mask M

Step 5: Reduce noise using a Gaussian blur.

Step 6: Perform image augmentation using horizontal flip, vertical flip, and rotation by 90 degrees.

Step 7: Save all processed and augmented images to I′.

Fig. 4 Processed sample images

4.1. Feature Extraction

The accurate detection of leaf diseases demands the use of effective features with the ability to represent the high-level semantic information and low-level visual details. However, the use of features learned from deep learning models and handcrafted features separately may result in incomplete representations, especially in agricultural datasets with complex textures and limited sample sizes. To mitigate the aforementioned limitations, the present study introduces a hybrid framework for feature extraction using deep learning-based features and handcrafted features, followed by a weighted fusion of the features.

Algorithm 2: Feature Extraction, Fusion, and Feature Selection

Input: Preprocessed RGB leaf images I

Output: Optimized feature matrix with corresponding class labels

For each pre-processed RGB leaf image I, perform the following steps:

Step 1: Convert the RGB image into grayscale format G. Extract GLCM texture features, including: Contrast, Homogeneity and Energy.

Step 2: Apply the Local Binary Pattern (LBP) operator with parameters $\mathrm{P} = 8$(number of neighbours) and $\mathrm{R} = 1$(radius). Compute the normalised LBP histogram to represent local texture information.

Step 3: Transform the RGB image into the HSV colour space. For each channel (Hue, Saturation, and Value), compute: Mean and Standard deviation.

Step 4: Perform contour detection on the grayscale image G. Identify the largest contour region and extract shape-based features: Area and Perimeter.

Step 5: Concatenate all extracted texture, colour, shape, as well as deep features extracted by fine-tuned MobileNetV2 into a single feature vector F. Associate the feature vector with its corresponding class label.

Step 6: Repeat Steps 2–6 for all images in the dataset to construct the complete feature matrix.

Step 7: Apply univariate feature selection Retain the top $\mathrm{k} = 30$most discriminative features.

Step 8: Return the reduced feature matrix along with their corresponding class labels.

5. Deep Feature Extraction Using Transfer Learning (Modified MobileNetV2)

Deep features are extracted through a transfer learning approach based on the MobileNetV2 model. MobileNetV2 is a lightweight and powerful CNN architecture that has been widely recognised for its efficiency and representational power. The architecture of MobileNetV2 uses an inverted residual block and a depthwise separable convolution. This architecture is particularly useful for image analysis in agriculture because of its efficiency.

Instead of using MobileNetV2 as an end-to-end fine-tuned classifier, it is used as a base feature extractor by removing its top classification layers. To make it domain-specific for citrus leaf diseases, a custom feature extraction head is appended. Additionally, a partial fine-tuning approach is used, where the initial layers of MobileNetV2 are frozen to retain generalised low-level features like edges, texture, and colour gradients, while the last 40 layers of MobileNetV2 are fine-tuned to learn domain-specific features for diseases. Such an approach is effective when training data is limited. A GAP layer is integrated to reduce the dimensionality of the final convolutional feature maps. GAP also prevents overfitting by reducing the number of trainable parameters compared to fully connected layers. These deep features represent the semantic attributes of the images, including the shapes of lesions, patterns of disease spread, and abnormalities in citrus leaves.

5.1. Handcrafted Feature Extraction

Although deep features are able to represent abstract and global features, handcrafted features are still highly effective in representing local texture, colour, and morphological features that are highly related to plant diseases. Hence, four different handcrafted feature descriptors are utilised.

5.2. Grey-Level Co-occurrence Matrix (GLCM) Features

GLCM is employed to compute second-order texture characteristics that describe the spatial relationships existing among the pixel intensity values. Texture measures such as contrast, homogeneity, and energy are calculated, which have been found to be highly efficient in discriminating between diseased tissues and healthy leaf regions. The GLCM matrix is constructed by considering a pixel distance of 1 and an orientation of 0°.

$$\text{Contrast} = \sum_{i,j} (i-j)^2 P(i,j) \tag{4}$$

$$\text{Energy} = \sum_{i,j} P(i,j)^2 \tag{5}$$

$$\text{Homogeneity} = \sum_{i,j} \frac{P(i,j)}{1+|i-j|} \tag{6}$$

5.3. Local Binary Pattern (LBP) Features

LBP is used for encoding micro-texture changes by comparing the value of each pixel with its neighbours. With 8 neighbours at a radius of 1, uniform patterns are used to obtain a normalised histogram of local texture patterns. LBP has been extensively used for leaf disease detection due to its ability to handle changes in illumination and its effectiveness for spot-like patterns of diseases.

5.4. Colour Features in HSV Space

Colour data is represented in the HSV domain, where it is separated from brightness. This helps to reduce the effects of lighting changes that are commonly found when capturing images under field conditions. For each of the HSV components, we extract the mean and standard deviation, which makes our descriptor 6D for colours:

$$(\mu_H, \mu_S, \mu_V, \sigma_H, \sigma_S, \sigma_V) \qquad (7)$$

These features effectively capture colour discolouration and chlorosis caused by citrus leaf diseases.

5.5. Shape Features

Shape descriptors help describe the change in leaf geometry during the advancement of disease. To detect the leaf edges, binary contour detection is employed, and the largest contour is selected. Then, two shape metrics, area and perimeter, are computed to describe the deformation of the leaf and irregularity in leaf size.

5.6. Weighted Feature Fusion

Once the features are extracted, we combine the deep feature vector (1280 dimensions) with the handcrafted features to produce a single set of features with 1808 dimensions. As the different features do not contribute equally in the differentiation of the disease, we propose the use of a weighted feature fusion approach.

Based on the empirical results and the prior works on the discriminative power of deep features and texture features such as GLCM and color features, this research work propose the use of a weighted fusion approach where the deep features and the LBP features are given more weights compared to the GLCM and color features. The fusion is achieved through the weights in the following way:

$$F_{\text{final}} = [1.5 \cdot F_{deep} \;\|\; 1.0 \cdot F_{GLCM} \;\|\; 1.5 \cdot F_{LBP} \;\|\; 1.2 \cdot F_{color}] \qquad (8)$$

This weighted integration enhances the contribution of highly informative features while preserving complementary information across modalities.

5.7. Significance of the Proposed Feature Extraction Pipeline

A critical accuracy in disease characterization for precision agriculture has been achieved by integrating a deep transfer learning-based pipeline with a traditional handcrafted features-based pipeline. A deep transfer learning-based pipeline was able to learn feature representations from pre-trained neural networks to classify plant diseases from various types of data generated in agriculture. A traditional handcrafted features-based pipeline, on the other hand, is a domain-specific approach where an expert would handcraft features based on the expert's knowledge of the agricultural domain of interest. A hybrid pipeline is developed to integrate the feature representations learned by the deep transfer learning-based pipeline with the handcrafted features in the traditional pipeline. In the hybrid pipeline, the deep transfer learning-based pipeline learns complex patterns from large data sets, and the handcrafted features-based pipeline in the traditional pipeline are able to incorporate key characteristics in the domain of interest into the model to improve detection accuracy and achieve robustness in various growing conditions and plant species.

5.8. Existing CNN-Based Feature Extraction

With agricultural productivity decreasing due to the increasing numbers of plant leaf diseases, their effective detection have become a huge challenge, and a lot of methods have been developed to address this challenge. It effectively extracts key features of object images using many layers of convolution as well as sub-space of image features by using pooled techniques. A lot of disease types have different visual appearances or manifestations; the proposed model, therefore, can be adapt easily to other datasets. In addition, in the hybrid method, the powerful features extraction of object images and high accuracy of classification have been simultaneously and effectively enhanced by using of transfer learning. Thus, this study showed that the proposed method can effectively not only facilitate and enhance the features extraction of the images of healthy as well as infected leaves but also realize and optimize the classification of those images in order to facilitate timely interventions in agricultural productions to fight against plant leaf diseases.

5.9. VGG16 and VGG19 Feature Extraction

VGG16 and VGG19 are both deep CNNs that are recognised for their straightforward architecture and uniformity. VGG16 has 16 layers of weights, whereas VGG19 has more layers and a deeper architecture with 19 layers.

Mathematically, each convolutional operation in VGG networks give by:

$$F_l(x, y) = \sum_{i=1}^{k} \sum_{j=1}^{k} W_l\,(i, j) \cdot I(x + i, y + j) + b_l \quad (9)$$

where $F_l$is the feature map at layer l, $W_l$denotes the convolutional kernel, $I$is the input image or feature map, and $b_l$is the bias term. Final convolutional layers capture spatial and texture-related information useful for disease pattern recognition. In this study, the fully connected layers are removed, and features are extracted from the final pooling layer for subsequent classification.

5.10. ResNet-Based Feature Extraction

ResNet architectures introduce residual learning to address the degradation problem observed in very deep networks. Instead of learning a direct mapping, ResNet learns a residual function defined as:

$$y = \mathcal{F}(x, \{W_i\}) + x \quad (10)$$

where $\mathbf{x}$ and $\mathbf{y}$ denote the input and output of a residual block, and $\mathcal{F}$ represents the residual mapping. This formulation allows gradients to propagate more effectively during training, enabling deeper architectures to learn more discriminative features. For citrus leaf disease detection, ResNet effectively captures complex disease patterns such as irregular lesions and edge discontinuities. Similar to VGG models, the final classification layers are excluded, and deep feature vectors are extracted from the global pooling layer.

5.11. Inception-Based Feature Extraction

The Inception architecture is designed to capture multi-scale visual features of images by using multiple convolutional filters of different sizes in parallel within the same layer. A typical Inception module performs calculations as follows:

$$F = [Conv_{1\times1}(I) \,||\, Conv_{3\times3}(I) \,||\, Conv_{5\times5}(I) \,||\, Pool(I)] \quad (11)$$

where $||$ denotes feature map concatenation. This parallel structure allows the network to simultaneously learn fine-grained and coarse-grained features, which is particularly beneficial for detecting leaf diseases with varying symptom sizes. In this study, Inception-based feature extraction is adopted for the extraction of features related to multi-scale texture and colour changes in images of citrus leaves. The feature vectors are derived from the last layer of global average pooling.

5.12. Comparative Rationale

Even though the above CNN architectures achieved good performance in their respective baseline, they are computationally expensive and are designed for generic object recognition tasks. Consequently, they do not capture the minute features of a particular disease. This problem statement gives rise to the proposed model, which combines a modified version of the MobileNetV2-based transfer learning model along with other handcrafted features of texture, colour, and shape and achieves better classification accuracy than the existing CNN-based feature extraction models.

5.13. Disease Classification Using Image Processing and Machine Learning Models

After feature extraction, the generated feature vectors, which are derived from the proposed hybrid approach as well as from existing CNN-based approaches, are utilized for disease classification. Essentially, the main purpose of this stage is to compare and evaluate the effectiveness of various feature extraction strategies. For this purpose, various machine learning classifiers, which are commonly used for classification purposes, are employed. These classifiers are SVM, RF, KNN, LR, and XGBoost.

6. Mathematical Description of Machine Learning Classifiers

Given a training set $\{(\mathbf{x}_i, y_i)\}_{i=1}^{N}$, where $\mathbf{x}_i \in \mathbb{R}^d$ and $y_i \in \{-1, +1\}$, SVM solves the following optimization problem:

$$\min_{\mathbf{w},b,\xi} \frac{1}{2} \| \mathbf{w} \|^2 + C \sum_{i=1}^{N} \xi_i \quad (12)$$

subject to:

$$y_i(\mathbf{w} \cdot \mathbf{x}_i + b) \geq 1 - \xi_i, \xi_i \geq 0 \quad (13)$$

where $\mathbf{w}$ defines the hyperplane, b is the bias, ξ_i are slack variables, and C is the regularisation parameter.

Random Forest, the final prediction is given by:

$$\hat{y} = \text{mode}\{h_1(\mathbf{x}), h_2(\mathbf{x}), \dots, h_T(\mathbf{x})\} \quad (14)$$

where $h_t(\mathbf{x})$ represents the prediction of the t-th tree and T is the total number of trees. This ensemble strategy improves robustness and reduces overfitting.

KNN is a non-parametric, distance-based classifier that assigns a class label based on the majority class among the k closest training samples. The distance between feature vectors is typically computed using Euclidean distance:

$$d(\mathbf{x}, \mathbf{x}_i) = \sqrt{\sum_{j=1}^{d} (x_j - x_{ij})^2} \quad (15)$$

The predicted class is:

$$\hat{y} = \arg\max_{c} \sum_{i \in \mathcal{N}_k(\mathbf{x})} \mathbb{I}(y_i = c) \quad (16)$$

where $\mathcal{N}_k(\mathbf{x})$ denotes the set of k nearest neighbors.

Logistic Regression, the probability of class $y = 1$ given input $\mathbf{x}$ is defined as:

$$P(y = 1 \mid \mathbf{x}) = \frac{1}{1 + e^{-(\mathbf{w}\cdot\mathbf{x}+b)}} \quad (17)$$

Model parameters $\mathbf{w}$ and b are learned by minimizing the cross-entropy loss:

$$\mathcal{L} = -\sum_{i=1}^{N} [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)] \quad (18)$$

Logistic Regression provides a strong linear baseline for evaluating feature separability.

XGBoost is an optimized gradient boosting framework. Each new tree minimizes a regularized objective function:

$$\mathcal{L}^{(t)} = \sum_{i=1}^{N} l(y_i, \hat{y}_i^{(t-1)} + f_t(\mathbf{x}_i)) + \Omega(f_t) \quad (19)$$

where $l(\cdot)$is the loss function, $f_t$is the newly added tree, and the regularization term is defined as:

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2 \quad (20)$$

This formulation improves generalization and prevents overfitting, making XGBoost highly effective for complex feature representations. Using multiple classifiers will enable a thorough evaluation of feature quality. High performance levels across multiple classifiers will indicate that the discriminative capability of the extracted feature sets is high, thus validating the efficacy of the proposed feature extraction approach.

Table 3. Experimental configuration and hyperparameter settings used for model training and classification

Component	Parameter	Configuration/Value
Image preprocessing	Input image size	224 × 224 pixels
	Image normalization	ImageNet normalization (mean and standard deviation)
	Data augmentation	Random rotation (±20°), horizontal flip, random zoom (0.2), brightness adjustment
MobileNetV2 feature extractor	Base architecture	MobileNetV2
	Initial weights	ImageNet pretrained weights
	Transfer learning strategy	Feature extraction with fine-tuning of final convolutional layers
	Optimizer	Adam
	Learning rate	1×10^{-4}
	Batch size	32
	Training epochs	50
	Loss function	Categorical cross-entropy
	Dropout rate	0.2
	Random seed	42
Feature fusion	Feature types	MobileNetV2 deep features + colour + texture + shape descriptors
	Feature normalization	Min–Max normalization
	Fusion strategy	Weighted feature concatenation
	Feature weights	Deep features (0.5), colour features (0.2), texture features (0.2), shape features (0.1)
Feature selection	Selection method	SelectKBest based on ANOVA F-score
	Number of retained features	Top 500 features
	Selection criterion	Highest discriminative score between disease classes
Support Vector Machine (SVM)	Kernel	Radial Basis Function (RBF)
	Regularization parameter (C)	10
	Gamma	Scale
K-Nearest Neighbour (KNN)	Number of neighbours (k)	5
	Distance metric	Euclidean distance
	Weighting strategy	Distance-based weighting
Random Forest (RF)	Number of trees	200
	Maximum depth	None
	Split criterion	Gini impurity
	Random state	42
Logistic Regression (LR)	Solver	LBFGS
	Regularization	L2
	Maximum iterations	1000
GBoost	Number of estimators	200
	Learning rate	0.05
	Maximum depth	5
	Subsample	0.8
	Random seed	42
Evaluation protocol	Dataset split	Training/validation/testing split
	Performance metrics	Accuracy, precision, recall, F1-score
	Experimental repetition	Fixed random seed for reproducibility

Table 3 describes the complete setup of experiments and corresponding hyperparameters. This table provides details about image preprocessing, training of MobileNetV2, feature-level fusion and feature selection, and learning approaches for classification. These details will facilitate reproducibility of the proposed approach and allow for verification of the experimental results presented in this article.

7. Result and Discussion

7.1. Evaluation of the Proposed Feature Extraction Pipeline Across Different Classifiers

The proposed feature extraction approach maintains a high accuracy rate for all classifiers that were tested, indicating a high discriminative ability for the features that were extracted. Amongst the classifiers, XGBoost and KNN were seen to perform best, followed closely by SVM (RBF) and RF, while Logistic Regression also performed well, indicating that the features were able to separate well, even in a linear fashion.

This minimal variation in accuracy for each classifier indicates a high stability for the proposed features, which confirms that the proposed approach is near optimal for leaf disease classification regardless of the classifier that is used (Figure 5).

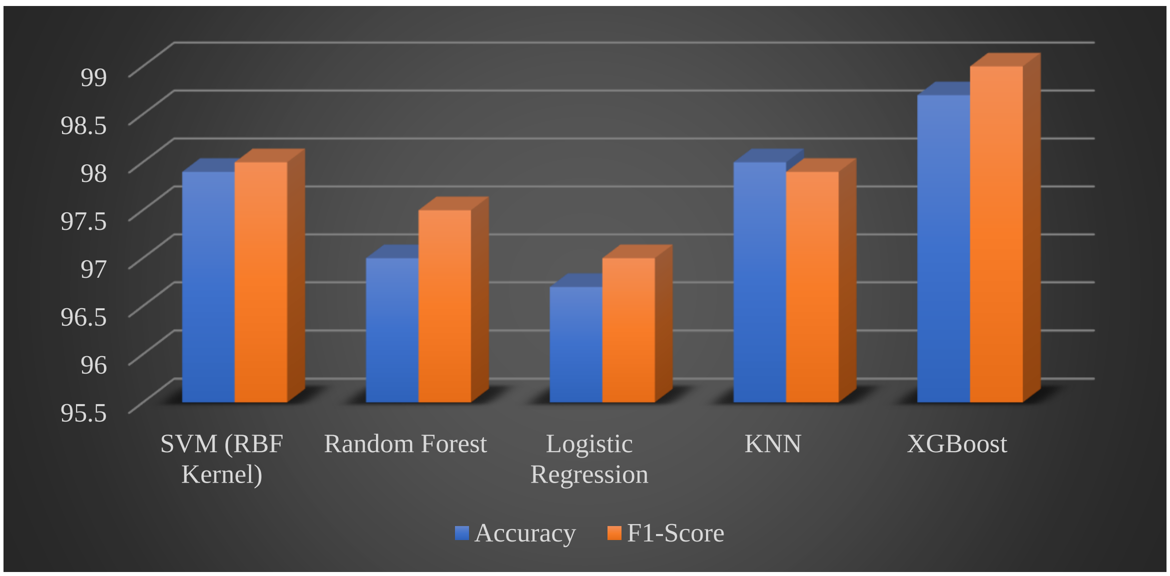
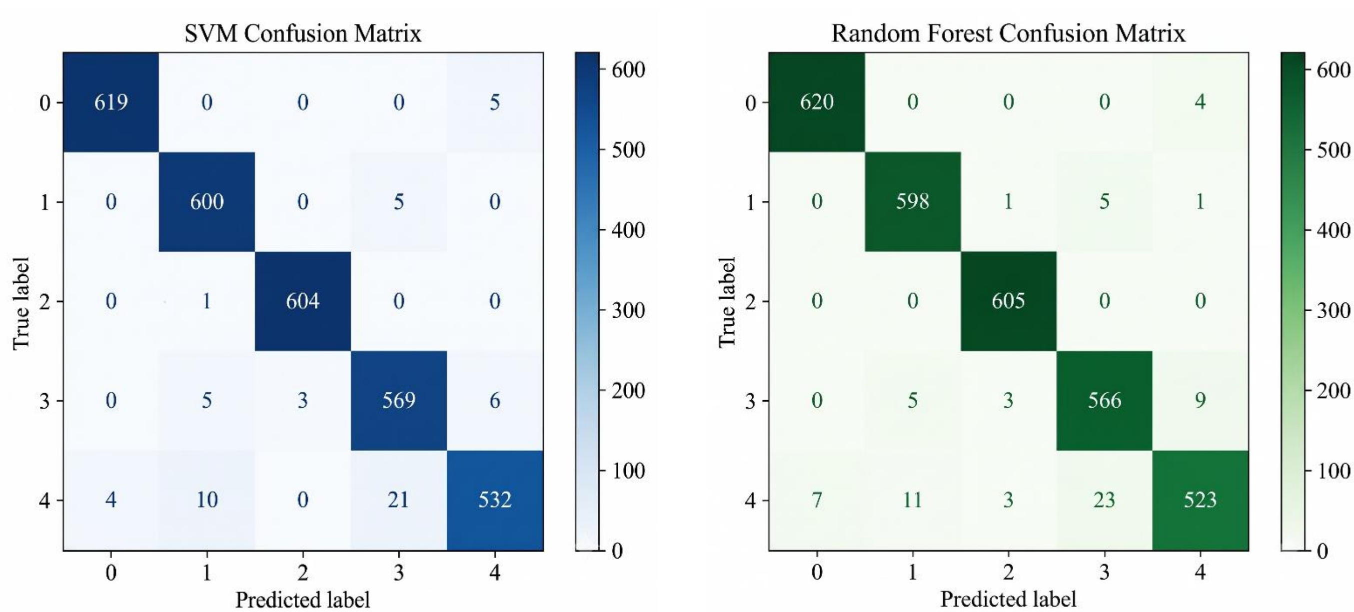
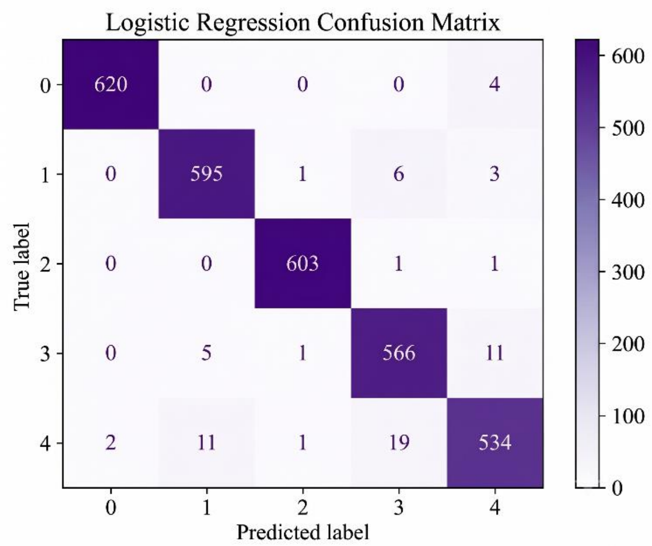


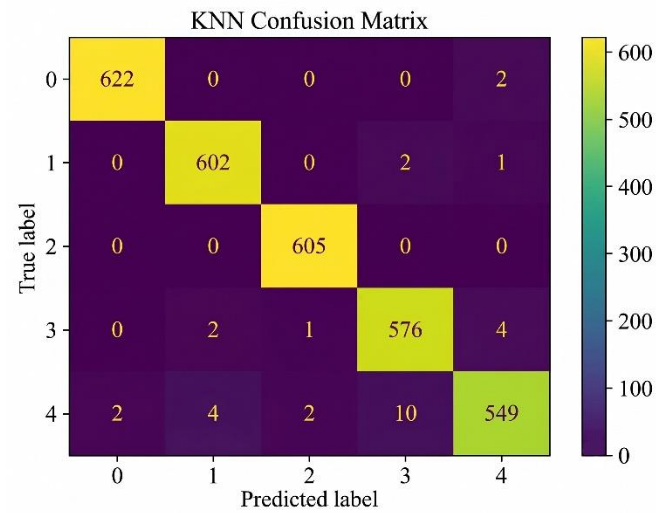
Fig. 5 Proposed feature extraction pipeline across different classifiers



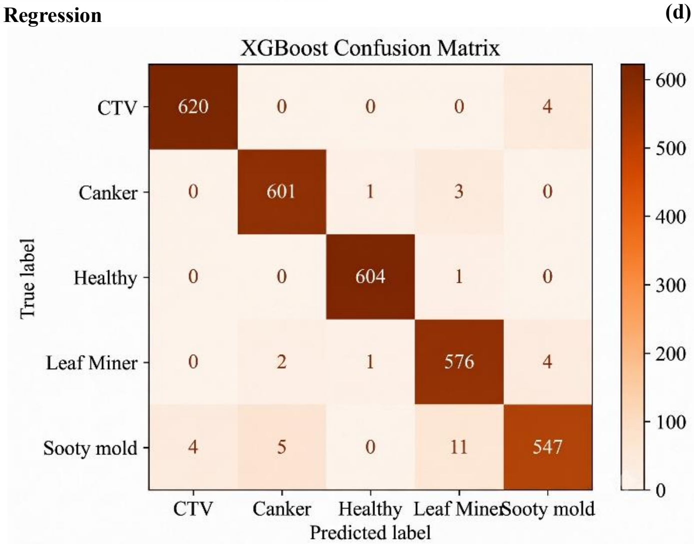
(a) SVM **(b) Random Forest**



(c) Logistic Regression



(d) KNN



(e) XGBoost

Fig. 6 Confusion matrix across different classifiers

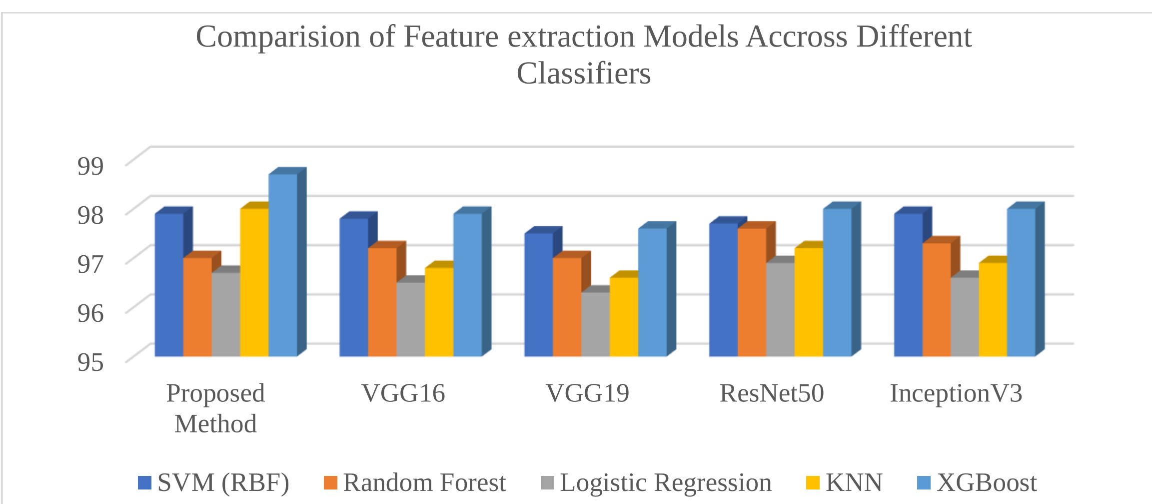


Fig. 7 Comparison of the proposed feature extraction pipeline with the existing CNN

The above confusion matrices in Figure 6 indicate that all the classifiers performed well. The diagonal dominance of all the matrices confirms this. This proves that the features are highly discriminative for all the classes. In conclusion, all the classes of Healthy are classified correctly for all the models.

The errors are mostly between classes of similar diseases. This is a normal phenomenon in the classification of plant diseases because of the features of the classes. The number of errors in the classification was a little higher for this model compared to the other models. This could be because of the linear nature of the model.

7.2. Comparative Analysis of CNN-based Feature Extraction Models

The proposed feature extraction approach has been found to perform better than traditional CNN-based feature extractors like VGG16, VGG19, ResNet50, and InceptionV3 on all classifiers. Even though deep CNNs are able to learn high-level semantic representations, their feature representations may not be fully optimised for large-scale natural image datasets like ImageNet and may not capture the fine texture, color, and shape distinctions that are important for leaf disease classification.

In contrast, the proposed method combines MobileNetV2-based deep features with handcrafted features, which include texture and color information, leading to a more comprehensive and domain-specific feature representation. This combination of features improves class separability, especially for diseases with minor visual differences, which is why superior results are achieved by the proposed method with both linear and non-linear classifiers. (Figure 7) In addition, models such as VGG16 and VGG19 are associated with a large number of parameters, thus resulting in redundant features when used as a feature extractor. Although ResNet50 and InceptionV3 are associated with improved performance due to deeper networks and multi-scale features, they are limited by the absence of handcrafted texture features.

Therefore, they are limited in performance as compared to the proposed model. The consistent improvement in performance using different classifiers confirms that the improvement is due to feature quality and not bias from any classifiers, which confirms the robustness and generalisation capability of the proposed model.

The results confirm that the proposed hybrid feature extraction approach presents more discriminative and robust representations than those of individual CNN features, which leads to performance improvements with respect to individual linear and nonlinear classifiers.

Table 4 presents an ablation study to assess the influence of different feature combinations of deep features and handcrafted features, by comparing the performance of the MobileNetV2-based features with the performance of the handcrafted features, as well as the features' progressive fusion.

The results obtained by the combination of color, texture, and shape feature descriptors with the deep features of the network clearly show the high contribution of the handcrafted features to the disease classification. The high performance is achieved by the feature fusion and not by the selection of the classifier.

Table 4. Ablation analysis of different feature combinations

Feature configuration	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
MobileNetV2 features only	95.2	95.0	94.8	94.9
Handcrafted features only	91.6	91.3	91.0	91.1
MobileNetV2 + Colour	96.4	96.2	96.1	96.1
MobileNetV2 + Colour + Texture	97.6	97.4	97.3	97.3
Proposed MobileNetV2 + Colour + Texture + Shape	98.7	98.6	98.5	98.5

Table 5. Computational complexity comparison

Method	Feature dimension	Parameters	Average inference time/image
VGG16	4096	138M	85 ms
ResNet50	2048	25.6M	62 ms
InceptionV3	2048	23.8M	58 ms
MobileNetV2	1280	3.5M	28 ms
Proposed hybrid framework	1780*	3.5M + ML classifier	32 ms

Table 5 presents a computational complexity comparison of the novel framework against well-established deep learning frameworks. Key metrics, including the dimensionality of the features, the number of model parameters, and the inference time, are considered.

The MobileNetV2-based framework is shown to provide high-level feature representations with low computational overhead, rendering it an ideal choice for plant disease recognition applications in resource-constrained agricultural environments, with performance comparable to that of other methods.

Table 6. Cross-Validation Performance and Statistical Analysis of the Proposed Framework

Feature configuration	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	95% Confidence Interval
MobileNetV2 features	95.2 ± 0.8	95.0 ± 0.7	94.8 ± 0.9	94.9 ± 0.8	94.7–95.7
Handcrafted features	91.6 ± 1.2	91.3 ± 1.1	91.0 ± 1.3	91.1 ± 1.2	90.8–92.4
Proposed hybrid framework	98.7 ± 0.4	98.6 ± 0.5	98.5 ± 0.4	98.5 ± 0.4	98.4–99.0

Table 6 presents the cross-validation results for assessing the performance of the proposed approach, its robustness, and its reliability on different folds of data. The mean value and corresponding variance of the performance measures, as well as the corresponding confidence intervals, are presented for a number of runs that were performed for each partition of data. This allows for an assessment of the consistency of the feature-level fusion approach and to assess whether the achieved performance improvements were significant and not data-fold specific.

8. Conclusion

This study proposed a robust hybrid feature extraction strategy based leaf disease classification framework that combines MobileNetV2-derived deep features with handcrafted texture, colour, and shape descriptors. Across several machine learning classifiers, our proposed technique maintains remarkable classification accuracy, ranging from 96.7% to 98.7%, based on experimental evaluation. In particular, the framework attained a maximum accuracy of 98.7% using XGBoost and 98% with KNN, outperforming established CNN-based feature extraction methods such as VGG16, VGG19, ResNet50, and InceptionV3, which achieved comparatively lower accuracies. The comparative analysis also showed that the proposed method has a stable and classifier-independent performance, where the other classifiers, such as Random Forest, SVM, and Logistic Regression, also reported competitive results with high accuracy rates above 95%. The small performance difference between the compared classifiers is an indication of the high separability of the features, and the results also prove that the improvement is due to the quality of the extracted features and not the classifier used for the classification process, thereby validating the effectiveness, robustness, and generalization of the proposed method for accurate leaf disease identification.

Future Scope

Although the proposed framework shows near-optimal performance, but there are several extensions to make it even more efficient. So, future work may focus on evaluating the model on larger, multi-crop, and multi-disease datasets to test cross-dataset generalisation. Integration of attention mechanisms, lightweight transformer encoders, or multi-scale feature learning may further enhance the identification of subtle disease patterns. Also, incorporating disease region segmentation before feature extraction could reduce complexity and improve robustness under complex field conditions.

Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

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