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A prediction of coconut and coconut leaf disease using MobileNetV2 based classification

Kavitha Magadi Gopalakrishna, Raviprakash Madenur Lingaraju
Department of Computer Science, Kalpataru Institute of Technology, Tiptur - affiliated to Visvesvaraya Technological University, Belagavi, India

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ABSTRACT

This research is aimed at effectively predicting coconut and coconut leaf disease using enhanced MobileNetV2 and ResNet50 methods. The stages involved in this implemented method are data collection, pre-processing, feature extraction, and classification. At first, data is collected from coconut and coconut leaf datasets. Gaussian filter and data augmentation techniques are applied on these images to eliminate noise during the pre-processing phase. Then, features are extracted using ResNet50 technique, while the diseases are classified using MobileNetV2 approach. In comparison to the existing methods namely, EfficientDet-D2, DL-assisted whitefly detection model (DL-WDM), and modified inception net-based hyper tuning support vector machine (MIN-SVM), the proposed method achieves superior classification values with 99.99% and 99.2% accuracy for coconut leaf and for coconuts, respectively.

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Corresponding Author:

Kavitha Magadi Gopalakrishna
Department of Computer Science, Kalpataru Institute of Technology, Tiptur - affiliated to Visvesvaraya Technological University
Belagavi, India
Email: kavitha.mg@kittiptur.ac.in

1. INTRODUCTION

In recent years, coconut has emerged as a key crop in tropical regions, playing a vital role in the economies of several countries of the south and southeast Asian regions such as Philippines, Indonesia, and India [1]. Recent observations have shown that a majority of coconut trees are afflicted with diseases, which progressively weaken and restrict the amount of coconut produced. Coconut trees are referred to as the ‘trees of heaven’ as all parts of this plant provide a source of income for farmers [2]. More than 93 countries cultivate coconuts on 12 million hectares of land, producing 59.98 million tons of nuts annually. With 10.56 million tons of annual coconut production, India ranks third in the world [3]. The Indian states that produce coconuts are Tamil Nadu, Kerala, Karnataka, Assam, Orissa, Goa, and West Bengal [4]. These trees provide a variety of valuable products that include edible fruits, coconut drinks, fiber for commercial use, edible coconut oil, and coconut shells for fuel and industrial purposes [5]. Significant damage to coconut palms from coconut leaf diseases result in lower crop yields and financial losses for growers. Additionally, nutrient deficiencies and insect infestations harm many tree leaves. Early detection and prediction are essential for implementing effective control measures and to reduce the impact of these diseases [6], [7]. Therefore, there is a need for sizable datasets to identify the symptoms of diseases and pest infections using various deep learning (DL) and machine learning (ML) models [8]. However, due to the difficult and time-consuming nature of data gathering on all diseases and pests, this study has been restricted to the detection of only three diseases: stem bleeding disease, leaf blight disease, and red palm weevil pest infection [9], [10]. Current trends demonstrate that ML and DL approaches exhibit great promises in predicting and managing plant diseases [11].

Coconut palms are vulnerable to various diseases such as leaf brightness, leaf spot, bud rot, and lethal yellowing. These diseases cause significant reduction in yields and economic uncertainty for coconut farmers [12]. Hence, the early detection of coconut leaf diseases is crucial due to various factors including limited source accessibility and the high time consumption of the existing models [13]. ML algorithms such as random forests, decision trees, and neural networks are effective in coconut leaf disease prediction [14]. It is now possible to deliver accurate and reliable predictions for coconut leaf diseases by efficiently training these algorithms [15]. Plant diseases and pests have consistently increased, causing an adverse effect on crops, lowering yields, food quality, fiber content, and biofuel yields. State-of-the-art models like Inception v3, convolutional neural network (CNN), and visual geometry group-16 (VGG16) are utilized to optimize disease detection, improve early diagnosis, and enhance crop output in the coconut industry with real-time/historical data [16].

Recent observations have shown that a majority of coconut trees are afflicted with diseases which progressively weaken and limit the amount of coconuts produced [17]. In order to maximize the benefits of coconut production, the primary focus is on improving the livelihood of coconut leaves through early disease detection. However, many farmers struggle to identify diseases, as multiple plants often exhibit similar symptoms of nutrient deficiencies. Since different fertilizers in the market contain varying levels of nutrients, selecting the right fertilizer is crucial [18]. Lakshmi and Savarimuthu [19] introduced an EfficientDet-D2 method, a DL technique designed to detect leaf disease regions. This method offered improved detection accuracy even under adverse conditions such as significant interclass variations, and small infected areas on diseased leaves. The developed deep learning approach provided significant output with minimal computational resources and parameters. Its advantages included cost-efficiency and minimal storage requirements, making it suitable for integration into smartphones or drones with limited resources. Kavithamani and UmaMaheswari [20] implemented a DL-assisted whitefly detection model (DL-WDM) for the identification of whiteflies in coconut tree leaves. This implemented method was employed to diagnose issues like blade pollution, insect infection, and root bleeding in coconut trees. The developed model improved the translocation efficiency of coconut tree leaves; however, the DL-WDM model required more resources in its non-pressurized form when compared to the pressurized form. Megalingam *et al.* [21] implemented a MIN-SVM model for the classification of coconut trees. The pre-processed image features of the coconut tree were extracted using four CNN models: Inception Net, ResNet, VGG) and MIN-SVM. The clustering analysis revealed that dwarf and tall accessions were separated into distinct clusters.

De Silva *et al.* [22] developed a nested polymerase chain reaction (PCR)-based method for detecting coconut leaf diseases in Sri Lanka. The model also tracked the systematic movement of pathogens by evaluating the suitability of various PCR combinations, distinguishing between tissue types and pathogen movements. While the method has a low success rate in pathogen detection, it successfully identified disease-free regions in the sample data. Pammit *et al.* [23] developed a transcript assembly of reference-aided full-length, molecular characterization and cDNA cloning of coronatine-insensitive 1b gene (COI1b) in coconut leaves. The full-length COI1b-1 of cDNA had 7919bp with ORF of 1176bp which was encoded for an inferred protein of 391 acids. On the other hand, the COI1b-2 had 2360bp with cDNA of ORF 1743bp which encoded an inferred protein of 580acids. This analysis proved that the isoforms were involved in various development procedures, including the plant's defense mechanism to pathogens and insects. Previous methods struggled with detecting pests due to limitations in factors such as space, edges, lighting, rotation, and spatial variations, which were retrieved for efficient pest detection.

With technological advancements, ML and DL techniques have become crucial for efficient coconut disease detection and prevention. From the overall literature analysis, it is seen that several DL approaches employed for coconut and coconut leaf disease identification experience certain setbacks. This is due to inefficient feature learning of the extracted features, which made it harder for the model to differentiate between diseased and healthy images, resulting in inaccurate prediction. This motivates the present study that proposes DL-based prediction model for accurate prediction of coconut and coconut leaf images dataset. Thus, in this research, the MobileNetV2 method is utilized to predict coconut leaf diseases with the presence of caterpillars, leaflets, drying of leaflets, flaccidity, and yellowing, for the classification of diseases with bud rot and nut fall. The major contributions of this study are listed below:

- In this study, the performance of the proposed MobileNetV2 is analyzed on coconut and coconut leaf image datasets.
- Pre-processing is carried out using a Gaussian filter for noise elimination, while data augmentation is deployed for improving the model's performance.
- Then, the ResNet50 is employed for the extraction of optimal features from the pre-processed image, after which classification is carried out using MobileNetV2. In the final stage, the effectiveness of the proposed MobileNetV2 is analyzed in terms of precision, accuracy, f-score, and recall.

This rest of this manuscript is organized as follows: the proposed method is detailed in section 2, classification using MobileNetV2 is explained in section 3, the comparative analysis is carried out in section 4, while the conclusion of this research is specified in section 5.

2. METHOD

The proposed MobileNetV2 method is implemented for the classification of coconut and coconut leaf diseases. The coconut and coconut leaf image datasets are utilized in this paper for gathering images, followed by Gaussian filter and data augmentation employed for image preprocessing for noise elimination. Then, ResNet50 is employed for feature extraction from the pre-processed images, and finally, MobileNetV2 is utilized for disease classification. The block diagram of the overall process is given in Figure 1.

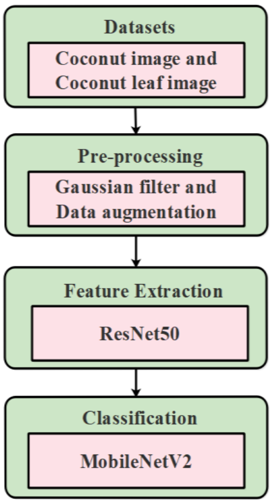

Figure 1. Overall block diagram of the proposed system

2.1. Datasets description

This research utilizes coconut and coconut leaf image datasets for analysis. The images are captured using digital imaging devices like digital cameras, cell phones, digital single-lens reflexes, and other similar devices. The images are captured in various natural environments, at different times of the day, with varying light intensities and angles to avoid redundancy in images. The coconut images are collected from in and around the farms of Tiptur, Tumakuru District, and Karnataka State. The coconut image dataset contains 315 images which are split into two categories: 150 images of healthy coconuts, and 165 images of infected coconuts. Similarly, the coconut leaf image dataset [24] consists of a total of 5,036 images, which are categorized into 5 classes as 795 images of leaflets, 990 images of caterpillars, 1084 images of leaf or fruit yellowing, 1088 images with dried leaflets, and 1079 images of flaccidity. Figure 2 represents the sample images of coconut image dataset, in Figure 2(a) represents healthy coconut sample and Figure 2(b) represents infected coconut sample. Figure 3 represents the sample images of coconut leaf image dataset, in Figure 3(a) represents caterpillars class sample image, Figure 3(b) represents leaflets class sample image, Figure 3(c) represents drying of leaflets class sample image, Figure 4(d) represents flaccidity class sample image and Figure 5(e) represents yellowing class sample image.

(a) (b)

Figure 2. Sample images of the coconut image dataset (a) healthy coconut and (b) infected coconut

(a) (b) (c) (d) (e)

Figure 3. Sample images of coconut leaf image dataset (a) caterpillars, (b) leaflets, (c) drying of leaflets, (d) flaccidity, and (e) yellowing

2.2. Pre-processing

Preprocessing is performed after collecting data from coconut and coconut leaf images. The preprocessing techniques, Gaussian filter and data augmentation are utilized to convert raw data into a usable format through noise removal and data balancing for all classes. Both gaussian filter and data augmentation techniques are explained below in detail.

2.2.1. Gaussian filter

Gaussian filter is applied to filter noise present in coconut and coconut leaf images before the classification process. Based on the Gaussian function's shape, this approach selects a linear filter through a weighted value for each component. The filter is chosen because it effectively refines the images while considering the kernel center. The values of each component in the Gaussian smoothing filter are mathematically computed using (1), where, the normalization constant is denoted as c, and the Gaussian kernel's standard deviation is represented as σ.

$$h(x, y) = \frac{1}{c} e^{\frac{x^2+y^2}{2\sigma^2}} \quad (1)$$

2.2.2. Data augmentation

The denoised image is then passed onto data augmentation for generating modified versions of the images to artificially increase the size of the dataset. This additionally helps overcome the issue of lack of data, along with overfitting, and also improves the models' capacity for generalization. After data augmentation, the coordinates of a point are obtained using the transformation matrix. The present study evaluates using the image augmentation techniques of flipping, shifting, cropping, and color change [25]. These pre-processed images are further transformed into features by being fed into the feature extraction phase which helps in the accurate classification of diseased images.

2.3. Feature extraction using ResNet50

After pre-processing, the augmented images are fed as input into the feature extraction phase which is an important step in the coconut leaf disease prediction for efficient feature extraction. Feature extraction helps extract significant informative and discriminative features that increase the prediction performance of the model. Furthermore, the ResNet50 is one of the deep neural networks, where the term "residual networks" is used, and there are 50 layers present in the ResNet50 architecture which is commonly used for feature extraction. The reason ResNet is selected in this case is that it presents the idea of residual units, which make it possible for deep layers to directly learn from shallow layers, thereby easing the process of network convergence. It also possesses better learning capacity with improvised image recognition capabilities. Moreover, it facilitates the training of deep networks by using skip connections which mitigate the issue of vanishing gradient. In relation to DenseNet, the ResNet50 architecture is simpler and computationally efficient. The ResNet50 [26] is particularly effective at extracting robust features from images and learning their underlying structure. Similar to the standard CNN, the ResNet50 includes pooling layers, convolution layers and residual blocks, which are central to the ResNet architecture [27]. These residual blocks aim to establish connections between the predictions and the actual input. The ResNet50 architecture is expressed in (2).

$$Y = F(x, W) + X \quad (2)$$

where, the residual block input is denoted as X, convolutional layers within block weights are denoted as W, and the residual block output is denoted as Y. The function of convolutional layers within the block is referred to as $F(x, W)$. It takes input (X) and weight (W) as arguments and applies different operations including batch normalization, activations, and convolutions. The ResNet50 has a three-channel input of the size 224×224. It begins with a max-pooling and convolutional layer with 3×3 and 7×7 kernel sizes, respectively. Each convolutional block in the ResNet50 architecture has three convolution layers, and each identified block also includes three convolution layers. The fully linked layer with 1000 neurons in the final layer is followed by average pooling layer and the previous five stages. The network also includes a fully connected layer with 1000 neurons in the final layer, followed by an average pooling layer and the proceeding five stages. In this research, ResNet50 serves as the base model, with additional fully connected layers built on top. For the final layer, 1024×7 fully connected layers are substituted. Using this ResNet50 model, 2048 features are extracted from each preprocessed coconut and coconut leaf images. ResNet50 offers a commendable performance for recognizing coconut leaf images. Then, optimal features are passed as input to the classification stage, and these optimal features are used to increase the classification outputs.

3. CLASSIFICATION USING MOBILENETV2

Following the feature extraction, the MobileNetV2 is employed to effectively classify the coconut fruit and coconut leaf diseases by utilizing the extracted significant features. MobileNetV2 is utilized for predicting coconut and coconut leaf diseases and is chosen for its lightweight architecture, allowing efficient implementation for accurate image classification. MobileNetV2 [28] possesses a strong and portable model for image classification tasks. The combination of the MobileNetV2's excellent accuracy and its effective architecture makes it an ideal choice for devices with limited resources. Additionally, it incorporates shortcut connections between bottlenecks to improve gradient flow and enhance training efficiency. The architecture of MobileNetV2 [29] is similar to that of the original MobileNet, with the main difference being the removal of nonlinearities in narrow layers, and the adoption of inverted residual blocks with bottlenecking characteristics. Compared to the original MobileNet, MobileNets has fewer parameters and handles all input sizes larger than 32×32 pixels more efficiently, performing better with large image sizes. The MobileNetV2 contains two types of blocks: a residual block with a stride of 1, and a block with a stride of 2 for downsizing. There are three layers for each block, including the first layer which is a 1×1 convolutional layer with ReLU6, followed by a depth-wise convolution and a final convolution 1×1 layer, without any activation function.

The MobileNetV2 method is used to enhance the system's capability for coconut and leaf disease classification. In relation to the existing methods, the MobileNetV2 enables real-time disease detection in resource-constrained environments, and provides an effective balance between computational efficiency and accuracy. The accuracy of MobileNetV2 in detection of coconut leaf diseases is further improved through optimization. Given that the MobileNetV2 has a complicated structure and multiple parameters, overfitting is common issue, especially when the training dataset is small. To mitigate overfitting, MobileNetV2 is optimized using the L2 regularization method, which helps prevent overfitting, reduces the impact of complex background filter noise, and ensures that the model can effectively handle the categorization of new data.

3.1. L2 regularization

L2 regularization adds a regularization item (penalty item) to the loss equation for preventing the model from overfitting to noise, including complex backgrounds in the training set. It also reduces the model complexity by limiting the weight ω with a maximum number of parameters. The mean square error loss function and the original loss function are employed during the training process. The loss function is denoted as $J_0(\omega, b)$, and is mathematically expressed in (3).

$$J_0(\omega, b) = \frac{1}{m}\sum_{i=1}^{m} L\left(y'^{(i)}, y^{(i)}\right) \tag{3}$$

where, the cost function is represented as L, and the number of elements in the sample dataset is denoted as m. The amount of bias during neuron transmission is denoted as b. The neuron's desired output value is represented as $y^{(i)}$, while the real value is $y'^{(i)}$. Following the regularization addition, $J_0(\omega, b)$ is not optimized directly, but is primarily optimized as $J_0(\omega, b) + c\lambda R(\omega)$. The model's complexity is described by the penalty term or regularization term denoted as $R(\omega)$, which is calculated using (4). Where, the number of fully connected layers is represented as l, and the jth neuron's weight is denoted as ω_j. The expression of the regularized loss function is represented in (5).

$$R(\omega) = ||\omega||^2 = \sum_{j=1}^{l} \omega_j^2 \tag{4}$$

$$J(\omega, b) = \frac{1}{m}\sum_{i=1}^{m} L\left(y'^{(i)}, y^{(i)}\right) + \frac{\lambda}{2m}\sum_{j=1}^{l} \omega_j^2 \tag{5}$$

where, the regularization factor is indicated by λ. In the experiment, the output and the all the connection layers are optimized using the L2 regularization technique. After cross-validation, λ is assumed to be 0.004 [30]. The results and analysis of the proposed method are given below.

4. RESULTS AND DISCUSSION

The following system setup is used for processing the simulation data for classification and prediction of coconut leaf diseases. The Anaconda Navigator version of 3.5.2.0 is used with Python 3.10, with the system specifications being: 16 GB RAM, Windows 10 (64-bit) operation system, and Intel Core i7 processor. The proposed method's effectiveness is analyzed in terms of accuracy, F1-score, precision, and recall. The mathematical representations of these parameters are represented in (6)-(9).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{6}$$

$$F1-Score = \frac{2TP}{2TP+FP+FN} \tag{7}$$

$$Precision = \frac{TP}{TP+FP} \tag{8}$$

$$Recall = \frac{TP}{TP+FN} \tag{9}$$

where, TP denotes true positive, true negative represents TN, false positive refers to FP, and false negative denotes FN.

4.1. Quantitative and qualitative analysis

The performance evaluation of MobileNetV2 is computed in terms of recall, precision, F1-score, and accuracy which are displayed in Tables 1 and 2. The implemented MobileNetV2 model is compared with the existing state-of-the-art methods namely, CNN, RsNet50, and VGG19. The ResNet50 method is compared with the feature extraction methods: Inception v3, CNN and VGG16. The analysis of ResNet50 method in terms of recall, precision, F1-score, and accuracy are represented in Tables 3 and 4. The MobileNetV2 automatically predicts coconut and coconut leaf disease images, as opposed to other methods. The implemented MobileNetV2 performs exceptionally well in the classification of plant leaf diseases due to its adaptability to extensive image variability, and efficient extraction and parameter management capabilities. Additionally, faster training and less memory consumption are also made possible due to the exceptional accuracy of the model. The MobileNetV2 is commendable at capturing elements necessary for disease categorization at both low and high levels. Advanced regularization methods are incorporated to prevent overfitting with the guarantee that the model performs effectively when applied on fresh, untested data. The MobileNetV2's superior performance in accurately classifying coconut leaf diseases is attributed to its optimized design, ability to handle a variety of leaf characteristics, as well as the regularization methods. This makes it a valuable resource for agricultural and disease management proposals.

Table 1 displays the performance of MobileNetV2 on the coconut image dataset with different classifiers. The performance of the ResNet50, CNN, and VGG19 are measured and matched with that of the implemented MobileNetV2 model. The obtained outcomes exhibit that the implemented MobileNetV2 model outperforms other models with recall, precision, F1-score, and accuracy values of about 99.99%, 99.99%, 99.99%, and 99.99%, respectively.

Table 1. Performance analysis of MobileNetV2 with different classifiers on Coconut image dataset

Datasets	Classifiers	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Coconut image	ResNet50	60.00	30.00	37.00	60.00
	CNN	87.00	91.00	83.00	85.00
	VGG19	94.00	95.00	93.00	94.00
	MobileNetV2	99.99	99.99	99.99	99.99

Table 2 demonstrates the performance of ResNet50 on the coconut image dataset with different FE methods. The performance metrics of Inception v3, CNN, and VGG16 are compared with the ResNet50 model. The accomplished outcomes reveal that the ResNet50 model achieves superior feature extraction results with recall, precision, F1-score, and accuracy values of about 99.99%, 99.99%, 99.99%, and 99.99%, respectively.

Table 2. Performance analysis of ResNet50 with different FE methods on coconut image dataset

Datasets	Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Coconut image	Inception v3	62.00	35.00	36.00	61.00
	CNN	88.00	91.00	83.00	85.00
	VGG16	94.00	95.00	93.00	94.00
	ResNet50	99.99	99.99	99.99	99.99

Table 3 displays the effectiveness of MobileNetV2 on the coconut leaf image dataset with different classifiers. The performance metrics of ResNet50, CNN, and VGG19 are measured and contrasted against that of the implemented MobileNetV2 model. The obtained outcomes surpass the existing models in terms of recall, precision, F1-score, and accuracy, with corresponding values of about 99.56%, 99.4%, 99.48%, and 99.2%.

Table 3. Performance analysis of MobileNetV2 with different classifiers on coconut leaf image dataset

Datasets	Classifiers	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Coconut leaf image	ResNet50	45.78	46.00	45.00	45.50
	CNN	30.54	30.00	29.00	29.50
	VGG19	89.86	90.00	88.00	89.00
	MobileNet	99.2	99.4	99.56	99.48

Table 4 presents the outcomes of ResNet50 on the coconut leaf image dataset with different FE methods. The metrics of the state-of-the-art methods namely, Inception v3, CNN, and VGG16 are compared with that of the ResNet50 model. The attained outcomes validate the ResNet50 model based on recall, precision, F1-score, and accuracy of about 99.56%, 99.4%, 99.48%, and 99.2%, thereby proving superior to other FE methods.

Table 4. Performance analysis of ResNet50 with different FE methods on coconut leaf image dataset

Datasets	Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Coconut leaf image	Inception v3	45.78	46.7	45.56	46.00
	CNN	31.54	30.54	28.9	30.00
	VGG16	88.9	91.00	89.00	90.00
	ResNet50	99.2	99.4	99.56	99.48

Figure 4 illustrates the confusion matrix for MobileNetV2 on the coconut image dataset, where the ROC curve is deployed for computing the classifier's performance. In the confusion matrix, 0 denotes the healthy coconut and 1 denotes the infected coconut. The implemented model's results are presented in this section, and the coconut disease performance prediction is executed based on the MobileNetV2 model. The model's classification accuracy during training and validation on the coconut image dataset is shown in Figure 5, where the accuracy is seen to differ between 0.4 to 1. The training and validation loss of MobileNetV2 on the coconut image dataset is illustrated in Figure 6. The training accuracy attained is observed to be 0.99, as shown in Figure 5.

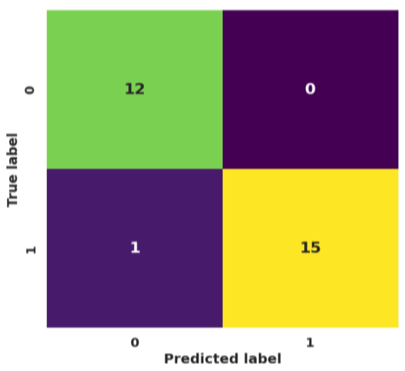

Figure 4. Confusion matrix of MobileNetV2 using coconut image dataset

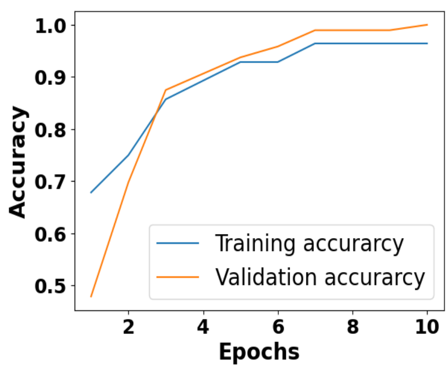

Figure 5. Accuracy training and validation's graphical representation on coconut image dataset

Figure 7 illustrates the confusion matrix for MobileNetV2 on the coconut leaf image dataset. In the confusion matrix, 0 represents Caterpillars, 1 represents Leaflets, 2 indicates Drying of Leaflets, 3 indicates Flaccidity, and 4 indicates Yellowing. The model's results and prediction accuracy of coconut diseases are presented in this section. This involves a binary classification task to categorize coconut leaves as either infected or healthy. Figure 8 displays the training and validation accuracy of the MobileNetV2 model using the coconut leaf image dataset, with accuracy values ranging from 0.955 to 0.995. The training accuracy is represented in blue, while the validation accuracy is shown in red. Figure 9 presents the training and validation loss of the MobileNetV2 model over 10 epochs using the coconut leaf image dataset. The training and validation losses range between 0.02 and 0.16, while the accuracy is 0.99, as shown in Figure 8.

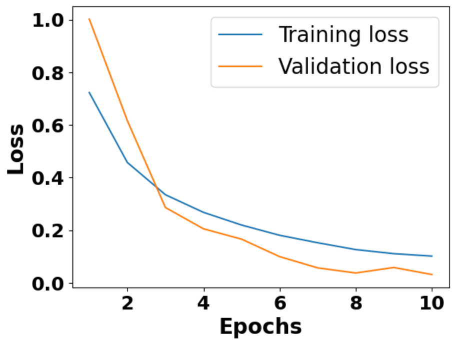

Figure 6. Loss training and validation's graphical representation on coconut image dataset

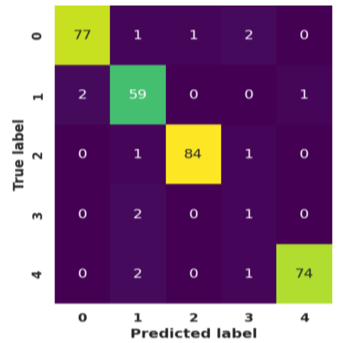

Figure 7. Confusion matrix of MobileNetV2 using coconut leaf image dataset

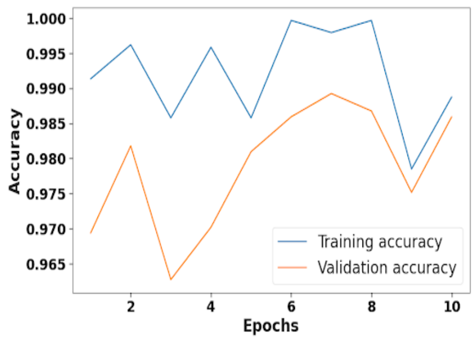

Figure 8. Graphical depiction of training and validation accuracy on coconut leaf image dataset

Figure 9. Graphical representation training and validation loss on coconut leaf image dataset

4.2. Comparative analysis

The effectiveness of the classifier is evaluated by comparing it with the existing methods in [19]–[21]. The proposed method is assessed using both the coconut image and coconut leaf image datasets. For the coconut image dataset, the accuracy is 99.99%, F1-score is 99.99%, recall is 99.99%, and precision is 99.99%. Similarly, for the coconut leaf image dataset, the accuracy is 99.2%, F1-score is 99.48%, recall is 99.56% and precision is 99.4%. Table 5 represents the comparative analysis of proposed method with existing algorithms.

Table 5. Comparative analysis of proposed and existing methods

Methods	Dataset	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
EfficientDet-D2 [19]	Plant village dataset & leaves image dataset	-	88.13	94.06	90.99
DL-WDM [20]	Coconut tree image dataset	95.71	N/A	N/A	N/A
MIN-SVM [21]	Coconut tree image dataset	95.35	N/A	N/A	N/A
	Coconut image	99.99	99.99	99.99	99.99
MobileNetV2	Coconut leaf image	99.2	99.4	99.56	99.48

4.3. Discussion

In this research, coconut and coconut leaf image datasets are exploited to analyze the effectiveness of the proposed MobileNetV2 by comparing with the existing models: EfficientDet-D2 [19], DL-WDM [20], MIN-SVM [21], PCR [22], and coronatine-insensitive 1b gene (COI1b) [23]. The feature vectors are extracted using the ResNet50 technique for high categorization. The accuracy of the coconut leaf image dataset is improved to 99.2%, with an F1-score of 99.48%, recall of 99.56%, and precision of 99.4%, as opposed to the existing EfficientDet-D2 [19], DL-WDM [20] and MIN-SVM [21].

Despite this, the existing EfficientDet-D2 [19] method requires minimal storage space, making it suitable for integration into smartphones or drones with limited resources. Similarly, the PCR [22] method does not identify pathogens in any sample data, thus making it ineffective for predicting disease-free regions. Additionally, the COI1b [23] model does not identify pathogens in any sample data, thus making it ineffective for predicting disease-free regions. Additionally, the Additionally, the COI1b model [23] does not analyze potential breeding approaches and focuses on a time-course investigation of gene expression in a signaling context. In comparison to these existing models [22], [23], the proposed MobileNetV2 offers a lightweight architecture specifically designed for mobile devices. This enables real-time image processing with low computational resources, providing competitive accuracy levels and making disease monitoring more effective and accessible, particularly in environments with limited resources.

From the overall result analysis, it is observed that the existing EfficientDet-D2 [19] obtains a precision of 88.13%, recall of 94.06% and F1-score of 99.48%, on the Plant Village Dataset and Leaves Image dataset. While the existing DL-WDM [20] and MIN-SVM [21] methods attain an accuracy of 95.71% and 95.35%, respectively on the coconut tree image dataset. It is hence clear that the proposed MobileNetV2 outperforms the existing methods with all performance metrics. The MobileNetV2 approach for coconut leaf disease prediction achieves an increased accuracy of 99.99%, F1-score of 99.99%, recall of 99.99% and precision of 99.99% on the coconut image dataset. Despite being lightweight, certain domain-specific tasks require more complex representations with greater computational resources. Additionally, due to the inherent accuracy trade-offs, MobileNetV2 is not very suitable for applications that demand higher precision.

5. CONCLUSION

In this research, the proposed MobileNetV2 technique is implemented to enhance the effective prediction of coconut and coconut leaf diseases. The coconut and coconut leaf images are collected from datasets, along with additional features. Feature vectors are extracted from the pre-processed data using the ResNet50 technique. These extracted optimal features are then fed into the classification process, where the implemented MobileNetV2 method is used for classification. When compared to the existing methods, the coconut image and Coconut leaf image datasets provide the best results from the implemented method. The implemented method achieves accuracy values of 99.99% and 99.2% respectively, on coconut image and coconut leaf image datasets, as compared to the existing methods for the prediction of coconut and coconut leaf disease. These findings highlight novel patterns in the application of DL models for disease identification and reveal research gaps that require further investigation. This dataset is widely used by the scientific community to create and assess DL models for the identification of plant diseases. Farmers will find this approach very helpful in learning about their crop yield. In the future, this research can be further extended by using a hybrid method to improve the accuracy of coconut leaf disease detection, by means of coconut leaf image dataset.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Kavitha Magadi Gopalakrishna	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Raviprakash Madenur Lingaraju		✓				✓		✓	✓	✓	✓	✓		

C	: **C**onceptualization	I	: **I**nvestigation	Vi	: **Vi**sualization
M	: **M**ethodology	R	: **R**esources	Su	: **Su**pervision
So	: **So**ftware	D	: **D**ata Curation	P	: **P**roject administration
Va	: **Va**lidation	O	: Writing - **O**riginal Draft	Fu	: **Fu**nding acquisition
Fo	: **Fo**rmal analysis	E	: Writing - Review & **E**diting		

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are openly available in Coconut leaf data repository at *https://www.kaggle.com/datasets/samitha96/coconutdiseases*.

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BIOGRAPHIES OF AUTHORS

Kavitha Magadi Gopalakrishna is a research scholar with a background in electronics engineering, computer science, AI, and ML. She is currently working as an assistant professor, with 10+ years of experience in the computer science field. Her current research focus lies in applying AI and ML techniques in the field of agricultural significance: disease prediction. Her current research delves into harnessing the power of AI and ML algorithms for the critical task of identifying and predicting diseases in trees. This innovative approach has the potential to revolutionize the coconut industry by enabling earlier detection and intervention, ultimately improving crop health and yield. Area of interest: specific areas of interest within AI and ML, IoT likely involve algorithms particularly well-suited to DL, CNN, image recognition, or pattern recognition. These techniques could be applied to analyze visual data of coconut trees, such as photographs, to detect signs of disease and predict future outbreaks. She can be contacted at email: kavitha.mg@kittiptur.ac.in.

Raviprakash Madenur Lingaraju has completed his Ph.D. (Computer Science & Engineering): Visvesvaraya Technological University. He has 13+ years of teaching experience in various fields such as ML and DL, data science, cloud computing, wireless ad hoc networks, image processing. He has published various research papers in reputed journals and conferences such as IEEE, and Springer. He has delivered various talks on ML, data science and its applications, cyber security. He has reviewed many national and international journals and conference papers. He has received certificate of appreciation as a session chair in International Conference, received certificate of appreciation from IEEE Bangalore section for outstanding dedication and support for IEEE International Conference. Research scholars have been awarded Ph.D., under his guidance and he is guiding over 6+ research scholars in various fields of ML, network security, DL. He has patent in an effective method for fake medicine detection and recommendation system and anomaly detection in cloud environment using deep learning application. He can be contacted at email: raviprakashml@kittiptur.ac.in.