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# Efficient Mobile ViT Based Framework for Early Detection and Classification of Coconut Leaf Detection

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**ABSTRACT:** Coconut plantations are crucial role in the agricultural economy in tropical regions. The detection of Coconut Leaf Disease (CLD) is significantly challenged by the presence of pests and other diseases in farming. Therefore, early detection of diseases in coconut leaves is essential for maintaining crop health and maximizing yield. Hence, this study presents a comprehensive approach to the classification of coconut leaf images through a robust image processing integrated with transformer based Deep Learning (DL) technique. The coconut diseases and pest infestations dataset is applied pre-processing stage using a Guided Image Filter (GIF), which enhances image quality by preserving edges while suppressing noise. Following this, Active Contour Method (ACM) is employed for precise segmentation, enabling accurate delineation of leaf boundaries. To extract meaningful texture features, the Local Ternary Pattern (LTP) technique is applied, offering improved noise resistance and discriminative pattern compared to traditional texture descriptors. Finally, a lightweight yet powerful transformer-based deep learning (DL) model, the Mobile Vision Transformer (MobileViT), is employed to classify healthy and infected coconut leaves. Using Python software, the proposed framework achieved higher accuracy, F1-score, precision and recall of 96%, is accomplished when compared to other techniques.

**Keywords:** Coconut Leaf Disease, Guided Image Filter, Active Contour Method, Local Ternary Pattern, Mobile Vision Transformer.

## 1. Introduction

Agriculture remains the backbone of many developing economies, providing employment, food security, and raw materials for various industries. In tropical and subtropical regions, coconut (Cocos nucifera) is one of the most important crops, valued for its diverse uses in food, cosmetics, oil production, and coir industries [1]. However, coconut cultivation is increasingly threatened by various diseases particularly that manifest in the leaves [2]. A coconut tree is a member of the palm family, the coconut tree bears fruit 5–6 years after planting and have an economic lifespan of 50–60 years [3]. With a crown of 30–40 leaves, the tree often reaches a height of 30 m, providing plenty of food and cover for numerous insects and pests to survive and procreate [4]. On the other hand, diseases and pests that affect coconut plants kill the palm and produce outbreaks, which results in significant financial losses [5]. Consequently, effective disease and pest management techniques are essential for CLD, such as leaf blight, yellowing, and leaf spot, significantly reduce photosynthetic efficiency, hamper growth, and ultimately lower crop yield and economic returns [6]. To address these challenges, various pre-processing, segmentation, feature extraction, and classification techniques are employed for improved diagnosis and differentiation.

The raw images from the original dataset are pre-processed by some of the following techniques. Coconut leaf image is processed using the pre-processing technique such as, Contrast Limited Adaptive Histogram Equalization (CLAHE) for image enhancement. CLAHE is for better enhancement of coconut leaf image in both dark and bright leaf regions. It enhances local contrast effectively, illuminating finer disease-related textures on the leaf surface. Nevertheless, it computationally more costly and extreme enhance in low-contrast region for leaf image [7]. Consequently, Median Filtering (MF) technique is utilized to remove the noise from the coconut leaf image. MF effectively captures small features such as disease spots, lesions, or streaks on the leaf surface. MF preserves sharp edges which are essential for detecting leaf edges and disease spots, computationally efficient and easy to implement. Nonetheless, it is slower for high-resolution images due to sorting operations, performance depends heavily on the window size. [8]. Additionally, to enhance the coconut leaf image, a High Pass Filtering (HPF) is utilized in [9]. This method enhance the leaf disease lesion, edge and vein HPF is achieved with high performance. However, amplifies noise along with edges, especially in noisy or low-contrast images, not suitable as a standalone method for smooth region enhancement. To overcome the above limitation proposed GIF based pre-processing technique is utilized to remove unwanted noise and preserve edges from coconut leaf image for further Processing.

Some of the following existing segmentation techniques are used to segment the CLD from the coconut leaf. Segmentation based on K-means clustering for segmenting coconut leaf region and lesion in the coconut leaf image. K-means clustering technique to segment the healthy and infected coconut leaf based on color, texture. It is simple, fast, and effectively separates different regions. Nevertheless, it is sensitive to noise and outlier, which lead to incorrect segmentation [10-11]. Moreover, an enhanced Fuzzy C-Means clustering based segmentation to segment the pest and healthy coconut leaf image. It is more suitable for handling the uncertainties and overlapping regions often found in diseased coconut leaf images. Enhanced Fuzzy C-Means clustering have better handling on fuzzy disease boundaries, more accurate and smooth segmentation. Nonetheless, it struggle with highly textured or low-contrast regions, and more computational cost [12]. For the above limitation the boundaries, region, areas and lesion are segmented using the ACM. In this research ACM approach is proposed that effectively segments the coconut leaf image.

Furthermore, feature extraction methods helps to pick important parts from coconut leaf images to detect the disease easily. In existing methods, Scale Invariant Feature Transform (SIFT) to detect the key points and describe local features, for identifying coconut leaf disease-affected regions. The SIFT extract the key points from the coconut leaf image and find the values for the features. Nevertheless, it's computationally expensive, slower feature extractors, and generates a large number of features, make this method more complex [13]. Additionally, to features the coconut leaf image pest GLCM is utilized with high accuracy and performance. GLCM identifies CLD areas and regions; it effectively finds the value of contrast, correlation, homogeneity, energy, and entropy. Also, it efficient and simple method for capturing local texture features in coconut leaf image. However, GLCM method high sensitive to leaf image resolution, noise, lighting variation, complex background [14-15]. Therefore, the proposed feature extraction technique utilizes LTP for addressing the above limitations and efficiently discriminative patterns from coconut leaf images.

The healthy and infected coconut leaf image is classified by some of the following technique. In existing method, to classify coconut leaf image using Modified Inception Net based Hyper Tuning Support Vector Machine (MIN-SVM) based on the three morphological parameters including height, inclination and orientation. MIN-SVM is to extract features from coconut leaf images, capturing both local and global patterns such as disease spots, blights, or fungal infections. Also, it achieves high classification accuracy and Inception modules capture multi-scale CLD patterns. However, this method make computationally cost, sensitive to diseased region and over fitting [16]. Moreover, Artificial Neural Network (ANN) to classify the diseased and healthy coconut leaf image. ANN handles multiple input features simultaneously, improving classification speed and robustness. However, requires a large, diverse, and well-labelled dataset to achieve high accuracy, which is a challenge in agricultural domains [17]. To overcome the limitations of existing classification, a proposed MobileViT is implemented for transforming the lightweight information to get high accuracy and efficiency of CLD detection.

## 2. Related Work

**Vidhanaarachchi *et al* (2025) [18]** have proposed a You Only Look Once (YOLO) detection model to classify the CLD. YOLO model identify the Coconut Leaf Wilt Disease and Coconut Caterpillar Infestation effectively. Also, it identify specific disease patterns such as leaf spots, yellowing, fungal patches, even they vary in size, shape, position in the coconut leaf image. Extremely fast and efficient, suitable for real-time disease detection and simultaneously performs detection and classification in a single step. Nevertheless, less accurate in detecting very small disease regions, especially in early infection stages.

**Kavithamani,V and S. UmaMaheswari (2023) [19]** have presented a VGG-16 to identify and classify the CLD image. Diseases like leaf rot, leaf blight, and yellowing are identified using the coconut leaf image. It is used to segregate and classify the disease types of CLD images with higher accuracy. Every layer in VGG-16 receives input from all previous layers, promoting reuse of learned features and improving representation. However, due to its depth and parameter size, prediction of leaf disease is slower.

**Thite *et al* (2023) [20]** have developed a ResNet-50 model for recognizing the diseases of coconut leaf. ResNet-50 identified the coconut leaf with higher accuracy and high performance. ResNet-50 is extremely better at recognizing images of coconut leaf diseases and outperforms the widely used pre-trained models. It is appropriate for real-time applications including its high speed, efficiency, and simplicity. Nonetheless, it takes more time to process the data when large datasets are used.

**Divyanth *et al* (2022) [21]** have proposed a Faster Regional-Convolutional Neural Network (Faster R-CNN) model to detect coconut clusters as non-occluded and leaf-occluded bunches. It accurately identifying and localizing disease symptoms such as leaf spots, blight, or discoloration. Faster R-CNN is capable of identifying small or overlapping diseased areas, performs well in complex backgrounds and images with subtle visual changes. Nevertheless, it occur more complex, high computational cost and memory usage due to the multi-stage detection

**Vinod *et al* (2024) [22]** have presented a Data-Efficient Image Transformer (DeiT) to identify and classify the coconut leaf image. DeiT capture the coconut leaf image color, texture, and shape, such as fungal infections, leaf blights, or discoloration. Performs well on small datasets due to data-efficient training and captures global and long-range dependencies.

However, requires more computational power and memory compared to lightweight CNNs, especially during training.

This study, propose an efficient MobileViT-Based framework for the early detection and classification of CLD**.** The primary goals of this research are to:

- GIF based pre-processing method applied to remove the unwanted noise and enhances image quality by preserving edges whereas suppressing noise on coconut leaf.
- An ACM based segmentation approach used to accurately segment the leaf boundaries from the coconut leaf.
- LTP based feature extraction utilized to efficiently capture the improved noise resistance and discriminative pattern from the segmented coconut leaf image.
- A MobileViT is proposed to improve the classification and detection of coconut leaf images, achieving high accuracy through depthwise separable convolution.

## 3. Proposed work

Figure 1 shows the proposed framework for CLD consists of a structured beginning with the input image of the coconut diseases and pest infestations dataset. The first stage is pre-processing, where a GIF is applied to enhance image quality by smoothing and noise reduction, whereas preserving edges. This filtered image is then passed to the segmentation stage, which employs the ACM to accurately isolate the Region of Interest (ROI) specifically, the affected area of the leaf. Following segmentation, the system performs feature extraction using the LTP technique, which is effective in capturing fine texture variations essential for distinguishing between different disease types.

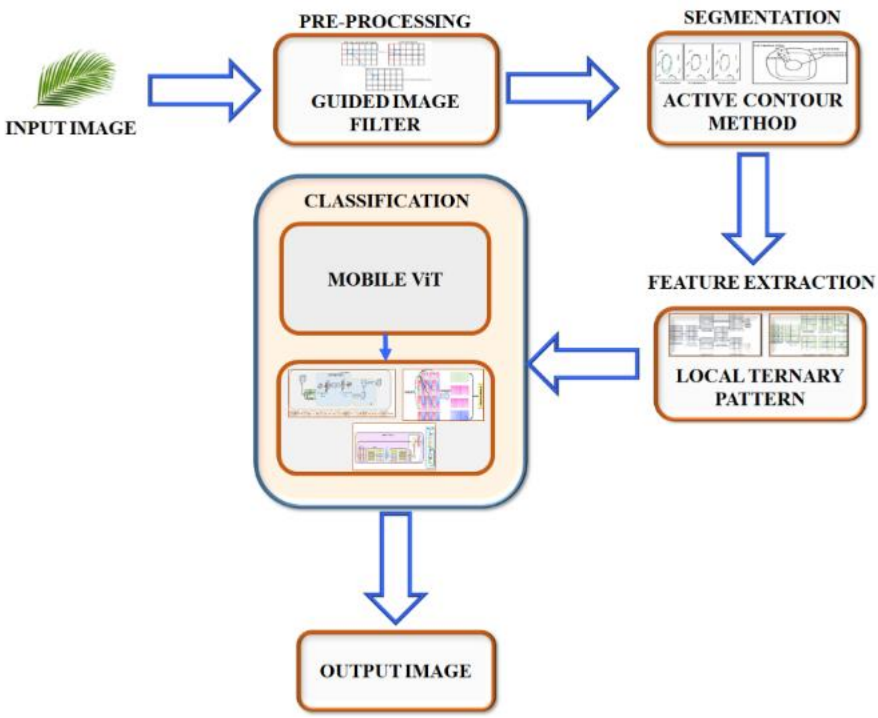


**Figure 1:** *Block diagram of proposed method*

The extracted features are then fed into the MobileViT-based classification module, where the hybrid architecture leverages both convolutional and transformer-based mechanisms to learn local and global patterns in the image. Finally, the classification result indicates the presence of disease in the coconut leaf, which is visually represented in the output image. The proposed MobileViT have better efficiency and accuracy, it suitable for real-time applications.

### 3.1 Pre-processing by Guided Image Filter

In the pre-processing stage of CLD, the GIF plays a crucial role in enhancing image quality by smoothing whereas preserving important structural details such as leaf edges and veins. The filter assumes a local linear model where the output image $q$ is a linear transformation of a guidance image $I$ within a local window $\omega_k$ mathematically, for each pixel $i$ in the window $\omega_k$ , the output is given by:

$$q_i = a_k I_i + b_k \tag{1}$$

Where $a_k$ and $b_k$ are linear coefficients assumed to be constant in the local window. These coefficients are computed by minimizing the cost function:

$$E(a_k, b_k) = \sum_{i \in \omega_k}((a_k I_i + b_k - p_i)^2 \tag{2}$$

Here, $p$ is the input image to be filtered, and $\epsilon$ is a regularization parameter that balances edge preservation with smoothing. Figure 2 shows the GIF for preserving the edges in CLD.

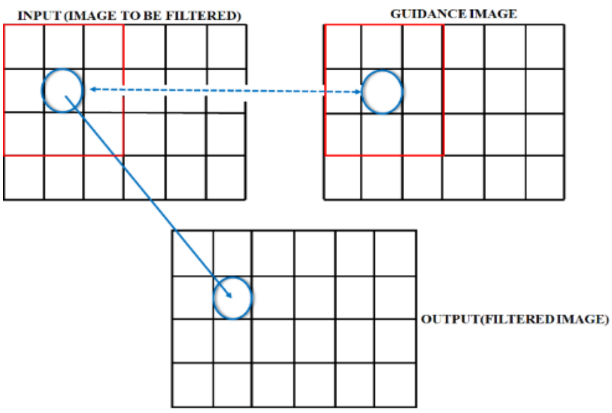


**Figure 2:** *Guided Image Filter*

The optimal coefficients are derived as:

$$a_k = \frac{\frac{1}{|\omega|}\sum_{i \in \omega_k} I_i p_i - \mu_k \overline{p_k}}{\sigma_k^2 + \epsilon} \tag{3}$$

$$b_k = \overline{p_k} - a_k \mu_k \tag{4}$$

Where, $\mu_k$ and $\overline{p_k}$ represent the mean of the guidance and input images in $\omega_k$ and $\sigma_k^2$ is the variance of the guidance image. The final filtered output $q$ is then obtained by aggregating the overlapping consequences:

$$q_i = \bar{a}_i I_i + \bar{b}_i \tag{5}$$

In CLD detection, by applying the GIF benefits in reducing background noise and enhancing leaf contours and vein patterns. The GIF output thus enhances the quality of the coconut leaf image. The processed image is fed to segmentation based on Active Contour Method.

### 3.2 Segmentation by Active Contour Method

In CLD detection, segmentation is a second step that isolates the leaf region from the background for accurate feature extraction. One of the effective techniques for segmentation is the ACM, it is also known as Snakes method. This method mechanism by evolving a curve within the image domain to lock onto object boundaries based on energy minimization principles. The contour is initialized close to the object (the coconut leaf) and iteratively moves under the influence of internal and external forces until it aligns with the actual leaf edges.

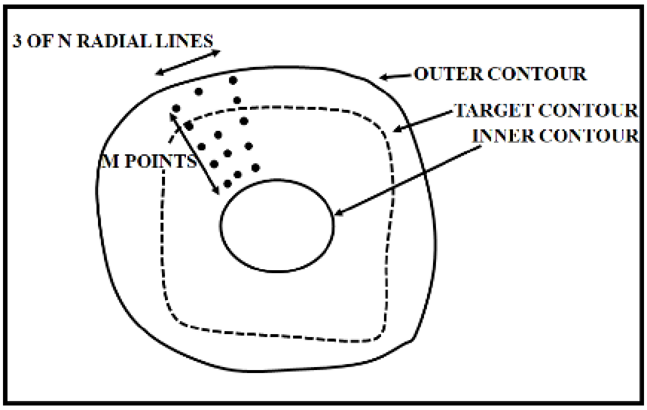


**Figure 3:** *Active Contour Method*

The internal forces ensure the contour remains smooth and continuous by penalizing stretching and bending, whereas the external forces are derived from image features such as gradients, which attract the contour toward high-contrast edges in figure 3. Mathematically, the ACM seeks to minimize energy functional defined as:

$$E_{snake} = \int(\alpha(|V'(S)|)^2 + \beta(|V''(S)|^2 + E_{ext}(V(S)))ds \tag{6}$$

Where $V(S)$ indicates the parametric representation of the contour, $\alpha$ controls tension (smoothness), $\beta$ controls rigidity (stiffness), and $E_{ext}$ is the external energy derived from image gradients, edges. ACM energy attracts the contour toward leaf boundaries for the segmentation. By allowing the contour to deform and adapt to the leaf's actual structure, this method provides precise segmentation that significantly improves the accuracy of subsequent classification or recognition tasks. In CLD detection, the ACM is useful to accurately define the complex and curvilinear shapes of leaves, including fine details like tips and edges, even in the presence of noise. Subsequent, the segmented output is fed to feature extraction technique for coconut leaf image.

### 3.3 Feature Extraction by Local Ternary Pattern

In the analysis of CLD detection, the LTP is a texture-based feature extraction method used to distinguish between healthy and diseased leaf regions. LTP effectively captures fine surface variations such as spots, streaks, or lesions common indicators of disease. LTP is designed to be more resilient to noise and illumination changes. Instead of encoding neighborhood pixel values into binary patterns in figure 4, LTP uses a three-value (ternary) encoding based on a predefined threshold $t$.

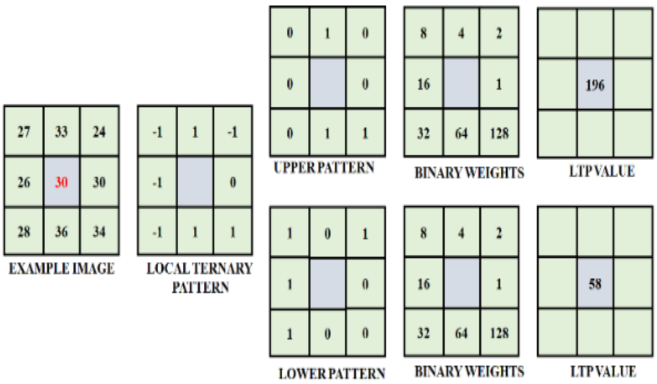


**Figure 4:** *Example for Local Ternary Pattern*

The LTP operator works by comparing each pixel in a grayscale image with its neighboring pixels and encoding the result into three possible values: +1, 0, or –1, based on a threshold value $t$. If the neighbor pixel intensity is greater than the center pixel by more than $t$, it is assigned +1; if it is less by more than $t$, it is assigned –1; otherwise, it is assigned 0. For a given center pixel $I_c$and a neighboring pixel $I_n$, the LTP is defined as:

$$LTP(I_n, I_c) = \begin{cases} +1, & if\ I_n \geq I_c + t \\ 0, & if |I_n - I_c| < t \\ -1, & if\ I_n \leq I_c - t \end{cases} \tag{7}$$

This ternary value is computed for each neighbor in a 3×3 window, generating a pattern of +1s, 0s, and –1s. To handle ternary codes in practical applications (since direct use leads to large feature sets), the LTP is often split into two separate binary patterns: one for the positive (+1) part and one for the negative (–1) part. Histograms of these patterns are then concatenated to form the final texture descriptor. In CLD, LTP approach differentiate between healthy and diseased areas by capturing subtle differences in texture roughness or damage caused by fungal, bacterial, or nutrient-related issues. The extracted LTP features are then used in classification models to accurately identify the type or presence of disease, even under varying lighting or imaging conditions. The extracted coconut leaf image is given to the proposed MobileViT for further classification.

### 3.4 Classification by Mobile ViT

In the classification of CLD detection, a proposed MobileViT is an efficient and transformer based architecture that combines the strengths of CNNs and ViTs. MobileViT is designed to be lightweight and suitable for mobile and edge devices, it is ideal for agricultural applications in remote environments.

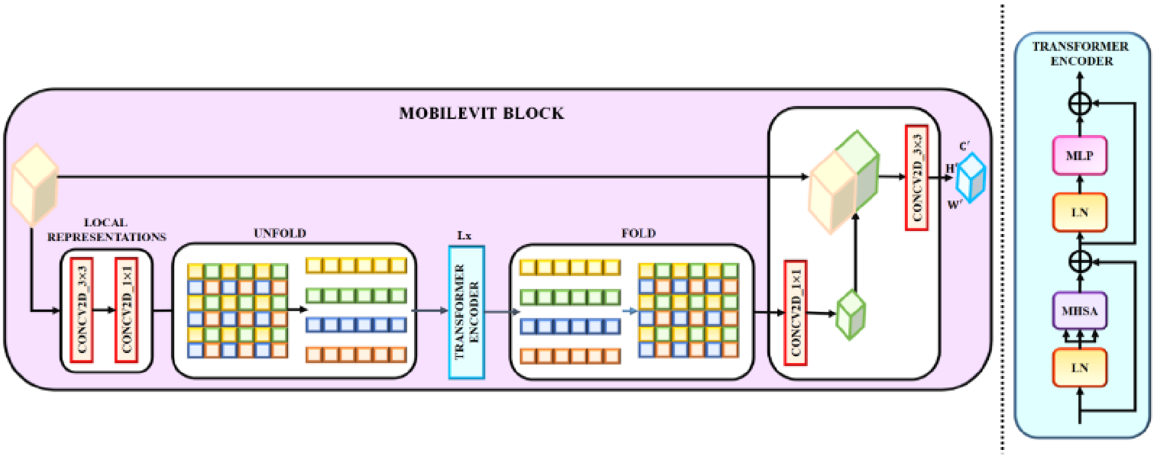


**Figure 5:** *components of the proposed MobileViT architecture*

Figure 5 shows the components of the proposed MobileViT architecture for CLD. It starts with a DepthConv block as the stem layer, which performs the initial classification operation and expands the channel dimension from 3 to 32. In essence, a DepthConv block uses Depthwise Separable Convolution, an effective variation of the standard convolution that operates in two stages: first, a single spatial filter (Depthwise Convolution) is used to convolve each input channel individually. The outputs from the depthwise stage are then combined, and information from different channels is mixed, using a 1x1 convolution (Pointwise Convolution). The next part of the GroupConv block is Group Convolution, which is a specific case when the number of groups is equal to the number of input channels. By dividing each input channel into user-defined groups and convolving them independently using a particular set of filters, it can be viewed as a generalized version of Depthwise Separable Convolution. Half of the input channels are grouped in each GroupConv block, as illustrated in figure 6.

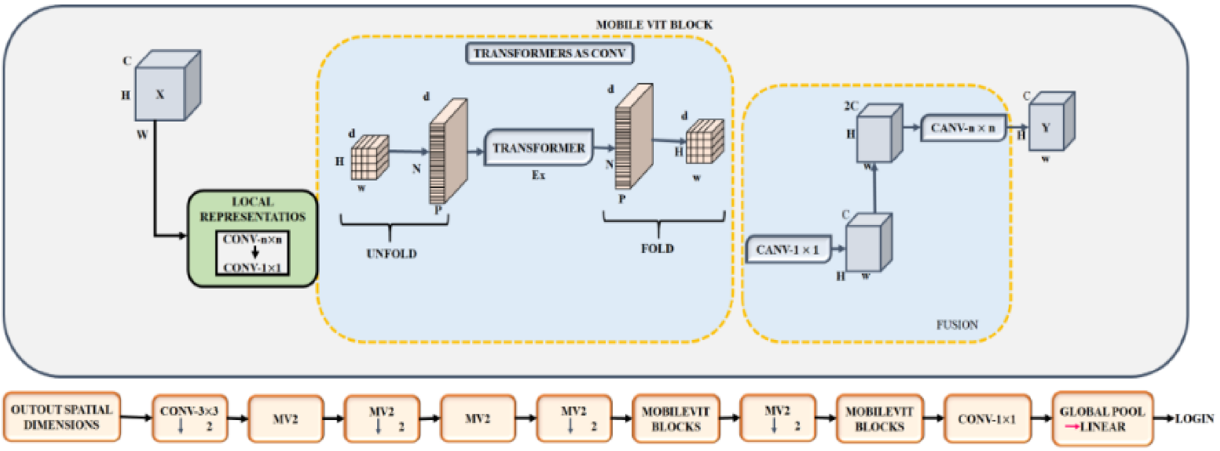


**Figure 6:** *Blocks in the Mobile ViT model*

These residual and multi-step processes allow for effective classification in deep networks whereas extremely lowering the computational burden of conventional convolution. By applying channel attention and spatial attention sequentially, the Convolutional Block Attention Module (CBAM), improves feature representation and enables the network to suppress less important aspects. By using Global Average Pooling (GAP) and Global Max Pooling (GMP) of the feature maps to learn a channel-wise attention map, the channel attention module focuses on identifying the key features. A Multilayer Perceptron (MLP) with sigmoid activation then generates attention weights. In mathematics, the channel attention $M_c(F)$ is as follows, where $F$ is the feature maps:

$$M_c(F) = \sigma(W_1\left(\delta\left(W_0(GAP(F))\right) + W_1\left(\delta\left(W_0(GMP(F))\right)\right)\right) \quad (8)$$

$$F' = M_c(F) \odot F \quad (9)$$

Where $W_0$ *and* $W_1$ are MLP weights, $\odot$ indicates element-wise multiplication, $F'$ is the enhanced feature maps with channel attention , $\sigma$ is the sigmoid function $(\frac{1}{1+e^{-x}})$, and $\delta$ is the ReLU activation, which is $max(0, x)$. The spatial attention module creates a spatial attention map by applying max and average pooling across channels, then using a 7 × 7 convolution to highlight significant areas in the feature map. The spatial attention $M_s(F')$ is equal to the refined feature maps $F'$ following the channel attention module.

$$M_s(F') = \sigma(f^{7\times7}([AvgPool(F'); MaxPool(F')])) \quad (10)$$

$$F'' = M_s(F') \odot F' \quad (11)$$

Where $f^{7\times7}$ is a 7 × 7 convolution, as well as $F''$ indicates refined feature maps output after CBAM. The patch embedding divides the input feature maps into fixed-size patches and then turns each patch into a high-dimensional vector to produce a set of image patches. To divide the features into patches, a DepthConv block whose stride and kernel sizes matched the patch size. This sorts it perfect for tasks requiring fast and precise processing of high quality images, like object detection and image categorization. Thus the proposed MobileViT performs high classification accuracy and good performance for the coconut leaf image.

## 4. Result and discussion

In result and discussion section the CLD are predicted using the proposed MobileViT for identifying disease in coconut leaf. Also, the coconut disease and pest infestations dataset is taken from the kaggle.com implemented using Python software. Total number of train image is 98 for healthy and infected coconut leaf. Total number of test image is 25 for healthy and infected coconut leaf.


**Figure 7:** *Test and train image distribution*

Figure 7 shows the train and test image distribution for coconut leaf images. The total train images have the count of 98, where the healthy train image have the count of 98 and test have count of 25 images. And the infected train images have the count of 98 images and test images have the count of 25 images.


**Figure 8:** *Random images in train*

Figure 8 shows random images in train set for CLD. The random images are taken from the coconut disease and pest infestations dataset for further process. Here, two types of coconut leaf images are taken from the dataset. The coconut leaf images have two classes healthy and infected images are randomly chosen from coconut disease and pest infestations dataset to train for further analysis.


**Figure 9:** *Input image*

Figure 9 shows the input coconut leaf image taken from the coconut disease and pest infestations dataset randomly chosen test and train images. The input leaf image contains large pixel size, raw image and blurry. The coconut leaf image is a raw image from coconut disease and pest infestations dataset from kaggle.com uses the following methods such as pre-processing, segmentation, feature extraction and classification for further processes.

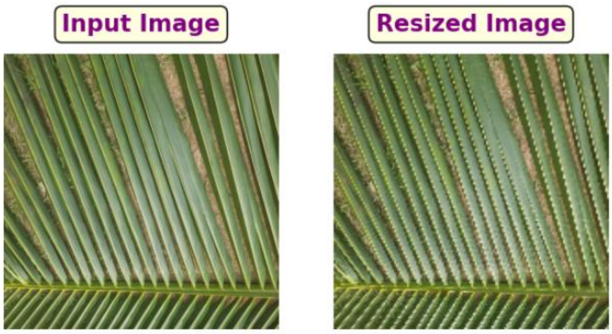


**Figure 10:** *Input image in to resize image*

Figure 10 shows the input image to resize image. Here the input coconut leaf image is resized using image resizing technique. The input raw coconut leaf image is converted in to resize image for further process. The noises present in the original image are removed and develop the better quality image. By resizing the input image to a fixed dimension, it becomes compatible and processed uniformly.

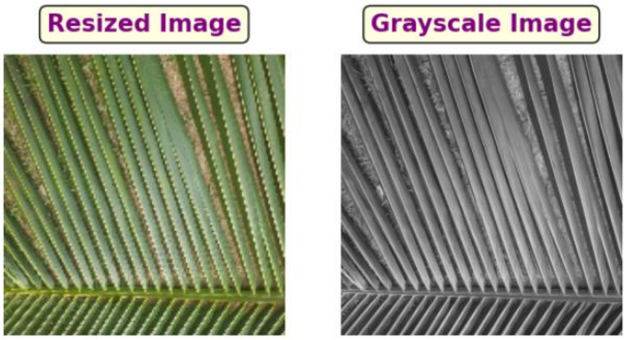


**Figure 11:** *Resized image in to grayscale image*

Figure 11 shows the resized image into gray scale image for CLD detection. Here resized image is transformed into grayscale image for enhancing the leaf region. Once resized, the image is converted to grayscale, which reduces the image from three color channels (Red, Green, and Blue – (RGB)) to a single intensity channel. This grayscale conversion simplifies the data by retaining only luminance information, effectively highlighting texture, edges, and structure without color distractions.

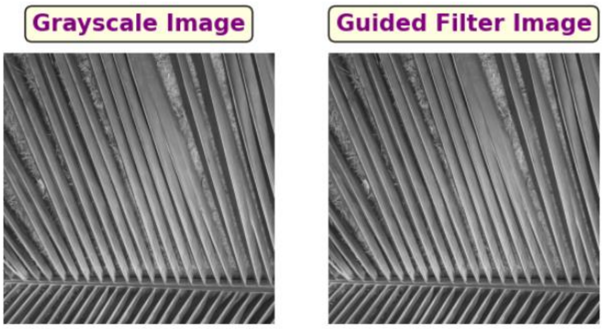


**Figure 12:** *Grayscale image in to guided image filter*

Figure 12 shows the grayscale image into GIF for CLD detection. The GIF removes the unwanted noise from the grayscale coconut leaf image and preserve the edges from the leaf image. By using the GIF the edges are preserved a get high quality filtered coconut leaf image. The captured GIF image is given as an input to the segmentation technique. Here the ACM is used as segmentation based technique.

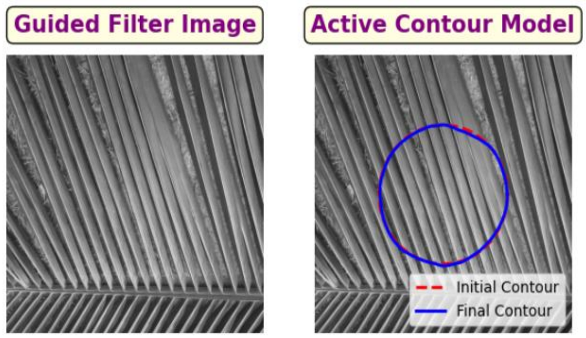


**Figure 13:** *Guided image filter to Active contour method*

Figure 13 shows the GIF in to ACM for CLD detection. The filtered image is given as an input to the segmentation based ACM. Here ACM segments the leaf boundaries as initial contour and final contour. The initial contour indicated by red dotted line and the final contour indicated by blue line. Using ACM the diseased leaf boundaries are segmented and fed as an input to the feature extraction. Here the LTP based feature extraction is used for CLD detection in coconut leaf image.

Figure 14 shows the Active contour model into LTP for coconut leaf. The segmented leaf image is given as an input to LTP based feature extraction technique. LTP image improved noise resistance and discriminative pattern. The patterns from the feature extraction technique are fed as an input to the proposed MobileViT.

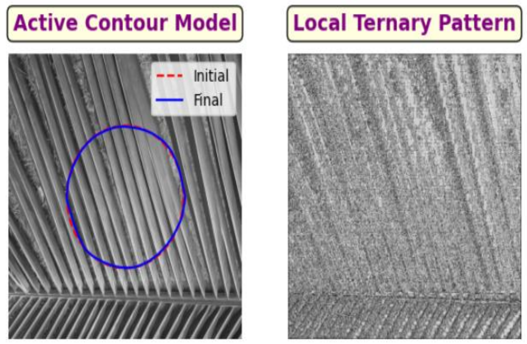


**Figure 14:** *Active Contour model in to local ternary pattern*

## 4.1 Performance metrics for CLD detection

Performance metrics, such as accuracy, sensitivity, and specificity, indicate that the coconut leaf can be correctly detected and appropriately analyzed as the probabilities calculated by MobileViT. The performance metrics in this study explained in table 1.

**Table 1:** *Performance Metrics*

| Performance metrics | Values |
|---|---|
| Accuracy | 96% |
| Precision | 96% |
| Recall | 96% |
| F1-score | 96% |

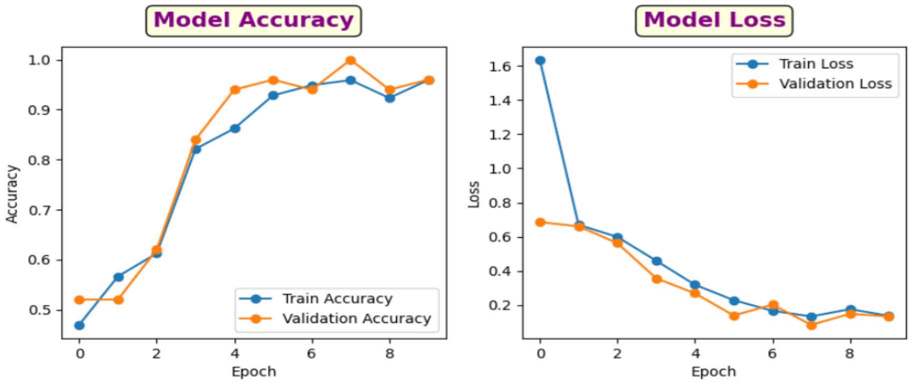


**Figure 15:** *Training and validation accuracy and loss*

Figure 15 shows the training and validation accuracy and loss. The X-axis denotes the epochs and Y-axis denotes accuracy for coconut leaf image. The model accuracy graph illustrates increasing accuracy of 96%, with the model achieving high performance and minimal over fitting. For model loss the X-axis indicates the epochs and Y-axis indicates the loss. Training and validation loss is reliably declining in training and validation loss, representing improved learning and reduced error.

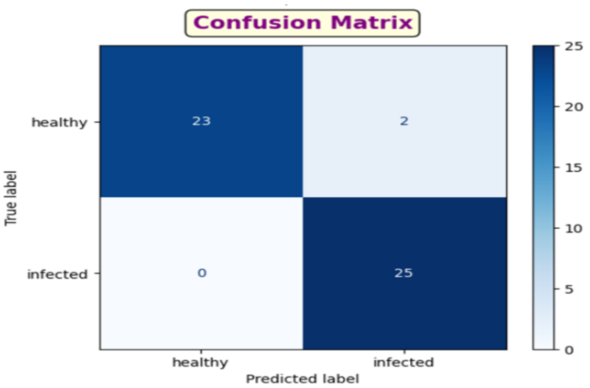


**Figure 16:** *Confusion matrix for coconut leaf image*

Figure 16 shows the confusion matrix for coconut leaf image. Proposed method evaluates the model's performance for two classes healthy and infected. The X-axis indicates the predicted label and Y-axis indicates the true label. Healthy have the value of 23 and infected have the value of 25 respectively.

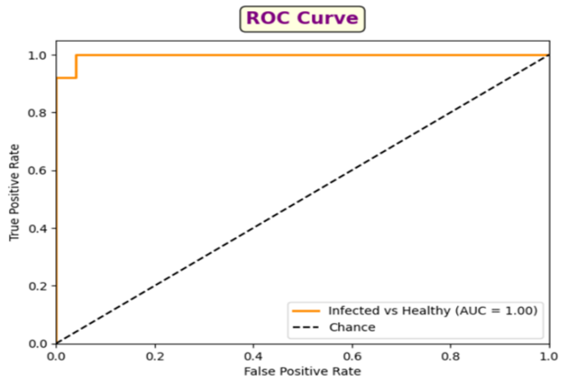


**Figure 17:** *ROC curve*

Figure 17 shows the ROC curve for proposed MobileViT continues to have the highest AUC value of 1 demonstrating the unique overview and flexibility of coconut leaf image approach. The X-axis indicates the false positive rate and Y-axis indicates the true positive rates. The ROC curve shows the orange color curve it have the value 1 for infected vs healthy coconut leaf image.

### 4.2 Comparison for the suggested method

The comparison of the suggested method with existing method is presented in table 2. The ResNet-50 have the classification accuracy of 94% [20], YOLO have the classification accuracy of 95% [18] and the proposed MobileViT have the higher accuracy of 96% compared to the existing method in table 2. The proposed MobileViT have better performance for CLD detection.

**Table 2:** *Comparison for the proposed method*

| Method | Accuracy |
|---|---|
| ResNet-50 | 94% |
| YOLO | 95% |
| MobileViT | 96% |

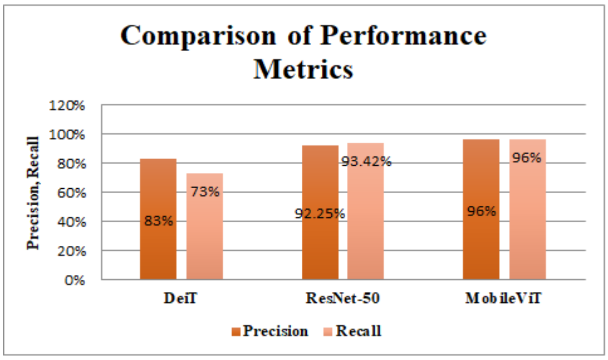


**Figure 18:** *Comparison of performance metrics*

Figure 18 shows the comparison of performance metrics for precision and recall value of proposed work and the existing work. The DeiT have precision value of 83% and recall value of 73% [22], ResNet-50 have the precision value of 92.25% and recall of 93.42% [20] and proposed MobileViT have the precision value of 96% and recall of 96% for identifying CLD. The proposed precision and recall value is high compared to the existing method.

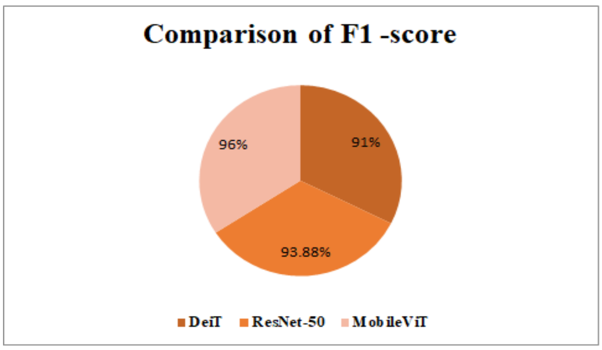


**Figure 19:** *Comparison of F1 score*

Figure 19 shows the comparison of F1 score value of proposed work and the existing work. The DeiT have F1-score value of 91% [22], ResNet-50 have F1-score value of 93.88% and proposed MobileViT have the F1- score value of 96% for identifying CLD detection. The proposed F1 score value is high compared to the existing method.

## 5. Conclusion

In this paper, MobileViT based model is proposed for the identification and classification of CLD detection. The two classes of healthy and infected images are classified successfully using the proposed MobileViT. The preprocessing stage reduced the noise and preserved the edges of the coconut leaf image. Also, ACM based segmentation separate a coconut leaf image boundaries and segment the coconut leaf image. Furthermore, LTP efficiently captures the discriminative patterns from the coconut leaf images. Finally, the proposed MobileViT classifies the coconut leaf image with better accuracy. The performance evaluation, conducted on the coconut disease and pest infestation dataset, demonstrates the superior capabilities of the MobileViT method. The improved accuracy, F1-score, precision and recall of 96%, is achieved as a greater accuracy and performance in contrast to the existing methods.

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