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Enhanced Watermelon Leaf Disease Diagnosis through Attention – Fused DenseNet Architecture

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ABSTRACT: Watermelon is a summer fruit which is one of the agricultural crops that have a lot of added value in worldwide. Early disease diagnosis for watermelon leaf disease is essential; depending on market demands and possible financial losses. In this paper, an Attention-fused DenseNet classification is proposed to quickly recognise watermelon leaf disease. Initially, using watermelon leaves disease dataset the denoising techniques reduces noise and maintain fine features using Adaptive Non local mean filter, to get high quality image. Next, the processed image is given to the morphological segmentation that transforms the leaf image based on their shapes by penetrating and modifying the image with a structural element (kernel). After that watermelon leaf image is featured by Scale Invariant Feature Transform (SIFT) to find the key points for further analysis. Finally, an Attention –fused DenseNet framework is processed to enhance the classification of watermelon leaf disease image. Using python software proposed framework have accuracy of 97% is accomplished when compared to other techniques.

Keywords: Attention-fused DenseNet, Scale Invariant Feature Transform (SIFT), Morphological Segmentation, Non local mean filter, Watermelon Leaf

1. Introduction

Watermelons (Colletotrichum species) are significant plant diseases that cause anthracnose in almost all crops cultivated worldwide [1].Whereas watermelon is the most prevalent and significant genus of saprobes, endophytes, and plant pathogenic fungi [2]. However, Citrullus Schrad is a xerophytic genus that includes watermelon (Citrullus lanatus (Thunb)). The Cucurbitaceae family of plants is one of the most significant commercial crops in the world [3]. According to China Agriculture Research System, it is the third most popular fruit crop in the country, after oranges and apples. With 1,471,581 hectares of harvested land and a yield of 60,861,241 in 2019, China accounted for 60.6% of global watermelon output [4]. However, an anthracnose infection is one of the major disease challenges in the commercial production of watermelon [5]. Consequently, in the fields anthracnose causes blights and patches on the plant's aerial portions. Anthracnose causes a 5–20% decrease in watermelon production or even no harvest at all [6]. Moreover, when the fruit is stored or placed on the market shelf, it becomes active, making it a significant post-harvest pathogen. When fruit isstored and transported, up to 100% of it is lost due to Colletotrichum disease [7].

To enhance the quality of leaf image histogram equalization is used. Histogram equalization is a simple and widely used method to improve the contrast of images. Improves contrast by redistributing pixel intensity values, especially in images with low contrast. Cause problems like noise amplification, distortion in extremely bright or dark areas [8].Consequently, to reduce the noise in the watermelon leaf an image enhancement technique is used. Enhanced contrast, noise reduction, and detail sharpening. Disadvantages need for careful balancing to prevent over-enhancement. [9]. Whereas, data augmentation is used to increase the size and diversity of dataset for watermelon leaf disease benefits like better model accuracy, less over fitting, and more generalization. Over fitting possibility to the enriched data, higher processing expenses [10].

To segment watermelon leaf disease K-Means clustering segmentation is used. It clusters each point in the watermelon leaf with good performance. Presumptions that not always be accurate regarding the distribution, structure of data and sensitivity to noise [11]. Consequently, using U-Net segmentation the watermelon leaf disease is converted as 256×256 to segment the image. Precise localization and high accuracy with minimal data is an advantage. It is computationally costly and sensitive to setup [12]. In order to classify watermelon leaf; the K-Nearest Neighbours (KNN) algorithm finds the K-nearest neighbours in the training data and uses their labels to make predictions. Euclidean distance is frequently used to calculate proximity. Experience from computing efficiency, particularly when dealing with big datasets [13].

However, Support Vector Machine (SVM) is classified with high accuracy to classify the watermelon leaf disease. Computationally costly, outlier-sensitive, and parameter-tuning-intensive, over fit and struggle with intricate, non-linear relationships [14]. Moreover, using Convolutional Neural Network (CNN) the watermelon leaf disease is classified. By combining several layers, the CNN model extracts complimentary discriminative characteristics. CNN have high processing difficulties and problems with interpretability [15]. To overcome this limitation Attention- fused DenseNet is proposed in this research.

2. Related work

Chen *et al* [16] (2021) have proposed a ResNet-18 (CNN) model for detecting disease in watermelon leaf. A ResNet-18 is used to classify healthy and diseased watermelon leaf, precise detection of diseases with higher accuracy. However, ResNet-18 have high processing difficulties, lacking a portion of labelled data.

Shin *et al* [17] (2022) have proposed a Deep Convolutional Neural Network (DCNN) for watermelon leaf disease identification. A deep CNN using RGB image would be a better option. RGB and hyper spectral imaging be used to detect crop stress. RGB imaging effectively identify surface crop faults, but it is unable to identify internal ones.

Sai Reddy *et al* [18] (2022) have proposed a 1D Convolutional Neural Network (1D-CNN) to classify the watermelon leaf disease. 1D-CNN model is used to detect specific parts of the disease with its severity degree**.** However, training period is computationally costly and demands a large amount of processing power.

Alhazmi *et al* [19] (2023) have proposed CNN VGG-16 to detect disease in watermelon plants. Reduces the time needed for model optimization and training, extremely precise image classification due to its structure and number of layers. CNN-VGG-16 have over-fitting due to a network issue.

Li *et al* [20] (2023) have proposed a Mask – Region Convolutional Neural Network (M-RCNN) to classify the watermelon leaves. Mask-RCNN reduces computational requirements, making it possible to employ low-footprint models involving both detection and classification. It is more difficult for Mask-RCNN to precisely locate things in complex surroundings or situations with overlapping objects.

The work's contributions include the following:

- Adaptive Non Local Mean filter is utilized to find pixel weights of the leaf image to enhance the good image quality for analysis

- Morphological segmentation is employed to segment watermelon leaf images, divides an image according to the structure and shape of the objects for better feature extraction and analysis.
- SIFT is employed to find the key points from the segmented watermelon leaf images.
- An Attention-fused DenseNet based framework is proposed, to classify the featured watermelon leaf image for identification.

3. Proposed Work

The proposed block diagram in Figure 1 shows the watermelon leaf disease classification. Firstly, the input image is given to the preprocessing step were a non-local mean filter is utilized to identify the pixel weights for good quality image. Secondly, the segmentation process uses the morphological segmentation for segmenting watermelon leaf disease image. Thirdly, by using SIFT feature extraction technique the segmented image are featured by its key points.

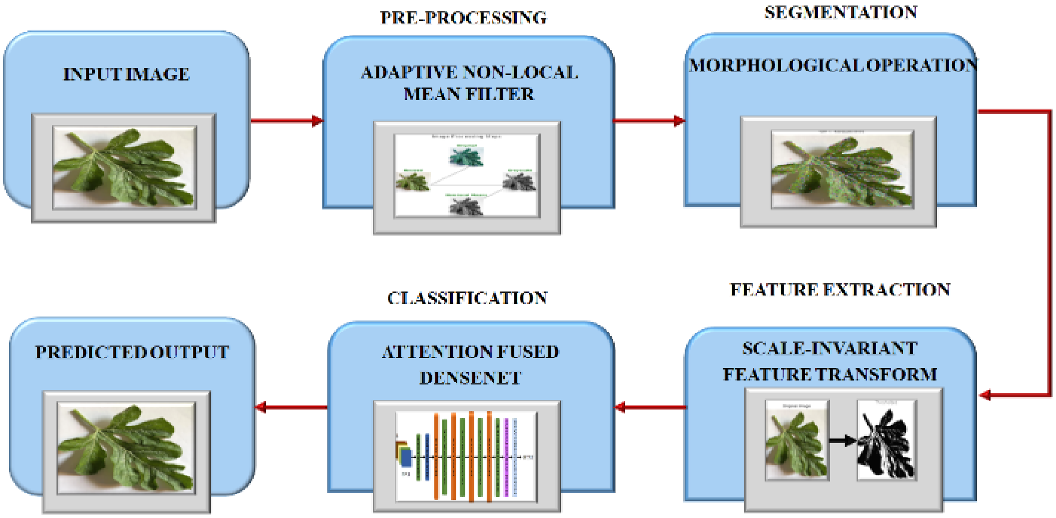

Figure 1: *Block diagram of proposed Attention - Fused DenseNet*

Finally, featured image is given to the classification process were a proposed Attention –fused DenseNet is used for classifying the watermelon leaf image. The Attention –fused DenseNet have decrease weighted mean which is used to classify the watermelon leaf image for getting better accuracy when compared to the other techniques.

3.1 Pre-Processing Using Adaptive Non Local Mean Filter

An adaptive Non Local Mean filter is a de-noising technique used to calculate a weighted average of neighboring pixels. Using a robust similarity measure the neighboring pixels and surrounding the pixel is compared. The weighted average of the voxel intensities $u(x_i)$in the volume, where M is the radius of v_t, is the restored intensity of $NL(u)(x_i)$ the voxel (x_i) in a volume u.

$$NL(u)(x_i) = \sum_{x_j \in V_t} w\left(x_i, x_j\right) u(x_j) \qquad (1)$$

Where $w\left(x_i, x_j\right)$denotes the weight assigned to value $u(x_j)$ to restore voxel. (x_i)

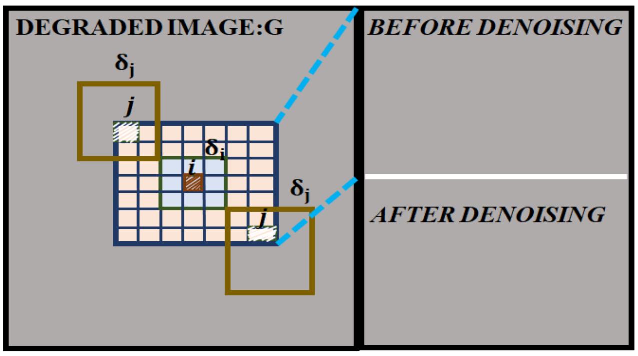

Figure 2: *Adaptive Non Local mean filter*

More precisely, the weight evaluates the similarity between the intensity of the local neighbourhood's $\left(N_i \text{ and } N_j\right)$ of radius r centeredx_i *and* x_j on voxels, such that:

$w(x_i, x_j) \epsilon [0,1] \;\; and \;\; \sum_{x_j \in V_t} w(x_i, x_j) = 1$

For each voxel (x_j) and V_t, the computation of the weight is based on the square of the Euclidean distance between patches $u(N_i) - u(N_j)$defined as:

$$w(x_i, x_j) = \frac{1}{Z_i} e^{\frac{(\|u(N_i)-u(N_j)\|)_2^2}{h^2}} \tag{2}$$

Where Z_i is a normalization constant ensuring that $\sum_{x_j \in V_t} w(x_i, x_j) = 1$; and h acts as a filtering parameter controlling the decay of the exponential function. Next by pre-processing segmentation is carried out by using morphological operation.

3.2 Segmentation using Morphological Operation

An edge is defined as the boundary between sudden, non-continuous shift in an image that aids in object detection and identification in watermelon leaf. The primary goal of the edge detection technique is to seek and identify the points in a digital image where the image's intensity varies. The threshold approach compares the watermelon leaf image's grayscale value to a predetermined threshold value. When the input pixel's grayscale value is high, its output value is either 1 or 0.

$$g(x, y) = 1, \;\; if \;\; f(x, y) > T \tag{3}$$

$$g(x, y) = 0, \;\; if \; f(x, y) \leq T \tag{4}$$

Two kinds of thresholding exist: Global Thresholding: Use a distinct threshold value to divide the entire image. Local Thresholding: Divide the image into smaller parts, and then give each part of its own threshold value. Figure 3 shows the dilation and erosion operation.

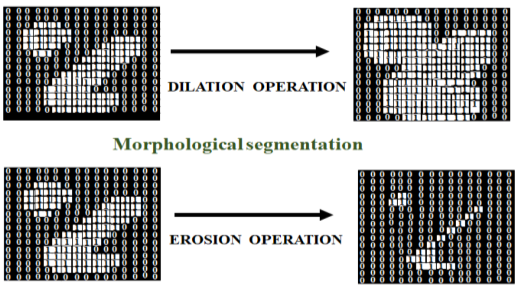

Figure 3: *Dilation and erosion operation Dilation*

Dilation is one of the fundamental operators in mathematical morphology. It is applied to grayscale images as well as binary images. The things get bigger due to dilation. As a result of this action, the foreground pixel borders will gradually expand, making the holes in that region smaller and the areas larger. The input image to be dilated comes first, followed by the structural element, also referred to as the kernel.

$$A \oplus B = \{x/(\hat{B})_x \cap A \neq \emptyset\} \tag{5}$$

Assume that B is a set of structuring element coordinates, A is a set of input image coordinates, and $B_x$is a translation of B such that its origin is at x. Therefore, the set of all positions of x such that the intersection of $B_x$with A is not null is the dilation of A by B. The definition of dilatation of A by B in terms of set operations in equation 5.

3.2.1 Erosion

Another fundamental operator in mathematical morphology is erosion. The objects become thinner or smaller as a result of erosion. In essence, erosion erodes away the foreground's boundaries, causing some pixel portions to get smaller and their gaps to get bigger. Therefore, erosion is used to partially separate the boundaries in order to make the boundaries of the items thinner for better results after diluting and filling the holes of the objects in some photographs.

Similar to dilatation, erosion splits data into two halves. The input image to be degraded comes first, followed by the structural element. The following is a mathematical definition of erosion: Assume that B is a set of structuring element coordinates, A is a set of input picture coordinates, and $B_x$is a translation of B such that its origin is at x. Therefore, the set of all points of x such thatB_x is a subset of A is the dilation of A by B. The definition of erosion of A by B in terms of set operations is

$$A \ominus B = \{x/(B)_x \cap A^c \neq \emptyset\} \tag{6}$$

3.2.2 Opening

Opening is a morphological process that involves dilatation and erosion. Its main purpose is to eliminate noise or little objects from an image keeping the larger objects' size and shape intact. The two components of opening are as follows:

Erosion: Erosion, which is the initial stage of opening, reduces the borders of small objects or details in the front (white areas).

Dilation: The size of the remaining items is restored by applying dilation after erosion. The smaller objects, however, are not restored because they were entirely corroded away in the initial stage, so eliminating them from the image.

3.2.3 Closing

Closing involves degradation after dilatation. It is used to seal off tiny holes, gaps, or voids inside the foreground objects, maintaining their general shape. It is basically the opposite of the opening operation. The two elements of closing are as follows:

Dilation: Dilation, the initial stage of closing, enlarges the borders of the binary image's foreground items (white areas). This procedure aids in closing any little gaps or holes in the objects.

Erosion: Erosion is administered following dilatation. By reducing the borders, the erosion phase returns the objects to their initial size. All tiny holes or gaps that were filled in the dilation process, however, will stay filled, so "closing" them. Next, feature extraction is carried out by Scale Invariant Feature Transform (SIFT).

3.3 Feature Extraction by SIFT

Scale Invariant Feature Transform (SIFT) technique, developed by Lowe (2004) created the strong robustness and tackle picture rotation, scaling, affine deformation, viewpoint shifts, noise, and lighting changes. There are four primary steps in the SIFT algorithm: detection of scale space extrema, localization of key points, assignment of orientation, and generation of descriptions. The first step is to determine the locations and scales of important points using scale space extrema. The following equation shows the Difference-of-Gaussian (DoG) function is convolved of images in scale space separated by a constant factor k in DoG functions with variable values of σ.

$$D(x, y, \sigma) = (G(x, y, k\sigma) - G(x, y, \sigma) \times I(x, y) \quad (7)$$

Where, G denotes Gaussian function and I indicates image.

To find the local maxima and minima of $D(x, y, \sigma)$, a pixel comparison of a 3×3 neighbourhood is performed. The DoG is now obtained by subtracting the Gaussian images, and then the Gaussian images subsample by factor 2 to obtain the DoG for the sampled image. By removing the key points the low contrast points where rejected, key point candidates are localized and improved in the key point localization stage. The orientation of the key point is determined using the local image gradient in the orientation assignment step. The local image descriptor for each key point is calculated during the description generation stage. Using the orientation and magnitude of the image gradient at each image sample point the key point centered at in a region.

4. Construction of SIFT Descriptor

The key point descriptor computation is shown in the figure 4c. The scale of the key point is used to choose the degree of Gaussian blur for the image after first sampling the gradient magnitudes and orientations of the image around the key point position. The gradient orientations are then rotated with respect to the key point orientation in order to attain orientation invariance using the descriptor's coordinates. Small arrows are used to indicate each sample location on the left side of the Figure 4c.

Figure 4c right side displays the key point descriptor. By generating orientation histograms across 4×4 sample sections, it permits a considerable shift in gradient positions. The gradient sample on the left contributes to the same histogram on the right even though it shifts up to four sample points. Thus, each sample have eight orientation bins and an 4×4 array placement grid. That the key point descriptors have 128-element dimension. Following to the feature extraction the watermelon leaf is classified using a proposed attention - fused DenseNet

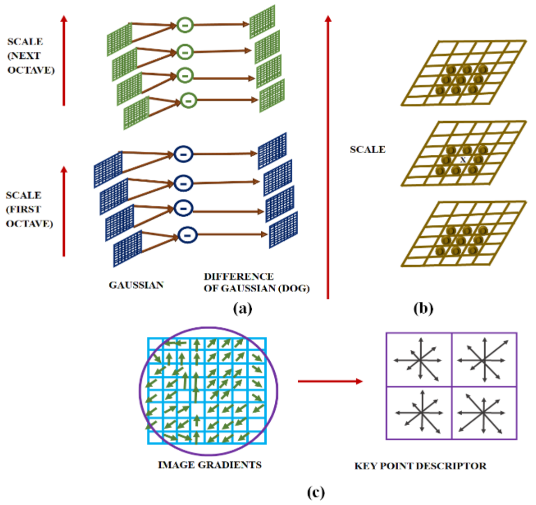

Figure 4: *SIFT (a) DOG, (b) Scale, (c) key point descriptor*

5. Classification by Attention - fused DenseNet

The proposed Attention - fused DenseNet is used to classify watermelon leaf disease. Each layer of CNN's feature extraction process have distinct characteristics, with the lower and middle layers having relatively high resolution and encompassing more location and detailed information.

DenseNet, a popular framework in many real-world applications, it is the first to propose dense connectivity (i.e., many connectivity patterns independent of the standard network). To optimize the flow of feature information between layers, all layers are typically connected one after the other. Every layer in this hierarchy transfers its output to the one behind it and receives as input the features of every layer that came before it. However, as illustrated in Figure 5, this paper suggests dense connections in addition to the attention mechanism among various inception network blocks, regardless of the conventional dense connections.

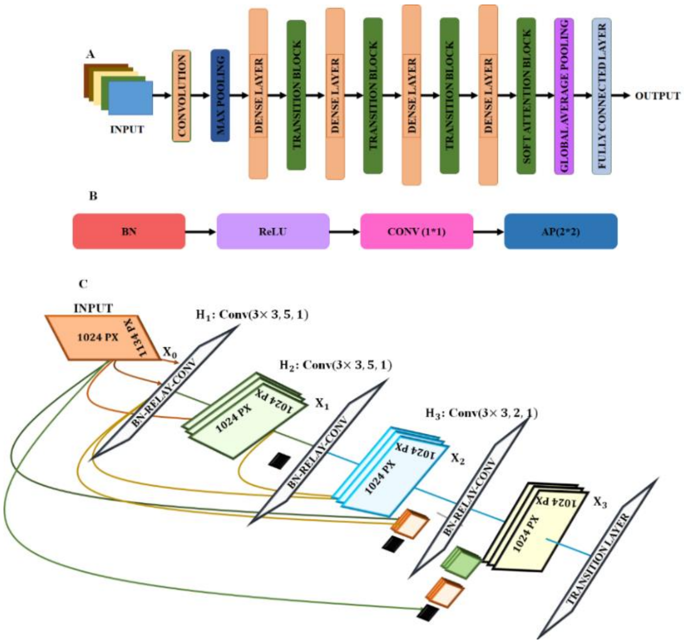

Figure 5: *Convolutional layers architecture*

Where, $X_o$is the output of previous convolutional block and X_i is the output of i^{th}block. As a result, the output of i^{th} convolutional block comprises the middle output of every preceding block in addition to the output of the $(i+1)^{th}$block. Each CNN block is intimately related to the associated CNN block's attention mechanism. In contrast, a 3×3 kernel is used for reshaping and max-pooling when the feature maps are connected. On the other hand, attention blocks are used to eliminate only the features that are necessary for classification; in other words, weakening information that isn't helpful for classification have been eliminated, creating a more discriminative feature representation that raises the class probability for each pixel. A convolutional layer is then used to aggregate the collected information once more following the fusion.

6. Result and discussion

Dataset is taken from kaggle.com for watermelon leaf disease identification. Deep learning models are then applied to train watermelon leaves disease dataset. Using python software the disease like downy_mildew, healthy and mosaic virus is classified. Here for watermelon leaf disease detection the test and train images are number of train images is 2400 and test images are 100.

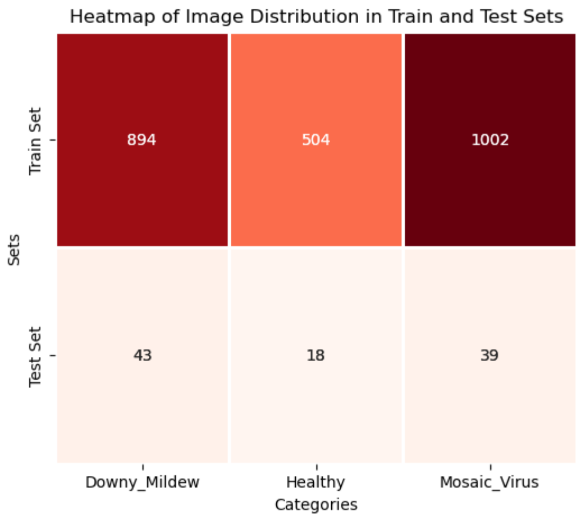

Figure 6: *Heatmap of Image Distribution in Train and Test Sets*

Figure 6 shows heatmap of image distribution in train and test sets for watermelon leaf disease. Here, total number of images used is 2400 and three classes of labels are downy-mildew, healthy, mosaic virus. The three classes' labels are trained using the watermelon leaves disease dataset. The train image for downy-mildew is 894 and test image for downy-mildew is 43, for healthy the train images is 504 and test images is 18, at last for mosaic virus train images is 1002 and test images is 39.

(a)

(b)

(c)

Figure 7: *Original image samples for (a) downy-mildew, (b) healthy and (c) mosaic-virus*

Figure 7 shows the image samples for downy-mildew, healthy and mosaic-virus for watermelon leaf. Here the original image is taken as a sample image for downy-mildew, healthy and mosaic-virus. The three classes of original images are converted into gray using grayscale conversion technique. Next the three classes of gray image is converted as sepia image.

Figure 8: *Input image*

Figure 8 shows the original input image for watermelon leaf disease. Here the input image is taken from the watermelon leaves disease dataset.

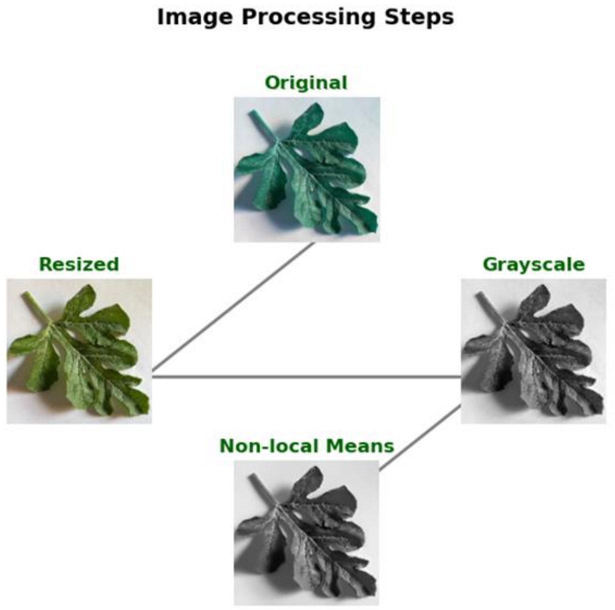

Figure 9: *Pre-processing step*

Figure 9 shows the pre-processing step using non-local mean filter. Here the original image is resized using image resizing technique, and then the resized image is given to the grayscale conversion technique. The watermelon leaf image is converted in to gray using grayscale conversion technique and the gray image is filtered using adaptive nonlocal mean filter. The adaptive nonlocal mean filter removes the noise from the watermelon leaf image.

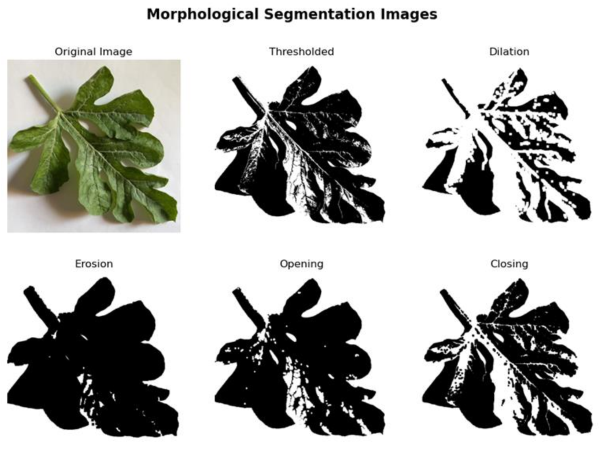

Figure 10: *Morphological segmentation images*

Figure 10 shows the morphological segmentation for watermelon leaf disease. Here the original image diminishes the foreground objects' borders and expand the foreground objects' bounds.

Figure 11: *SIFT key points*

Figure 11 SIFT key points for watermelon leaf disease. Here, each key points are calculated using scale invariant feature extraction.

7. Performance metrics

Using various performance metrics the suggested outline to training data is evaluated. And these metrics are accuracy, precision, recall, F1 score and AUC. Using the following equation each metrics are defined as

i) Accuracy:

$$Accuracy = \frac{(TN+TP)}{TS} \tag{8}$$

ii) Precision:

$$Precision = \frac{(TP)}{TP+FP} \tag{9}$$

iii) Recall:

$$recall = \frac{(TP)}{(TP+FN)} \tag{10}$$

iv) F1 score:

$$F1 - score = \frac{(2*\text{Precision}*\text{Recall})}{(Precision + Recall)} \tag{11}$$

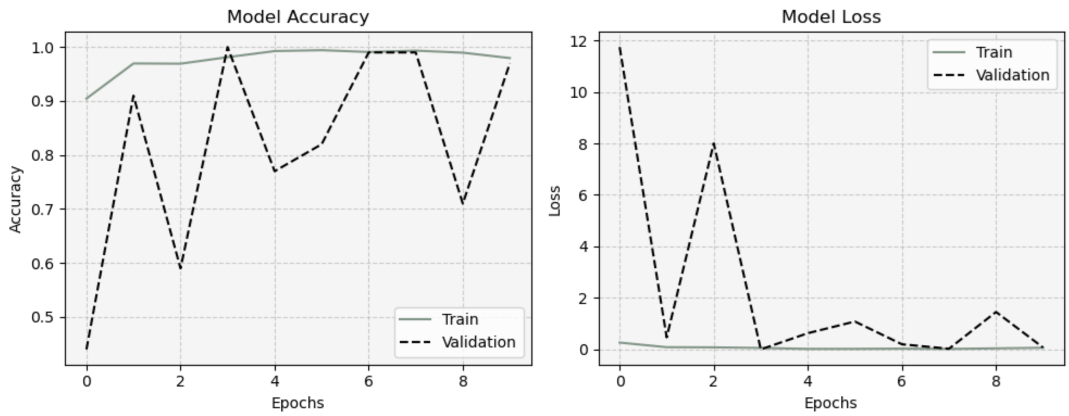

Figure 12: *Model accuracy and model loss*

The model Accuracy graph in figure 12 illustrates increasing accuracy of 97%, with the model achieving high performance and minimal over fitting. The model Loss graph figure 12 shows a reliable decline in training and validation loss, representing improved learning and reduced error. The X-axis denotes the epochs and y-axis is loss. The validation loss is going on increasing and decreasing, the training loss is decreased and constant still 8 epochs.

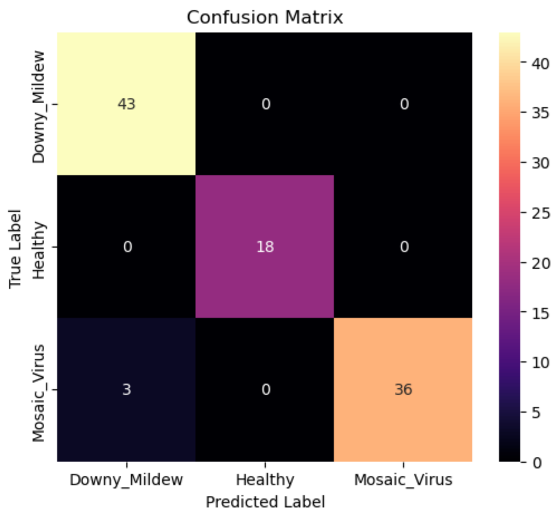

Figure 13: *Confusion matrix for proposed Attention –fused DenseNet*

Figure 13 illustrates the confusion matrix for proposed attention–fused DenseNet. This matrix shows the values for true and predicted labels. Here the three classes of watermelon leaf disease image for downy-mildew is 43, healthy is 18 and mosaic virus is 36 are matrixes.

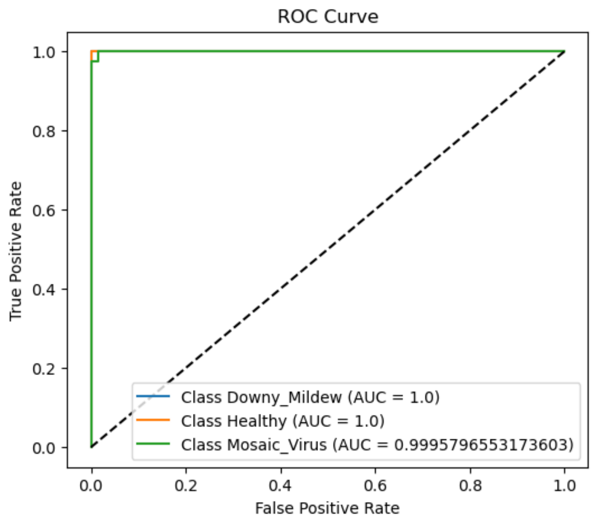

Figure 14: *ROC curve*

According to the AUC results shown in Figure 14, the watermelon leaves disease dataset significantly lowers the AUC value, the sub-optimal model on datasets, to 0.99 for mosaic-virus, and 1 for both healthy and downy-mildew. In comparison, the suggested attention –fused DenseNet continues to have the highest AUC value of 1, demonstrating the exceptional overview and flexibility of this approach.

8. Comparison for the proposed method

The comparison of the proposed method with existing method is presented in table 2. The SVM have the classification accuracy of 84.3% [14] and the proposed Attention –fused DenseNet have the higher accuracy of 97% compared to the existing method in Table 2. The proposed XG Boost have better performance.

Table 2: *Comparison for the proposed method*

Study	Method	Accuracy

Mukasa *et al* [14]	SVM	84.3%
Proposed approach	Attention –fused DenseNet	97%

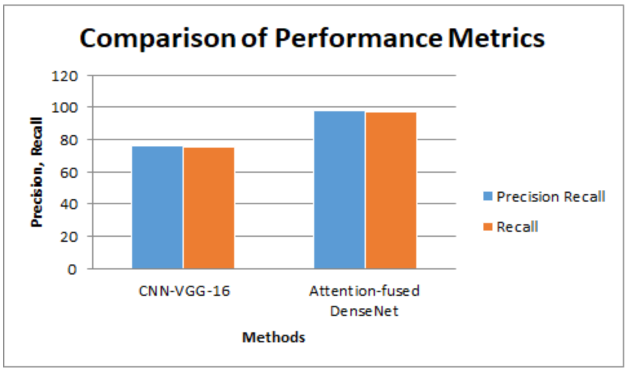

Figure 15: *Comparison of performance metrics*

The Precision and recall value for classifiers CNN-VGG-16 and the proposed is presented in Figure 15. The CNN-VGG-16 have the value of 76% and 75% [19] and proposed Attention –fused DenseNet methods have the precision value of 98% and recall of 97% respectively.

9. Conclusion

In this study, Attention-fused DenseNet is proposed for the classification of watermelon leaf disease. The integration of advanced preprocessing techniques, such as resizing, grayscale conversion, adaptive non- local mean filtering, ensures that the input images are optimized for segmentation. The use of approximate morphological segmentation for further enhances the precision of identifying shape and structure in the images. Additionally, the SIFT feature analyzed the key points. The performance evaluation, conducted on the watermelon leaves disease dataset, demonstrates the superior abilities of the attention-fused DenseNet related to existing methods. The improved accuracy of 97% is achieved as a higher accuracy when compared to the existing techniques.

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