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An Intelligent Hybrid Framework for Brinjal Leaf Disease Detection using Residual VGG-16 and Weighted Fuzzy C-Means Segmentation

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ABSTRACT: Brinjal Leaf disease (Eggplant) identification have become a significant agricultural issue with an alarming rise in recent years, necessitating effective prediction algorithms. In this paper, Residual VGG-16 classifier is proposed for prediction of brinjal leaf disease such as diseased leaf and healthy leaf. Initially, adaptive Gaussian filtering is applied to the brinjal leaf dataset to supress the noise and smoothens out for better image quality. Next, the processed image is given to the Weighted Fuzzy-C-Means clustering, to calculate the cluster weight value. After that brinjal leaf image is featured using Local Binary Patten (LBP) for analysing local texture structure. Finally, a Residual VGG-16 framework is processed to enhance the classification of brinjal leaf disease for analysis. Using python software proposed framework have accuracy of 95% is accomplished when compared to other techniques.

Keywords: Residual VGG-16, Local Binary Pattern (LBP), Weighted Fuzzy C-Means Clustering (WFCM), Adaptive Gaussian Filtering (AGF), Brinjal Leaf Disease.

1. Introduction

Brinjal is vegetable crop which is also known as eggplant (Solanum melongena) widely grown. [1]. However, infections carried on by bacterial, viral, and fungal pathogens as well as insect pests commonly endanger its production, resulting in large output losses and deterioration of quality [2]. Moreover, if not detected and treated quickly, common diseases including Wilt disease, Mosaic Virus disease, Leaf Spot disease, and White mold disease significantly reduce crop output and quality [3]. Some are a healthy leaf which is bright green, smooth, and free of blemishes, discolorations. Eggplant leaves impacted by insect pest's exhibit damage like holes, bite marks, discoloration, or withering, which makes them essential to identify pest infestations and aid in pest control [4].

Whereas, leaf spot disease on eggplant leaves are little, round, or irregular brown to black dots, frequently with a halo or discolored edge. These patches have the ability to expand, weakening the leaf and possibly resulting in leaf drop [5]. However, eggplant leaves with mosaic virus disease have mottled green, yellow, or white areas that are frequently distorted or curled [6]. Moreover, the symptoms of white mold disease in eggplant leaves include withering, browning, and white, cotton-like fungal growth. Wilt illness Due to a disturbance in the plant's water flow, wilt disease in eggplant leaves results in drooping, yellowing, and finally browning [7].

Using the pre-processing technique called median filtering the brinjal leaves noises are removed. Median filter successfully eliminates background noise and ambient noises in the brinjal leaf. Highdensity noise is difficult to handle and computational costs associated with sorting operations [8]. To eliminate noise in the eggplant leaf, quick Euclidean clustering, point cloud filtering, and voxel filtering were used. Voxel filtering drawback is blurring and information loss, whereas cloud filtering induce information loss and sensitivity to noise [9]. Whereas, wave shit augmentation is to simulate light dynamics in order to increase model generalization and adaptability to different image conditions for brinjal leaf. When simulate the light dynamics it takes more processing time [10].

To improve the accuracy of the brinjal leaf K-Means clustering is used. It clusters each point in the brinjal leaf with good performance. Presumptions that not always be accurate regarding the distribution, structure of data and sensitivity to noise [11]. Whereas, using Bag of Feature (BOF) the brinjal leaf diseases are detected with high performance. Here the brinjal leaf types are retrieval with high accuracy. It takes the small images to retrieve fast others takes much time [12]. However, Support Vector Machine (SVM) and Decision Tree (DT) models are classified with high accuracy to classify the brinjal leaf. Computationally costly, outlier-sensitive, and parameter-tuning-intensive, over fit and struggle with intricate, non-linear relationships [13].

Conversely, using Convolutional Neural Network –Support Vector Machine (CNN-SVM) and CNN-Softmax pipelines, along with a model for inferring the illness classes in brinjal leaf an essential step in raising agricultural yields is the automatic detection and identification of diseases [14]. Moreover, brinjal leaf is classified using Convolutional Neural Network (CNN). To improve the classification accuracy of brinjal leaf the CNN is used. CNN produces less accurate localizations because it requires a fixed-size input [15].

2. Related Work

Shafik *et al* [16] (2024) have proposed a Lead Voting Ensemble (LVE) integrated with Convolutional Neural Networks (CNNs) to classify the brinjal leaf. It accurately identifying and classifying different brinjal leaf diseases, eventually paving the way to more efficient agricultural disease control. It takes more time to train its parameters because of its large network.

Abisha *et al* [17] (2022) have proposed an Artificial Neural Network (ANN) to detect the healthy leaf and diseased leaf. The ANN model is reliable enough to accurately and efficiently identify and classify leaf disease. When identifying leaf diseases, several issues are increased, such is poor identification speed, high computation costs, and inadequate precision.

Rangarajan *et al* [18] (2021) have proposed a VGG-16 to classify five diseases in eggplant (Solanum melongena). VGG-16 is used to detect brinjal leaf with high performance. Greater computational difficulties, over fitting risk are some of the drawback of VGG-16.

Shafik *et al* [19] (2025) have proposed a hybrid Inception-Xception (IX) using a Convolution Neural Network (CNN) to identify and classify the healthy and diseased brinjal leaf. Inception and depth-separable convolution layers are combined in this model to reduce over fitting and model complexity when capturing multiple-scale information. It takes larger time to process the network.

Singh *et al* [20] (2024) have proposed a Cloud-Enabled Artificial Neural Network (ANN) to classify the eggplant leaf. Here using Cloud-Enabled ANN (FRCNN) the normal objects are detected successfully. ANN produces less accurate localizations because it requires a fixed-size input.

The contribution of this study is summarized as follows:

- Introduces Adaptive Gaussian filter to supress the noise and smoothen out for better image quality.
- Better segmentation and feature selection using Weighted Fuzzy C-Means clustering and Local Binary Pattern for classification.
- Develops a Residual VGG-16 classifier to enhance brinjal leaf disease accuracy and efficiency.
- Validates the proposed model using metrics like accuracy, precision, recall, F1-score, and AUC, demonstrating significant improvement over existing methods.

3. Proposed Work

The proposed block diagram in Figure 1 for brinjal leaf disease classification by deep learning technique is applied to brinjal leaf datasets. Initially the input brinjal leaf dataset supress the noise and smoothens out using Adaptive Gaussian filtering technique. Then the processed brinjal leaf image is given as input to weighted Fuzzy C-means clustering here it calculate the clusters weighted value to segment the brinjal leaf disease.

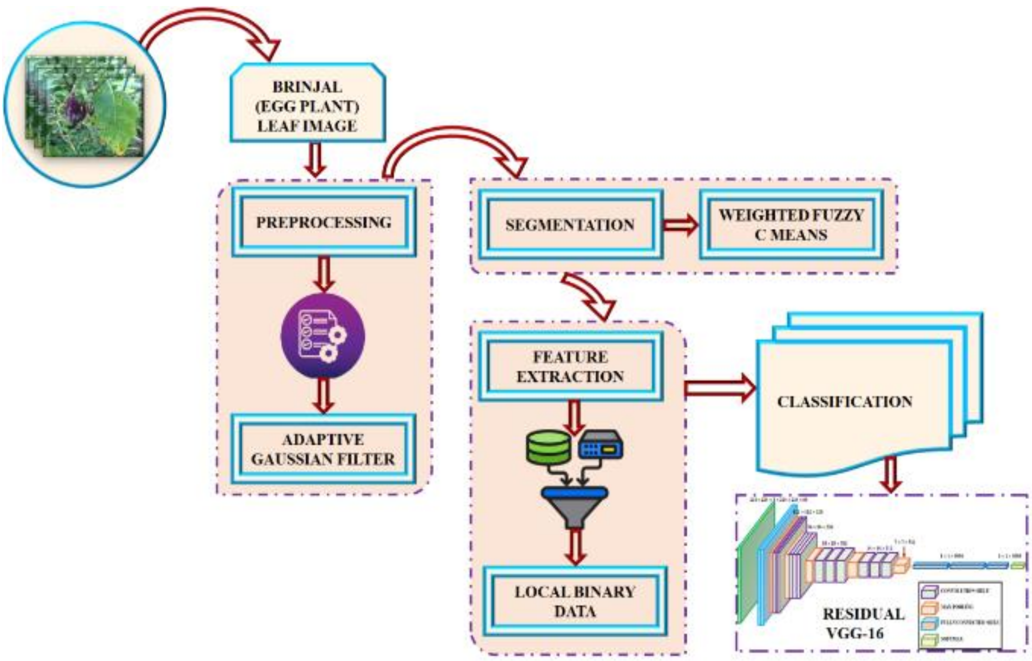

Figure 1: *Block diagram of proposed Residual VGG-16*

Next, the segmented brinjal leaf image is given as input to feature extraction by Local Binary Pattern. Here the local texture structure is extracted. Finally, model training is optimized using the extracted image for classification. In classification stage, a Residual VGG-16 is utilized to increase the accuracy and efficiency. To improve model accuracy, performance of brinjal leaf illness the classification technique is used.

3.1 Pre-processing by Adaptive Gaussian Filtering

By using a Gaussian filter for noise suppression the signal is corrupted although the noise is smoothed out. A pre-processing step for edge detection a Gaussian filter is edge position displacement, edge disappearance, and phantom edges. The two-dimensional digital Gaussian filter can be expressed as

$$G(x,y) = \frac{1}{\sqrt{2\pi\sigma}} exp(-(x^2 + y^2)/2\sigma^2) \qquad (1)$$

Where $\sigma^2$is the variance of Gaussian filter, and the size of the filter kernel $l(-l \leq x, y \leq l)$is often determined by omitting values lower than five percent of the maximum value of the kernel. The one-dimensional Gaussian filter is expressed as:

$$G(x) = \frac{1}{\sqrt{2\pi\sigma}} exp(-x^2/2\sigma^2) \qquad (2)$$

The adaptive Gaussian filtering challenge involves minimizing the mean square error whereas ensuring that the filter variance doesn't fluctuate significantly between pixels. If $G\ and\ F$ stand for the two-dimensional Gaussian filter and the image, respectively, then minimizing $E(\sigma)$ in the following equation yields the ideal filter variance

$$E(\sigma) = \iint((F - G * F)^2 + |\Delta\sigma^{-1}|)^2)dxdy \quad (3)$$

Where, $*$ indicates convolution. Following the pre-processing technique Segmentation is carried out using Weighted Fuzzy C-Means clustering.

3.2 Segmentation by Weighted Fuzzy C-Means clustering (WFCM)

The FCM clustering algorithm is the source of the enhanced algorithm known as WFCM. In order to construct the clustering solution of brinjal leaf, each data element must have a weight value assigned to it that specifies its relative relevance. The following objective function is what WFCM seeks to minimize:

$$Q_{WFCM} = \sum_{k=1}^{C}\sum_{i=1}^{N} w_i u_{ki}^m (\|x_i - v_k\|)^2 A \quad (4)$$

High weights have a bigger influence on the clustering process than objects with a low weight. Here, w_i is the corresponding weight of each datumx_i. The fuzziness parameter, which controls the impact of the members' ratings, is $m > 1$. Figure 2 shows the basic WFCM clustering.

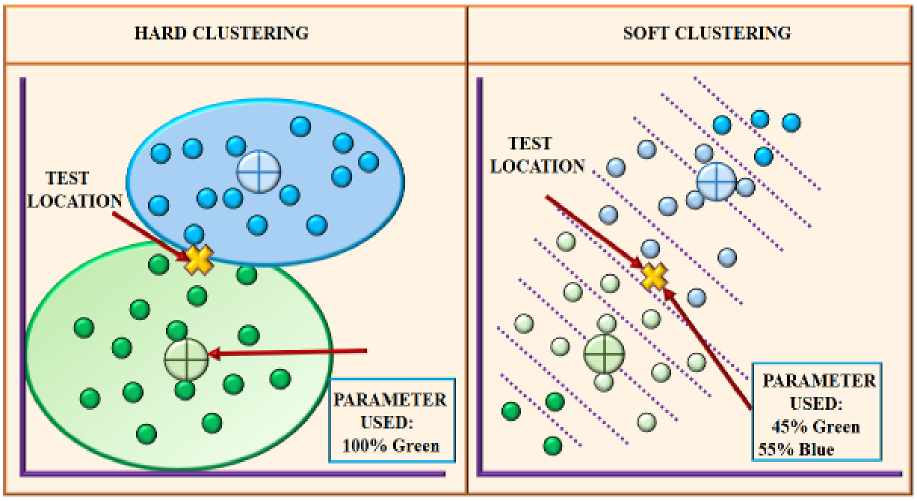

Figure 2: *Basic Weighted Fuzzy C-Means Clustering*

When $k = 1 \ldots . C$, u_{ki} indicates that observation $x_i$is a member of the k^{th}cluster.The number of clusters is C . The values of u_{ki} fall between 0 and 1, where 0 denotes non-membership and 1 denotes total membership. According to vectors, $u_i$are grouped as $C \times N - matrix$ columns. $U = [u_{ki}]C \times N$ the following isu_{ki} are calculated:

$$u_{ki} = \frac{1}{\sum_{j=1}^{C}\left(\frac{\|x_i - v_k\|}{\|x_i - v_j\|}\right)^{\frac{2}{m-1}}} \quad (5)$$

Where $v_k$denotes to the centroid of the k^{th}cluster and be updated by the following equation:

$$v_k = \frac{\sum_{i=1}^{N} w_i u_{ki}^m x_i}{\sum_{i=1}^{N} w_i u_{ki}^m} \quad (6)$$

Where, $v_k$is a weighted sum of the feature vectors since each object $x_i$have n alternative predicted impact provided by a relative weightw_i. Determining the weight assigned to every observation be performed after healthy and diseased brinjal leaf t strategies. Following by segmentation the brinjal leaf disease is given to the feature extraction.

3.3 Feature Extraction by Local Binary Pattern (LBP)

In feature extraction the Local Binary Pattern (LBP) extract brinjal leaf. By using LBP the brinjal leaf image is an effective and consistent feature for analyzing local texture structures. Texture formation at the pixel level, is defined on the basis of local patterns. LBP describes complex structures in a grape leaf image using the several simple primitives. LBP takes into account both the placement rule property of structural analysis and texture primitives. One of the most effective texture descriptors is assumed to be local binary patterns. A 3x3 pixel window is the definition of the traditional LBP operator in Figure 3.

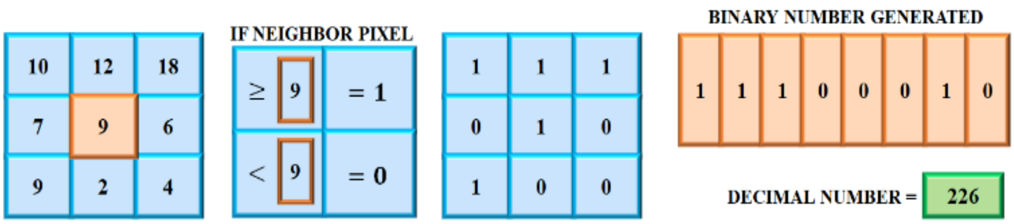

Figure 3: *Traditional LBP operator*

The pixel value is designated as 0 if the value of the nearby pixel is less than the threshold value. This window's central pixel acts as a threshold. If not, it have the label 1.

$$LBP_{I,J}(g_c) = \sum_{j=0}^{J-1} G(g_i - g_c)2^j \qquad (7)$$

Where,

$$G(m) = \{0, m < 0; 1, otherwise. \qquad (8)$$

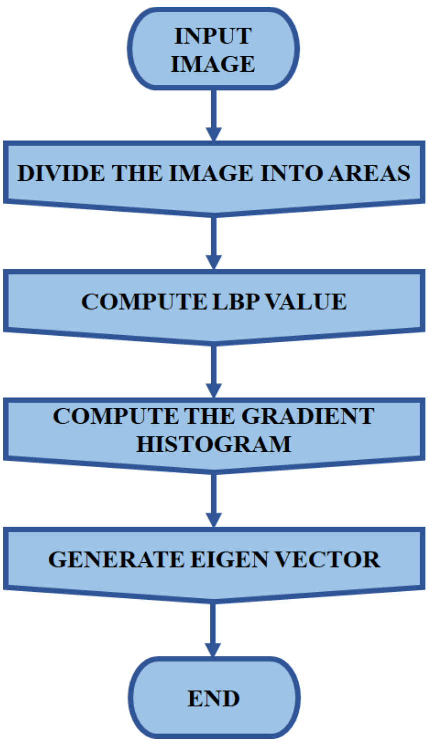

Figure 4: *Flow chart of Local Binary Pattern*

Figure 4 shows the flowchart of Local binary pattern. At last, by feature extraction the extracted brinjal leaf image is given to the proposed Residual VGG-16 classifier.

3.4 Classification by Residual VGG-16

To classify the brinjal leaf disease (eggplant) the proposed Residual VGG-16 is used.

A CNN architecture is proposed that incorporates a number of elements, for the brinjal leaf are classified using Asymmetric Convolution (AC), Residual (R), Residual Block (RB), and Batch Normalization (BN). AC used two pairs of asymmetric filters (3 × 1 and 1 × 3 filters) in place of the fifth block of VGG-16, increasing the number of layers but decreasing the kernel size. We normalized each convolution output using AC using BN to avoid internal covariate shift (ICS) and shorten the epoch training. By adding a skip connection to each AC, it further reinforced this block with a residual block, preserving the convolution results from each layer until the final layer.

4. Residual VGG-16

At the end of the fourth block, the low-level elements of the first three blocks are integrated to form the Residual-VGG-16 architecture design depicted in Figure 5. At the end of the fourth block, combined the high-level features with the low-level characteristics from the end of the first, second, and third blocks to employ residual using$N = 3$. The dimensions of the first, second, and third blocks are $1122 \times 64, 562 \times 128,$ and 282×256, respectively. Using max-pooling in conjunction with DSC to make everything 142×512

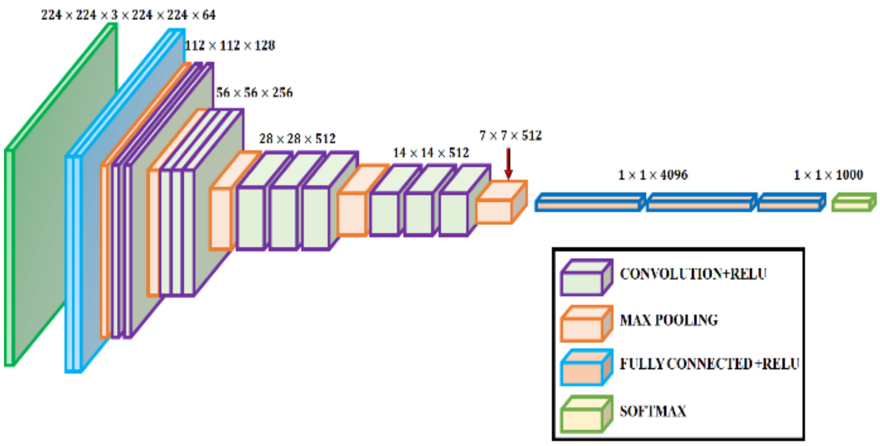

Figure 5: *Proposed Residual VGG-16*

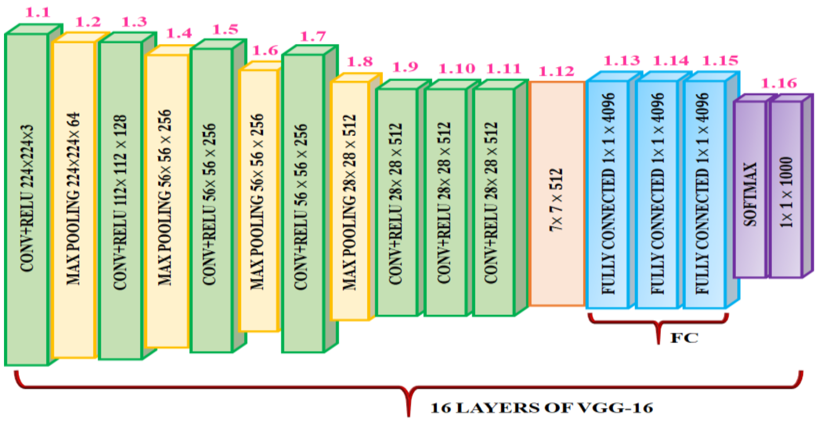

Figure 6: *VGG-16 Architecture*

In contrast to the convolutional and fully connected layers of VGG16, the modules and convolutional layers of the proposed residual VGG16 are depicted in the figure 6. We add a scaling layer to the first convolutional layer and all fire modules. The kernel in the layer is given a size of 3 x 3 and a stride of 2. Next, swap out VGG16's second convolutional layer for a single fire module. Because the module has nine times less parameters than its corresponding (3 x 3) filter, this is done. Only three-by-three filters remain in the input channels. Multiply the number of input channels by the number of filters to determine the number of parameters in the module.

4.1 Result and Discussion

Dataset is taken from kaggle.com for brinjal leaf disease identification. Deep learning models are then applied to train brinjal leaf dataset. Using python software the diseased and fresh brinjal leaf is classified.

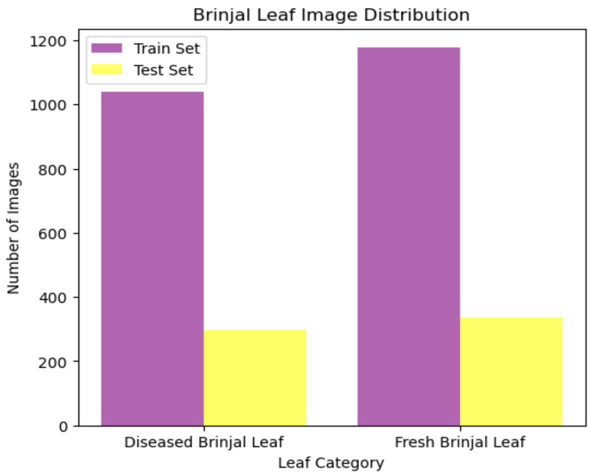

Figure 7: *Brinjal leaf image distribution*

Figure 7 shows the brinjal leaf image distribution. Here total number of train samples is 2216 and test samples 633.The train diseased brinjal leaves have the images of 1039 and the test diseased brinjal leaf have the images of 297. Whereas, train fresh brinjal leaves have the images of 1177 and the test fresh brinjal leaf have the images of 336.

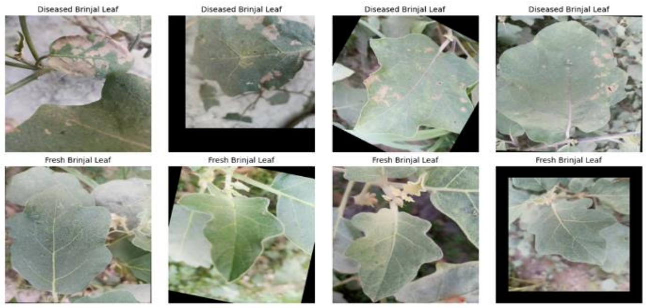

Figure 8: *Sample images from dataset*

Figure 8 shows the sample brinjal leaf images. Here the brinjal leaf images are of two classes as fresh brinjal leaf and diseased brinjal leaf images. These sample images are taken from the brinjal leaf dataset. Each image is shown as a sample image for identification.

Figure 9: *Input brinjal leaf image*

Figure 9 shows the input brinjal leaf images. Here the input image is taken from the brinjal leaf dataset. Using the pre-processing, segmentation, feature extraction and classification techniques the input brinjal leaf image are processed.

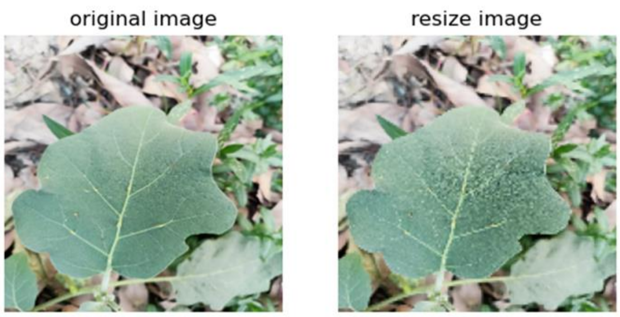

Figure 10: *Resized image*

Figure 10 shows the input image and resized images of brinjal leaf image. Here the input brinjal leaf image is resized for processing.

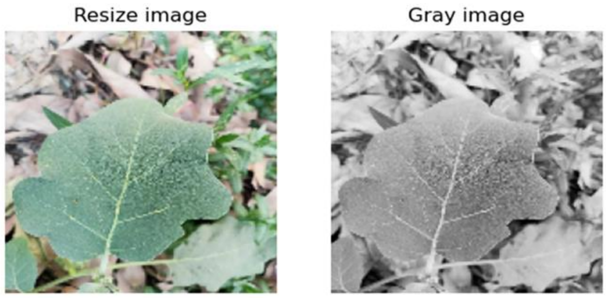

Figure 11: *Gray image*

Figure 11 shows the resized images into grayscale image. A resized image into grayscale conversion for brinjal leaf is converted by using the grayscale conversion technique. Here R, G, and B image is converted into gray image

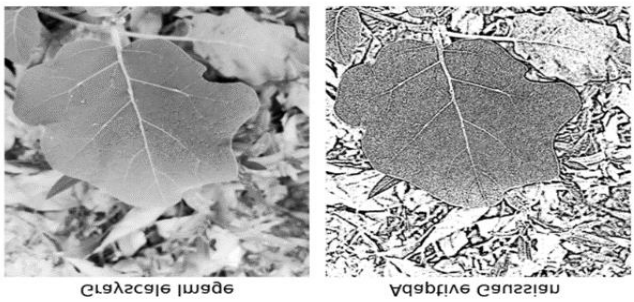

Figure 12: *Adaptive Gaussian Filter*

Figure 12 shows the gray scale conversion to adaptive Gaussian filter. After conversion of gray scale image, the gray image is given as an input to adaptive Gaussian filter. Here AGF removes the noise and smoothen the image.

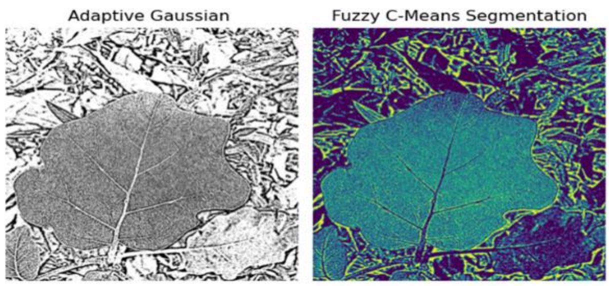

Figure 13: *Weighted Fuzzy C-Means clustering*

Figure 13 shows the adaptive Gaussian filtered image into Weighted Fuzzy C-means clustering images. Here the brinjal leaf image is clustered using weighted fuzzy C-Means clustering. WFCM clustering segmentation segments leaf with color formation.

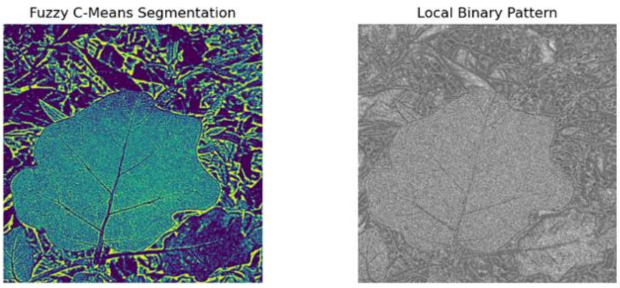

Figure 14: *Local Binary Pattern*

Figure 14 shows the local binary pattern for brinjal leaf image. Using local binary pattern each pixel values in a leaf image are textured for better pattern.

5. Performance Metrics

Proposed residual VGG-16 is examining accuracy, precision, sensitivity, specificity, Area Under the Curve (AUC), classification with "positive" and "negative" labels, the performance of each classification model in this study explained in Table 1.

Table 1: *Performance metrics*

Performance metrics	Formula
Accuracy	$\frac{(TN+TP)}{TS}$
Precision	$\frac{(TP)}{TP+FP}$
Recall	$\frac{(TP)}{(TP+FN)}$
$F1-score$	$\frac{(2 * \text{Precision} * \text{Recall})}{(Precision + Recall)}$

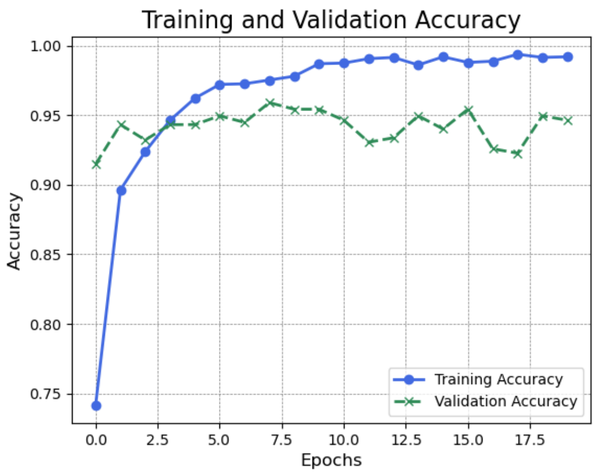

Figure 15: *Training and validation accuracy*

In Figure 15 training vs validation accuracy for brinjal leaf is calculated. Here X-axis denotes the Epochs which have the values from 0.1 to 18 Epochs and Y-axis denoted the accuracy which ranges up to 100%. The accuracy for the proposed Residual VGG-16 method is 95%.

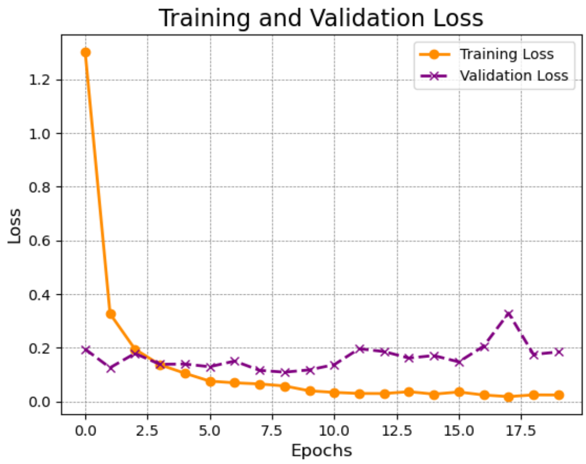

Figure 16: *Training and validation loss*

Figure 16 shows Training vs validation loss for brinjal leaf is calculated. The X-axis denotes the epochs and y-axis is loss for training loss vs validation loss. Training loss value is going on decreasing from 1.3 to 0.1 after 0.1 also it is going on decreasing. Whereas, validation loss is the high than the training loss for brinjal leaf image which ranges in between 0.2 to 18 it is going on increasing and decreasing.

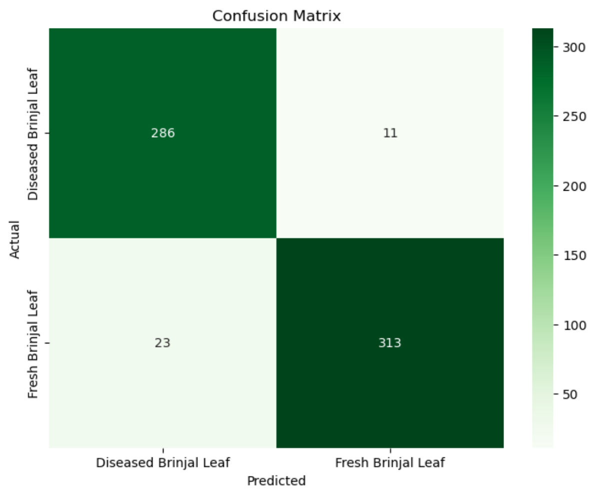

Figure 17: *Confusion matrix for proposed residual VGG-16*

Figure 17 illustrates the confusion matrix for residual VGG-16. This matrix shows the values for true and predicted labels. Here diseased brinjal leaf is 286 and fresh brinjal leaf is 313.

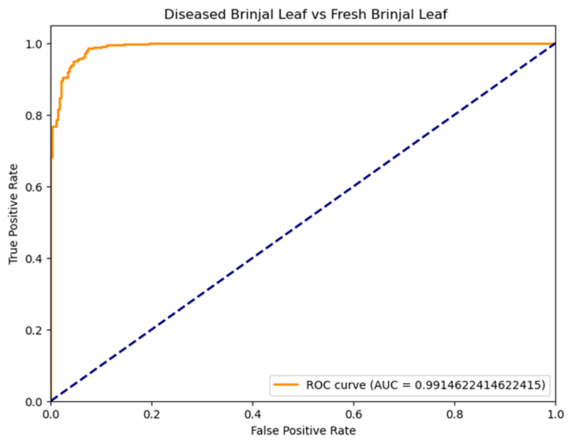

Figure 18: *ROC curve for diseased vs fresh brinjal leaf image*

Figure 18 shows the ROC curve for diseased vs fresh brinjal leaf image. Here the ROC value for proposed Residual VGG-16 is 0.99.

6. Comparison for the Proposed Method

The comparison of proposed method with existing method is presented in table 2. The SVM-DT have the classification accuracy of 94.1% [13] and VGG-16 have the accuracy of 94.3% [18]. The proposed Residual VGG-16 have the higher accuracy of 95% compared to the existing method in Table 2. The proposed Residual VGG-16 have better performance.

Table 2: *Comparison for the proposed method*

Study	Method	Accuracy
Anand *et al.* [13]	SVM-DT	94.1%
Rangarajan *et al.*[18]	VGG-16	94.3%
Proposed approach	Residual VGG-16	95%

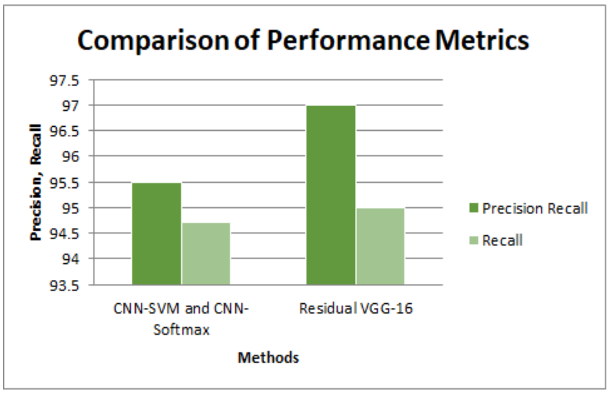

Figure: *Comparison of performance metrics*

The Precision and recall value for classifiers CNN-SVM with CNN-Softmax and the proposed is presented in Figure 20. The CNN-SVM with CNN-Softmax have the value of 95.5% and 94.7% [10] and proposed Residual VGG-16 method have the precision value of 97% and recall of 95% for brinjal leaf.

7. Conclusion

In this study, Residual VGG-16 is proposed for the classification of brinjal leaf image. The integration of advanced preprocessing techniques, such as resizing, grayscale conversion, adaptive Gaussian filtering, ensures that the input images are optimized for segmentation. The use of approximate Weighted Fuzzy C-means clustering for segmentation further enhances the precision of identifying weighted data points in the images. Additionally, the Local Binary Pattern feature analyzed the binary pattern. The performance evaluation, conducted on the brinjal leaf dataset, demonstrates the superior capabilities of the Residual VGG-16 related to existing methods. The improved accuracy of 95% is achieved as a greater accuracy in contrast to the existing techniques.

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