International Journal of Advanced Trends in Engineering and Management
(ISSN 2583-7052)

Vol. IV, No. 09, pp. 1-12, September

Convnext-Driven Deep Learning Framework for Accurate Identification and Classification of Sunflower Leaf Diseases

Sumesh Joe Cherian[1*]

[1]Lecturer in Electronics Engineering, Mahakavi Vennikulam Gopalakurup Memorial Government Polytechnic College, Vennikulam, Pathanamthitta, 689544, India.

[1*]**Corresponding Author E-mail:** sumeshjoecherian1@gmail.com

ABSTRACT: Sunflower leaf disease significantly cause damage to the yield and the quality of crop, which emphasize the need for accurate leaf disease detection and classification. This research examine the integration of both processing and an advanced Deep Learning (DL) classification technique for the prediction of disease in the leaf of the sunflower. The image of Sunflower Fruits and Leaves datasets are inserted for preprocessing based on Contrast Limited Adaptive Histogram Equalization (CLAHE) technique to enhance the image brightness and provide clear prediction of disease in the leaf image. The preprocessed image is segmented based on Fuzzy C-means (FCM) clustering, an effective segmentation technique that clusters multiple data with the different relationship. Local Binary Pattern (LBP) utilized for extracting the texture of the images and enables improved differentiation of normal and infectious leaf. A Contemporary Architecture for Convolutional Neural Networks (ConvNext) employed for image classifier of sunflower leaf for attaining enhanced accuracy in leaf disease prediction. The proposed model is implemented using Python software and evaluated based on performance metrics, achieving an accuracy of 93%, with precision, recall, and F1-score reaching 96%, effectively predicting disease in sunflower leaves. Finally, the proposed methodologies improves the prediction level and contribute to early prediction of the disease which leads to reduce the losses of the crop.

Keywords: Contrast Limited Adaptive Histogram Equalization, Fuzzy C-means, Local Binary Pattern, A Contemporary Architecture for Convolutional Neural Networks.

1. Introduction

Sunflower is the essential production of oil seed as well as possibly fit in cultivated organization and it is the oil manufacture sector of India. While sunflower yield gets spoiled by the effect of many infections and insects which destroy the plant results in extensive range of loss in manufacture. It often enters the plant through wounds of the leaf. It leads to economic losses include reduced seed quality and quantity, harvest losses, and increased production costs. One of the Gray mold disease in sunflower leaf which caused by the fungus botrytis. This fungus spread by wind, water splashing and even on plant waste since it grows best in damp, shaded areas with little air circulation. When the spores germinate under moist, cool to warm conditions, they create a web on plant tissues and produce additional spores to repeat the infection cycle which severely impacting sunflower crops by affecting various parts of the plant, including leaves, stems, and flower heads. Early detection of disease enables timely prevention which reduce the loss and spreading of infection among the plant. In traditional technique of disease detection in sunflower leaf is observed by naked eye and this technique faces complexity in monitoring the large farms. Thus, early detection of sunflower leaf disease reduces the losses and leads to increase the yield of the crop.

The image processing method is to preprocess the input image by removing unwanted background and noises from the image. In existing approach, Histogram Equalization (HE) is an image processing method, it ensures the quality of the image by distributing the values to create the uniform histogram. HE variants is used to enhance the image contrast which enable for the effective prediction. However, HE produce noise in the area with low intensity [2]. The Bilateral False Contour Elimination Filter (BEF) removes false contours from image by repeatedly refine the input image with incorrect contours of diverse masses gradually removed as the increment of number of iterations. However, BEF face complexity in time constraints to process the image [3].Singular Value Decomposition (SVD) produce grayscale images that more accurately represent the texture of the original color images, making it particularly valuable for processing the image to accurately detect the disease from the images. Nevertheless, SVD requires decomposition of each color of the image requires more processing time and memory [4]. To address these above issues, in this work explore the CLAHE method which enhance the image contrast and making infected regions of leaf.

Moreover, *K*-means clustering algorithm used to segment the images and it is applied to increase the quality of the image. It minimise the unwanted clusters used to generate the initial center which are then utilized for the segmentation of image. On the other hand, errors significantly disturb the center positions, affecting the accuracy of the segmentation [5]. Segmentation of Images Using Watershed Arcs (WA) effectively capture border of image across multiple dimensions to improve segmentation accuracy in complex image datasets. This technique utilised for the applications to detect leaf diseases like leaf scars, Downy mildew and Gray mold. Although, WA face difficulties in texture and color changes across image are critical for identifying symptoms [6]. To overcome these problem, FCM is proposed to accommodate varying degrees of cluster membership in the processed leaf, thereby increase the accuracy of the disease. Further, the image segmented image is fed into the feature extraction process, which enhance the relevant functionalities to detect the disease in the leaf of sunflower.

The Global and Local feature extraction used to identify and extract meaningful information from images to predict the leaf disease. The global feature capture the overall characteristics of image and local features highlight the infected region of image. However, extraction of local feature computationally expensive when dealing with larger images [7]. Principal Component Analysis (PCA) is a feature extraction method to extract valid features from the images, which are then processed to identify infected regions of image. It improves the detection accuracy by focusing on the changes observed in affected part. However, PCA is a linear technique, which fail to capture the complexity present in the images. [8]. Color Histogram (CH) is a feature extraction used to compute the similarities between the images and the reference frame, which enables the accurate detection of color evolution during the titration process. Nevertheless, CH lacks texture, edges and shape information and it is sensitive to varying light condition of the image [9]. Henceforth, this work, proposed system LBP is implemented for feature extraction which effectively captures local structure of the image such as ends, corners, and plane areas. To categorize disease in the sunflower leaf, the images are loaded into the classification method.

Support Vector Machine (SVM**)** for classification, the method effectively enhances accuracy while reducing the necessity for huge labeled datasets. This classifier performed by defining the optimal hyperplane that splits diverse classes, maximizing the margin between them to accurately predict the disease rate in the image. However, error leads to skew the hyperplane, which impacts the classification of new data points [10]. Extreme Learning Machine (ELM) classification algorithm used to improve the accuracy and efficiency of hyper spectral remote sensing image classification, making it more suitable for processing large-scale datasets in remote sensing applications. On the other hand, ELM has a single level architecture, which presents challenges in processing the multi-layer data structure [11]. The neural network classification is based on the Xception classifier, which is designed for image classification with high computational efficiency. This styles the ideal mostly suitable for disease recognition and real-time resource-constrained. This approach addresses challenges in medical imaging, such as limited data and high variability, by optimizing network architecture and training strategies. Nonetheless, this approach need a lot of labeled data, which is costly and time consuming to process [12].To tackle these problems, ConvNext is implemented for classification of images which is main process for prediction of the disease in sunflower leaf. The contribution of proposed work are:

- The CLAHE preprocessing method implemented to eliminate noise and unwanted background from images, significantly improves clarity and quality of the images, ensuring better visibility.
- The FCM clustering used to separate an image into meaningful sections, enabling pixels to be a part of many clusters with different levels of membership.
- LBP method utilized to efficiently extracts the texture of segmented images, ensuring high performance and reliability in prediction systems.
- ConvNext used to automatically classify the disease in the different types of images with the presence of leaf spots, lesion, leaf scars, downy mildew and Gray mold.

2. Related Work

A. Salam *et al* [13] have proposed Transfer Learning (TL) modal based CNN technique is employed to classify the plant leaf diseases. TL is a lightweight modal that significantly advance in agricultural disease detection. Also, the detection of leaf disease evaluated and trained using TL models involves modified MobileNetV3Small classifier to increased accuracy of the leaf prediction. However, TL faces difficulties when processing the large dataset leads to computationally expensive to implement.

F. Abramovich *et al* [14] have implemented ML based Sparse Multinomial Logistic Regression (SMLR) technique for the prediction of disease in the plant leaf. It enables effective classification of multiple disease based on different dataset It operate on the extracted image and classify the small set of relevant features classes accurately predict the disease in the image. Nevertheless, SMLR is a linear classification layer that difficulties to capture complex nonlinear pattern data and sparse in the data extracted from the raw image data.

S. Mumtaz *et al* [15] proposed a Gaussian distribution-based classifier is used for the classifying image to predict the disease of the sunflower leaf. It effectively captures the underlying data distribution within the image, thereby enhancing classification performance.. This approach has important applications of agriculture, allowing farmers to monitor crop health, increase yields, and detect plant illnesses at an early stage to protect the plant. However, it face difficulties when processing a complex datasets for different plant species.

3. Proposed Model Description and Modelling Block Diagram

The processing of sunflower leaf images enables the timely detection of diseases, helping to reduce crop losses and improve overall yield. To anticipate the disease, the procedure starts with the insertion of the image into preprocessing, which is followed by image segmentation, feature extraction, and classification. Figure.1 represent the block diagram of proposed system that illustrate performance of processing the image to predict the disease in the leaf of sunflower.

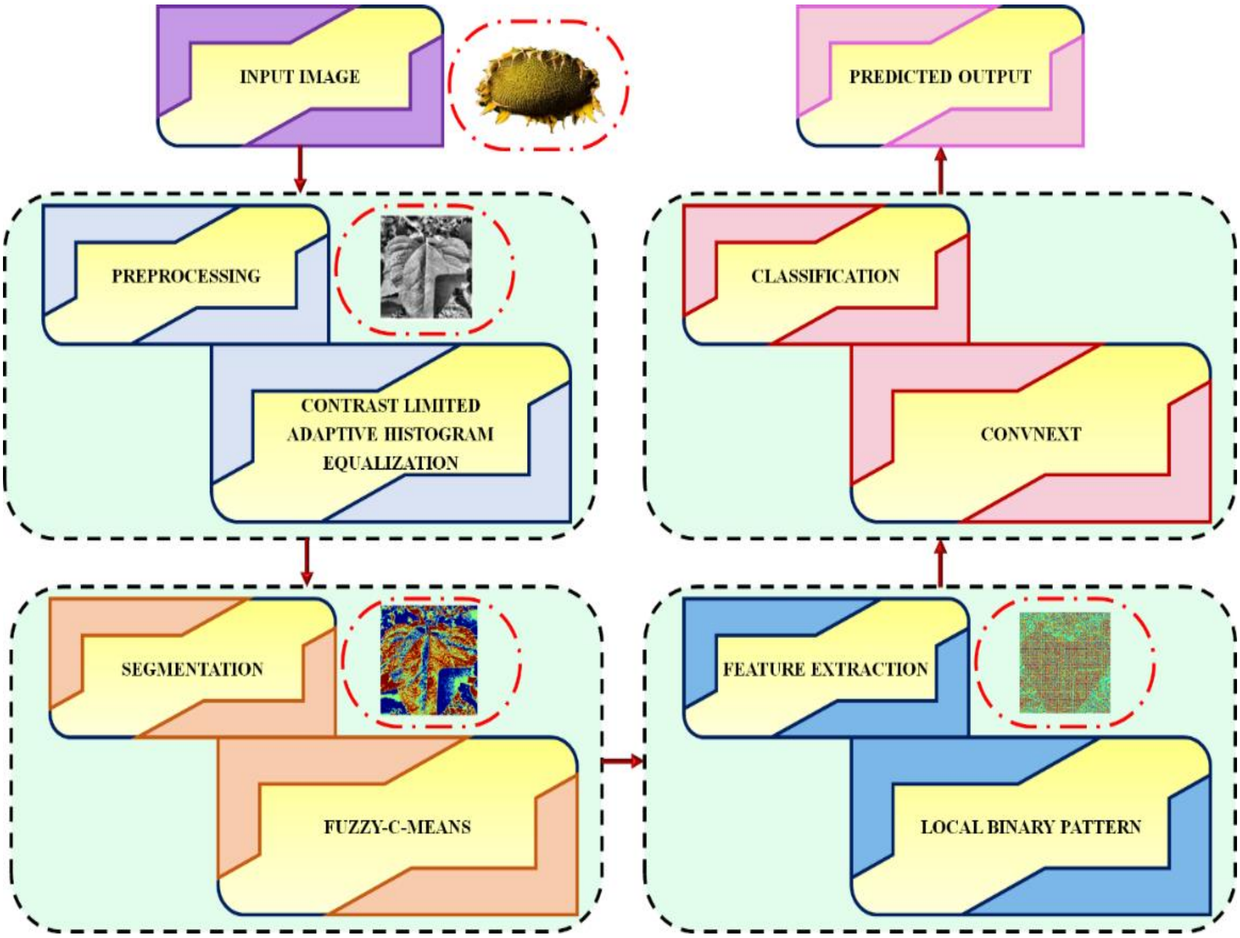

Figure 1: *Block Diagram for proposed system*

To determine whether a sunflower leaf is infected, the image is provided as input for image processing techniques. In order to detect sunflower leaf disease effectively, the input image is preprocessed using the CLAHE technique to improve contrast and visibility of the disease spots to enhance the segmentation process for accurate prediction of disease. The output is then fed into an image segmentation process that uses the FCM algorithm to cluster data with different relationships for a clear prediction. The LBP used for the feature extraction which enable improved differentiation of normal and infectious leaf. Also, it increases the prediction level of infected leaf of the sunflower. Finally, the ConvNext-based classification uses the extracted image to categorize the anticipated image from earlier stages, thus providing estimated outcome. The combination of image preprocessing, segmentation, feature extraction and Classification result in robust system for the prediction of sunflower leaf for the early prediction which reduces the losses.

4. Proposed System Modelling

4.1 Preprocessed Based Contrast Limited Adaptive Histogram Equalization

Preprocessing is essential for enhancing input images to ensure accurate prediction of the leaf disease. CLAHE is an image processing method used to increase the difference of an image. It operates by dividing the image into small sub images and it process on each sub images to predict the infection of the leaf. The CLAHE filter is applied to reduce noise, improve image quality, and enhance contrast, thereby optimizing the image for more reliable diagnostic results. Preprocessing technique have several key steps to process the image of the leaf. The adaptive process is to analyse the role of the state of being disparity color to change every sub images. The histogram result is increased by the distributed value for each kernel contrast. In order to avoid induced boundaries, the adjacent sub images are combined. To prevent enhancing any noise in the image, the contrast kept to a minimum, mostly in areas that are uniform. It reveals the image's hidden features and the distribution of grayscale values. To remove induced boundaries, adjacent sub images are combined using bilinear interpolation.

The histogram of ordinal image with amount levels in the range $\big(0,(L-1)\big)$ is a distinct task:

$$h(rk) \;= n_k \tag{1}$$

The equation (1) represent that r_k is the strength value of the image, n_k is the sum of pixel in image with strength r_k. A normalized histogram is given by:

$$p_r(r_k) = \frac{n_k}{MN} \tag{2}$$

where, k=$(0,1,2,\dots,L-1)$

Equation (2) represents that $p_r(r_k)$ is an predictable of prospect of rate of strength level r_k in an image. The sum of all components of normalized histogram is equal to 1.

A histogram the number i is defined as image gray level, and equalization is gray on image i. An image's pixel image from level I is computed as follows:

$$P_{x(i)} = P(x=i) = \frac{n_i}{n}, \Rightarrow 0 \le \mathrm{i} < \mathrm{L} \tag{3}$$

- The variable L is the total an amount of gray levels existent at image,
- The variable n is the amount of pixels from dataset image,
- The variable $p_{x(i)}$ a depiction of the image histogram for the pixel into directory to i.

The CLAHE technique refers to two pixels representing varying brightness levels, one with a certain percentage of brightness and the other with no brightness shown as gray-level pixels. The CLAHE technique used to enhance contrast and eliminate unwanted noise from the image. The computation of the image histogram to identify its peaks and valleys, which are then used to calculate other parameters. Beginning with the first sub-image and concluding with the final one based on the optimal parameters used to improve the prediction. After processing the images proceed to segmentation to accurately identify and classify the different feature.

4.2 Segmentation Based Fuzzy C-Means

The approach for image segmentation is FCM Clustering which is widely used technique because of its robustness for segmentation. This algorithm depends on the selection of the initial cluster center and the initial relationship value. FCM define initial clustering and it define which have high repeated cluster to find the accurate detection.

Using a specific internal invention standard metric as a likeness quantity on $R_p \times R_p$, the FCM algorithm approximates minima of an objective function that belongs to a family and functional through iterative optimization. When a weighted exponent m is applied to the association standards used in definition of the efficient family, the difference between family members is the outcome $J_m\colon M_{fc} \times R^{cp} \to R^+$ is defined as

$$J_m(U,v) = \sum_{k=1}^{n}\sum_{i=1}^{c}(u_{ik})^m\,(d_{ik})^2 \tag{4}$$

The fuzzy c partition of X;

$$v = (v_1, v_2, \dots, v_c)\epsilon R^{cp} \tag{5}$$

With $v_i \in R^p$ the collection center of the class and

$$d_{ik}^2 = ||x_k - v_i||^2 \tag{6}$$

The m^{th} control of the relationship of data i in cluster I is used to weight the squared distance. Hence, J_m is a criteria for squared errors, and its reduction generates optimal fuzzy clusters in the sense of generalized least squared errors. FCM clustering is first applied for segmentation, grouping the data into distinct clusters based on similarity. After segmentation, the image undergoes feature extraction to identify key characteristics that define each cluster and enhance the analysis.

4.3 Feature Extraction Based Local Binary Pattern

LBP is highly recommended for the texture analysis. It works on the principle of comparing the center intensity value with its neighborhood pixel of an original image of sunflower leaf.

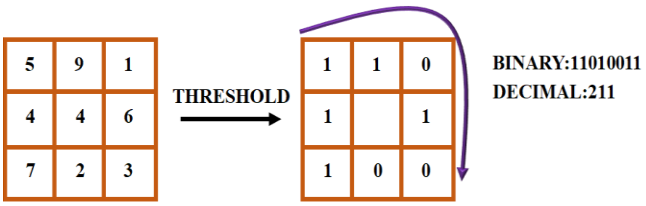

Figure 4: *Linear Binary Pattern*

Discretely middle pixel is equated with its 3x3 neighborhood pixel values. If neighborhood value is less than the center value, then it became 0 and if it is greater than center value it become 1. Formerly it process from the top-left and moves on circular direction, then the binary value is calculated. After, the calculation of binary value, the values are combined to produce the binary code and it converted to the decimal value. This process is repeated until all the neighbor pixel are processed.

LBP is a modest and well-organized and efficient texture operator which labels the pixels of an image by 3*3 neighborhood of each pixel with rate of the middle pixel and expects the outcome as a binary number. Figure. 4 shows a sample of LBP design. The rate of the LBP code of a pixel (x_c, y_c) is given by:

$$LBP_{P,R} = \sum_{p=0}^{P-1} s\left(g_p - g_c\right) 2^p \qquad (7)$$

Where g_c resembles to the gray value of the middle pixel (x_c, y_c), g_p mentions to gray values of p correspondingly spaced pixels on a loop of radius$R$, and s expresses a thresholding purpose. To generate binary code to generate the feature of the sunflower leaf diseases. Once the feature extraction process is completed, the image classified to categorize the sub image either they are fresh or infected leaf to predict the disease in the leaf of sunflower.

4.4 Classification Based a Contemporary Architecture for Convolutional Neural Networks for Image Classification

The ConvNext is a CNN-based system that projected to additionally expand the presentation of models for visual tasks, subsequent the several varieties that produced based on Transformer. ConvNext, which improves the model's ability of classification of image, makes the ideal concentrate more on classification of background data. To develop the model adaptability for disease classification at different scales and rally the network classification performance by Multi-Scale Feature Fusion (MFF) module is introduced into the ConvNext model used to extract diverse disease information through convolutional computation of different image dataset.

$$D_K \times D_K \times M \times N \times D_F \times D_F \qquad (8)$$

D_K Refers to spatial dimensions of a convolutional kernel defines the quantity of input networks, N is Number of output channels. D_F Refers to spatial measurements of the involved feature map or the output feature map.

$$D_K \times D_K \times M \times D_F \times M \times N \times D_F \times D_F \qquad (9)$$

The above formula (9), represent the convolution computation between the sub-images of the image.

$$\frac{D_K \times D_K \times M \times N \times D_F \times D_F}{D_K \times D_K \times M \times D_F \times D_F + M \times N \times D_F \times D_K} = \frac{1}{N} + \frac{1}{D_K} \times D_K = \frac{1}{N} + \frac{1}{9} \qquad (10)$$

The above formula (10), represent comparison between computational convolutions of the extracted image to define the disease.

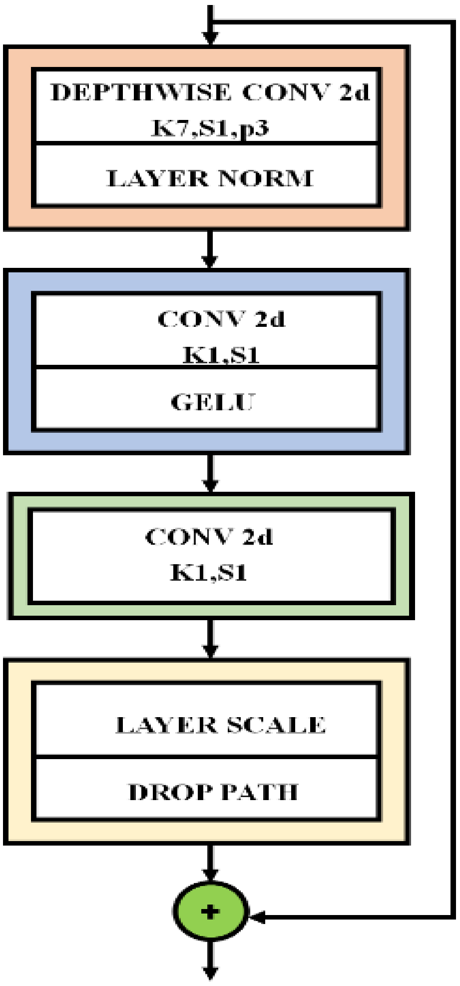

Figure 5: *ConvNext Block*

Fig 5 process on extracted image inserted into a depthwise separable convolution that operate on each part of the image with Kernel size = 7, stride = 1, padding = 3, applies Layer Normalization on the convolutional network. A pointwise ($1x1$) convolution, usually used for changing the channel dimensions. The extracted convolutional layer uses the Gaussian Error Linear Unit (GELU) activation function to enhance smoothness and improve performance; it then applies a 2D convolution to restore the channel dimension, while the layer scale introduces a learnable parameter to the output of the previous branch, helping to stabilize the deep network. Layer scale evaluated with Drop scale which randomly drops entire paths for the precision of disease in sunflower leaf with 96% and it leads to early prediction of disease which reduces the loss of crop and increase the production of sunflower crops. This method provide a better performance to detect the disease in sunflower leaf with the higher accuracy.

5. Result and Discussion

This work introduced a ConvNext-based classification system for precisely recognizing the various forms of infection on sunflower leaves. Furthermore, this work implemented by Python software tool with sunflower fruits and leaf dataset and the obtained results are given below.

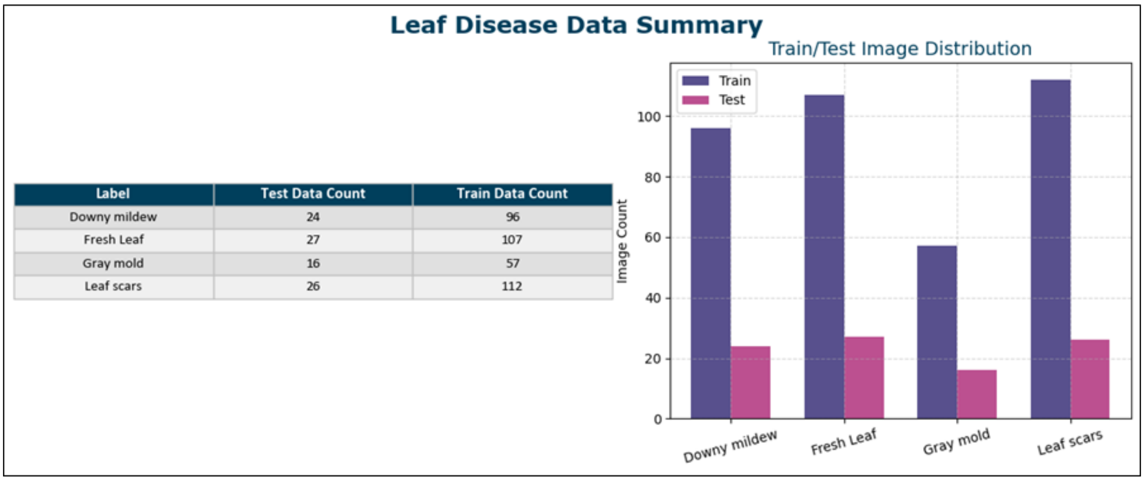

Figure 6: *Leaf disease data summary*

Figure 6 represents the leaf disease data summary which illustrate the trained and test data count. The categories Downy Mildew, Fresh Leaf, Gray Mold, and Leaf Scars have respective data counts of 24, 27, 16, and 26 for testing, and 96, 107, 57, and 112 for training, illustrating the distribution of samples used during the model's evaluation and training phases.

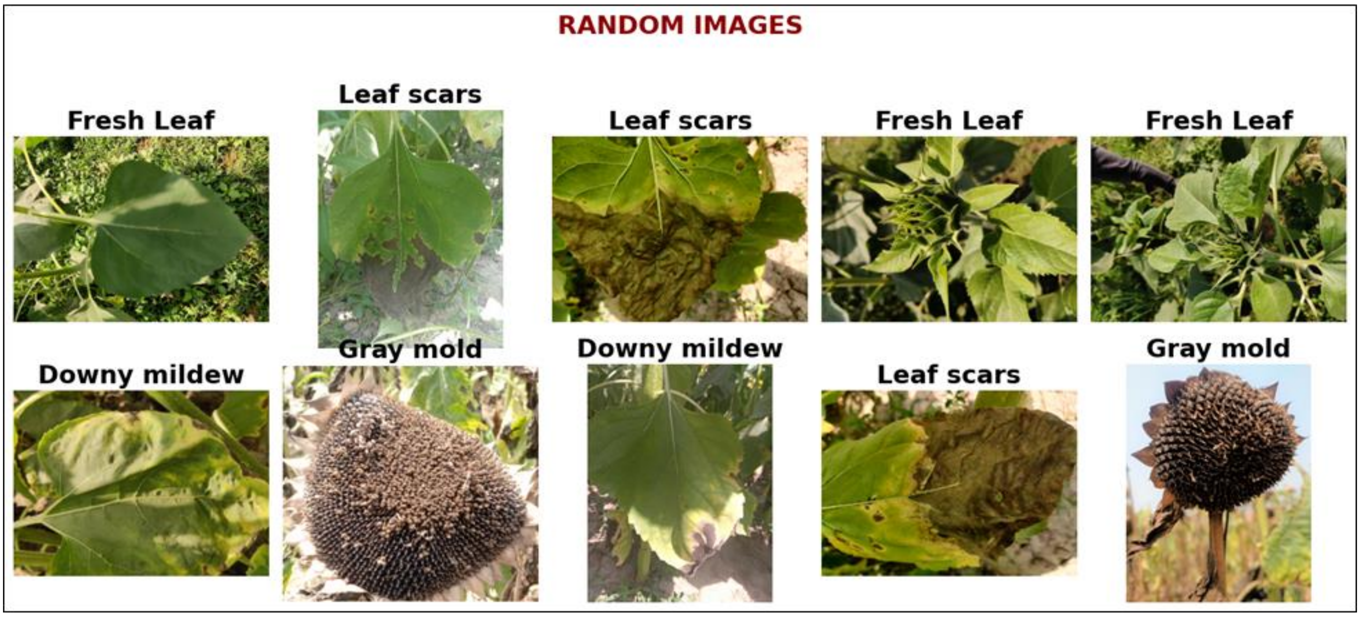

Figure 7: *Random images of infected sunflower leaf*

Figure 7 represents the random images of sunflower leaf. The dataset have different images with Fresh Leaf, Leaf scars, Leaf Downy, Gray mold, Downy mildew and gray mold. The system is better trained to differentiate between healthy and unhealthy leaf states thanks to these varied classifications.

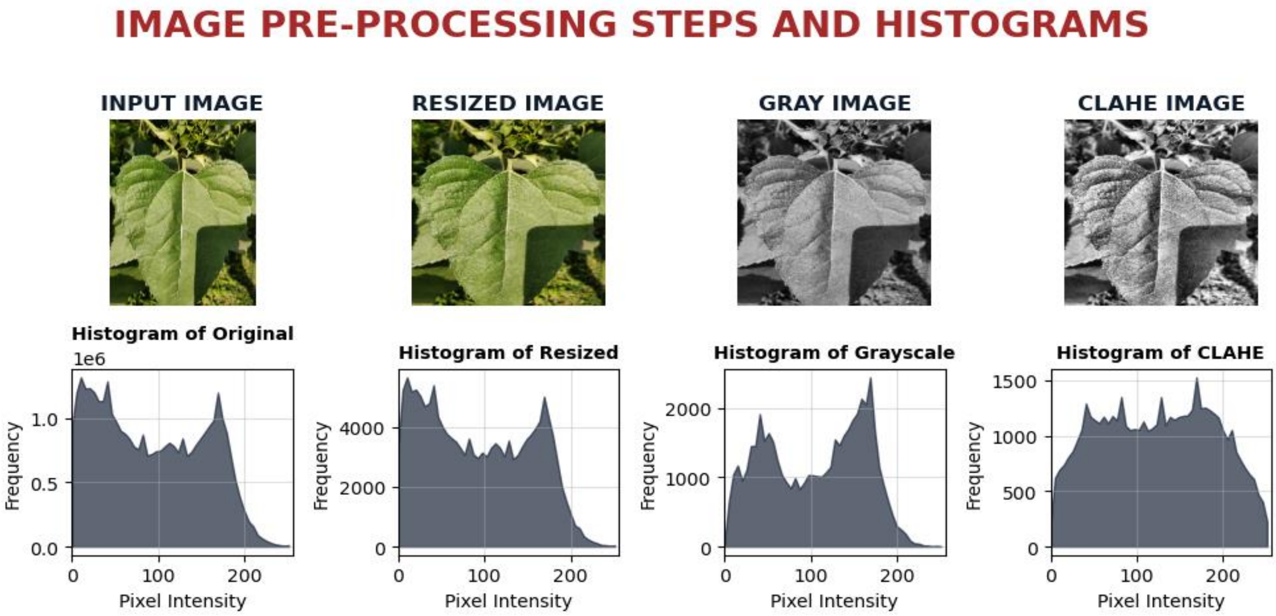

Figure 8: *Image preprocessing*

Figure 8 represent the steps involved in image pre-processing using the CLAHE technique for removing the unwanted noises, and background from the image. The inserted image is resized for enhancing the image visibility and the gray image differentiate the intensity based on the lighter and darker part of the image. Also, it used to improve the clarity of visual and provide the images by increasing the range of pixel intensity values within each part of the image.

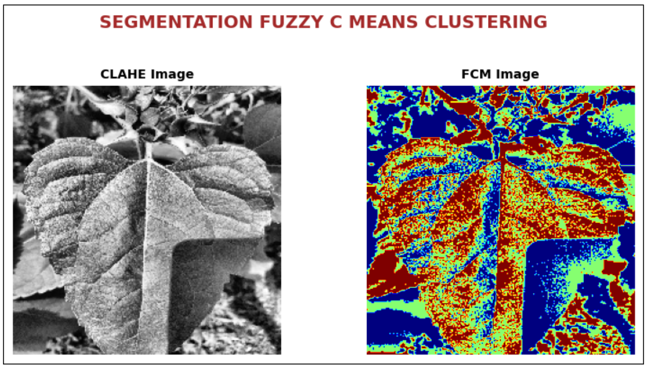

Figure 9: *Image segmentsation using FCM clustering*

Figure 9 represents the image segmentation using the FCM clustering from the CLAHE images. FCM algorithm work based on the selection of the initial cluster center and the initial relationship value.The image is clustered on the basis of similarity on each center point and it matches with each cluster to define whether the image is infected or not.

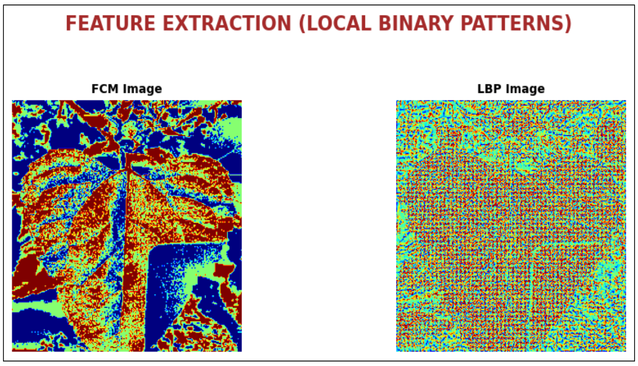

Figure 10: *Feature Extraction using LBP*

Figure 10 represent extraction of texture from the image using LBP. It is highly recommended for the feature analysis. Each midpoint pixel is compared with its 3x3 distinct pixel standards. If distinct value is less than midpoint value, then it became 0 and if it is greater than midpoint value it become 1. Then it process from the top-left and moves on clockwise direction, then the binary value is calculated. After, the calculation of binary value, the values are combined to produce the binary code and it converted to the decimal value. This process is repeated until all the neighbor pixel are processed.

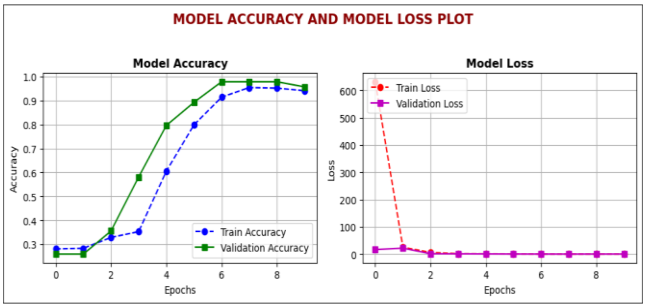

Figure 11: *Model Accuracy and Model Loss Plot*

Figure 11 represent the model accuracy and loss between the training and validation of data. The model demonstrate strong routine with high accurateness and low loss on both training and validation sets, portentous effective learning without any overfitting. Also, the Final Training and validation accuracy achieves 94% and 93% respectively.

Performance Metrics	
Accuracy	93%
Precision	96%
Recall	96%
F1-Score	96%

Table 1: *Performance Metrics*

Table 1 represents the model performance very fine across all metrics with high precision, recall, and F1-scores with the rate of 96%. Also, the proposed classifier achieve higher accuracy rate of 93%.

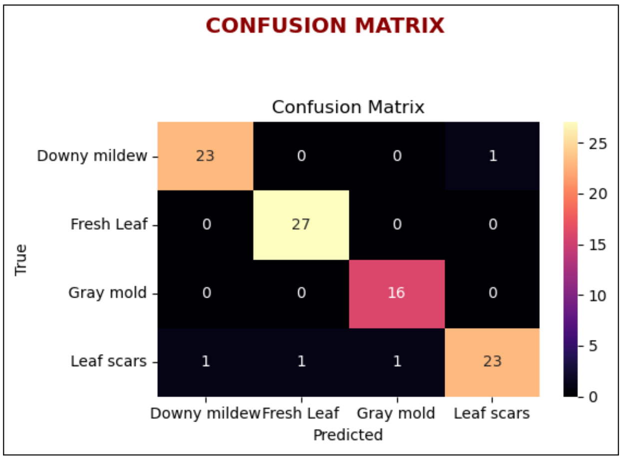

Figure 13: *Confusion Matrix*

Figure 13 represents the result of ConvNext classification with Fluffy mildew, Fresh leaf, Gray mold and Leaf blemishes are correctly classified with the count of 23, 27, 16 and 23. The misclassified rate of downy mildew leaf with 1 and leaf scars with 3 misclassified as 1 in Downy mildew, another one is Fresh Leaf and one in gray mold. Overall fresh leaf is perfectly classified and Leaf scars have highest misclassification with the rate of 3.

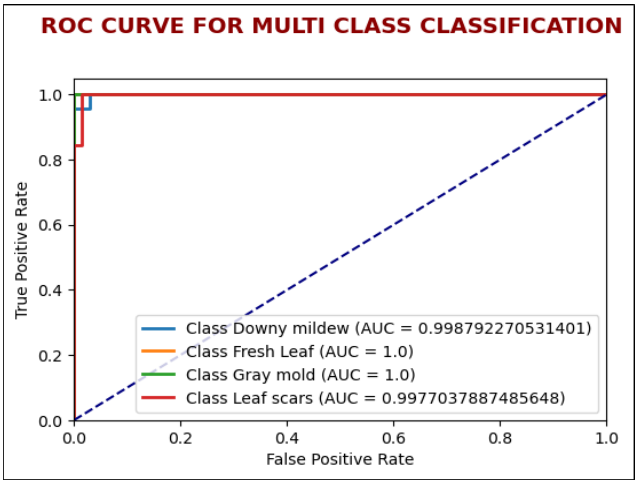

Figure 14: *ROC curve for multi class classification*

Figure 14 represents the ROC analysis confirms the strong performance observed in the classification report and confusion matrix. The Downy mildew have AUC value of 0.9987. The fresh leaf have AUC value of 1.0 and Gray mold have AUC value of 1.0 which have same result as fresh leaf. The classification of multi class using ROC curve value have both positive and negative rate.

METHOD	ACCURACY
CONVNEXT	93%
ELM[12]	91.73%
SVM [10]	85.3%
NN [11]	72%

Table 2: *Comparison classification of accuracy*

Table 2 represent the comparison of various classification of sunflower leaf disease detection system highlighting that the ConvNext achieves highest accuracy at 93%, ELM outperform with the accuracy of 91.73%, SVM performs with the accuracy of 85.3% and NN outperform with the accuracy of 72%. The proposed ConvNext have highest accuracy compared to other classification.

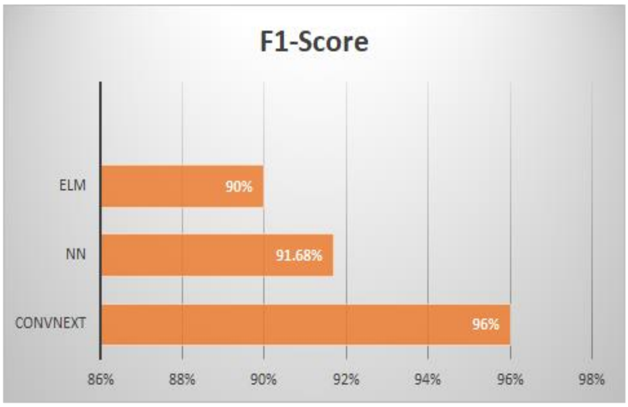

Figure 15: *Comparison of F1-score*

Figure 15 represent the comparison of F1-score between ConvNext, NN [11], SR [13] and ELM [12]. ConvNext have the F1-Score of 96%, NN have 91.68% of F1-Score and ELM have 90% score. The propossed classifier ConvNext have highest score of 96% compared to other method. ConvNext classifier have highest score for the prediction of disease in the leaf of sunflower.

6. Conclusion

This work represent the ConvNext based classification for the timely detection of sunflower leaf disease to increase crop yields. With the use of CALHE method successfully remove the unwanted noises and background in the image to enhance the prediction of the disease in the leaf. The FCM algorithm effectively divided image into portions that have the pixels belong to multiple clusters with varying degrees of membership. The integration of LBP feature extraction captures key textural information from the sunflower leaf image by splitting it into sub-images and calculating the intensity of each pixel to produce a binary output. Using Python-based software with the sunflower fruit and leaf dataset, providing a reliable test harness for evaluating the prediction of sunflower leaf diseases Thus, the ConvNext classifier provide remarkable performance with the accuracy rate of 93%. The combined methodology demonstrated high accuracy and reliability in identifying sunflower leaf diseases, validating the strength of integrating image processing methods. Future work could explore real-time deployment and the incorporation of additional modalities such as hyperspectral imaging to further enhance detection accuracy.

Reference

1. K. P. Asha Rani and S. Gowrishankar, Year: 2023, “Pathogen-Based Classification of Plant Diseases: A Deep Transfer Learning Approach for Intelligent Support Systems”, in IEEE Access, Vol: 11, pp. 64476 – 64493.

2. Samer Hameed Majeed, Nor Ashidi Mat Isa, Year: 2021, “Adaptive Entropy Index Histogram Equalization for Poor Contrast Images”, in IEEE Access, Vol: 9, pp. 6402 – 6437.

3. Changmeng Peng, Maohan Xia, Zhizhong Fu, Jin Xu, Xiaofeng Li, Year: 2021, Bilateral False Contour Elimination Filter-Based Image Bit-Depth Enhancement”, in IEEE Signal Processing Letters, Vol: 28, pp. 1585 – 1589.

4. Zaid Nidhal Khudhair, Ahmed Nidhal Khdiar, Nidhal K. El Abbadi, Farhan Mohamed, Tanzila Saba, Faten S. Alamri, Amjad Rehman, Year: 2023, Color to Grayscale Image Conversion Based on Singular Value Decomposition”, in IEEE Access, Vol: 11, pp. 54629 – 54638.

5. Ji Ma, Yazan Ahmad Muad, Jinjin Chen, Year: 2021, “Visualization of Medical Volume Data Based on Improved K-Means Clustering and Segmentation Rules”, in IEEE Access, Vol: 9, pp. 100498 – 100512.

6. Le Zhang, Fuping Wu, Kevin Bronik, Bartlomiej W. Papiez, Year: 2025, “DiffuSeg: Domain-Driven Diffusion for Medical Image Segmentation”, in IEEE Journal of Biomedical and Health Informatics, Vol: 29, No: 5, pp. 3619 – 3631.

7. Mohammad A. Alzubaidi, Mwaffaq Otoom, Hamza Jaradat, Year: 2021, “Comprehensive and Comparative Global and Local Feature Extraction Framework for Lung Cancer Detection Using CT Scan Images”, in IEEE Access, Vol: 9, pp. 158140 – 158154.

8. Bing Nan Li, Xinle Wang, Rong Wang, Teng Zhou, Rongke Gao, Edward J. Ciaccio, Peter H. Green, Year: 2021, “Celiac Disease Detection From Video capsule Endoscopy Images Using Strip Principal Component Analysis”, in IEEE/ACM Transactions on Computational Biology and Bioinformatics, Vol: 18, No: 4, pp. 1396 – 1404.

9. Xiongbing Huang, Hongqiu Zhu, Can Zhou, Fei Cheng, Yonggang Li, Year: 2021, “A Similarity Method of Color Frequency Histogram with Dynamic Reference Frame for Image Visual Titrations”, in IEEE Transactions on Instrumentation and Measurement, Vol: 70, pp. 1 – 10.

10. Manish Pratap Singh, V. Gayathri, Debasis Chaudhuri, Year: 2022, “A Simple Data Preprocessing and Post processing Techniques for SVM Classifier of Remote Sensing Multispectral Image Classification”, in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, Vol: 15, pp. 7248 – 7262.

11. Xinpeng Wang, Bingo Wing-Kuen Ling, Huimin Zhao, Shaopeng Liu, Year: 2023, “The Tensor Discriminant Ridge Regression Model With Extreme Learning Machine for Hyperspectral Image Classification”, in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, Vol: 16, pp. 8102 – 8114.

12. Shin Kim, Kyoungro Yoon, Year: 2022, “Deep and Lightweight Neural Network for Histopathological Image Classification”, in *Journal of Mobile Multimedia*, Vol: 18, No: 6, pp. 1913 – 1930.

13. Abdus Salam, Mansura Naznine, Nusrat Jahan, Emama Nahid, Md Nahiduzzaman, Muhammad EH Chowdhury, Year: 2024, “Mulberry Leaf Disease Detection Using CNN-Based Smart Android

Application", in IEEE Access, Vol: 12, pp. 83575 – 83588.

14. Felix Abramovich, Vadim Grinshtein, Tomer Levy, Year: 2021, "Multiclass Classification by Sparse Multinomial Logistic Regression", in *IEEE* Transactions on Information Theory, Vol: 67, No: 7, pp. 4637 – 4646.

Sara Mumtaz, Shabbab Algamdi, Haifa F. Alhasson, Dina Abdulaziz AlHammadi, Ahmad Jalal, Hui Liu, Year: 2025, "Leaf Classification for Sustainable Agriculture and In-Depth Species Analysis", in IEEE Access, vol. 13, pp. 17043 – 17053.