SSRG International Journal of Electronics and Communication Engineering
ISSN: 2348-8549/ https://doi.org/10.14445/23488549/IJECE-V13I11P110

Volume 13 Issue 11, 170-183, November 2026
© 2026 Seventh Sense Research Group®

*Original Article*

# Hybrid Pre-Processing Method based on Discrete Wavelet Transform With Pre-Weiner Filtering and CNN for Plant Leaf Disease Prediction

G. Geetha[1], K P Lochanambal[2]

[1,2]*Department of Computer Science, Government Arts College, Udumalpet, Tamil Nadu, India.*

[1]*Corresponding Author: Geetha7wi@gmail.com*

Received: 09 September 2026 Revised: 13 October 2026 Accepted: 31 October 2026 Published: 27 November 2026

***Abstract -*** *A significant portion of the primary agricultural commodities. Plant pathology is contributing to lost output and is manageable with continuous inspection. Monitoring plant diseases manually is time-consuming activity and prone to mistakes. Artificial Intelligence (AI) and computer vision, combined with the pre-symptomatic diagnosis of pathogens, mitigate the pathological changes and address the limitations of ongoing human surveillance. Hence, farmer-centric automated diagnostic systems are optimal. To diagnose the illness at an early stage, it is important to precise lesion components of the foliage. However, the presence of noise in digitally captured images, as well as variations in background, shape, and brightness in sick plant leaf photos, m ade accurate detection problematic. Researchers have already used methodologies to achieve this goal, but emerging paradigms related to eyesight. In this study, we suggest using a novel filtering technique for leaf disease detection with a classification method. Deep representation learning, such as deep learning models are among the influential AI methodologies. This method synthesizes multi-scale input to the Discrete Wavelet Transform with Pre-Weiner filtering technique with Convolutional classification algorithms and plant disease identification. The analysis is grounded in a plant leaf image dataset, and leaf disease dataset was utilised as the training set. For the testing dataset, we are also collecting some leaf photos. Numerous varieties of leaf diseases affecting agricultural plants have been analysed. In leaf image recognition, the presented method was trained for pattern recognition of leaf spot. The presented method enhances precision disease identification. Utilising the presented Discrete Wavelet Transform with Pre-Weiner thresholding, it delivered the required data, such as Mean Squared Error of 41.36, Peak-Signal-To-Noise Ratio of 38.12, interrelation of 0.95, and 18.58 milliseconds CPU time duration, of plant leaf disease high predictive accuracy of the other Exponential Moving Average (EMA) like averages, normal, Median, and Weiner filters.*

***Keywords -*** *Plant leaves, Leaf disease prediction, Pre-Processing, Discrete wavelet transform, Pre-Weiner filter, Convolutional Neural Network, Performance evaluation.*

## 1. Introduction

Thousands of years ago, agriculture helped to contribute the major food crops and animals of today under domestication. The major global challenge of global systemic risk is food deprivation, which is a major factor in phytopathology [1]. Pathogens are accountable for about 16% loss of allocation in total factor productivity, as indicated by the study.

Plant pathogens are classified into several primary classes, including mycota, microorganisms, subviral particles, microbiota, and phytoparasites [2]. Computer vision, deep learning, and Artificial Intelligence (AI) have been multi-functional, such as in medicine and renewable resource power prediction [3].

The capacity to generate enough food to meet societal needs has been made possible by enhanced methodologies. Farmers encountered challenges from variables such as declining pollinators, plant diseases, and global heating [4]. Modern technology for analysis and detection procedures aids farmers in eliminating these issues [5]. A plant's natural products, such as stems and leaves, are just a few of the parts where diseases can be discovered. Around the world, in every season, leaves offer a few interesting things about flowers and natural products [6].

The different plant components manifest the traits of photo pathology. The virus is endemic, nevertheless, in lamina. Some researchers utilize automated methods to detect plant illnesses from leaf photos utilizing computer vision and soft computing systems. Diagnosing plant

This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/)

pathology is important for crop production and management. Although it takes a great deal of experience and expertise, it can be successfully accomplished by scouting specialists using optical observation of changes in plant leaves [7]. Artificial Intelligence (AI)-based novel technologies that analyse data can enhance the reliability of diagnoses, which can then be integrated into instruments for the right course of therapy. Plant disease detection can be made even more successful by employing techniques that combine Artificial Intelligence (AI) with picture feature analysis. It is difficult to identify plant diseases from their visual characteristics. When it is automated, it gets even harder. Moreover, the lighting conditions make it harder, in addition to the morphological aspects [8].

The key innovation of this paper lies in:

1. A specialized terminology of pre-processing methods are analysed to design and advocate a solution filtering framework by model validation to the reference data pre-processing images.
2. Classification performance evolution with modifications and compares to the convnet structure for classification of plant leaf diseases. Several experiments employing pre-processing methods and CNN architectures were conducted.
3. The attained yield in this study surpasses the existing literature in this field.

### *1.1. Artificial Intelligence*

Artificial Intelligence (AI) has many real-world applications across many different industries these days, and it is a discipline with many ongoing research projects. AI's primary challenge is to solve tasks that are computationally doable by humans yet intuitive for them to accomplish.

Therefore, the method by which AI systems must learn machine learning will able to identify patterns in unprocessed data. Therefore, while traditional methods would not be effective, AI-based techniques are particularly helpful in solving complicated situations [9]. Investigators and innovators can integrate predictive analytics to address real-world knowledge-related challenges using computational methods. Through the development of algorithms for pattern recognition renders extrapolations and self-learning to behave autonomously [10]. A widely adopted learning approach for neural networks. The capacity of representation learning to recognize image features and its high abstraction stages automatically are two of its key features. Shift-invariant neural networks, specifically the deep neural network architecture utilized in data visualization processing. Deep learning that employs convnets in minimum requirement of their feature maps [11].

### *1.2. Image Processing*

The practice of using neural network processing to involve, analyse, and modify data visualization as AI image enhancement. Data acquisition additionally requires refining the specification of the images [12].

The structural representation processing method is explained in Figure 1. The initial stage is pre-processing. In pre-processing, the unwanted noises are removed using filtering methods.

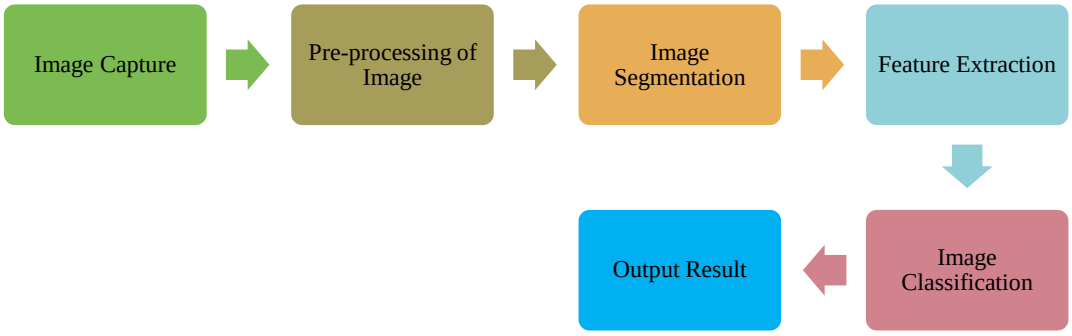


**Fig. 1 Image processing technique**

Once the pre-processing is done, the image is given for segmentation. After the segmentation is completed, feature extraction occurs. The final stage is image classification. Here, the given input images are classified using classifiers [13].

### *1.3. Noise Removal in Pre-Processing*

One important factor that degrades the input image fidelity is noise. In addition to the noise level typically reducing the amount of useful information that may be recovered from the image, some important image sections are also frequently deformed. Many analysts have played around with image noise because noise occurs during the acquisition process when there is an unplanned change in illumination or colour information [14].

Errors resulting from various sources, including the climate and the instruments used, have led to noise in leaf images. This noise is additionally a consequence of errors that occur during picture processing, encoding, and storage. So, these unwanted noises are removed by using various filtering techniques [15].

[16] suggests that different kinds of sources produced sensor data are commonly included in computer vision systems. Because of this, to complete the appropriate task for pomology, the feature selection must be isolated and analysed using computational methods. Hence, identifying fruit in stores or accurately detecting fruit in an orchard for harvesting are requirements.

The rest of the paper proceeds as follows: A brief overview of the work is provided in Section 1. The literature review, which covers the many methods previously used to identify leaf diseases, is discussed in Section 2. The work's suggested methodology and technical specifications for the pre-processing methods are provided in Section 3. The study findings and debates are presented in Section 4, and Section 5 outlines the conclusions.

## 2. Systematic Review

Latest improvements in Artificial Intelligence (AI) and computer vision have substantially enhanced computerized plant leaf disease prediction systems. Prior researches primitively concentrate on traditional Machine Learning (ML) and handcrafted attribute derivation approaches. However, latest studies has transferred towards integrated Deep Learning (DL) frameworks to enhance classification reliability, robustness, and practical usability. In spite of these improvements, various difficulties still exist, incorporating inadequate preprocessing techniques, sensitive to atmospheric noise, computational overhead and poor generalization within changing area conditions.

[8] developed an attribute derivation architecture for tomato leaf disease identification aiming minimum-computational devices. Their study compared various DL frameworks incorporating AlexNet, Res Net50, VGG16, VGG19, and MobileNet utilizing a dataset comprising 10 disease classes and healthy leaves. Even though the architecture illustrates the feasibility of lightweight disease detection systems, the high accuracy attained was restricted to 87% presenting that the derived attributes were still impacted by noise, illumination changes, and deficiency in preprocessing framework. Further, the research majorly underscored implementation effectiveness other than enhancing image quality earlier for feature learning.

Simultaneously, [12] used histogram balancing, threshold masking, denoising and handcrafted descriptors, namely haralick texture, colour histograms, and Hu moments, integrated with conventional ML classifiers. Their Random Forest (RF) model accomplished assuring classification accuracy, however the reliability on physically engineered attributes limits adaptability through heterogeneous datasets and complicated disease trends. Additionally, traditional preprocessing methods often break down to conserve discriminative disease areas when images comprise background artifacts or improper lighting conditions. Parallelly, [19] developed a multimodal fusion architecture for rice plant disease identification utilizing bilateral refining, segmentation, and several DL models. The hybridization of modified algorithms improved classification reliability. However, the architecture produced increased framework complications and computational issues. The dependence on several attribute derivation networks also increases issues related to scalability and deployment effectiveness in real-world agricultural systems.

In upcoming studies, [10] includes explainable AI utilizing the LIME architecture to enhance the interpretability of DL-based disease classification. Their model attained high reliability while facilitating vison explanations for estimations. Even though interpretability was enhanced, the study primitively concentrated on transparency of model other than refining preprocessing and attribute derivation levels, which remain significant for improving generalization of model across heterogenous datasets. Simultaneously, [16] developed the ViTal architecture utilizing visual transformers and linear trajectory for computerized plant disease recognition. The architecture enhanced attribute representation and decreased memory needs for implementation on embedded systems. Somehow, transformer-based methods commonly need large training datasets and high computational resources, which makes them less appropriate for resource-complicated farming atmospheres without effective preprocessing assistance. At the same time, [17] integrated UNet-based segmentation with EfficientNet for disease categorization. Their research illustrates that segmentation importantly enhances disease localization and classification accuracy. However, the preprocessing workflow majorly concentrated on segmentation and was insufficient for advanced denoising frameworks which are capable of conserving informative disease attributes in noisy leaf images. Concurrently, [18] proposed a multi-scale attribute fusion-based adaptive deep Network hybridizing VGG16, changing autoencoder, and Vision Transformer attributes with an attention-based CNN classifier. Although the combining technique enhanced classification performance, the model framework became computationally overhead, raised training expenditure and restricted real-world practical implementation in minimal-resource farming usability.

In later years, [11, 13] presented complete review research on CNN-based disease identification and hyperspectral imaging strategies. These researches recognized vital research gaps incorporating imbalancement of dataset, environmental changes, computational lacking, and deficient preprocessing framework for practical agricultural situations. The reviews underscored the requirement for strong preprocessing architectures that are capable of enhancing quality of image while conserving disease-specific texture details. Next, [9] proposed a CNN-based practical plant disease diagnosis architecture that

accomplished high accuracy with fast inference speed. The research unscored the efficiency of DL for scalable framing surveillance. Nonetheless, the architecture importantly focused on classification effectiveness and did not particularly inspect the impact of preprocessing approaches on attribute conservation and noise suppression, which are required for managing field-acquisition leaf images comprising illumination changes and background noise.

The evaluation of prior researches showcases that most of the existing studies gave importance for classification accuracy while comparatively ignoring effective preprocessing techniques that can simultaneously decrease noise, conserve fine disease trends, and enhance attribute representation. Many DL models also suffer from raised computational overhead and restricted robustness under practical atmospheric changes.

Therefore, these retains a important need for need for efficient integrated preprocessing architecture combining Wiener refining and discrete Wavelet transform with CNN-based classification to improve quality of image, enhanced attribute derivation, and accomplish reliable plant disease estimation with decreased computational complexities.

## 3. System Architecture

The developed architecture hybrids preprocessing with CNN-based classification for accurate plant leaf disease estimation within noisy farming conditions. Initially, the collected leaf images are resized and standardized to mange image stability and enhance computational efficiency. Since practical leaf images may comprise noise, illumination changes and background interference, Pre-Wiener filtering is implemented to compress unwanted distortions while conserving significant disease-relevant edge and texture details. After denoising Discrete Wavelet Transform (DWT) is implemented to decompose the refined images into several frequency sub-bands for multi-resolution attribute improvement. The decomposition process conserves both minimal-frequency structural details and high frequency lesion characteristics, namely discoloration, spots and texture irregularities. The improved images are then forwarded to Convolutional Neural Networks for computerized attribute derivation and disease classification. The CNN model learns discriminative disease trends through convolutional and pooling tasks, succeeded by fully connected layers for final classification. The combination of Pre-Wiener filtering, DWT, and CNN enhances noise robustness, attribute isolations, and classification performance for healthy and diseased plant leaf images.

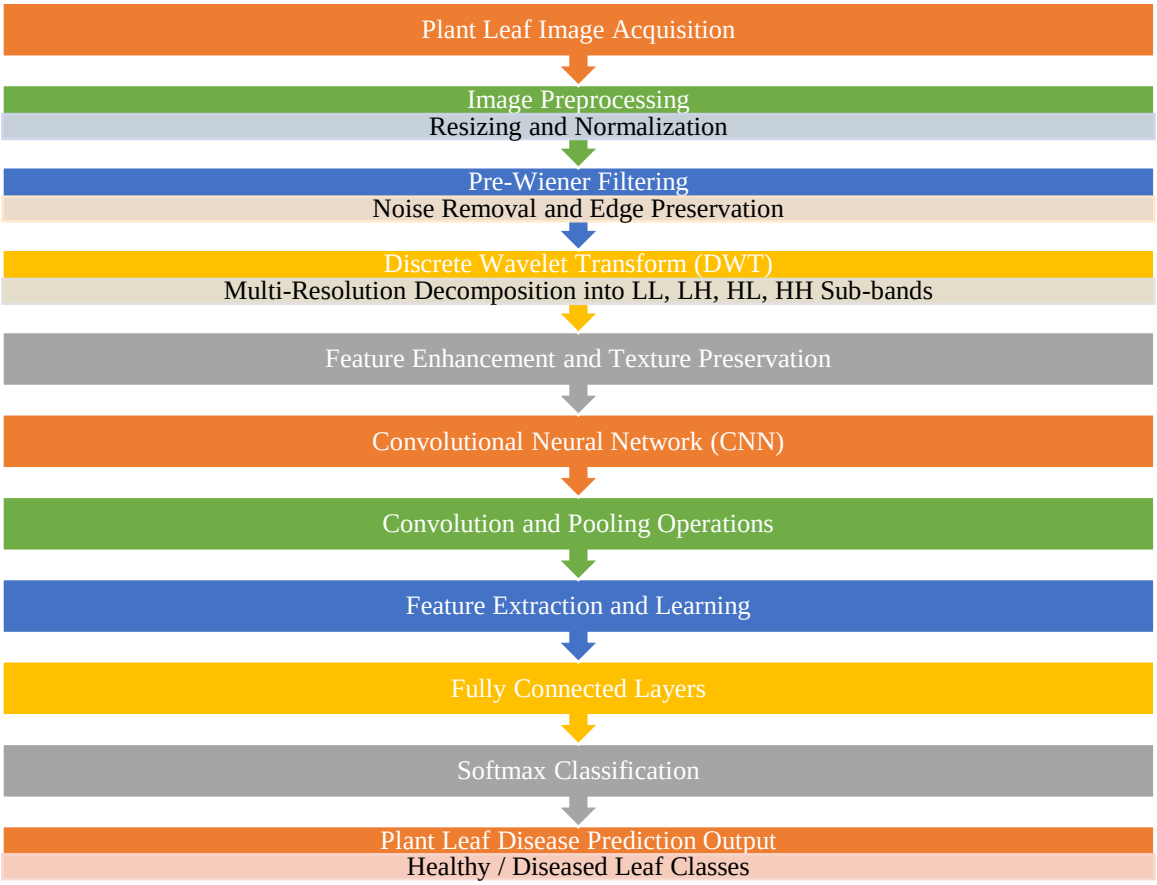


**Fig. 2 Architecture of CNN-based plant leaf disease classification framework**

### *3.1. Dataset Collection*

The proposed architecture utilized a dataset which was gathered from publicly accessible repositories, incorporating GitHub, UCI ML Repository and Kaggle, along with classified plant leaf image libraries. The dataset comprises of both healthy and diseased plant leaf images belonging to several disease classes, incorporating foliar disease and potyvirus infections. The gathered images contain changes in lighting conditions, background complications and leaf orientation, which enhances the robustness of the developed model within practical farming atmospheres. Before model training, all leaf images were resized to a unified resolution and subjected to preprocessing for noise decreasing and attribute improvement. The dataset was partitioned into 80% training data and 20% of testing data to guarantee reliable model training and unbiased performance analysis. The training dataset was used for attribute learning and variable refinement, while the testing dataset was utilized to assess the categorization performance of the developed integrated preprocessing and CNN-based disease forecasting architecture.

### *3.2. Pre-Processing*

Plant leaf images are acquisitioned from various farming atmospheres often comprise changes in illumination, background complications, noise and quality of image that can impact disease categorization performance. Therefore, preprocessing was executed to enhance image stability and improve the attribute derivation quality. Initially, all input leaf images were resized to an equilibrium geometric resolution to handle computational stability during training of model the resized images were then standardized to normalize pixel intensity distributions and enhance learning consistency.

These preprocessing tasks decreased data irregularities and provide effective attribute representation for subsequent improvement and categorization levels. After preprocessing, the images are forwarded to the developed discrete wavelet transform with pre-wiener refining architecture for noise suppression, multi -resolution attribute improvement and disease-specific texture conservation earlier to CNN-based classification.

### *3.3. Discrete Wavelet Transform with Pre-Wiener Filtering Method*

The developed integrated preprocessing architecture hybrids Pre-Wiener refining with Discrete Wavelet Transform (DWT) to enhance quality of image and conserve disease-specific texture details earlier to classification. Plant leaf images gathered from different farming atmospheres commonly comprise illumination changes, background interference and collection noise that can negatively impact attribute derivation and classification reliability. Therefore, an efficient denoising and multi-resolution improvement framework is needed before CNN-based learning. Initially, the input RGB leaf images are resized and transformed into grayscale representations for effective processing.

As noisy images may comprise unwanted distortions that compress fine lesion systems, Pre-Wiener refining is implemented as a flexible denoising approach. The Wiener filter decreases the mean square prediction residual while conserving significant local statistical and edge details correlated with disease areas. In contrast to traditional smoothing filters, the Pre-Weiner filter performs modified refining based on local image variance, thereby decreasing noise without extremely smoothing disease boundaries and lesion textures. The Wiener filtering process is mathematically represented as below.

$$\hat{F}(u,v) = \left[\frac{H^*(u,v)}{|H(u,v)|^2 + \frac{S_n(u,v)}{S_f(u,v)}}\right] G(u,v) \quad (1)$$

Where $G(u,v)$ denotes the degraded image, $H(u,v)$ represents the degradation function, $S_n(u,v)$ corresponds to the noise power spectrum, and $S_f(u,v)$ indicates the original signal spectrum.

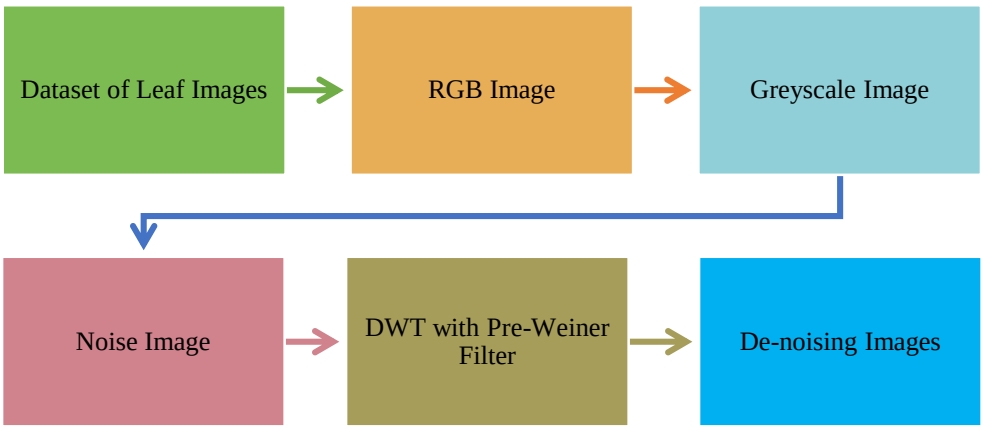


**Fig. 3 Image De-Noising based on DWT with Pre-Weiner filter**

Next, Discrete Wavelet Transformation (DWT) is deployed to execute multi-resolution decomposition of the refined leaf images. The wavelet shifting isolates the image into several frequency sub-bands for efficient derivation of both structural and texture-relevant disease details. The decomposition process creates 4 sub-bands, namely LL, LH, HL, and HH.

$$I(x, y) = LL + LH + HL + HH \quad (2)$$

The sub-band LL comprises minimal-frequency approximation details. While LH, HL, and HH represent horizontal, vertical, and diagonal detail coefficients, respectively, respectively as presented in Figure 5. Diseases behaviours, namely lesions, spots, discoloration and edge irregularities, are primitively focused under high-frequency sub-bands. Therefore, DWT provides efficient conservation of disease-specific texture trends while maintaining significant structural details.

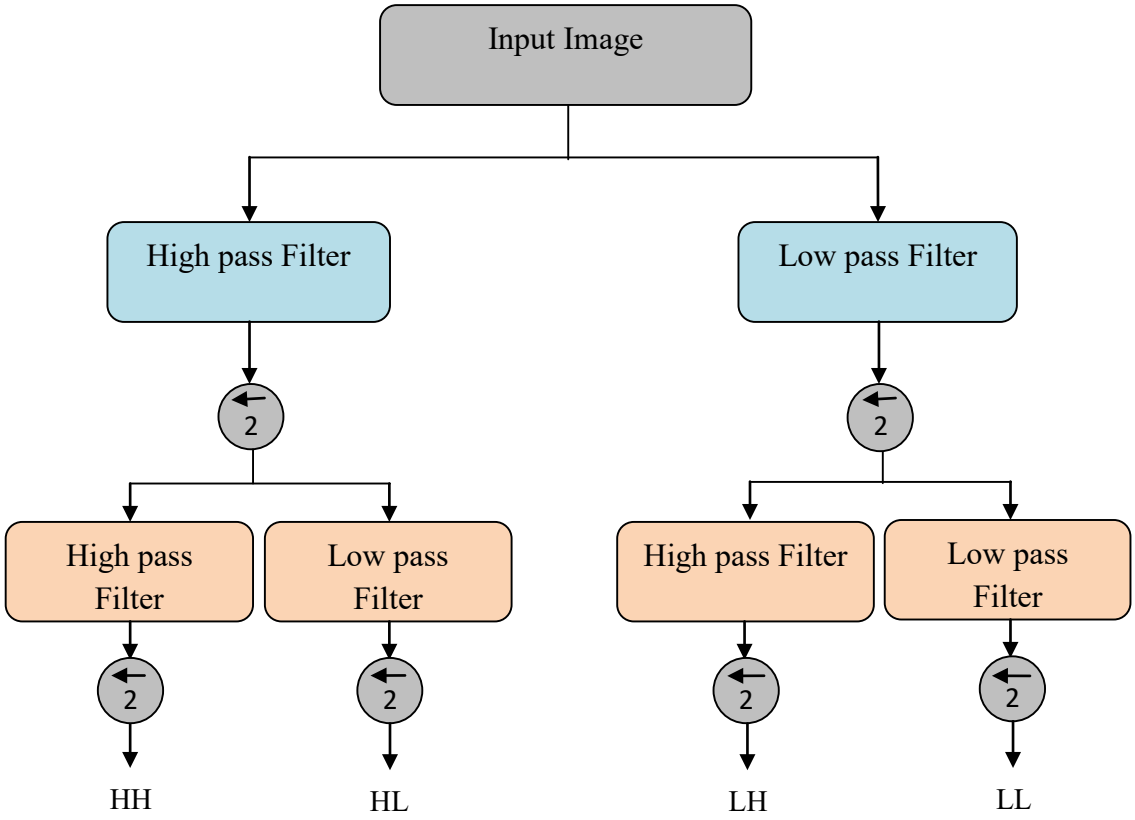


**Fig. 4 Pyramid algorithm structure**

The wavelet decomposition flowchart follows a hierarchical pyramid structure in which the approximation coefficients are recursively decomposed into lower resolution sub-bands.

This multi-level decomposition provides effective derivation of both coarse and modified bands' disease attributes from plant leaf images. High-frequency bands conserve edge and lesion details, whereas minimal frequency bands remain illumination and structural behaviours.

To future improve disease representation, 2-stage signal decomposition is implemented to evaluation the leaf image through several frequency resolutions. This process enhances the localization of disease-impacted areas and improves discriminative attribute representation earlier for CNN-based classification.

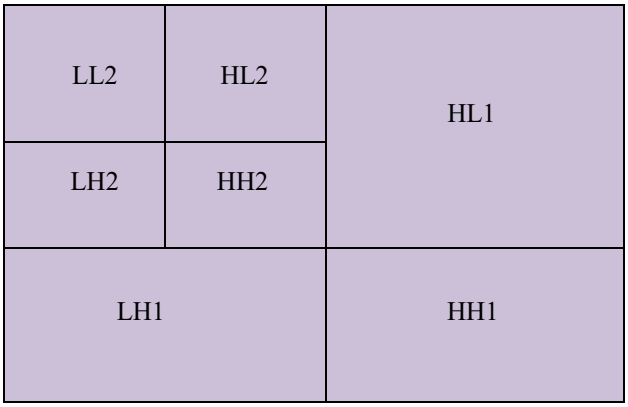


**Fig. 5 Two levels of signal decomposition**

The hybridization of Pre-Weiner filtering and DWT facilitates complementary merits for plant disease evaluation. The Weiner refining enhances quality of image via modified noise compression in the geometric sector, whereas DWT improves multi-scale frequency-sector representations of disease features. This integrated preprocessing technique enhances lesion vision, attribute isolation and robustness against atmospheric distortions prior to CNN-based classification. Further the developed architecture decreases the impact of Noise and illumination instabilities while conserving discriminative disease textures required for accurate plant preprocessing; the method was verified via comparative empirical evaluation and classification performance analysis.

**Algorithm 1: DWT with Pre-Wiener Filtering for leaf image denoising**

**Input:** Noisy leaf images obtained after DWT transformation
**Output:** Filtered leaf images
**Begin**

1. Initialize $sct$ as the clean leaf image signal
2. Determine $nt$ as the noise component added to the image
3. Set $m$ as the Hamming window length
4. Split the clean image signal $sct$ and noisy image signal $nct$ based on the window length $m$
   For each value of $n = 0,1,2, \dots, m$
      Multiply the separated clean image signal $sct(t)$ using the Hamming window function
      Compute the peak image response value $\alpha(n)$
   End For
      For each value of $n = 0,1,2, \dots, m$
         Multiply the separated noisy leaf image signal $nct(t)$ using the Hamming window function
         Compute the peak noisy image response value $\beta(n)$
   End For
5. Substitute the computed values of $\alpha(n)$ and $\beta(n)$ into the Wiener filtering function

### *3.4. Classification using CNN*

The output of the noise-free leaf images is fed into this classifier system. To identify Multi-Crops Leaf Disease (MCLD), deep learning models are utilized. By employing representation learning, the leaves that were sick and those that were healthy were categorized. We have classified the leaf diseases using this deep learning model, which is by far the most sophisticated one ever. It also needs high-performance computing because it is really sophisticated. When it comes to picture categorization issues, this is the neural network that is most frequently used. The shift invariant neural network; it is utilized to categorise the plant leaf condition analysis. Moreover, it consists of four-stratum: the activation layer, pooling stratum, convolutional layer, and dense layer. Figure 6 consists of four layers: the feature extractor, the spatial aggregation, the activation layer, and the dense layer. The local connection of neurons on neighbouring layers takes advantage of the spatial dependency of the image's pixels.

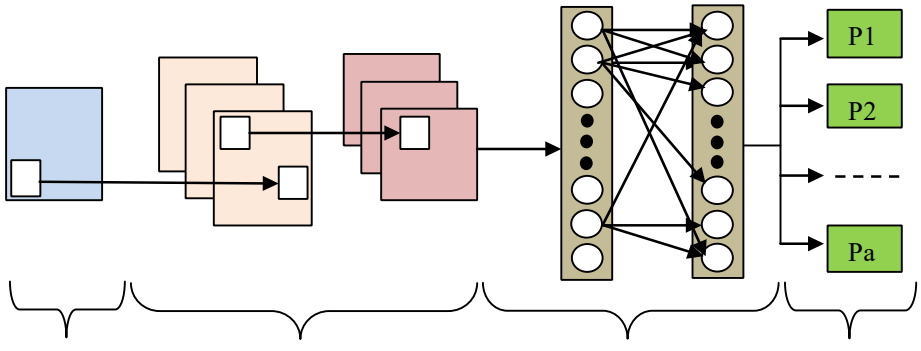


**Fig. 6 Architecture of CNN-based plant leaf disease classification framework filter layer**

It is the feature extraction architecture, and network provisioning is its designation. To extract the image descriptors, a few arithmetic logic units are implemented in this layer. It is made up of strainers with the same dimensions as the input leaf image but with less width and height.

*3.4.1. Down Sampling*

The previous layer activation was significantly reduced in size due to this layer. Although 2*2 filters are typically chosen, a strainer of other dimensions can also be implemented in this layer. The sub-sampling layers that are employed are average and maximum pooling. Inherently, max aggregation removes the maximum value, whereas mean pooling removes mean value.

*3.4.2. Activation Function*

The non-linear transformation is crucial to neural networks since it facilitates representation learning. There are various kinds of transfer functions, such as ReLU, Sigmoid, and Leaky ReLU. This signal is ingested into the subsequent layer, which is the dense layer.

*3.4.3. Fully Connected Layer*

The output is sent into a regular neural network for classification purposes once all of the computations from the earlier layers have been completed. As a result, it has seen extensive use in the fields of data detection and categorization. CNNs will quickly run into exploding gradients and stratified dense layers because the curse of dimensionality. Based on the above classification process, the given pre-processed leaf image is classified as healthy and unhealthy leaves using CNN classifier. Implementation work results are explained clearly with obtained leaf images in the next upcoming section.

## 4. Findings and Interpretations

This paper examines the output performances of proposed methodology with existing methods. The experiment's evaluation was successful, producing many findings for various parameters. The experimental examination of the suggested Discrete Wavelet Transform with Pre-Wiener filtering method and conventional approaches such as Mean, Gaussian, Median, and Wiener filters was effective and produced several outcomes for different evaluation parameters of structural similarity index measure and also the processor time. The newly constructed Discrete Wavelet Transform with Pre-Wiener filter system for leaf disease pre-processing and also the classification was done using CNN, and it is evaluated using MATLAB 2013A. When removing noise from plant leaf photos, the combination of DWT with Pre-Wiener filter produces better results in terms of preserving the information within the leaf image. The below Figure 7 shows the input noise image of plant leaf.




**Fig. 7 Leaf noise image**

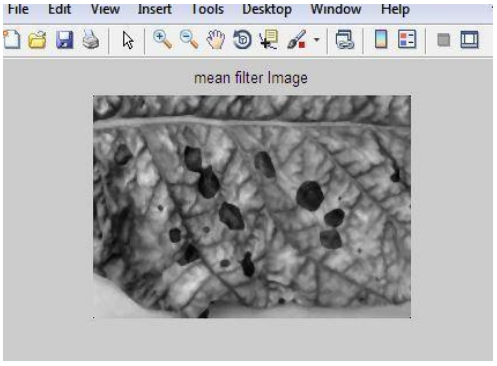


**Fig. 8 Pre-Processed image by Mean Filter**

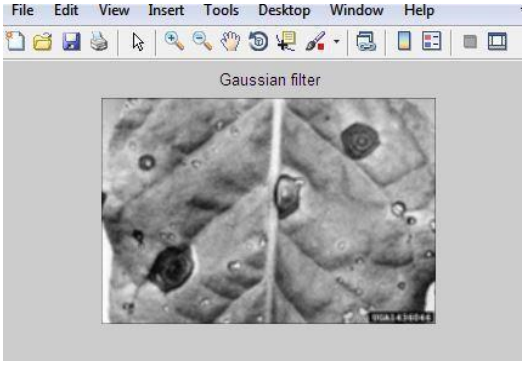


**Fig. 9 Pre-Processed image by Gaussian Filter**




**Fig. 10 Pre-Processed image by Median Filter**




**Fig. 11 Pre-Processed image by Wiener Filter**

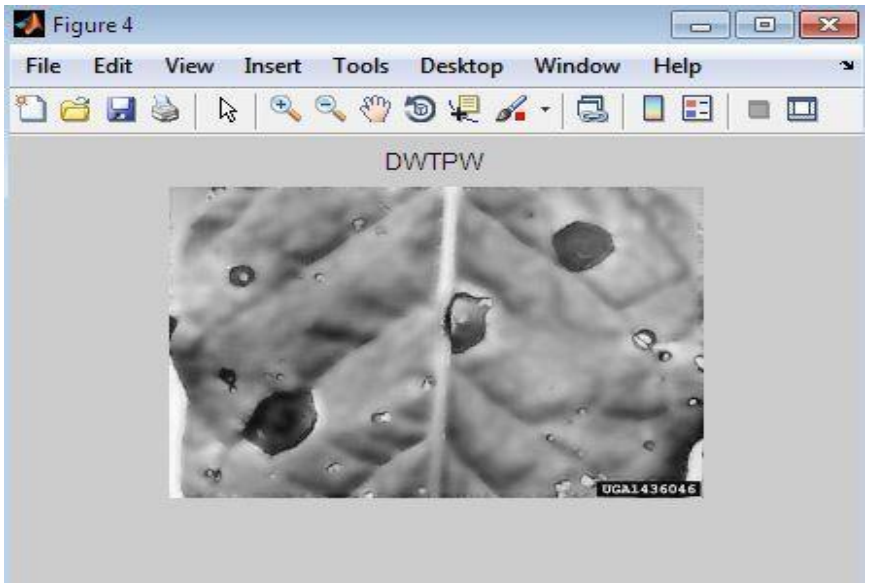


**Fig. 12 Pre-Processed image by discrete wavelet transform with Pre-Wiener Filter**

Figures 8 and 9 depict the noise-removed pre-processed image of a plant leaf by using the mean and Gaussian filters, respectively. The Median and Wiener filters processed and removed the unwanted noise of the leaf image, as shown in Figures 10 and 11, respectively. Our suggested hybrid pre-processing system of Discrete Wavelet Transform with Pre-Wiener filter is used to remove the unwanted distortion in a plant leaf image, which is shown in Figure 12.

### *4.1. Mean Squared Error (MSE)*

The image quality assessment is evaluated by using the mean squared error. The mean squared error between the prototype and image optimization; the higher model fidelity. MSE is computed as:

$$MSE = \frac{\sum_{i=1}^{n} (x_i - y_i)^2}{M \times N} \quad (3)$$

Comparative performance evaluation (MSE) of the filtering technique as indicated in Table 1. The Root Mean Squared Error (RMSE) of the smoothing filter is 74.70, Gaussian filter is 68.25, the median filter is 60.82, the Wiener filter is 54.10, and the proposed system of Discrete Wavelet Transform with Pre-Wiener Filter is 41.36. These presented methodologies minimize MSE against the conventional approaches. Additionally, Figure 13 below shows its MSE output graph.

**Table 1. Mean Squared Error**

| Algorithm | MSE |
|---|---|
| Mean Filter | 74.70 |
| Gaussian Filter | 68.25 |
| Median Filter | 60.82 |
| Weiner Filter | 54.10 |
| Discrete Wavelet Transform with Pre-Weiner Filter | 41.36 |

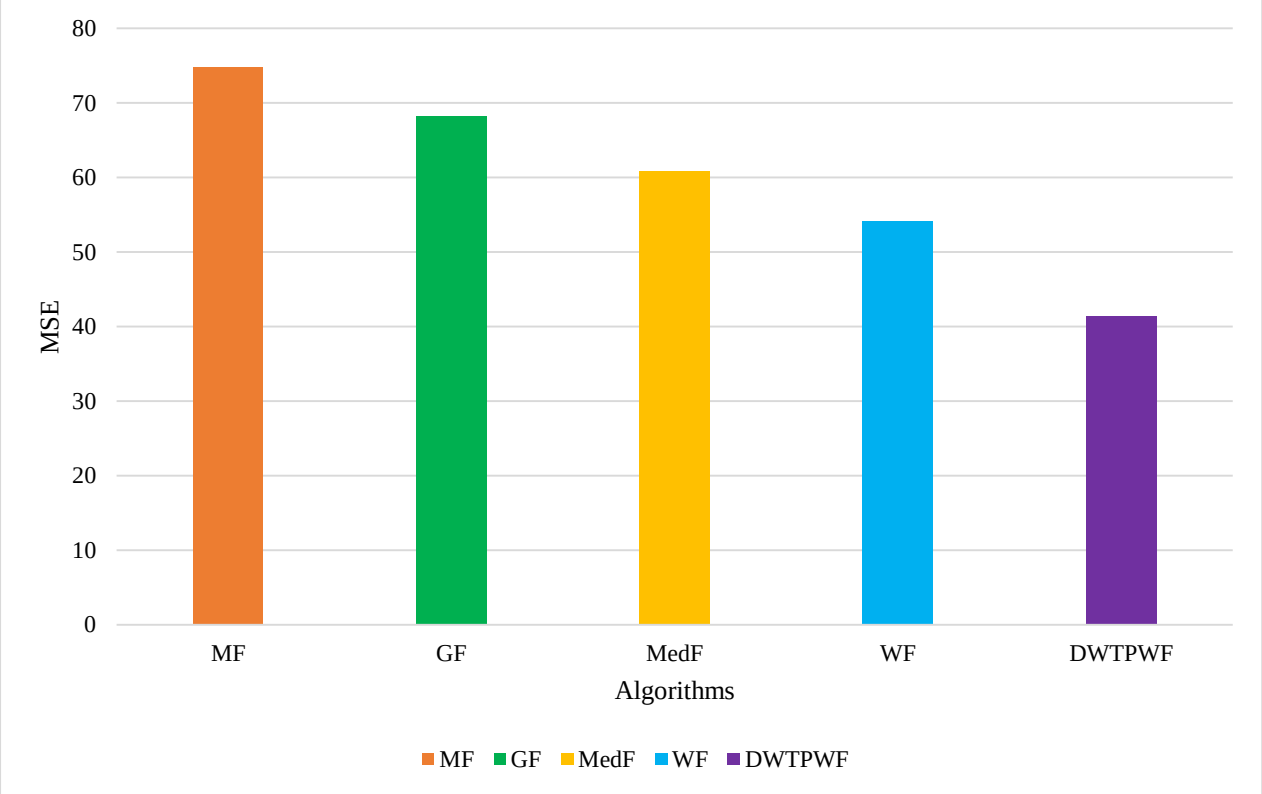


**Fig. 13 Comparative analysis of Mean Square Error between existing methods and proposed hybrid DWT–Pre-Wiener CNN model**

### *4.2. Peak Signal-to-Noise Ratio (PSNR)*

The weighted peak signal-to-noise ratio, which is logarithmic, is determined between image similarity. This percentage difference and image optimization enhanced fidelity in maximum information preservation. PSNR is derived utilizing the equation,

$$\text{PSNR} = 10 * log_{10}\left(\frac{R^2}{MSE}\right) \quad (4)$$

The existing algorithms of Mean, Gaussian, Median, and Wiener filter's PSNR output are mentioned in the above Table 2. They gives the output values of 22.63, 27.35, 31.15, and 35.66, respectively. The proposed Discrete Wavelet Transform with Pre-Weiner Filter delivers a PSNR value 38.12, which is a high performance. Figure 14 provides an explanation of the PSNR graph based on the output data.

**Table 2. Peak Signal-to-Noise Ratio**

| Algorithm | PSNR |
|---|---|
| Mean Filter | 22.63 |
| Gaussian Filter | 27.35 |
| Median Filter | 31.15 |
| Weiner Filter | 35.66 |
| Discrete Wavelet Transform with Pre-Wiener Filter | 38.12 |

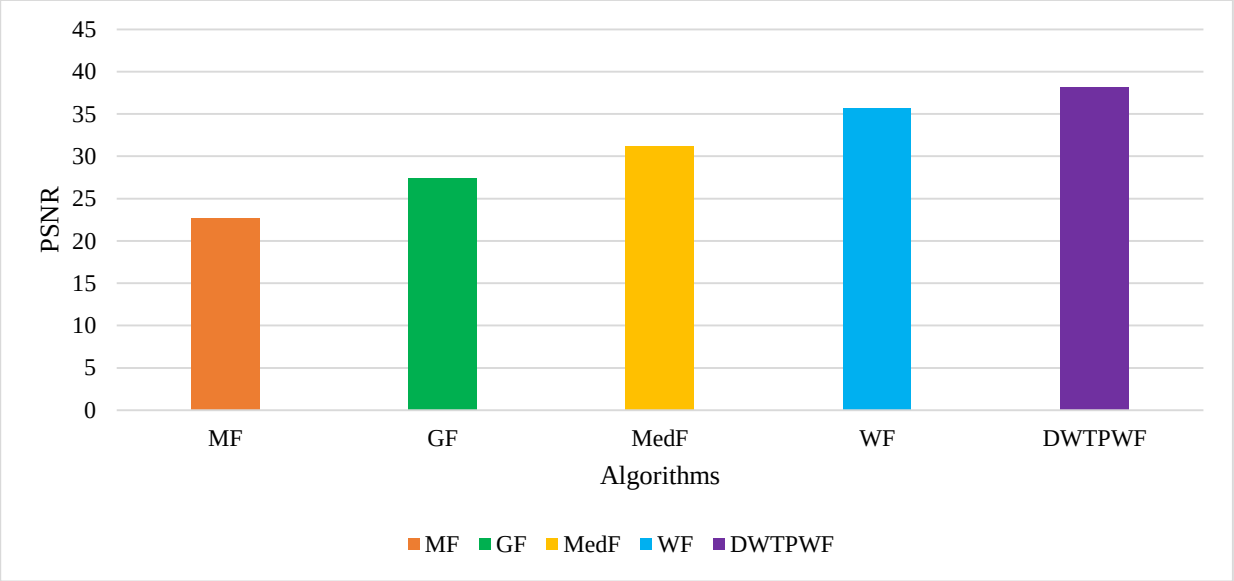


**Fig. 14 Comparative analysis of psnr between existing methods and proposed hybrid DWT–Pre-Wiener CNN model**

### *4.3. Interdependence*

Linear spatial filtering, also called module, is performed by compositing the sum of products at the pointwise level. Spatial shift-invariance. Correlation coefficient is defined as,

$$r = \frac{n\sum xy - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}} \quad (5)$$

Where,

- $r$ = correlation coefficient
- $x, y$ = input variables
- $n$ = total number of observations/sample points

Table 3 outlines the filter response and the presented filter. Correlation coefficients are 0.876, 0.838, 0.897 and 0.925 for the smoothing filter, the Gaussian smoothing, the adaptive median filter, and least squares filter. Our newly designed Discrete Wavelet Transform with Pre-Weiner Filter computes correlation coefficient of 0.950. This outperforms existing systems. As shown in Table 3, the correlation matrix and presented framework are illustrated in Figure 15.

**Table 3. Correlation**

| Algorithm | Correlation |
|---|---|
| Mean Filter | 0.876 |
| Gaussian Filter | 0.838 |
| Median Filter | 0.897 |
| Weiner Filter | 0.925 |
| Discrete Wavelet Transform with Pre-Weiner Filter | 0.950 |

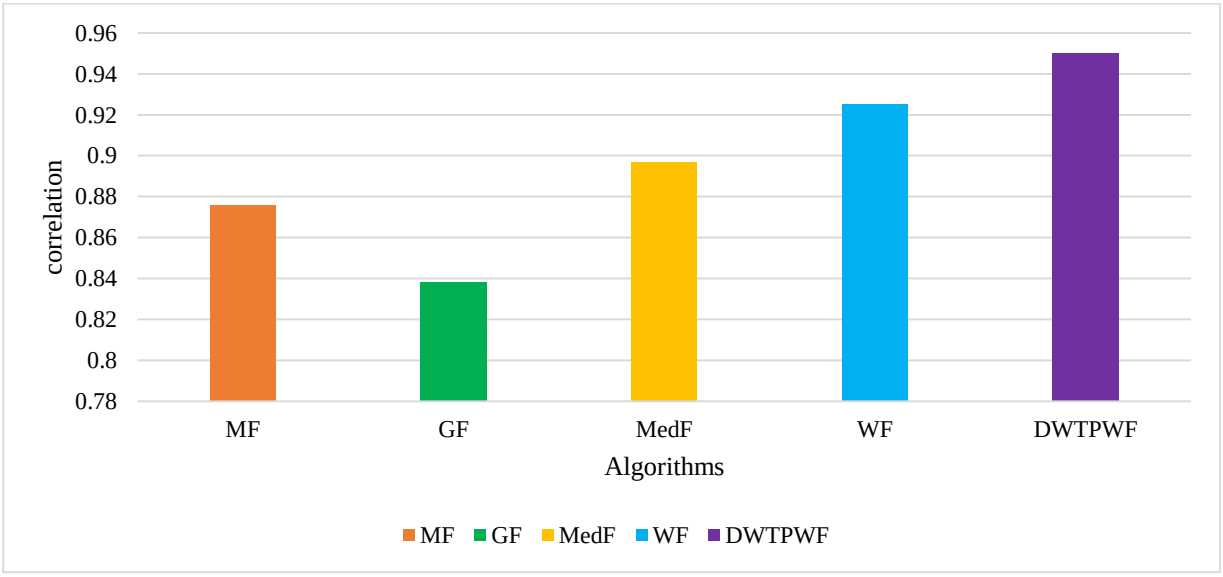


**Fig. 15 Comparative analysis of correlation between existing methods and proposed hybrid DWT-Pre-Wiener CNN model**

### *4.4. Time-Intensive*

The throughput time of the active processing, also known as processing time, can be derived from the formula.

$$Time\ Duration = IC * CPI * T \quad (6)$$

**Table 4. Time-Intensive**

| Algorithm | CPU Time (ms) |
|---|---|
| Mean Filter | 42.16 |
| Gaussian Filter | 34.83 |
| Median Filter | 40.35 |
| Weiner Filter | 24.62 |
| Discrete Wavelet Transform with Pre-Wiener Filter | 18.58 |

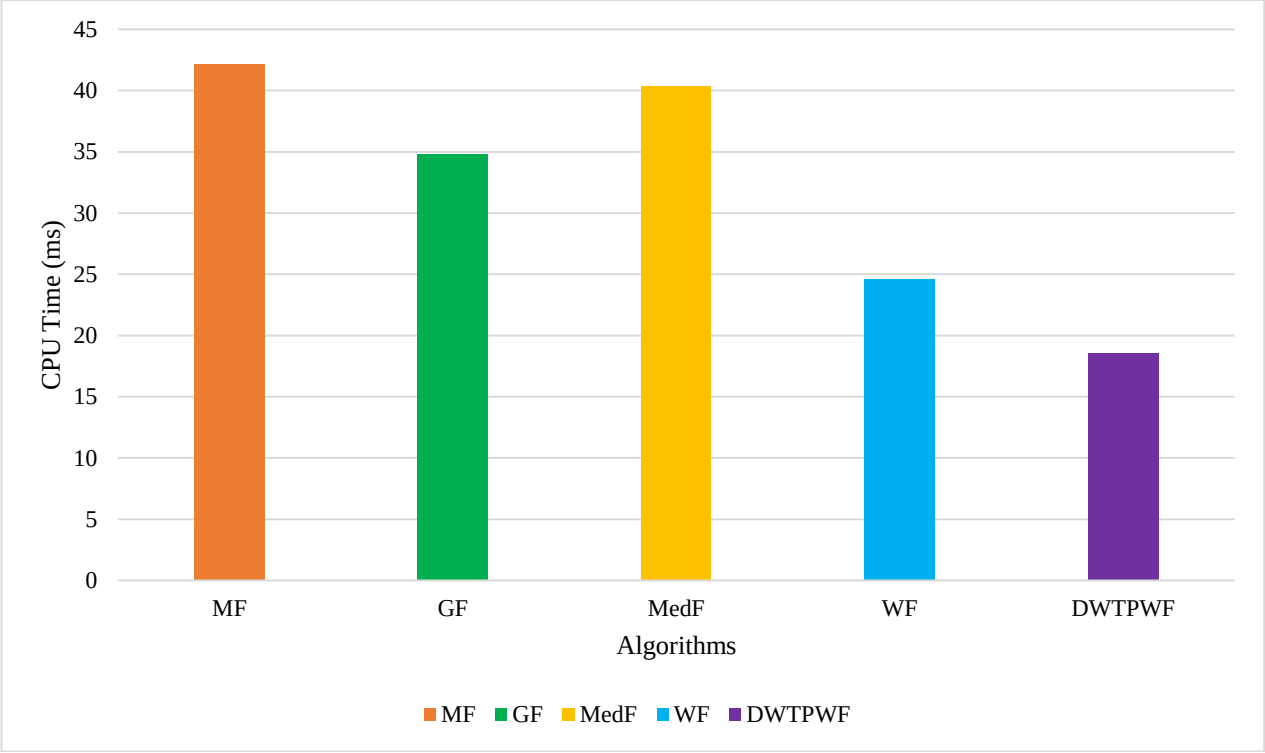


**Fig. 16 Comparative analysis of correlation between existing methods and proposed hybrid DWT-Pre-Wiener CNN model**

The execution time for the pre-processing process of the conventional method is shown in Table 4. The previous method takes the time complexity of 42.16ms for Mean, 34.83ms for Gaussian, 40.35ms for median, and 24.62ms for Weiner filters. Our newly designed Adaptive Discrete Wavelet Transform with Pre-Weiner impulse response duration of 18.58 milliseconds and takes less duration of CPU execution time than the state-of-the-art. As presented in the preceding data, the time duration graph is charted in Figure 16.

Plant leaf image properties were gathered, and the CNN classification approach was applied to forecast and classify leaf illnesses.

Using performance assessment metrics including accuracy, sensitivity, specificity, and precision, the classification performances of the suggested and current Discrete Wavelet Transform with Pre-Weiner Filter with CNN classification are assessed.

**Table 5. Classification performance of the legacy system**

| Algorithm | Accuracy | Sensitivity | Specificity | Precision |
|---|---|---|---|---|
| Mean +CNN | 82.12 | 80.67 | 85.87 | 83.25 |
| Gaussian +CNN | 86.29 | 83.18 | 84.29 | 82.46 |
| Median +CNN | 84.84 | 86.54 | 87.52 | 88.67 |
| Weiner +CNN | 92.78 | 90.45 | 91.43 | 90.90 |
| Discrete Wavelet | 95.64 | 93.28 | 94.16 | 92.53 |

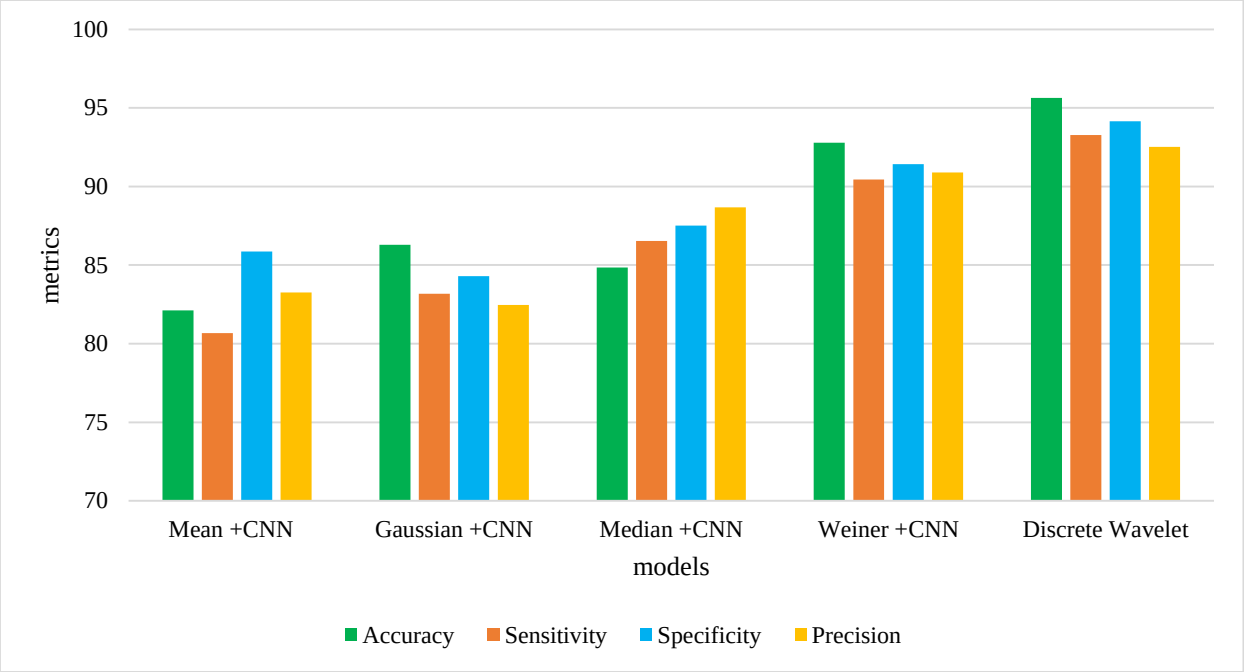


**Fig. 17 Performance graph of existing and proposed system**

For the special method of leaf disease prediction, the suggested Discrete Wavelet Transform with Pre-Weiner Filter with CNN classification methodology will perform better than the current Mean + CNN, Gaussian + CNN, Median + CNN, and Weiner + CNN classification systems. Figure 17 and Table 5 both provide an explanation of the overall categorization output performance. In tests, the proposed system with CNN model was able to provide 95.64% accuracy; it is currently the best classifier out of all of them.

## 5. Conclusion

The use of machines in research could be highly helpful, given how effectively they can do challenging tasks like plant recognition. On the other hand, time and resources should be conserved by using them. With a larger database of leaf images that have previously been classified. Automation and high-throughput detection of leaves purity have not been possible due to limitations in the existing approaches for detecting variety authenticity. Pre-processing is a necessary step in order to enhance the incoming image data for later analysis and development in order to provide the desired outcomes. One important way to save memory usage and computation time is to trim or resize the image and remove any unneeded elements. As part of pre-processing, a variety of filtering techniques are applied to remove noise and other distortions. This research presents a highly precise method for pre-processing and categorizing various plant leaf diseases that are pre-processed by utilizing the pyramid algorithm with a Pre-Weiner filter and a feature extraction network that automatically categorises the healthy and unhealthy leaves. This proposed system obtains the output results such as MSE of 41.36, PSNR of 38.12, correlation of 0.950, and also it takes the CPU time duration of 18.58 milliseconds. Also, this suggested system achieves a classification accuracy of 95.64%. The obtained result using the proposed pre-processing with the classification system is better than all other existing pre-processing methods.

## References

[1] Raquel P. F. Guiné, "The Challenges and Strategies of Food Security under Global Change," *Foods*, vol. 13, no. 13, pp. 1-3, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[2] Marc Venbrux, Sam Crauwels, and Hans Rediers, "Current and Emerging Trends in Techniques for Plant Pathogen Detection," *Frontiers in Plant Science*, vol. 14, pp. 1-25, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[3] R. Sujatha et al., "Advancing Plant Leaf Disease Detection Integrating Machine Learning and Deep Learning," *Scientific Reports*, vol. 15, no. 1, pp. 1-14, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[4] Arndt Feuerbacher, "Pollinator Declines, International Trade and Global Food Security: Reassessing the Global Economic and Nutritional Impacts," *Ecological Economics*, vol. 232, pp. 1-14, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[5] Khadija Javed et al., "Artificial Intelligence in Crop Protection: Revolutionizing Agriculture for a Sustainable Future," *Information Processing in Agriculture*, pp. 1-33, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[6] Md. Motaher Hossain et al., "Plant Disease Dynamics in a Changing Climate: Impacts, Molecular Mechanisms, and Climate-Informed Strategies for Sustainable Management," *Discover Agriculture*, vol. 2, pp. 1-35, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[7] Jaime Cubero et al., "New Approaches to Plant Pathogen Detection and Disease Diagnosis," *Phytopathology®*, vol. 114, no. 9, pp. 1989-2006, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[8] Rikathi Pal et al., "A Novel Feature Extraction Model for the Detection of Plant Disease from Leaf Images in Low Computational Devices," *National Conference on Control Instrumentation System Conference*, pp. 393-402, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[9] D. Devarajan et al., "AI based Real Time Disease Diagnosis in Plants using Deep Learning Driven CNNs," *Scientific Reports*, vol. 16, pp. 1-22, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[10] Natasha Nigar et al., "Improving Plant Disease Classification with Deep-Learning-based Prediction Model using Explainable Artificial Intelligence," *IEEE Access*, vol. 12, pp. 100005-100014, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[11] Tanko Daniel Salka et al., "Plant Leaf Disease Detection and Classification using Convolution Neural Networks Model: A Review," *Artificial Intelligence Review*, vol. 58, no. 10, pp. 1-66, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[12] S.M. Kiran, and D.N. Chandrappa, "Plant Leaf Disease Detection using Efficient Image Processing and Machine Learning Algorithms," *Journal of Robotics and Control*, vol. 4, no. 6, pp. 840-848, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[13] Yimy E. García-Vera et al., "Hyperspectral Image Analysis and Machine Learning Techniques for Crop Disease Detection and Identification: A Review," *Sustainability*, vol. 16, no. 14, pp. 1-31, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[14] Shyam Venkatraman et al., "Automated Coffee Leaf Disease Classification via Deep Feature Extraction with PhytoV2Net and InceptionV3 Architectures," *Frontiers in Agronomy*, vol. 8, pp. 1-20, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[15] Adelaide Dorothy Esenam Agordo et al., "Crop Production in Ghana in the Era of Global Climate Change: Challenges, Impacts, and Adaptation Strategies," *International Journal of Environment and Climate Change*, vol. 15, no. 12, pp. 121-135, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[16] Abhishek Sebastian et al., "ViTaL: An Advanced Framework for Automated Plant Disease Identification in Leaf Images using Vision Transformers and Linear Projection for Feature Reduction," *International Conference on Computing and Machine Learning*, pp. 31-45, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[17] Jameer Kotwal et al., "Enhanced Leaf Disease Detection: UNet for Segmentation and Optimized EfficientNet for Disease Classification," *Software Impacts*, vol. 22, pp. 1-4, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[18] Bathula Nagachandrika, Prasath R, and Praveen Joe I.R, "An Automatic Classification Framework for Identifying Type of Plant Leaf Diseases using Multi-Scale Feature Fusion-Based Adaptive Deep Network," *Biomedical Signal Processing and Control*, vol. 95, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[19] Damien Raj Felicia Rose Anandhi, and Selvarajan Sathiamoorthy, "Enhanced Sea Horse Optimization with Deep Learning-based Multimodal Fusion for Rice Plant Disease Detection and Classification," *Engineering, Technology & Applied Science Research*, vol. 13, no. 5, pp. 11741-11749, 2023. [CrossRef] [Google Scholar] [Publisher Link]