INTERNATIONAL JOURNALOF RESEARCH AND INNOVATION IN APPLIED SCIENCE (IJRIAS)
ISSN No.2454-6194 | DOI:10.51584/IJRIAS |Volume XI Issue II February 2026

A Robust Image Enhancement System Designed to Improve Plant Leaf Images for Machine Learning based Disease Detection

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DOI: https://doi.org/10.51584/IJRIAS.2026.110200043

Received: 10 February 2026; Accepted: 19 February 2026; Published: 03 March 2026

ABSTRACT

Plant disease detection is critical for ensuring agricultural productivity and food security, yet the performance of machine learning models is often limited by the quality of input images. This study presents a robust image enhancement system designed to improve plant leaf images for machine learning-based disease detection. The system integrates three complementary techniques such as Non-Local Means (NLM) filtering which was used for noise reduction, then Wiener filtering used for image deblurring and Contrast Limited Adaptive Histogram Equalization (CLAHE) which was finally used for contrast enhancement and haze removal. Plant leaf images were collected from three farms in Uzu-Uwani, Enugu State, Nigeria and they underwent preprocessing steps including resizing, normalization and class balancing using SMOTE. Then the enhanced images were evaluated using a YOLOv5-based plant disease detection model for cassava and maize leaves. The results from the system implementation demonstrate that images processed with the proposed enhancement techniques significantly improved disease detection accuracy, thereby enabling the identification of multiple disease types that were otherwise missed in raw images. The findings highlight the importance of image enhancement in agricultural machine learning pipelines, providing a practical tool for researchers, agronomists, and farmers to improve disease monitoring and crop management.

Keywords: Plant Disease Detection; Image Enhancement; Non-Local Means (NLM) filtering; Wiener Filter; CLAHE

INTRODUCTION

As the world's population continues to rise, there is an increasing demand for agricultural development every day. Meanwhile, 90% of the world's population depends on agriculture. The production of food that feeds 80% of the world's population is acknowledged to be fuelled by the dedication and hard work of farmers (Mukti and Biswas, 2019). A vital source of food, revenue, profits, and jobs, agriculture is a major pillar of the world economy. To boost food production and satisfy the rising demands of a growing population, societies all over the world are constantly implementing cutting-edge agricultural technology (Baheti et al., 2023). Agricultural plants damaged by insects lose productivity, which has a detrimental effect on our economy. Plant diseases have a major impact on the growth and development of food plants (Sony, 2019). Plant diseases are a major problem in the agriculture sector right now, lowering harvest yield and quality. Lack of skilled workers in the farming sector, inadequate knowledge of fertiliser application, and understanding of diseases and insects are all causing disruptions in the agricultural economy (Kalita et al., 2016).

Significant threats are posed by plant diseases that are brought on by bacteria, viruses, fungi, and protozoa (Shin et al., 2023; Shamsul-Kumar et al., 2023). Plant health, structural integrity, yield, and financial returns can all be negatively impacted by outbreaks or pandemics caused by poor management or a delayed reaction to these diseases. Timely detection of disease signs is a key problem in plant protection, since it is essential for putting effective control measures in place (Poyatos et al., 2023). A key component of agricultural decisionmaking and the cornerstone of effective plant disease control is early identification. Plant disease detection has become more and more important in recent years. Because they frequently show early signs of disease, plant leaves are important markers of plant health (Kaur and Gautam, 2021). Early damage detection is essential to stop the disease from spreading to other plant sections.

In order to reduce agricultural output losses and detect plant diseases early, visual evaluation of leaves is crucial. Traditional plant disease classification techniques are still in use in many places, especially in underdeveloped nations (Goel and Nagpal, 2022). These techniques, which regularlydepend on farmers' expertise, are labour-intensive, time-consuming, and sometimes ineffective (Islam et al., 2021; Kumar et al., 2021). They are more likely to make mistakes while being identified. Inaccurate disease identification might result in untimely treatment since various diseases require different approaches to remedy. Overuse of agricultural chemicals (such as fertilisers, insecticides, herbicides, etc.) can lead to environmental contamination and financial losses if appropriate guidelines are not followed. Botanists and agricultural specialists must go to impacted regions to offer advice during outbreaks, which takes a lot of time and labour (Monowar et al., 2022).Because it offers substantial advantages for both the early identification of leaf-based disease signs and large-scale crop monitoring, automated plant disease recognition has consequently become a crucial study subject (Bashish et al., 2011; Pooja et al., 2017; Khirade and Patil, 2015).

In recent years, research on plant disease identification has advanced significantly thanks to deep learning approaches. Using the PlantVillage dataset, Dwivedi et al. (2021) successfully learnt disease traits and identified three tomato plant diseases by employing an attention mechanism within a residual module. To extract key characteristics from the dataset, Gadekallu et al. (2021) used a hybrid-principal component analysis–whale optimisation approach.A Deep Neural Network (DNN) approach was adopted by AlexNet (Lu et al. 2019) has also achieved good performance in image processing for object classification (Budach et al., 2022; Chidi et al., 2024). However, in real-world applications, a variety of influences happen throughout the image capture process, which affects how successful the suggested method is. These influences may come from camera parameters, illumination, or weather (Kaur et al., 2023). Rain, snow, fog, wind, shadow, and darkness are examples of weather conditions (Kapoor et al. 2016), whereas lens blurriness, dirtiness, and distortions (such as barrel distortion) are examples of camera characteristics (Buades et al. 2005a).

To get the desired result, image pre-processing which usually includes scaling, cropping, and removing noise from the source image for enhancing particular image attributes that are necessary for further processing, which is the primary goal of the preprocessing stage. In this step, some unwanted elements from the supplied image must be eliminated. The second preprocessing step divides the image into clusters (Rathore and Prasad, 2021).

Some unnecessary parts of the image, such the backdrop and unimportant parts, are eliminated in order to shorten the processing time (Islam et al., 2018; Kekon et al., 2019).Reduced image quality finally results in the removal and loss of crucial information from the image that is needed for classification, according to Thambawita et al. (2021). particularly if the crucial information is concealed in minor characteristics like the surface of the lesion, pit appearance, blood vessels, and other patterns of the results. In order to improve an image's quality, clarity, and interpretability and make it simpler for medical experts to identify and diagnose diseases, the image enhancement technique was established. Therefore, this study introduces the application of image enhancement approach for the improvement of plant leaf image datasets to increase the efficiency of machine learning models in detection and classification of plant diseases.

RESEARCH METHODOLOGY

The methodology adopted for the development of this study is the Extreme Programming (XP) methodology. Considering that during the data collection process for plant disease detection, some constraints which affects the quality of data collected such as speed, clarity of camera lens caused by dust or haze or fog caused by environmental factors. Hence, the XP methodology applied in the study involves the collection of data and applying an image enhancement technique for improving the quality of the image. Then, the image is fed into a machine learning technique for the detection and classification of the plant diseases. The performance of the techniques applied is further evaluated before the machine learning approach is deployed for real world implementation to detect plant diseases.

Data Collection

The data used for the work was collected from 3 disease infected farm sites located at Umezeke village, in Adaba community, Uzu-Uwani local government, Enugu State, Nigeria. The geographical coordinate of the regions is 6°45′N latitude and 7°12′E longitude. The instrument used for data collection is high-definition

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camera. The plant leaves considered in this study are economic crops found in most areas of Nigeria. The data collected used for experimenting the proposed image enhancement technique is made up of flawed images of leaves. The images are basically blurry, less detailed and wrongly represents the supposed plant image. Hence, the proposed technique is applied to them to improve their image quality.

Data Pre-processing

This section presents a very necessary stage which improves the standardization of the data to be fed into the NLM model for enhancement. The first stage of the process is the resizing and normalization of the image using Min-Max scaling technique (Sochima et al., 2025). This stage resizes all the image inputs in the system to match the model's required input and normalizes the pixel values to improve the convergence during training. Up next is the data cleaning stage which removes duplicate data to ensure informative images and avoid biased learning. Finally, the class imbalance which exists in the data is handled using Synthetic Minority Over-sampling Technique (SMOTE) (Ulagwu et al., 2021) through generation of synthetic images for underrepresented image classes and reducing the number of majority class images to impose balance on the dataset.

The NLM Denoising Technique for Image Denoising

The image denoising framework using the blend of NL-means Filter and its Method noise Thresholding using wavelets (NLFMT) (Liu et al., 2023) is shown in Figure1. A difference between the original image and its denoised image shows the noise removed by the algorithm, which is called as method noise. In principle, the method noise should look like a noise.

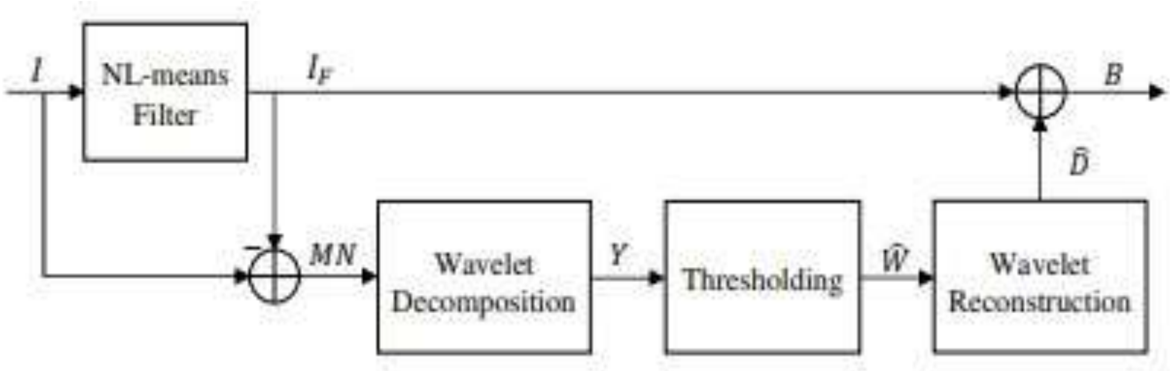

Figure 1: Image Denoising Framework using NLFMT (Liu et al., 2023)

Since even good quality images have some noise, it makes sense to evaluate any denoising method in that way, without the traditional "add noise and then remove it" trick. Mathematically, it is given by (Liu et al., 2023):

$$MN = A - I_r \qquad (1)$$

where, K is the original image (not necessarily noisy) and L is the output of denoising operator for an input image A. The application of NL-means filter on the noisy image removes the noise and cleans the edges without losing too many fine structures and details. Eventhough the NL-means filter is very effective in removing the noise at high SNR (with less noise) but as the noise increases, its performance deteriorates. This is because; the similar local patches which are used to find the pixel weights are also noisy. To capture what is removed from the noisy image by the NL-means filter, the definition of the method noise is redefined as the difference between the noisy image and its denoised image. Hence, Equation (2) is rewritten as

$$MN = I - I_F \qquad (2)$$

where, = K + C is a noisy image obtained by corrupting the original image K by a white Gaussian noise C and, L is the output of NL-means filter for an input image I.

At low SNR, the NL-means filter not only removes the noise but at the same time it blurs the image thereby removing much of the image details. Consequently, the method noise will consist of noise as well as image

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details along with some edges. Hence, the method noise MN can be considered as a combination of image details D and a white Gaussian noise N and is written as (Shreyamsha and Kumar, 2012)

$$MN = D + N \quad (3)$$

Now the problem is to estimate the detail image M, which has only the original image features and edges/sharp boundaries that are removed by NL-means filter, as accurately as possible according to some criteria and is added with the NL-means filtered imageI_F to get better denoised image with details. In wavelet domain, Equation (4) can be represented as

$$Y = W + N_w \quad (4)$$

where Y is the noisy wavelet coefficient (method noise), W is the true wavelet coefficient (detail image) and $N_w$is independent Gaussian noise. The Flowchart for the NLM denoising technique is presented in Figure 2

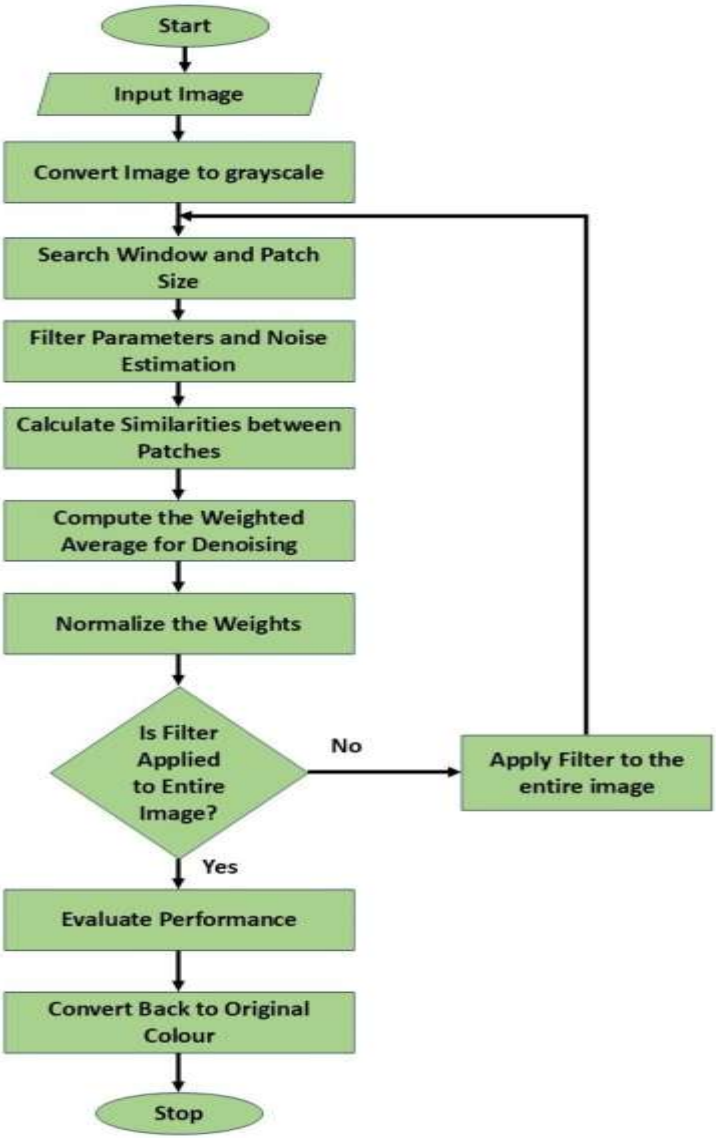

Figure 2: Flowchart of the Proposed NLM denoising technique

In Figure 2, the flowchart shows how the NLM technique is applied for image denoising. The search window defines the area for the pixels, then the size of the small image patches is used for comparing similarities. The similarities between patches is computed by extracting small patches and computing the Gaussian-weighted Euclidean distance between reference patch and neighbouring patches. The weighted average is computed for denoising then new intensity values are assigned to the weighted sum of the pixel intensities from similar patches. The weighted sum is normalized to 1 before the filter is applied to the entire image repeatedly till the image is fully denoised.

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Wiener Filter for Image Deblurring

The Wiener filter is a deblurring technique used in image processing to restore images that have been degraded by motion blur, defocus blur, or noise. It is a linear filter based on frequency domain processing that aims to minimize the Mean Squared Error (MSE) between the original and degraded images. It works by applying inverse filtering while considering the noise and blur characteristics in the image.

The observed (blurred and noisy) image G(x, y) can be represented as in Equation 5:

$$G(x,y) = H(x,y) \cdot F(x,y) + N(x,y) \tag{5}$$

Where:

- $G(x,y)$ = Degraded (blurred) image
- $H(x,y)$ = Blur function (Point Spread Function - PSF)
- $F(x,y)$ = Original image • $N(x,y)$ = Additive noise

The Wiener filter reconstructs the original image $F(x,y)$ using the Fourier transform in Equation 6:

$$F'(x,y) = \left[\frac{1}{H(x,y)}\right] \cdot G(x,y) \tag{6}$$

Where:

- $H(x,y)$= Conjugate of the blur function
- $|H(x,y)|^2$= Power spectrum of the blur

The flowchart of the proposed Wiener Filter model applied for image deblurring is presented in Figure 3

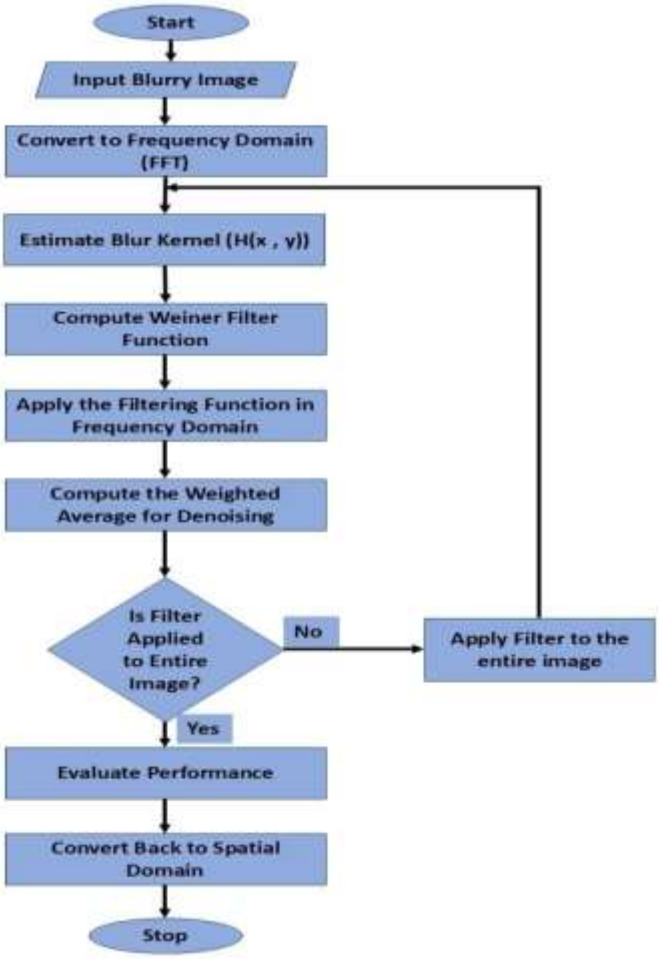

Figure 3: Flowchart of Weiner Filter for Image Deblurring

The flowchart presented in Figure 3 presents the steps applied by the Weiner filter technique for deblurring of the plant image, from the input level to the export of the image as a spatial domain. The image is first converted to frequency domain to obtain the frequency representation using Fast Fourier Transform, then the blur kernel is estimated before applying Weiner filter through computing the filter function and performing inverse filtering with noise suppression. The image is reconstructed back to the spatial domain before the image is deployed.

CLAHE Technique for Haze Removal and Improving Brightness of Low Light Images

CLAHE technique is an advanced version of histogram equalization that enhances image contrast while preventing over-amplification of noise. It operates on small regions (tiles) of an image rather than the entire image, making it usable forHaze removal by improving visibility and contrast and brightness enhancement in low-light images without over-exaggerating noise. The flowchart for the application of CLAHE algorithm for Haze removal and improving brightness is presented in Figure 4

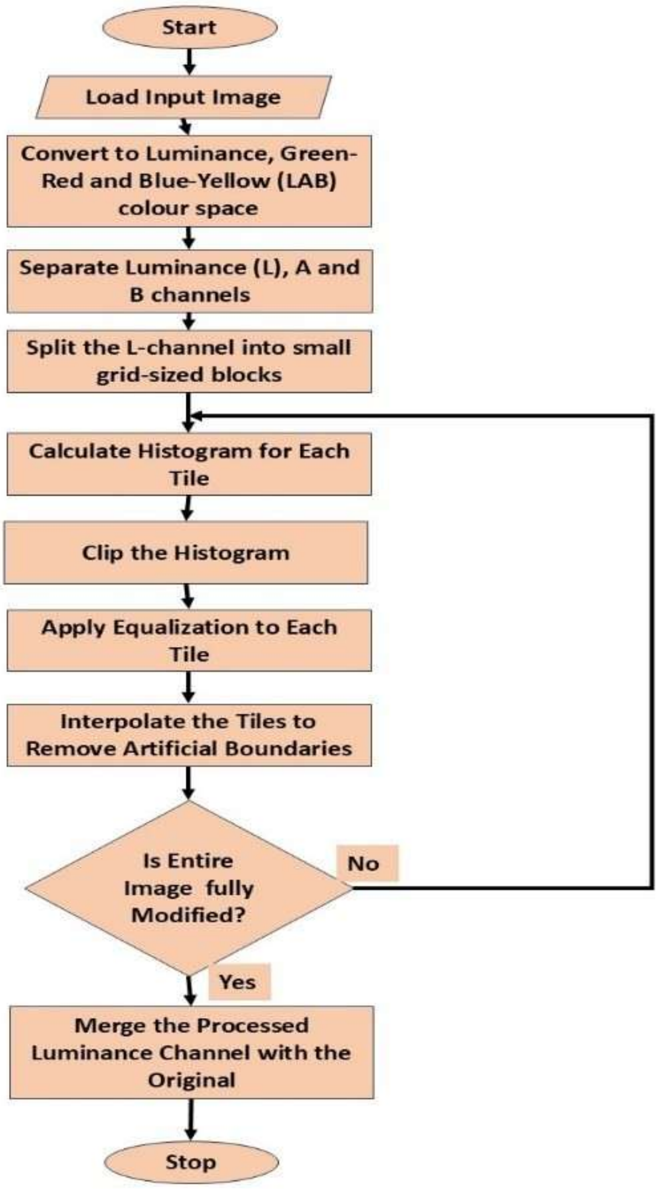

Figure4: Flowchart for CLAHE Technique for Haze Removal and Improving Brightness

In Figure 4, the flowchart for improving the brightness of and haze removal from images. The technique first converts the loaded image to Convert to Luminance, Green-Red and Blue-Yellow (LAB) colour space channels which is then divides the luminance channel into small tiles in order to compute the histogram of each tile using intensity distribution within the local regions. The clip limit is defined to prevent overenhancement before redistribution of excess pixels evenly across. Histogram Equalization (HE) is applied to each tile which interpolates the tiles to remove artificial boundaries to smoothly blend neighbouring tiles. The system then merges the processed luminance channel with the original A and B channels before the image is deployed for display.

Integration of The Techniques for The Enhancement of The Plant Images

To achieve effective image enhancement, we integrate three powerful techniques, the CLAHE technique to enhance contrast and brightness, especially in low-light or hazy images. TheNLM filtering for removal of noise while preserving image details and wiener filter for reduction blur and restores sharpness in degraded images. The flowchart of the integrated technique for an improved image enhancement system is presented in

Figure 5

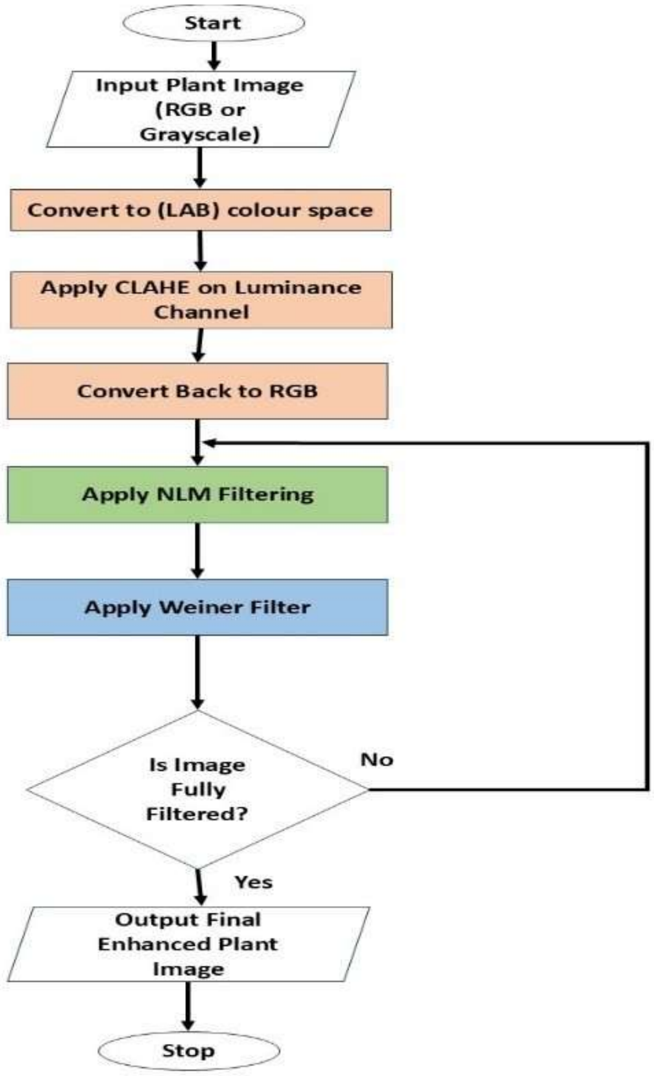

Figure 5: Flowchart of the Plant Image Enhancement Technique

The image in Figure 5 presents a structured flowchart outlining a process for enhancing plant images which starts with an input image, either in RGB or grayscale format, which is converted to the LAB colour space. CLAHE is applied to the luminance channel to enhance contrast, followed by conversion back to RGB format.

Noise reduction is handled using NLM filtering, with an additional Weiner filter applied for further refinement. The process includes a decision loop used to verify if the image is fully filtered and ensuring optimal enhancement. This systematic approach is essential for improving image quality, making it particularly useful for applications in plant research and agricultural analysis.

System Architectural Design

This section presents the structural solution that meets all the technical and operational needs of the image enhancement system to ensure the quality attributes such as performance, precision and manageability of the system. The architectural diagram of the proposed system is presented in Figure 6 where the major components

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of the system is presented. The architecture presents the process of plant image enhancement and performance evaluation of the system

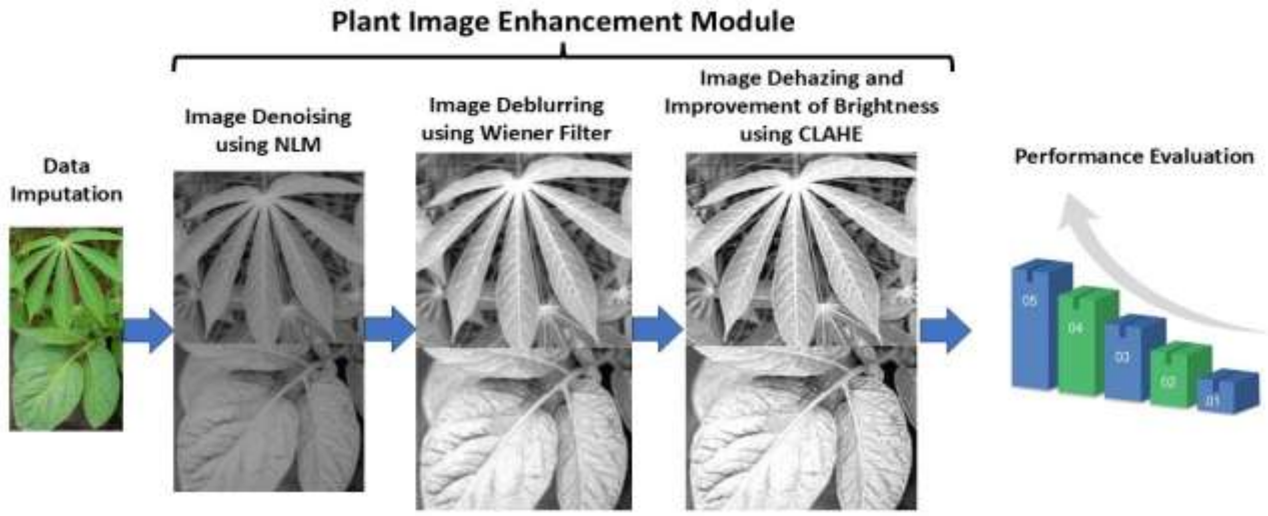


Figure 6: Architecture of the proposed system

The diagram in Figure 6 illustrates the proposed plant image enhancement system designed to improve the quality of plant images before they are used in machine learning models for smart agriculture applications. The process begins with plant image data imputation, where a raw plant image of the plant sample is input into the system, then, the first enhancement step applies NLM filtering to remove noise while preserving essential texture details. This is followed by Wiener filtering, which effectively deblurs the image to sharpen features and improve clarity and the final enhancement phase involves CLAHE application, which dehazes the image and enhances brightness which is especially beneficial for images captured in low-light or hazy conditions. The result of the image enhancement is a visually and structurally improved image that better supports accurate and robust performance in classification or analysis tasks, as indicated by the performance evaluation section of the module.

Architectural Integration

The proposed image processing and enhancement architecture proposed in this study is further integrated into the plant disease classification by Ezeani et al., (2024) which is based on YOLOv5 model. The integration is illustrated in Figure 7

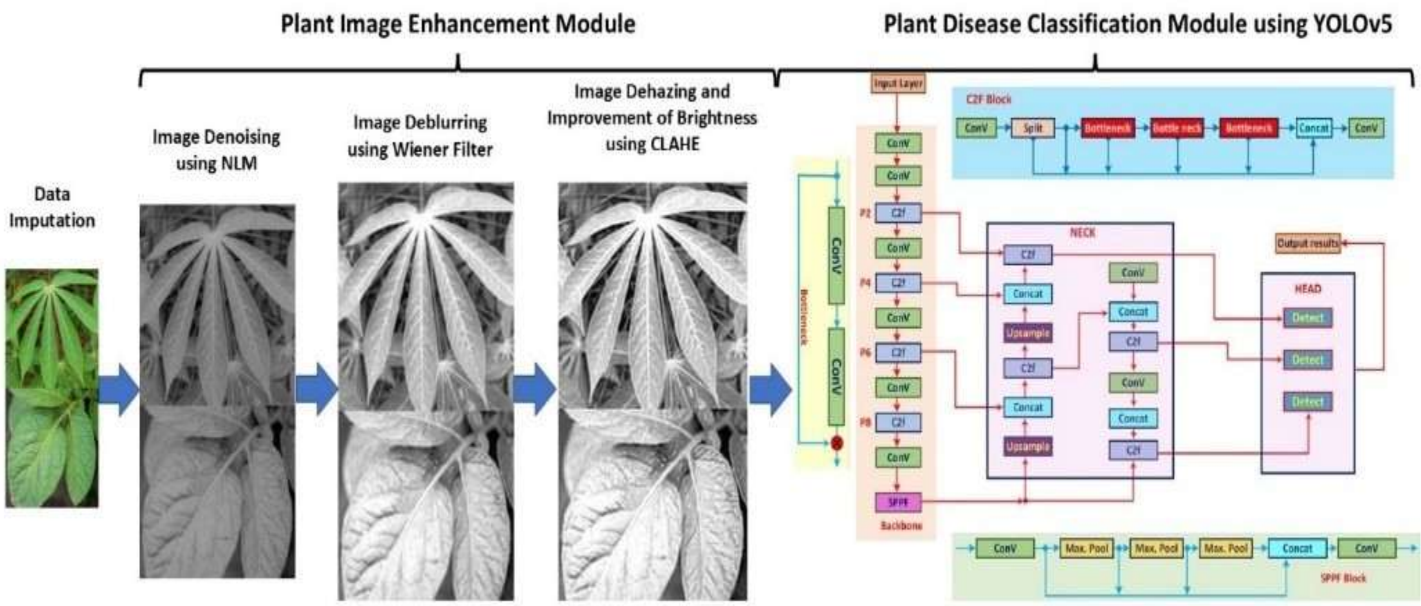


Figure 7: The Proposed Architectural Integration

The architecture presented in Figure 7 shows how the image processing and enhancement technique proposed in this study is integrated into the YOLOv5 model adopted for plant disease classification. The model is focused on the detection of disease on Cassava and Maize leaves.

System Implementation

The system was developed as a web application based on Python programming language deployed using Flask and Streamlit web framework. The work was executed as a web-based application where a user can upload the plant image for image enhancement.

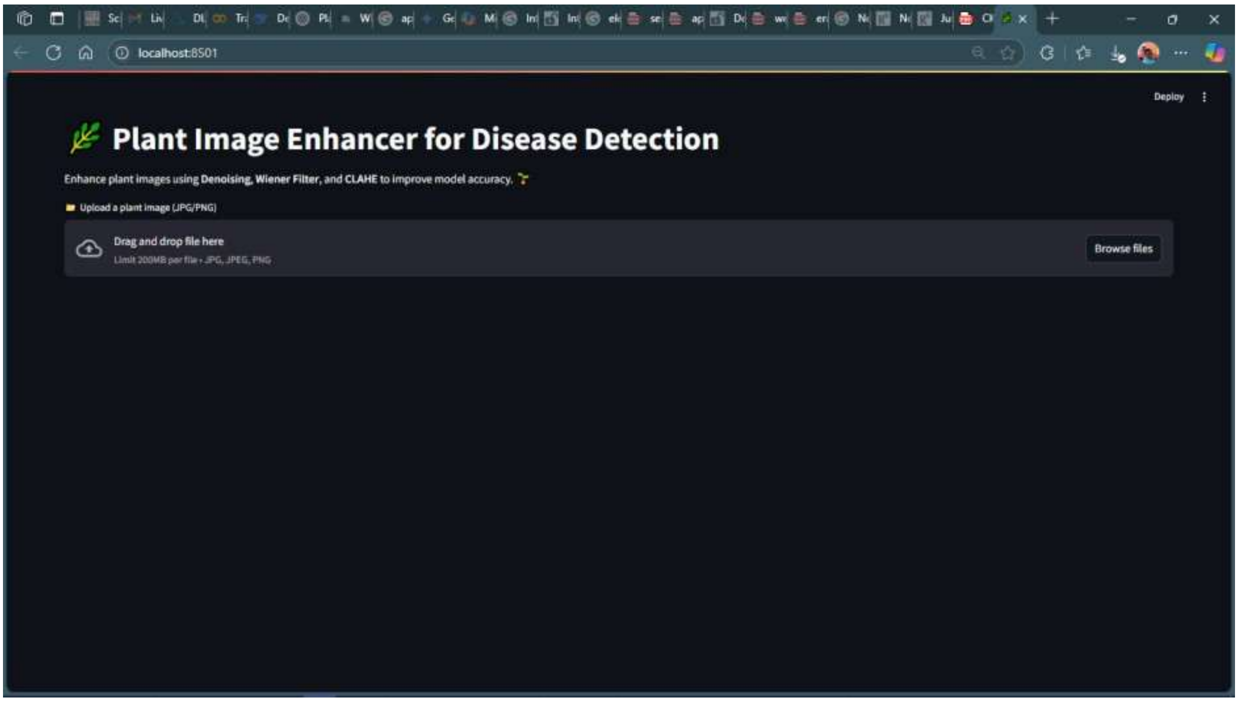


Figure 8: The system integration page

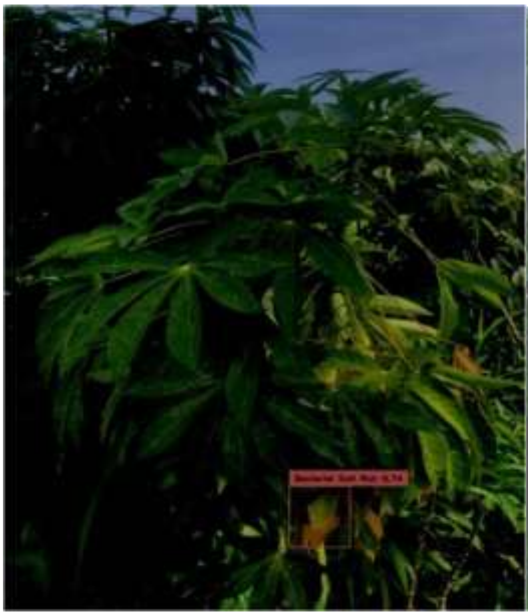
From Figure 8, the system integration as a web-based application is presented and from its image can be uploaded to the platform using the browse file button to apply the image enhancement techniques proposed in the study.

PLANT DISEASE DETECTION RESULTS

In this study, after the image processing has been implemented in the previous section, the processed image was further sent to the proposed model for disease detection on the images. The results attained after execution are presented in this section with a comparison of the model before and after image processing.

(a)Before Image Processing (b)After Image Processing

(a)Before Image Processing (b)After Image Processing



(a) Before Image Processing (b) After Image Processing

Figures 9: Cassava Plant Disease Detection

(a) Before Image Processing (b) After Image Processing

(a) Before Image Processing (b) After Image Processing

(a) Before Image Processing (b) After Image Processing

Figure 10: Maize Plant Disease Detection

From the presented in this section, Figure 9 (a) results shows how the system managed to detect fewer diseases on the cassava plant leaves, while Figure 9 (b) shows the detection of more diseases like bacteria spot rot, stem blight and mosaic virus by the same model after the data has undergone image processing and enhancement. Furthermore, Figure 10 (a) presents when the model has been applied for the detection of Maize plant disease without going through image processing and enhancement and in the scenario, only yellow curl or no diseases were detected. Then, the after the data has gone through the image processing and enhancement proposed in this study, brown streak and more diseases were further detected as shown in Figure 10 (b). The results presented in this section shows that without the application of image enhancement, only one disease was detected by the model on the cassava plant image data, but after image processing was applied, the model managed to recognise the presence of additional kind of disease on the same scene. These results depict how the image processing and enhancement designed in this study can be used to improve the performance of the YOLOv5 model.

CONCLUSION

This study improved the quality of plant image data used in machine learning-based plant disease detection by developing a robust image enhancement system. After reviewing existing literature, it was identified that while machine learning techniques like KNN, SVM, ANN and RF have been widely used for disease classification, their performance is often hindered by poor-quality input images. This gap in the preprocessing stage of plant disease detection informed the need for a dedicated image enhancement system and to address this gap, the study developed a web-based application that incorporates three powerful image enhancement techniques such as NLM filtering, Wiener filtering and CLAHE. These techniques were applied individually and in combination to enhance plant images captured in various challenging conditions such as low lighting, blurriness and noise.

System testing of the implemented approach which included unit, integration and usability testing, confirmed that the platform functions effectively and is user-friendly. Hence, experimental results showed that while combined filtering sometimes leads to over-smoothing and loss of important features, applying individual techniques, especially CLAHE which yielded sharper, brighter and more detailed images that are more suitable for machine learning analysis. In conclusion, this study demonstrates that enhancing image quality before classification significantly improves the reliability and accuracy of plant disease detection models. The developed system serves as a practical tool for researchers, agronomists and farmers, and it lays a foundation for future work in intelligent preprocessing pipelines for agricultural image analysis.

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