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**Research Article**

# Enhancing Image Quality in Crop Disease Diagnosis: A Comparative Evaluation of Laplacian and Average Filtering with Established Techniques

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**ABSTRACT**

The agricultural sector is vital to ensuring global food security, yet plant diseases caused by various environmental factors lead to significant reductions in crop yields. Early detection of such diseases is critical, as crop health directly affects both yield and quality. This research introduces a novel pre-processing algorithm designed to enhance the accuracy of crop disease detection from leaf images. The proposed algorithm is compared against three widely used filtering techniques: Median filtering, Wiener filtering, and Gaussian filtering. Before implementing the proposed approach, a detailed assessment of these conventional methods is conducted.The algorithm integrates Laplacian filtering and average filtering to optimize image pre-processing. The effectiveness of this approach is evaluated using performance metrics such as Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), and Mutual Information (MI). Results indicate that the proposed method achieves a 0.34% increase in PSNR, a 0.92% reduction in MSE, and a 0.48% improvement in MI compared to existing techniques. These improvements underscore the algorithm's ability to enhance image quality and outperform traditional methods.The findings suggest that incorporating Laplacian and average filtering into the pre-processing pipeline introduces a more efficient methodology for image enhancement. This approach holds potential for advancing image analysis and interpretation in agriculture and other fields, providing a foundation for further innovation in image processing technologies.

**Keywords:** Dynamic Region Growing, Leaf disease detection, Otsu Segmentation, Pre-processing.

## 1. INTRODUCTION

Timely and accurate detection of crop diseases is crucial for reducing agricultural losses and maintaining the health of crops, which directly influences food production. Over the last decade, there has been significant progress in the application of image processing techniques integrated with artificial intelligence (AI) to address the challenges of early disease identification in plants [1-9]. Many studies have applied these methods, particularly pattern recognition and image analysis, to agricultural settings to improve disease diagnostics [10-19]. However, there is still considerable room for enhancement in disease detection systems, especially in the accuracy and efficiency required for horticulture and large-scale agricultural practices. Improving disease detection precision is essential to minimizing the negative impacts of plant diseases and ultimately increasing crop productivity.This research focuses on the development of a computational model for the prediction of fungal diseases from crop leaf images, utilizing advanced image processing techniques. The study introduces a novel pre-processing algorithm and evaluates its performance in comparison with three established filtering methods: Median filtering, Wiener filtering, and Gaussian filtering. Prior to presenting the proposed approach, a detailed analysis of these conventional techniques is conducted to assess their strengths and limitations [1-6]. The proposed pre-processing algorithm incorporates two filters: (1) a filter based on the Laplacian operator, and (2) an average filter. This combination improves the efficiency of the pre-processing pipeline, offering superior noise reduction and edge detection when compared to existing methods. The Laplacian filter, which is a second-order derivative operator, enhances edge detection by capturing changes in image intensity gradients, allowing for better distinction between sharp edges and gradual transitions. In addition to detecting edges, the Laplacian filter acts as a spatial filter, reducing noise, thereby improving the accuracy of image-based disease detection models. Laplacian filters are commonly used in image processing to identify regions of rapid intensity change, such as edges. However, as derivative filters are sensitive to noise, it is common practice to first smooth the image using a Gaussian filter before applying the Laplacian filter [20-27]. This combined methodology balances the removal of noise and the accurate detection of edges, making it particularly effective for pre-processing images in plant disease detection systems. By leveraging these techniques, the proposed method offers a robust solution for enhancing image quality, leading to more reliable and accurate crop disease detection.

## 2. LEAF DISEASE DETECTION USING IMAGE PROCESSING

Crop disease categorization and identification are critical technical and economical issues in the agricultural industry as manual detection of plant diseases is a time-consuming and error-prone process. A colour digital image of a sick leaf serves as the starting point for agricultural image processing. Disease identification and plant health monitoring are essential for property agriculture. Plant diseases have impacted human society and the earth as a whole. The classification techniques are extensions of the detection,however; these techniques try to identify and give names whatever ailment affects the plant, rather than focusing on identifying and labeling a specific disease among multiple illnesses and symptoms. Plant pathologists will detect crop issues based on pictures of the plants. Computer systems were developed for use in agriculture, including the diagnosis of ailments in fruit and leaves, among other things. Identification and classification of plant diseases require the use of some basic image processing techniques for plant leaf disease detection. The procedures includes picture capture, image pre-processing, feature extraction, and leaf disease diagnosis[4,5].

In this study, we are developing an efficient pre-processing technique and a segmentation algorithm. Among all feature extraction approaches[6-22], the suggested hybrid feature extraction method demonstrated a considerable improvement in performance with the shortest detection time. We have alsoused support vector machine (SVM), k-nearest neighbors (KNN), and artificial neural networks (ANN)classifiers in conjunction with the ensemble technique and discovered five performance parameters on four different features: color, shape, texture, and hybrid.

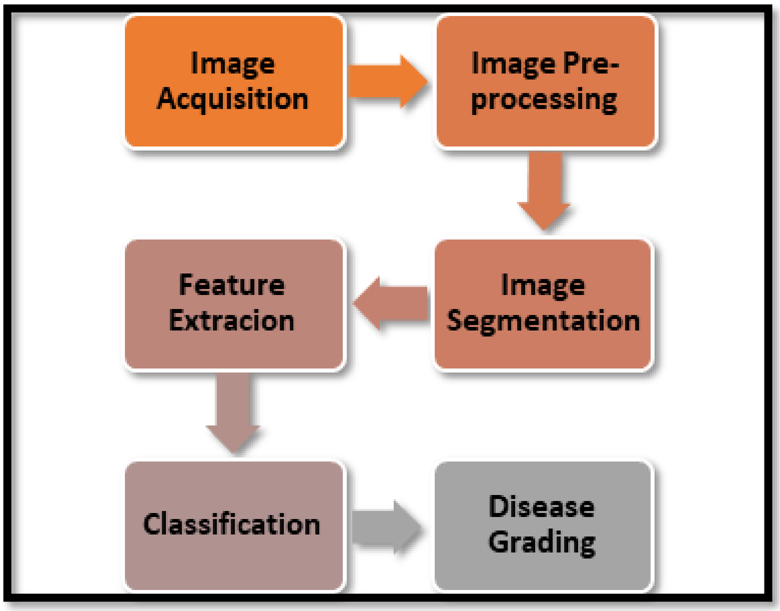


***Figure 1.*** *Planned Methodology*

### 2.1 Pre-processing

The lowest level of abstraction operations on images are the primary uses for image pre-processing. Pre-processing techniques are used to improve picture data by suppressing unwanted distortions or enhancing certain visual properties that are important for subsequent processing and analysis, such as segmentation and classification. Instead of true pixel values, pixels in the image show different intensity values. The noise removal technique is the process of removing or reducing the noise from the image. In this research work, we have designed the pre-processing algorithm utilizing the existing filters (Fig. 2). Next, the suggested pre-processing algorithm's performance is contrasted with three other methods, including median filtering, wiener filtering, and Gaussian filtering. Before presenting the proposed steps, we have analyzed the functionality of these three filtering methodsand found that the recommended filter delivers the best results. Indicating considerable improvements in all performance measures, we saw an increase in PSNR of 0.34 percent, a rise in MSE of 0.92 percent, and an increase in mutual information of 0.48 percent.

#### a) Median Filtering

The contrast-enhanced image was cleaned up of noise using the median filter. It's conceivable that changing the image's intensity levels could cause noise, and cropping the image will also likely cause noise. A non-linear digital filtering method median filtering is used to remove noise from images. It is generally used as it is very helpful at removing noise while preserving edges. It is effective mainly at removing "salt and pepper" type noise.

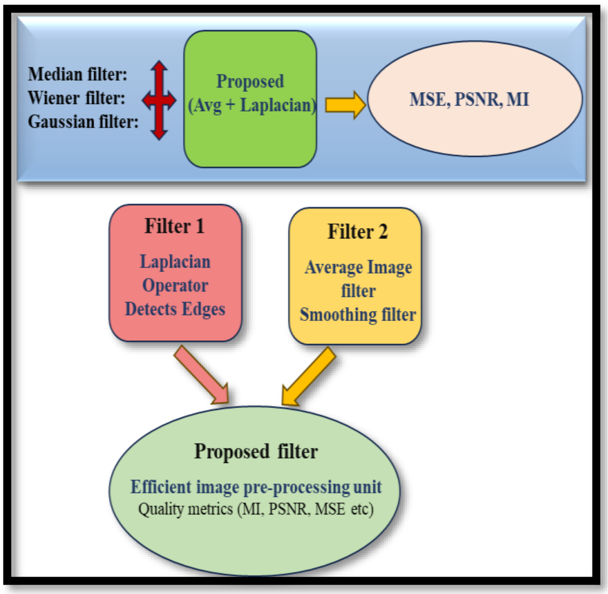


***Figure 2.*** *Pre-processing approach in the proposed research*

#### b) Weiner Filtering

The Wiener filter is a signal processing filter that uses additive noise, known stationary signal and noise spectra, and linear time-invariant (LTI) filtering to predict a target or desired random process from an observed noisy process. The mean-square error (MSE) between the estimated and planned random processes is decreased by the Wiener filter. Using a similar signal as an input and filtering it to produce the estimate as an output, the Wiener filter calculates a statistical estimate of an unknown signal. For example, the known signal could be additive noise-tainted unknown signal of interest. To estimate the underlying signal of interest and eliminate noise from a distorted signal, apply the Wiener filter. The Wiener filter is based on a statistical method, and the MSE estimator page provides a more statistical exposition of the idea [7-9].

#### c) Gaussian Filtering

A Gaussian filter is a type of low-pass filter used to blur certain portions of an image and eliminate noise, or high frequency components. The filter is constructed as an Odd sized Symmetric Kernel (DIP version of a Matrix) that is processed through each region of interest (ROI) pixel in order to produce the intended effect. In the fields of electronics and signal processing, a filter is referred to as a Gaussian filter if its impulse response is a Gaussian function or at least, an approximate version of one, as a real Gaussian response would have an infinite impulse response. The ability to reduce rise and fall times without overshooting to an input step function characterizes Gaussian filters. This behaviour is quite similar to the smallest feasible group delay Gaussian filter. The uncertainty principle's key component is that a Gaussian filter will have the ideal balance between minimizing spatial dispersion and suppressing high frequencies [7].

**d) Proposed Filtering**

In this study, we haveproposed a better filtering approach by combination of filters at processing stagesuch as the Laplace filter, the smooth filter, binarization, and ultimately smoothing procedures [8]. When compared to the other basic pre-processing processes, this enhances the quality of the input raw image the most. The pre-processing algorithm is as discussed below:-

## 2.1 Algorithm 1: Image Pre-processing

**a) Image Acquisition**

- Digital cameras are used to take pictures of leaves.
- After that, photos of leaves are digitally turned into picture format for additional processing.
- Browse Input Leaf Image I.

**b) Pre-processing (I)**

- The input I process in order to raise the image quality.
- The MATLAB function resize (.) is used to first resize the I to a size of 256 * 256.
- 2D conversion: Since most image processing techniques are only applicable to 2D images, a 3D input image must first be converted to a 2D format. To put it briefly, a grayscale image is created from an RGB image.
- The MATLAB function rgb2gray (.) does this conversion.
- Smoothing and de-noising images is the next step in the pre-processing stage. Two filters can be used for this, as shown below.
- $A1 = filter\_1\ (I)$ // To locate boundaries in image
- $A2 = filter\_2\ (I)$ // To smooth the image pixels
- $I^{proposed} = Substrate\ (A1, A2)$ // this gives the accurate noise removal and quality improvement result of input image.
- $I^{proposed}$ is final pre-processed image
- Return $(I^{proposed})$

Here filter 1 is based on well known Laplacian operator and filter 2 is based on an average image filter. Both filters together generate efficient image pre-processing as compared to existing methods. A Laplacian filter is an edge detector that computes an image's second derivatives while detecting the pace at which the first derivatives change. This specifies whether a change in neighbouring pixel values is caused by an edge or by continuous progression (Fig.3). The surface Laplacian can minimize spatial noise and improve prediction when used as a spatial filter. Laplacian filters are derivative filters used in image processing to detect areas of fast change (edges). Because derivative filters are extremely sensitive to noise, it is usual practice to smooth the picture (e.g., with a Gaussian filter) before applying the Laplacian [12-16].

## 3. PRE-PROCESSING RESULTS ANALYSIS

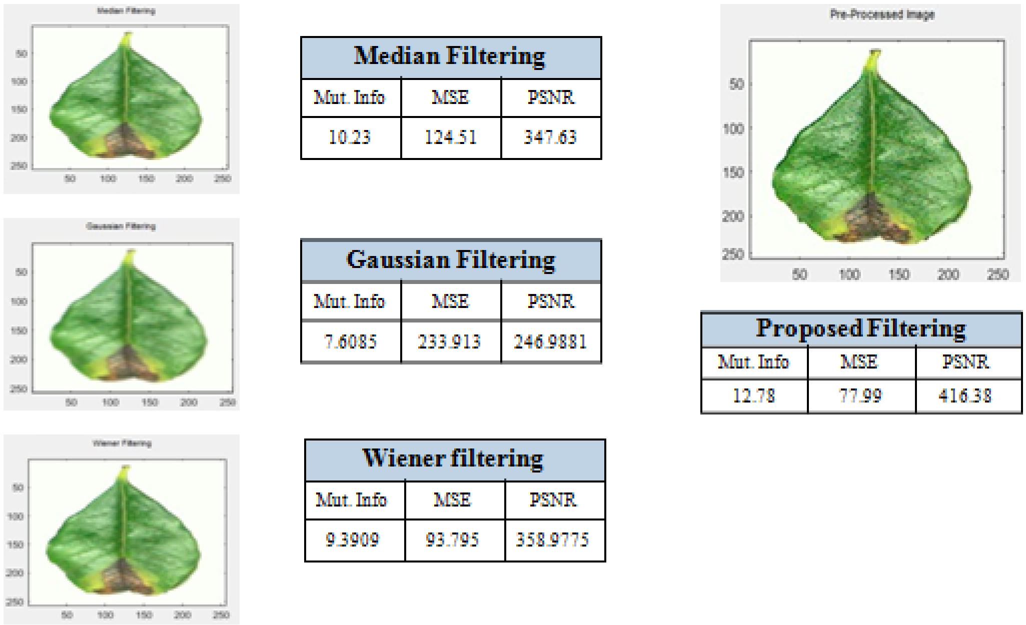


***Figure 3.****Example of image pre-processing*

Table 1. shows the outcome of pre-processing methods for random ten images. Graphs for the peak signal-to-noise ratio (PSNR) (Fig.4) and MSE serially (Fig. 5) demonstrates that the proposed filter is superior to all other existing filters. Since PSNR and MSE are inversely proportional to one another and need to be high and low respectively, to have high quality image, we may infer from the graph that Mutual Information and PSNR have high values while MSE has low values [25-27].

**Table 1**. Comparison of three existing filters with the proposed filter

| Sr.no. | Median filtering | | | Gaussian filtering | | | Weiner filtering | | | Proposed filtering | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Image No. | Mut. Info | MSE | PSNR | Mut. Info | MSE | PSNR | Mut. Info | MSE | PSNR | Mut. Info | MSE | PSNR |
| 1 | 2.12 | 16.19 | 108.20 | 1.62 | 250.36 | 72.44 | 1.98 | 12.69 | 111.44 | 1.85 | 78.60 | 87.97 |
| 2 | 1.89 | 16.68 | 107.95 | 1.45 | 238.29 | 73.08 | 1.77 | 13.30 | 111.09 | 1.74 | 101.30 | 84.47 |
| 3 | 2.95 | 15.25 | 108.44 | 2.25 | 58.77 | 90.90 | 2.81 | 10.98 | 112.76 | 2.38 | 2.28 | 87.40 |
| 4 | 1.70 | 28.13 | 100.92 | 1.35 | 278.10 | 71.07 | 1.56 | 20.74 | 104.89 | 1.46 | 148.43 | 79.37 |
| 5 | 1.32 | 50.34 | 93.63 | 1.09 | 302.12 | 70.04 | 1.26 | 35.90 | 98.05 | 1.18 | 235.91 | 73.41 |
| 6 | 1.70 | 28.13 | 100.92 | 1.36 | 278.08 | 71.07 | 1.56 | 20.73 | 104.89 | 1.46 | 148.46 | 79.36 |
| 7 | 2.78 | 14.99 | 106.99 | 1.72 | 100.80 | 82.21 | 2.45 | 12.77 | 109.08 | 1.90 | 81.58 | 84.92 |
| 8 | 3.05 | 15.48 | 108.75 | 2.18 | 98.08 | 84.69 | 2.81 | 11.92 | 112.13 | 2.38 | 87.85 | 86.18 |
| 9 | 3.46 | 5.70 | 121.88 | 2.45 | 57.44 | 91.66 | 3.14 | 4.54 | 124.72 | 2.62 | 36.96 | 97.45 |

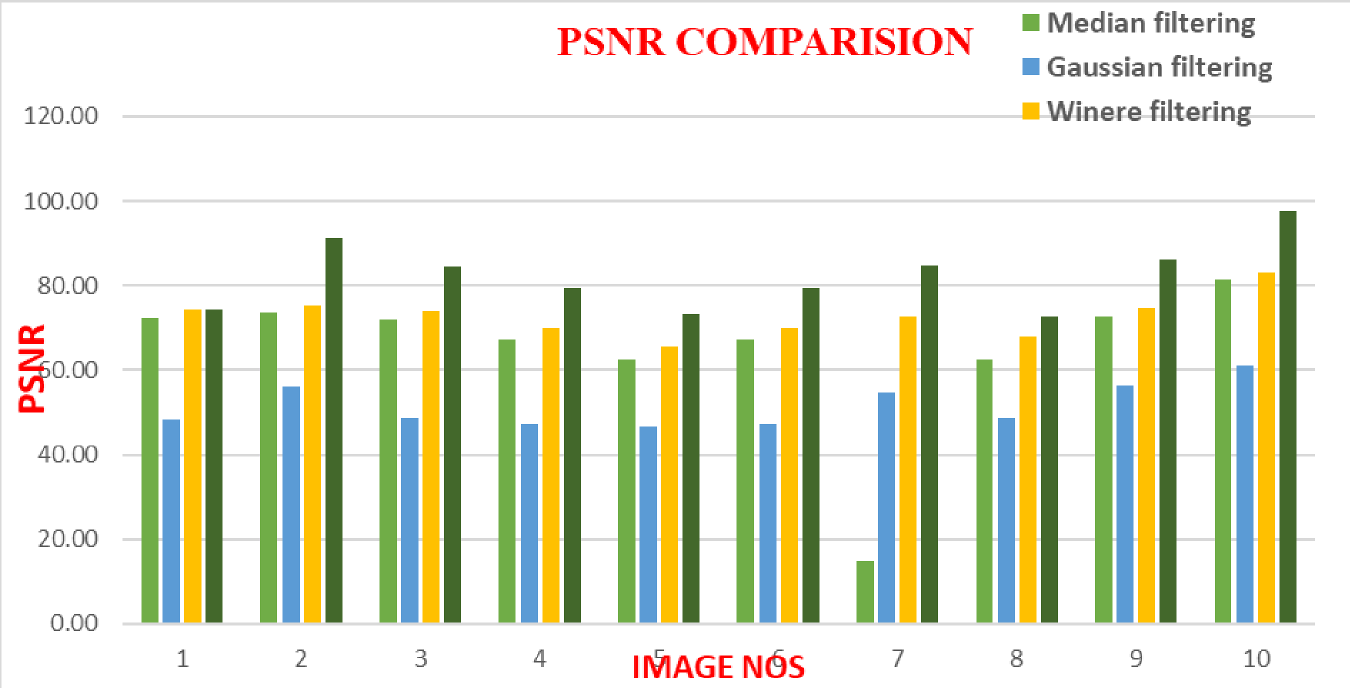


***Figure 4.*** *PSNR Analysis for 10 Random Images*

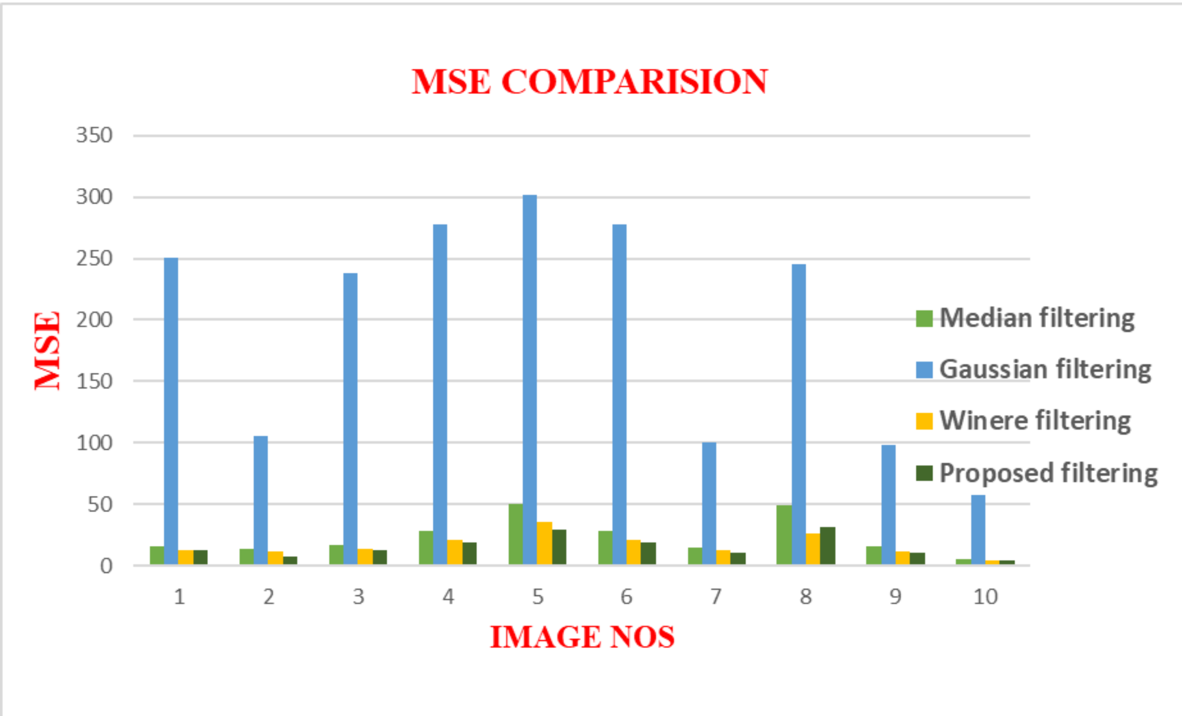


***Figure 5.*** *MSE analysis for PSNR Analysis for 10 Random Images*

We have collected and created four different datasets with and without fungi diseases of vegetable crops like fenugreek, Spinach, Onion, Potato, Tomato in consultation with agriculture expert namely DSC (110), DS-6 (5,152), DS-2 (1,152) and DS-A6 (10,304).

**Data Set 1 (DS2):** This data set consists of total 1152 potato crop images in two categories such as healthy (152) and late blight fungal disease crops (1000). Two disease classes of potato crop i.e. two classes healthy leaf and late blight disease are considered for experimentation, so the data set name is DS2.

**Data Set 2 (DS6):** This is extended version of DS1 with potato and tomato crop samples under early blight, late blight, and healthy crops. This data set is consisting of total 5152 crop images. Potato healthy crops (152), potato late blight (1000), potato early blight (1000), tomato healthy crops (1000), tomatolate blight (1000), and tomato early blight (1000). Six disease classes (3 each i.e. healthy, early blight and late blight) of potato crop and tomato crop are considered so the data set name is DS6.

**Data Set 3(DSA6)**: This is extended version of DS2 with potato and tomato crop samples under early blight, late blight, and healthy crops. This data set is consisting of total 10152 crop images. Potato healthy crops (152), potato late blight (2000), potato early blight 2000), tomato healthy crops (2000), tomatolate blight (2000), and tomato early blight (2000). Six disease classes (3 each i.e. healthy, early blight and late blight) of potato crop and tomato crop are 48 considered, also in order to increase the no of images augmentation procedure is used with rotation of angles and so the data set name is DSA6.

**Data Set 4 (DSC):** This data set consists of total 110 images of different crops in two categories healthy (47) and diseased (63). These crop images are collected from the real-time basis with mobile camera of model Vivo 2022E, with 64 megapixel camera. This data set is created data set for leafy vegetables like onion, fenugreek, spinach, and potato etc. with fungi diseases, since it is created data set its name is DSC data set.In addition we have investigated and proposed efficient pre-processing method which is combination of Laplace and average filter and it outperforms over all other methods. We proposed Efficient segmentation method and found DRG gives significant results over other methods and analyzed important features responsible for effective classification and found Hybrid method is suitable. Finally validated proposed selected features and ensemble classifier experimentally and got 94.65% average accuracy for all four datasets.The data set has been organized in decreasing order of the total number of images. As the number of images are decreased, it can be seen that accuracy, F1, specificity, and precision continue to increase by a certain percentage depending on the image quality, but recall rate gradually decreases. It is observed that if we double the images, our accuracy has decreased by 3.96 %, as mentioned in table 2.

**Table 2.**Ensemble Classifiers Result on Four different types of Datasets

| Dataset | Accuracy | F1 | Specificity | Precision | Recall |
|---|---|---|---|---|---|
| DSC (110) | 91.3 | 88.56 | 86.53 | 81.31 | 97.23 |
| DS-6 (5,152) | 94.37 | 92.36 | 94.45 | 88.8 | 96.29 |
| DS-2 (1,152) | 96.34 | 96.36 | 97.65 | 94.82 | 93.08 |
| DS-A6 (10,304) | 97.65 | 96.52 | 98.43 | 97.74 | 92.33 |

## 4. CONCLUSION

The experimental analysis of the proposed methods for the plant disease classification is presented in this chapter. We have collected total four data set both publicly available crop images (both diseased and normal) and real-time healthy and diseased crop images. The outcome of each methodology is then evaluated to show the efficiency against the existing methods. The results are analyzed using all the investigated methods and also compared with the existing similar solutions also.we have designed the pre-processing algorithm utilizing the existing filters. The performance of the proposed pre-processing algorithm is compared with three techniques such as Median filtering, Wiener filtering, and Gaussian filtering. We examined the operation of these three filtering methods before giving the suggested steps and discovered that the suggested filter produces the best results. Validated proposed selected features and ensemble classifier gives 94.65% average accuracy for all four datasets.

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