Adaptive thresholdingStein's unbiased probability Estimate + CNN Classification Based Plant Leaf Diseases Detection

E.Banu[1], Dr. A. Geetha[2],

PhD Research Scholar[1],Assistant Professor and Head[2],

PG and Research Department of Computer Science[1,2]

Chikkanna Government Arts College, Tirupur, Tamil Nadu, India – 641602.[1,2]

Abstract:

In the last two decades, lack of agricultural yield has caused various diseases caused by fungi, bacteria and viruses. These illnesses, which directly interfere with photosynthesis in plants, are among the fastest increasing ones. Early signs are difficult to discern and can't be seen with the naked eye, and they vary greatly with variety and cultivation. Only once acervuli are built to assign host-pathogen connections are microscopic studies carried out. In the end, this causes a lack of time and subpar disease management. Therefore, early and accurate detection of the plant illness is crucial for prompt disease management and lower initial costs.The proposed research will lead to image processing based early detection of plant diseases, which will be more efficient and reduce the subjectivity arising from human experts in plant disease diagnosis.Analyzing plant leaf photos of various standards involves a lot of image processing. Images of agricultural plant leaves are frequently analysed using the method of image segmentation under the plant image enhancement technique, which is one of the image enhancement, reconstruction, and compression pre-processing approaches. new adaptive thresholding methods for classifying plant leaf diseases from images Stein's impartial probability This study suggests estimate preprocessing methods using convolutional neural networks. The plant leaf image dataset was enhanced and its noise was reduced using four data pre-processing approaches. Convolutional neural networks were then utilised to classify illnesses.Pre-processing performance parameters such as MSE. PSNR, co-relation and time consumption for noise removal considered to evaluation of proposed and existing methods. proposed Adaptive thresholding Stein's unbiased probability Estimate with CNNproduce better leave diseases diagnose with the efficiency of 90.22%. Performance parameters compared with other existing methods median+CNN, Wiener+CNN,Gaussian+CNNand proposed ATSUPE+CNNtechnique.

Keywords: convolutional neural network, pre-processing techniques, plant leaves diseases detection, Adaptive thresholding.

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I. INTRODUCTION

The main method used in the modern world to feed the expanding population is agriculture. About 18% of GDP is accounted for by agriculture, forestry, and fisheries. However, the contribution of agricultural products to India's GDP is gradually decreasing year by year.Plant diseases are the major cause of this huge decline in agricultural production (Chauvin Nicolas Depetris et al., 2012). Visual assessment of pathogen symptoms and identification of disease symptoms are traditional methods of quantifying disease severity.A competent person must observe and evaluate the seriousness of the disease and these skills can only be acquired through intensive investigation and research. This requires more time and increases the need for people skilled in diagnosing plant diseases.To boost crop development and productivity, it is essential to identify plant leaf diseases. The four key steps in the process of identifying disease from a leaf image are pre-processing, segmentation, feature extraction, and classification. For the identifier's correctness and effectiveness, each of the processes is thought to be crucial(Mokhtar, Usama, et al..

2015).Figure 1 displays a general block design for the system used to identify leaf diseases via image processing. It entails determining the key system components and how they communicate with one another.

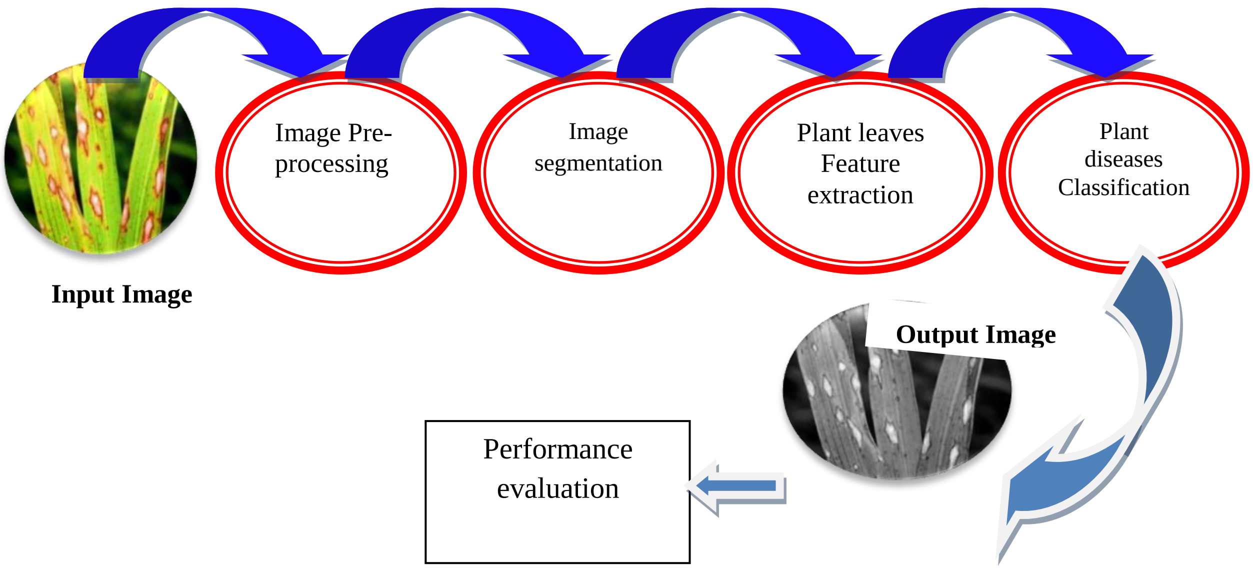

Figure 1 general block diagram for plant leaves diseases detection

1.1 Pre-processing:Pre-processing is the procedure for raising the calibre of an input image. It is a crucial phase in the recognition process since a noisy image directly affects the classification of diseases' outcomes. Denoising, contrast correction, and edge enhancement are the three stages this approach takes to improve an input image of plant leaves. For accurate distinguishing proof using input photographs after pre-processing, proficient and powerful picture division is crucial. The pre-processing method isolates a region of interest (ROI) namely leaves input images from its experience.Among the different strategies utilized, wavelet based methodologies was more reasonable for fragmenting pictures from its experience(SivananthamKalimuthu et al., 2022).

1.2 Segmentation:In image segmentation, each image is split as a large number of parts or regions. The number of parts mostly depends on the application and requirements of the user. In image segmentation, the image is divided starkly and accurately. A section of an image is the outcome of image segmentation, which consists of a removed group of contours of the total image.The major intention of segmentation is to modify or to simplify the representation present in the image in an effective way, for conducting the evaluation. As a result of image segmentation, the image is divided efficiently for further processing (SivananthamKalimuthu., 2022).

1.3 Feature extraction:The primary objective of the second phase is to transform the image data into a format that makes it easier to match paddy photos. The two steps that make up this phase are feature extraction and feature selection. The feature extraction process looks for several traits that best describe an image of plant leaves. Because there are generally many features chosen, a feature selection algorithm is used in the second stage to choose the most noticeable features. Five categories of features were extracted during feature extraction. They are paddy-related features, geometric features, colour features, texture features, and fractal features. The majority of paddy image identification research solely considers paddy, colour, and texture aspects. In this investigation, the geometric and fractal characteristics were also considered (Akhtar Md Shad et al., 2017).

1.4 Classification:The work of identifying the plant to which the input paddy belongs is the study's final phase, and it is crucial for the discipline of botany. The core of the algorithm is an iterative recognition process that compares characteristics taken from the input image with feature vectors corresponding to photos of plant leaves from the pre-built dataset(Wäldchen Jana, and Patrick Mäder., 2018).

This paper's summary is structured as follows. Chapter 2, explain various techniques in involved to noise removal of plant diseases detections and its related work, Section 3 explained to proposed Adaptive thresholding Stein's unbiased probability Estimate, section 4 presents proposed ATSUPE+CNN and existing Median+CNN, Wiener+CNN, Gaussian+CNNcomparability of experimental outcomes. Section five elaborates on the proposal's conclusion and potential future application.

II. LITERATURE REVIEW

The following section discusses the Pre-processing techniques for image noise removal techniques in various fields, and conventional data pre-processingtechniques with machine learning algorithm.

Rothe et al.(2015) presented a technique for the extraction of diseased leaves using Gaussian filter. Gaussian filter was implemented to eradicate noise in the pictures earlier to segmentation.A variety of likeness-based reclamation and visualisation techniques used the colour scheme descriptor, and form parameters were retrieved as features. The illnesses chosen for study were alternaria, myrothecium, and bacterial blight. Prior to the implementation of the Gaussian filter, noise in the images was present. The Color layout descriptor was employed for a variety of likeness-based retrieval. The remaining attributes were not taken into consideration, only shape factors and content filtering were used as features.

SarangdharAdhaoAsmita and V. R. Pawar(2017) proposed a method to categorize downey mildew and anthracnose watermelon leaf diseases by making use of Gaussian filter pre-processing techniques with support vector machine classification approach. A few unhealthy leaves were composed and were captured using a digital camera having precise calibration. The identification of the watermelons leaf diseases was based on the colour feature extraction from RGB colour system where RGB pixel colour indices were computed from the recognized regions of interest. The recommended computerised classification system made use of a statistics package for the social sciences and a neural network for a pattern recognition algorithm. According to calculations in this endeavour, the accuracy of the RGB mean colour constituent was 75.9%.

RewarEkta et al.,(2017)proposed Wiener filter used to noise removal for RGB leaf diseases image. For the purpose of detecting vegetable leaf viruses, an additional pre-processed image was linked to three colour modules and applied to three-channel convolutional neural networks. Every channel in the model benefited from single-color modules of the RGB sick leaf image. In order to create a deep levelling illness detection feature vector, the features were fused over a fully linked fusion sheet. Last but not least, the input image was catalogued into the pre-established classes using a layer of the feature vector. The study's findings verified that the recommended method outperforms contemporary methods for identifying vegetable diseases, but other plant elements, like leaves and tendrils, have poor disease detection precision.

Rani, FA Princi, et al.(2019) performed a transform on an RGB image to isolate the location of a disease. They compared the CIELAB and HSI effects for illness spot detection in their study using the aYcbCr colour space. The median filter was used to smooth the images and create an algorithm that was noise-free. Finally, the threshold technique was employed to apply the procedure to the colour component. An algorithm was created and tested on various dicot and monocot plant leaves. Classification was accomplished using the support vector machine technique, which performed poorly.

Gadade H. D and D. K. Kirange(2021) proposed an innovative method of diagnosing tomato leaf diseases based on support vector machine technique. At first median filter method was implemented to eradicate noise from the picked up images of tomatodiseased leaf. Then method known as the static pattern recognition was familiarized to segment unhealthy regions of tomatodiseased leaf. Lastly, texture and colour features were extracted and SVM was used for recognition of cucumber diseases. Experimental outcomes showed that the classification presentation by SVM was superior to the neural networks technique. Median filter was implemented to remove and static pattern recognition to segment the leaf image. Features such as textural, shape and colour of disease spot on leaf were extracted.

Zhu Juanhua et al.,(2020) proposed a disease image detection system for graph leaf constructed on image processing. Conferring to the texture features of corn infections, Wiener techniques used noise removal and it makes use of the YCbCr colour space tools to segment diseased parts, and also makes use of co-occurrence matrix gray level cover to extract disease spot texture feature, and to classify the maize disease, BP neural network was used. The experimental outcomes show that the procedure can successfully classify the disease. The method provided hypothetical foundation to perception of diseased leaf. The poor noise removal performance result in corn leaf diseases images.

Mishra Bharat et al.,(2017) advanced a computationally competent and robust plant leaf disease detection process and functional it to the classifying the three crops i.e. maize/corn, canola and radish. The sobel noise removal techniques are used to removing noise in input multi diseased datasets. This process grouped local binary pattern operators, for feature extraction of the crop leaf and SVM algorithm was used for the multiclass plant classification. The proposed system validated plant classification accurateness as more as 89.85%, for all the three plants diseases.

Jothiaruna N., K.et al (2021) provided a method for obtaining sick tissue to diagnose tobacco illnesses like the frog eye spot and anthracnose that affect leaves. The affected areas with these spots were segmented by using the contrast stretching transformation method with a modifiable factor and morphological processes. Initially the input image pre-processed using laplacian filter. The textural features taken out were employed for the categorization purpose. A probabilistic neural network was also utilised to categorise anthracnose and frog eye marks on tobacco leaf. The proposed methodology meritoriously detected the diseases achieving accuracy of 88.59 %.

The analysis aims to seek out higher ways for cumulative throughput and reducing judgement ascending from human specialists in investigation of the plant disease. The aim is to design an efficient algorithm for suitable pre-processing techniques and cataloguing of plant leaf diseases. Thisanalysis clearly states the suitable noise removal techniques need to remove noises especially Gaussian and salt pepper noises effectively. Existing methods Laplacian, Wiener, median, Gaussian and sobel filter related pre-processing techniques and it implementation are discussed in this section.Leaf images typically contain Gaussian and salt-and-pepper noise, but previous methods have focused on removing only Gaussian or salt-and-pepper noise. The following section explain the Adaptive thresholding Stein's unbiased probability Estimate techniques (ATSUPE) pre-processing techniques used remove the Gaussian, salt and pepper noises also performance compared with the conventional techniques.

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III. SYSTEM DESIGN

Any noise reduction technique's goal is to eliminate all noise while preserving the images' key details.This section details explanation for proposed system noise removal techniques and existing techniques (Median filter, Wiener filter and Gaussian filter) system design. Figure 2 shows the proposed system ATSUPE+ CNNblock diagram for plant leaves diseases detection

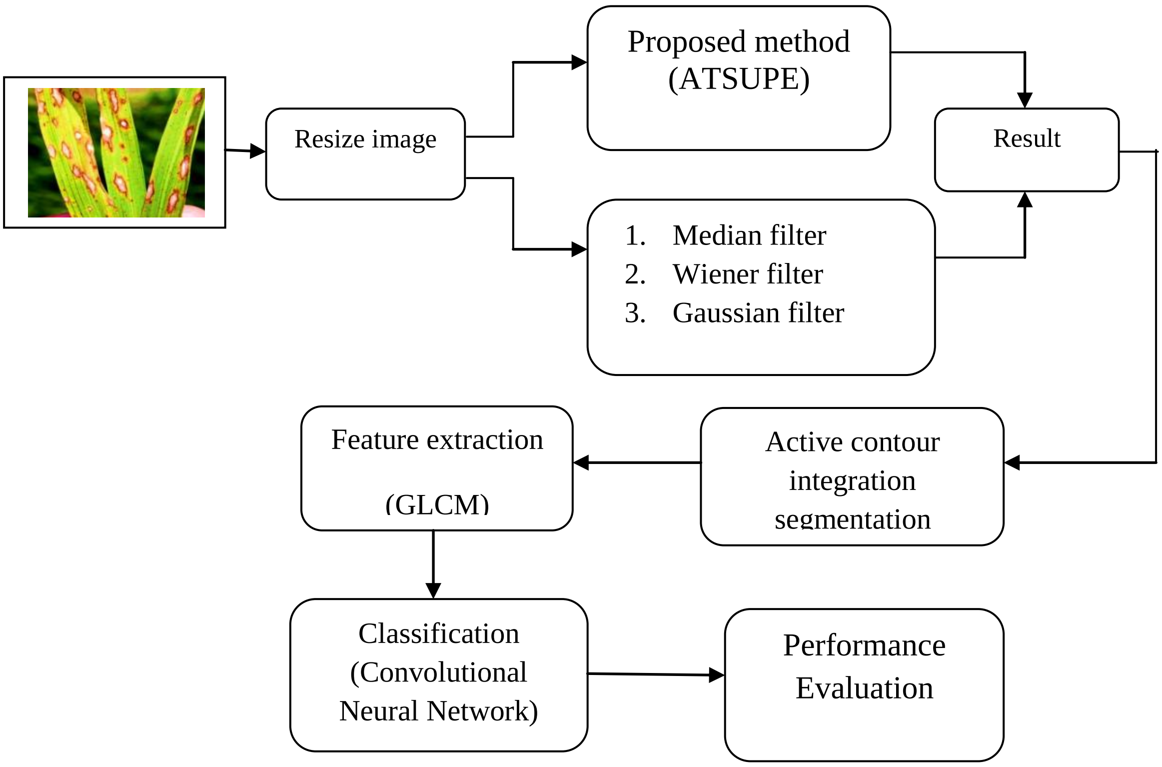

Figure 2 proposed system architecture diagram

3.1 Median filter

Median filters (Toprak Abdullah and InanGüler. 2007) are commonly used to reduce noise while maintaining edges. When half of a set of values are less than or equal to m and the other half are more than or equal to m, the set of values has a median m. To find the neighborhood's median, the values in the filter are sorted. The median value is assigned to the generated image. The median filter's objective is to increase the similarity between spots with various intensities and their surrounding pixels.

All of the image's pixels had the median filter applied consistently. It is therefore used to denoise the image at the price of features with distortions and excessive smoothing of the fine details in the image.

The steps for median filter is given by,

- A kernel of any central symmetric, a round disc, a square, or a rectangle shapes and of any size can be designed and centredon the pixel (i, j).
- The region's pixel intensity values are arranged in increasing order..
- The middle value is chosen as the new pixel value (i, j).

3.2 Wiener Filter

Wiener filter (Anwar and Syed. 2007) is based on a statistical method that removes the noise from the image. By executing the best possible trade-off between noise smoothing and inverse filtering, the blurring and additive noise in the image are eliminated. They operate in the frequency domain, which makes them relatively sluggish. Wiener filter is given in theequation (3.1)

$$f(u,v) = \left[\frac{H(U,V)^*}{H(U,V)^* + \left[\frac{Sn\,(u,v)}{sf\,(u,v)}\right] G(u,v)}\right] \text{eqn (3.1)}$$

G(u,v) represents a degraded image where H(u,v) is the degradation function and H(u,v)* is the complex conjugate of that function. The power spectra of the original image are shown by Sf(u,v), whereas the power spectra of the noise are shown by Sn(u,v).

3.3 Gaussian Filter

Bilateral filter (Yu H et al., 2009) use a method that considers both the space between pixels and the fluctuations in image intensityBecause it combines the domain filter with the range filter, it is distinct from other filters. In mathematical terms, it is the outcome of the domain and range filters. Therefore, if one of the weights is close to zero, smoothing is precluded. It might divide the picture into two parts: the residual picture and the filtered picture. The features or noise that the filter has filtered out are present in the residual image. Even though it preserves edges better, the method is quite expensive. S and R are two parameters on which it depends. As the range parameter r increases, the bilateral filter eventually approaches Gaussian convolution. As the spatial parameter is increased, larger features are smoothed. Equation is given for the bilateral filter (3.2)

$$BF[I]_P = \frac{1}{W_P} \sum_{q\varepsilon s} G_{\sigma_S}(||p-q)\, G_{\sigma_r}(||I_P - I_q) I_q \text{eqn (3.2)}$$

Where

$$W_P = \sum_{Q\varepsilon S} G_{\sigma_S}(\| p-q \|) G_{\sigma_r}(\| I_p - I_q \|) \text{eqn (3.3)}$$

GS represents the spatial Gaussian, WP represents the range Gaussian, and Wp represents the normalisation factor represented by Equation. I represent the image value at pixel position p, S represents the set of all possible image locations, || p-q || represents the Euclidean distance between the pixels p and q, and GS represents the spatial Gaussian (3.3).

3.4 Adaptive thresholdingStein's unbiased probability Estimate

Intelligent thresholding Stein's unbiased likelihood When choosing thresholds for wavelet domain filtering, shrinkage denoising techniques are utilised, and they are called estimate. The properties such as sparsity and multi-resolution structure makewavelet to perform well for image denoising. The transients and singularities can be represented as sparse piecewise regular one dimensional image pixels usingwavelet basis. In two dimensional images, large wavelet coefficients are inthe edges and irregular textures. Based on the functionalities, wavelet can beclassified as continuous, discrete, stationary, multiwavelet etc. The continuousWavelet deals only with 1D image pixels whereas Discrete Wavelet Transform(DWT) is used for 2D images to capture frequency and location information.Even though DWT works well for many image applications, they lack intranslation invariant property. Using DWT, the pictures are divided into low- and high-frequency components. These components are half thelength of the original image. During the analysis phase, the downsamplersalong with the filters are used to produce the frequency components and insynthesis phase, upsamplers are used.

The Stationary wavelet transform (SWT) was developed to get around the translation invariant property by removing the downsamplers and upsamplers in the DWT. In order to maintain the same length of theimage, redundant scheme is used. It is otherwise referred as undecimatedwavelet transform. The first step in SWT is to apply high and low pass filtersto the image at each level. The resultant components are not decimated. Then,the filters are modified at each level by padding zeroes. The followingFigure 3.The image's division into low- and high-frequency subbands is shown.

LL1 stands for the image's low-frequency smooth area, LH1, HL1, and HH1 for its high-frequency detailed edge features, and i=1,2... I represent the degree of decomposition.

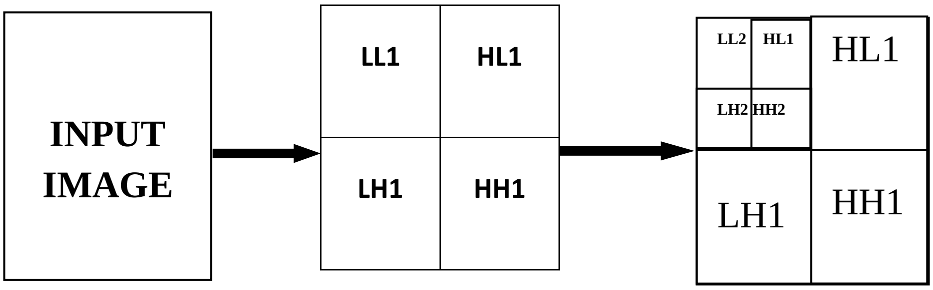

Figure 3 first and Second level decomposition of image using SWT

The waveletbasis differentiates the image into large coefficients which are the originalsignals and small coefficients represent the noise. While modifying thecoefficients the noise can be removed from the meaningful signal that is partof the image.Threshold selection technique proposed by (Xiao and Zhang., 2011). The threshold is calculated by the following Equation 3.4.

$$T = \sigma\sqrt{2\log(I)} \quad \text{eqn (3.4)}$$

Where;T - The calculated threshold, σ- Standard deviation of the noise,I- Input image.

Based on the number of input arguments either hard thresholding orsoft thresholding techniques are used. Because it is produced under the high probability restriction that the estimate should be as smooth as the image, this threshold is known as the universal threshold. For edge features, the calculated threshold will be high, while for noise, it will be very low. As a result, the threshold struggles to adjust to signal discontinuities. Although the ATSUPE technique delivers a substantially smoothed denoised image, the features are lost due to the high threshold. It also fails to adapt to the various statistical and structural properties ofthe wavelet tree.

Step1: Calculate the threshold from the image.

$$T = \sigma\sqrt{2\log(I)};$$

Where, T - The calculated threshold,

σ - Standard deviation of the noise,

Input image.

Step 2: Call the function hardthresh or Softthresh based on nargin which the number of input arguments.

if(*n arg in < 2*)

type = 'softthreshold';

x =softthresh(*I* , *T*);

else

Type = 'hardthreshold';

x=hardthresh (*I*,*T*);

Functionhardthresh(*I*,*T*) // *hard threshold function definition*

Figure 4 Procedure for Stein's unbiased probability Estimate

The figure 4 explains the Stein's unbiased probability Estimate techniques threshold calculation. ATSUPE follows an adaptive technique for threshold selection. Ifthe image contains more features, the reconstruction will also have preservedfeatures. If the image contains more smooth areas, the reconstructed imagewill also have more smooth areas. The advantages of the ATSUPE areevident when the image has more features on a smooth background. All thedetailed sub-bands are extracted from the image using SWT. The image pixelsize is computed and the noisy sub-band is filled using zero. Then thethreshold vector is produced based on the sorted values of all neighborhoods.The threshold is selected based on the risk which is minimum. The following figure 5 explains the threshold calculation for modified proposed implementation.

1. *Calculate the threshold using Surethresh function*

Function*thresh=Surethresh(I) // Surethresh function definition*

```
l=length (I);
s=sort(abs(I)).^2;
s1=cumsum(s);
risk =(l-(2*(1: l)) +s1)/l ;
[guess,best] = min(risk);
Thresh = sqrt(s(best));
```

Figure 5 Procedure for Adaptive thresholding Stein's unbiased probability Estimate

The ATSUPEdifferentiates the image into large coefficients which are the plant leaves original image pixel and small coefficients represent the noise. While modifying thecoefficients the noise can be removed from the meaningful pixel that is partof the image. Remove the noise effectively from plant leaves and extracted the pre-processed image.

IV. RESULT AND DISCUSSION

The experimental findings and performance evaluations in this section demonstrate that traditional filtering methods do not sufficiently reduce image noise. However, Adaptive thresholding Stein's unbiased probability Estimate methods and image decomposition utilising SWT produce good plant leaf image denoising. For the experiment, 256x256 plant leaf images from the plant village dataset are used. There is no need for image resizing because all of the images used for the experiment are the same size.

Input image	

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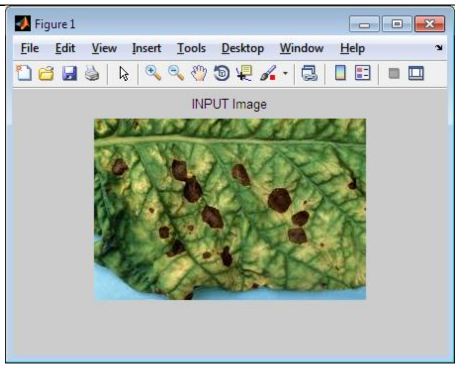
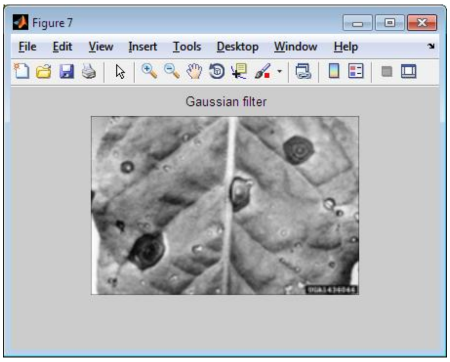
<tr><td></td><td>
</td></tr>
<tr><th>Filter</th><th>Pre-processed image</th></tr>
<tr><td>Gaussian filter</td><td>
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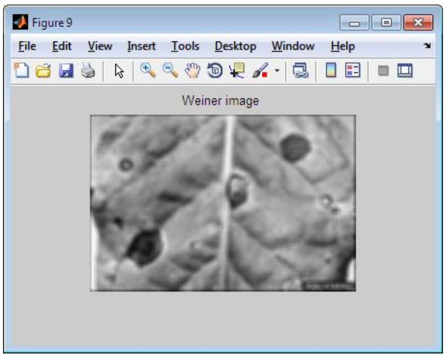
<tr><td>Wiener filter</td><td>
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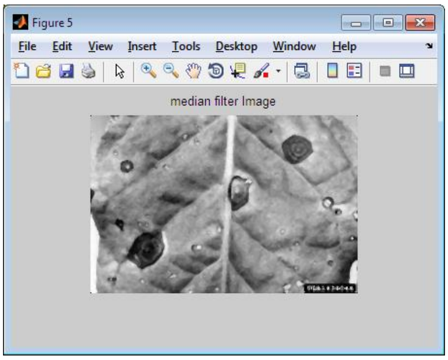
<tr><td>Median filter</td><td>
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<tr><td>Proposed ATSUPE filter</td><td></td></tr>
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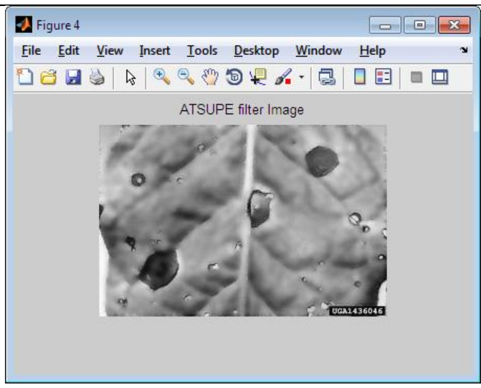

Figure 6 Performance comparisons for pre-processing

The input image of the leaf contains some noise in it when the image has some noise it will make more difficult to get the values from image. We therefore have a distinct pixel process in the first stage of our proposed system to eliminate the noise from the input image. After this process based on proposed and existing method leaf image will be make a filter process of (median, Wiener, Gaussian) to extract the noise removed image. The images shows, the sample input leaf image in Figure 6 (a), Gaussian filter image in 6 (b), Wiener filter image in 6 (c),Median filter image in 6 (d) and Proposed ATSUPE filter resultant images in 6 (e).

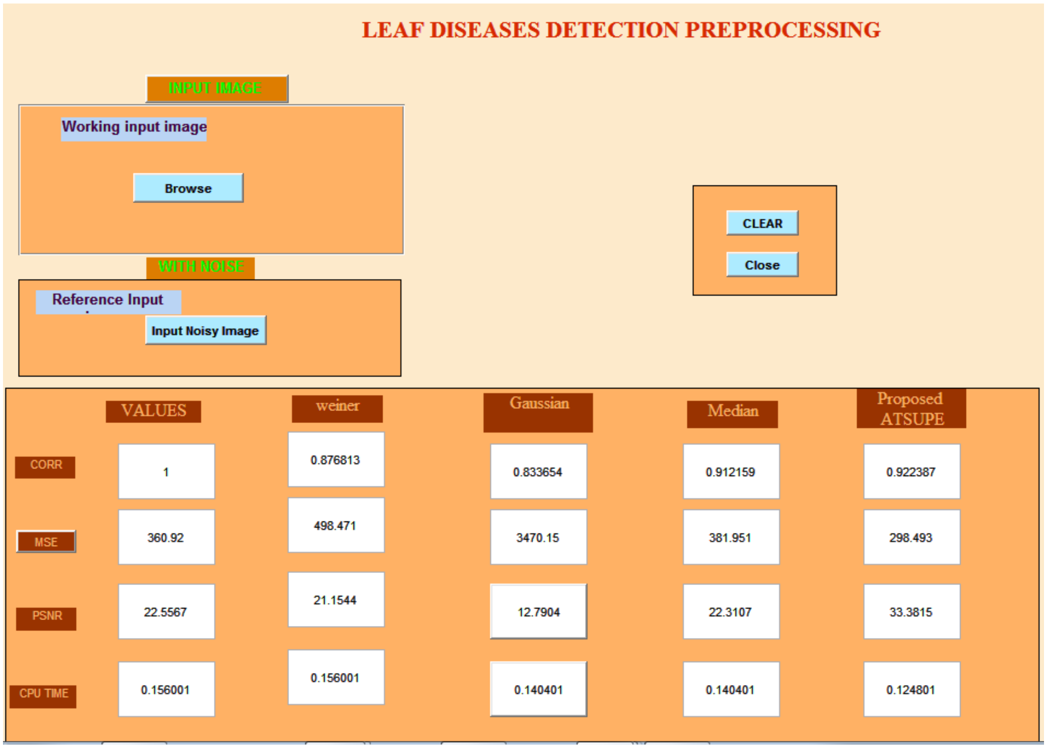

Figure 7 pre-processing techniques performance result

As the figure 7 shows that the pre processing techniques performance result from the input image of plant leaves. The four pre-processing performance evaluation parameters such as correlation, CPU time, MSE, and PSNR values are compared with existing and proposed methods.

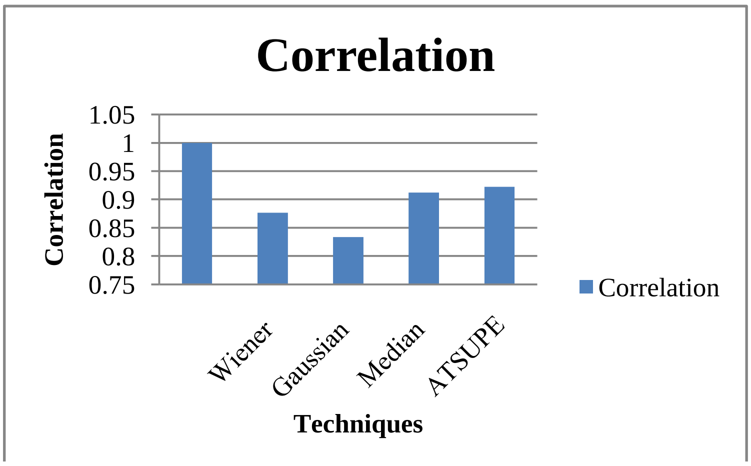

Figure 8 correlation values for the techniques.

When two variables rise or decrease simultaneously, there is a positive correlation; when there is a negative correlation, one variable increases as the other falls. From the correlation matrix and plot above, we can clearly see that there are many features correlated to other features such as plant leaves highly correlated withpre-processed image features correlation. The graph on the figure 8 clearly explains the correlation values are plotted in graph. the correlation calculation for before pre processing the image obtained the value of 1, for wiener filter obtained value of 0.876813, for Gaussian filter obtained a value of 0.833654, the median filter the resulted output is 0.912159, this values are have some error rate in it, but on the side of proposed system obtained resulted output of 0.922387 for leaf diseases prediction techniques. Comparatively existing techniques, proposed system features are highly correlated pre-processed image features.

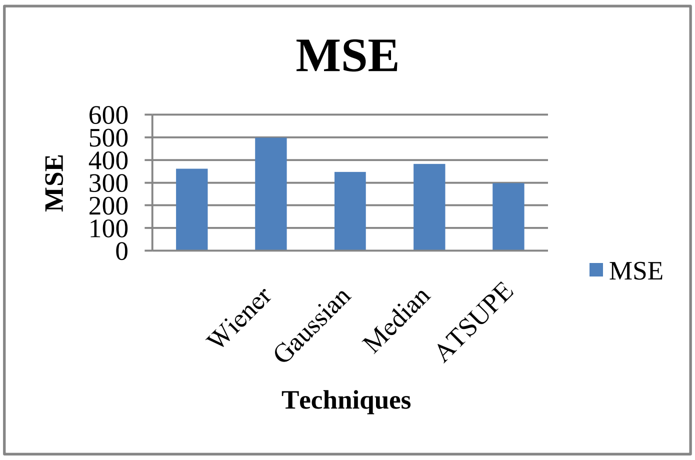

Figure 9: MSE values for the techniques.

The MSE shows the cumulative squared error between the original leaves image and the pre-processed plant leaves image.The graph on the figure 9 clearly explains the values are plotted as graph. the MSE calculation for before pre processing the image obtained the value of 360.92, for wiener filter obtained the value of 498.471, for Gaussian filter obtained the value of 3470.15, the median filter obtained the value of 381.951, and proposed system obtained MSE is 298.493. The MSE number tells us how much of an error is present in the pre-processed image. Compared to the current system, the proposed ATSUPE has a lower mean square error rate.

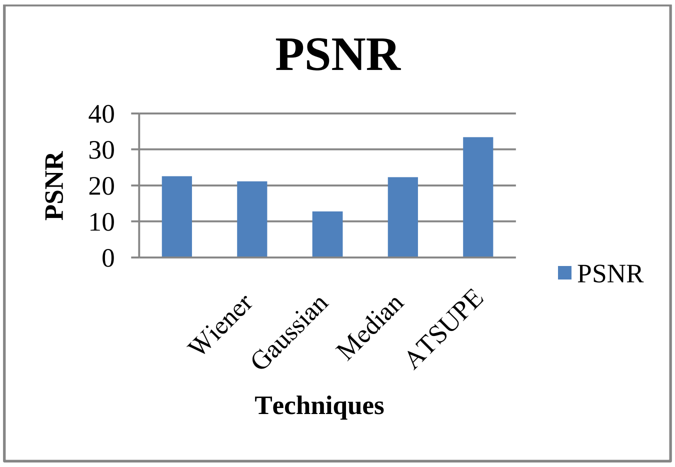

Figure10 peak signal noise ratio with graph

The peak signal-to-noise ratio (PSNR) measures how well a picture may be represented by comparing its maximum power to the power of corrupting noise. Peak Signal Noise Ratio values are explained in detail by the graph in Figure 10.the PSNR calculation for before pre processing image obtained the PSNRvalue 22.5567, the wiener filter obtained PSNRvalue is 21.1544, the Gaussian filter obtained PSNRvalue is 12.7904, the median filter resulted PSNR value is 22.3107, and proposed ATSUPE system obtained the PSNR value is 33.3815. The quality of the pre-processed leaves image improves with increasing PSNR. Compared to current pre-processing methods, the suggested ATSUPE pre-processed image has a superior quality.

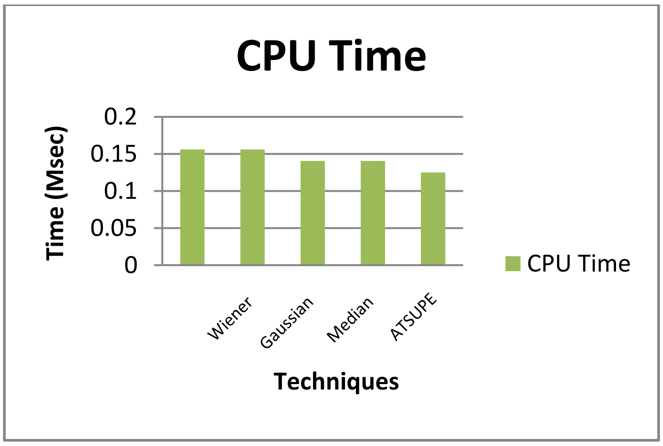

Figure 11 CPU time for the techniques in (M.sec)

The time consumption for input leaves image into pre-processed image (noise removed image). The graph on the figure11 clearly explains CPU time consumption comparison. TheCPU timeconsumption for wiener filter 0.156001 milliseconds, the Gaussian filter 0.140401milliseconds, the median filter 0.140401 milliseconds,and proposed system obtained in 0.124801milliseconds for input image into noise removal image. Lower cpu time consumption indicates the input image noise removal speed. Comparatively the proposed ATSUPE system lowers time taken and higher speed than exiting approaches.

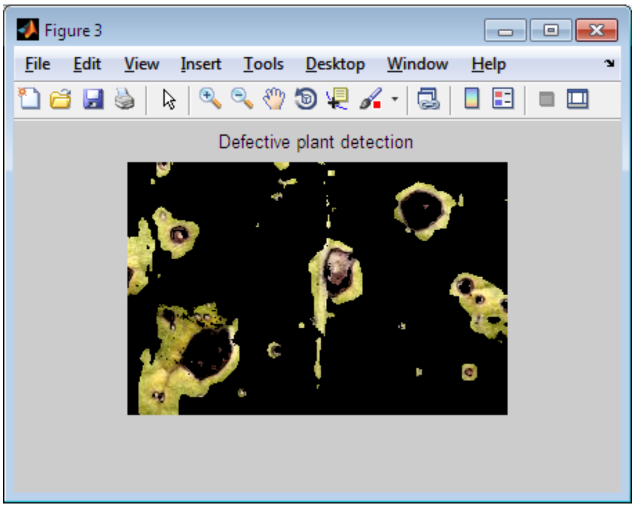

Figure 12segmentation result

The pre-processed image applied to the segmentation process, During the channel separation stage, Red (R), Green (G) and Blue (B) channels are split to form separate image.The Green channel consists of moreinformation about the diseases in the plant and it will be used for further processing and otherchannels are discarded. The separated green channel image is a monochromatic image andit will be used as the input to the algorithm. The active contour integration techniques are used to segmentation, the figure 12 explains the segmented resultant image, the diseases part of pre-processed leaves image separated. The segmented image features extracted and CNN classification techniques applied to the diseases prediction. Figure 13 classification techniques and predicted result.

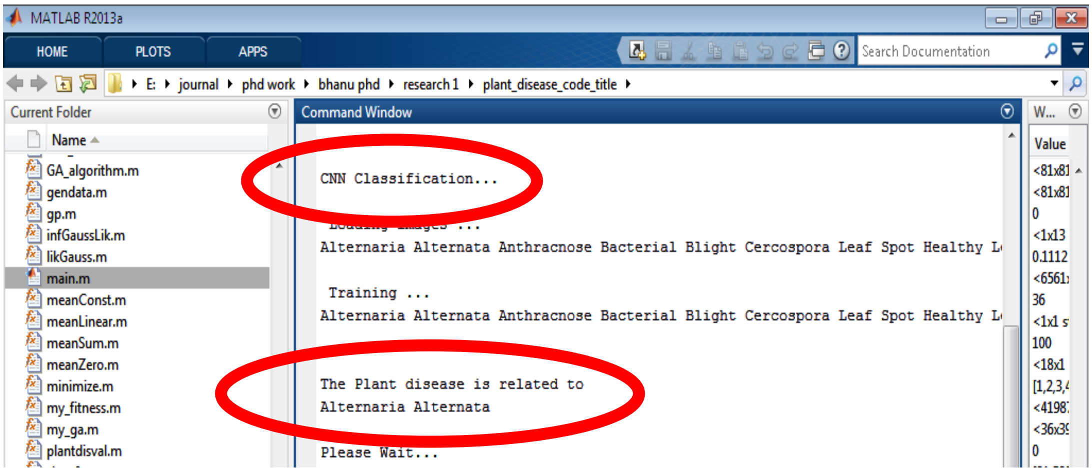

Figure 13classification result

Performance result: Convolutional Neural Network with each pre-processing technique further applied, and performance evaluatio. The following section explains the Gaussian+CNN, Wiener+CNN, median+CNN, and proposed+CNNperformance parameters such as accuracy sensitivity specificity and precision.

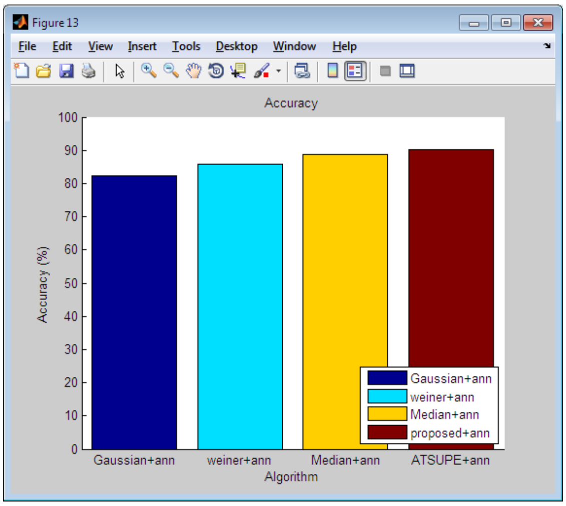

Figure 14accuracy result

The figure 14 shows accuracy comparison graph for conventional and proposed system. The accuracy result of Gaussian pre-processing techniques with CNNis 82.22%,Wiener pre-processing techniques with CNNis achieved 85.86%, medianpre-processing techniques with CNNis 88.66%, and proposed ATSUPE pre-processing techniques with CNNsystem achieved 90.22%. Accuracy indicates classification problems used to the percentage of accurate predictions. Comparatively the proposed system better efficiency then conventional techniques.

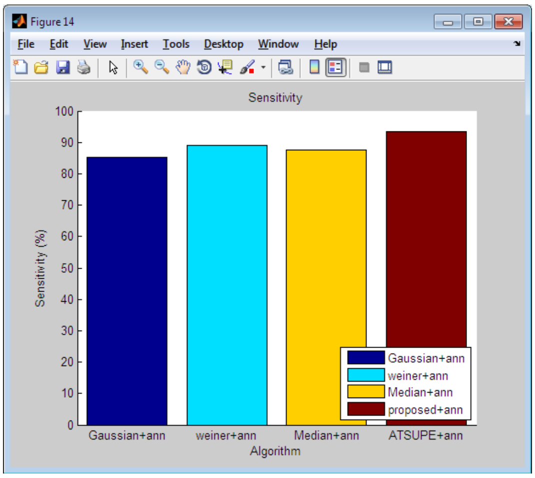

Figure 15sensitivity result

The figure 15 shows sensitivitycomparison graph for conventional and proposed system. Thesensitivityresult of Gaussian pre-processing techniques with CNNis 85.32%,Wiener pre-processing techniques with CNNis achieved 89.00%, medianpre-processing techniques with CNNis 87.63%, and proposed ATSUPE pre-processing techniques with CNN system achieved 93.33%. Sensitivity is a measure of the percentage of cases that were positive but were misclassified as positive (or true positive). Comparatively speaking, the proposed system is more sensitive than traditional methods.

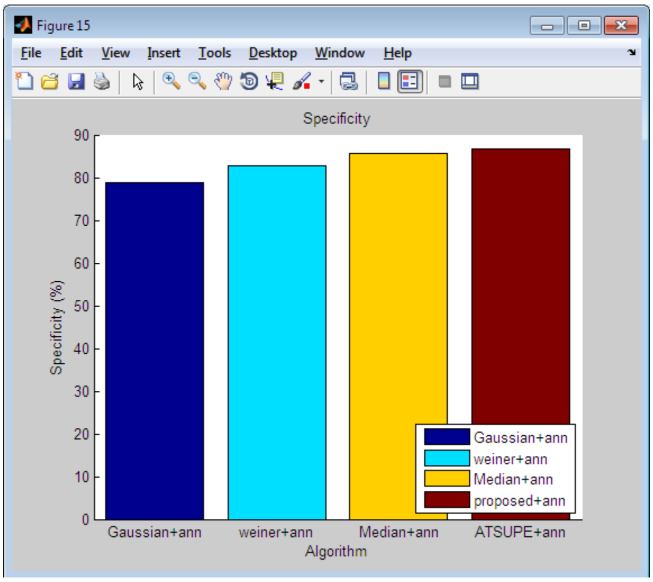

Figure 16specificity result

The figure 16 shows specificity comparison graph for conventional and proposed system. The specificity result of Gaussian pre-processing techniques with CNN is 78.79%, Wiener pre-processing techniques with CNN is achieved 82.65%, median pre-processing techniques with CNN is 85.33%, and proposed ATSUPE pre-processing techniques with CNN system achieved 86.67%.The statistic known as specificity assesses a model's capacity to forecast true negatives for each available category. In comparison to conventional approaches, the suggested system has improved specificity, indicating ATSUPE+CNN's superior capacity to forecast true negatives for each accessible category.

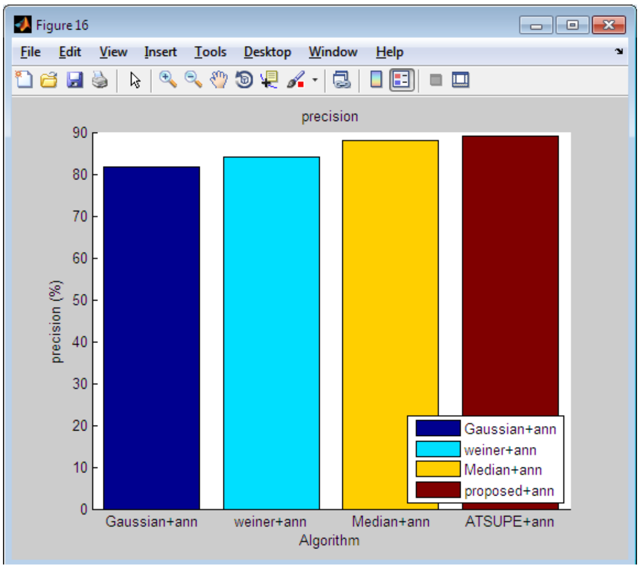

Figure 17precision result

The figure 17 shows precisioncomparison graph for conventional and proposed system. Theprecisionresult of Gaussian pre-processing techniques with CNN is 81.56%, Wiener pre-processing techniques with CNN is achieved 83.65%, median pre-processing techniques with CNN is 89.47%, and proposed ATSUPE pre-processing techniques with CNN system achieved 91.48%.A machine learning model's precision, or how accurately it makes a good prediction, is one measure of its effectiveness.Comparatively the proposed system better precision then conventional techniques, indicates ATSUPE+CNN better perform the quality of a positive prediction. From the perform evaluation proposed pre-processing techniques yield better performance in both per-processing evaluation parameters (correlation, MSE, PSNR, and CPU time)and classification performance (accuracy, sensitivity, specificity, and precision). The result of proposed system indicates remove the noises better than existing noise removal approaches.

V. CONCLUSION

This Research aims at denoising the leaf images in the waveletdomain basedIntelligentthresholding Stein's unbiased likelihood Estimate functions. The distinctive quality of the leaf picture makes it possible for spatial domain filters to provide output that is of low quality throughout the denoising process. The ATSUPE has been proved to be successful forleaves image denoising. The leaf images are decomposed usingStationary Wavelet Transform (SWT) to obtain low and high frequencycomponents. Then, for removing the noise, the ATSUPEare applied to the high level coefficients. Theplant leaf images normally contain textures of diseased part, sediments andexternal objects. The empirical evidences such as PSNR, MSE, co-relation and time duration have proved that the ATSUPE technique preserved the edges along theobjects.The pre-processed image was then segmented using active contour integration and based on features extracted using GLCM, and then classified using convolution neural network. Results from ATSUPE with CNN were compared to those from the previous systems using Gaussian, Wiener, and Median with CNN. The experimental results such as Accuracy, sensitivity, precision and specificity have proved that the ATSUPE with CNN technique better than the other existing approaches.

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