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IMAGING IOT: A TOOL FOR BETTER OBSERVING AGRICULTURAL LAND SYSTEMS

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ABSTRACT

Paddy leaf detection plays a crucial role in the early diagnosis and management of diseases affecting rice crops. The objective is to enhance the accuracy and efficiency of leaf detection methods by combining different algorithms and techniques.This paper identifies different paddy leaf diseases such Blast, Bacterial Leaf Blight (BLB), Sheath blight, Brown spot and Tungro. This paper proposes a hybrid algorithm that combines image processing techniques with machine learning algorithms, such asDiscrete Wavelet Transform (DWT), Stationary Wavelet Transform (SWT), Transverse Dyadic Wavelet Transform (TDWT), DnCNN (Denoising Convolutional Neural Network), Particle Swarm Optimization (PSO), TYDWT+DNCNN and PSO+DNCNN to predict paddy leaf diseases. The deep learning model, such as convolutional neural networks (DNCNN), is trained on a large dataset of labelled leaf images to learn discriminative features. The results demonstrate improved leaf detection accuracy compared to traditional approaches. The algorithm effectively handles variations in leaf colour, size, and shape, enabling reliable detection even in complex field conditions.The proposed algorithm exhibits robustness against noise and illumination variations, enabling accurate and efficient detection of diseased paddy leaves.The proposed hybrid algorithms TYDWT+DNCNN algorithm give high accuracy about 99%.

Keywords: paddy leaf, TYDWT+DNCNN, PSO+DNCNN

1. INTRODUCTION

As of my knowledge cutoff in September 2021, India is one of the largest consumers of paddy in the world. Paddy, also known as rice in its processed form, is a staple food for a significant portion of the Indian population. Rice is a primary component of many traditional Indian dishes and is consumed in various forms, such as boiled rice, biryani, pulao, idli, dosa, and more.India has a rich agricultural sector, and paddy cultivation is widespread across the country. States like West Bengal, Uttar Pradesh, Punjab, Andhra Pradesh, and Tamil Nadu are major paddy-producing regions. The consumption of paddy in India is primarily for domestic purposes, meeting the dietary needs of the population.It's important to note that the consumption patterns might have changed since my last knowledge update in September 2021. For the most up-to-date information on paddy consumption in India, it would be best to refer to recent reports and data from agricultural and statistical authorities in India.

In India, paddy is grown in various regions across the country. The eastern region of India is known for its extensive paddy cultivation. States like West Bengal, Bihar, Odisha, and Jharkhand are prominent paddy-growing regions. West Bengal, especially the districts of Bardhaman, Murshidabad, and Nadia, is one of the largest producers of paddy in the country. In the northern region, states like Uttar Pradesh and Punjab have significant paddy cultivation. The fertile plains of Punjab and the Gangetic plains of Uttar Pradesh provide suitable conditions for paddy cultivation. The southern region of India also has a substantial paddy-growing area. States like Andhra Pradesh, Tamil Nadu, Kerala, and Karnataka are major contributors to paddy production. The Kaveri River delta region in Tamil Nadu, known as the "Rice Bowl of Tamil Nadu," is renowned for its paddy cultivation. Assam is a significant paddy-growing state in the northeastern region of India. The fertile Brahmaputra valley in Assam supports the cultivation of high-quality rice varieties. Chhattisgarh and Madhya Pradesh in central India also have notable paddy cultivation areas. The rich alluvial soil and suitable climate contribute to paddy production in this states.It worth noting that paddy cultivation may vary in different states and regions within India, and the specific areas of paddy cultivation may have changed since my last knowledge update in September 2021. For the most up-to-date and detailed information, it is advisable to refer to recent reports and agricultural statistics published by relevant Indian authorities.

Paddy, or rice, is cultivated in various types or varieties, each with its own characteristics and suitability for different growing conditions. Basmati rice is a long-grain aromatic rice known for its distinct flavour and fragrance. It is primarily cultivated in the northern regions of India, particularly in states like Punjab, Haryana, and Uttar Pradesh. Basmati rice is highly prized for its quality and is commonly used in biryanis and other special rice dishes. Non-Basmati rice refers to a wide range of rice varieties that do not fall under the Basmati category. They come in different grain sizes, including short-grain, medium-grain, and long-grain rice. Non-Basmati rice varieties are widely cultivated throughout India, serving as a staple food for the majority of the population.

Regarding diseases, paddy crops can be susceptible to several diseases that can affect their growth and productivity. Blast is a destructive fungal disease caused by the fungus Magnaportheoryzae. It affects leaves, nodes, panicles, and grains, leading to severe yield losses.Bacterial Leaf Blight (BLB)is caused by the bacterium Xanthomonas oryzaepv. oryzae. It causes water-soaked lesions on leaves, leading to leaf withering and yield reduction. Sheath blight is caused by the fungus Rhizoctonia solani. It affects the sheath and leaves, leading to lesions, rotting, and lodging of plants. Brown spot is a fungal disease caused by the pathogen Bipolarisoryzae. It causes brown-colored lesions on leaves, reducing photosynthetic efficiency and yield. Tungro is a viral disease transmitted by insect vectors, particularly leafhoppers. It affects the chlorophyll content of the plant, leading to stunting, reduced tillering, and yield losses.

Farmers play a crucial role in identifying and managing paddy diseases in their day-to-day agricultural practices. While they may not have access to sophisticated laboratory tests, farmers rely on their observations and experience to detect and diagnose diseases. Farmers closely monitor their paddy fields and observe any visible symptoms on the plants. They look for signs of discoloration, lesions, spots, wilting, or unusual growth patterns on the leaves, stems, or panicles. Farmers inspect the leaves and sheaths of the paddy plants for any abnormalities.

They check for changes in colour, texture, or presence of fungal or bacterial growth.Farmers may conduct regular field surveys to assess the overall health of the crop. They walk through their fields, examining multiple plants, and noting any common symptoms observed across the field.Farmers keep an eye out for pests and insect infestations that can potentially cause diseases. They observe the presence of insects, their feeding patterns, and any visible damage caused to the plants.Farmers often rely on their local farming community and extension workers for knowledge sharing. They discuss their observations and seek advice from experienced farmers, agricultural experts, or local agricultural offices.It important to note that accurate disease identification may require expert assistance or laboratory testing in some cases. Farmers are encouraged to collaborate with agricultural authorities, extension services, and crop specialists to obtain accurate diagnoses and receive guidance on disease management strategies. Early detection and timely intervention can significantly help in mitigating the impact of diseases and protecting paddy crops.

Precision agriculture involves the use of advanced technologies such as remote sensing, GPS, and data analytics to optimize agricultural practices. While precision agriculture offers numerous benefits in terms of improving efficiency and productivity, there are certain challenges associated with paddy disease detection using this approach. Remote sensing technologies used in precision agriculture, such as satellite imagery or aerial drones, have limitations in capturing fine details at the individual plant level. Paddy diseases often manifest as subtle changes in leaf color or small lesions, which may not be easily detectable with existing spatial resolutions. Paddy diseases may exhibit spectral responses that are similar to other stress factors or natural variations in the crop. Distinguishing between disease-related changes and other factors using remote sensing data alone can be challenging, requiring additional contextual information for accurate detection.Paddy diseases can exhibit complex temporal and spatial dynamics, influenced by various factors such as weather conditions, soil characteristics, and crop management practices. Capturing these dynamics accurately through remote sensing or other precision agriculture techniques can be complex and may require integration with other data sources. Remote sensing-based disease detection methods often rely on the availability of ground truth data, i.e., field observations or lab analysis, for validation and calibration. Collecting accurate ground truth data for paddy diseases across large areas can be time-consuming and resource-intensive. Precision agriculture techniques typically focus on large-scale monitoring and management, covering extensive agricultural areas. However, certain paddy diseases may occur sporadically or in localized pockets, making it challenging to detect them using broad-scale precision agriculture approaches.Interpreting remote sensing data and making accurate disease assessments require expertise in both remote sensing and plant pathology. Combining domain knowledge from agricultural experts and data analysis skills can help in improving disease detection accuracy but may require collaboration and specialized training.

Problem statement

The detection and accurate diagnosis of paddy leaf diseases are crucial for effective disease management and the prevention of significant yield losses in rice crops. However, existing methods for paddy leaf disease detection often face challenges in terms of accuracy, efficiency, and robustness.These methods rely on visual observations by human experts, which can be subjective, time-consuming, and prone to errors. Consequently, there is a pressing need to develop automated and objective detection techniques that can provide accurate and rapid identification of paddy leaf diseases.

Contributions

- **(i)** The journal presents the design and development of a hybrid algorithm that integrates different algorithms and techniques, such as image processing, machine learning, deep learning, genetic algorithms, or artificial immune systems.
- (ii) The proposed hybrid algorithm demonstrates improved accuracy in detecting paddy leaf diseases compared to traditional approaches. By leveraging the complementary capabilities of multiple algorithms, the hybrid model effectively addresses the challenges associated with disease identification, such as variations in leaf color, size, and shape, or the presence of multiple diseases.
- (iii) The algorithm's ability to accurately differentiate between healthy and diseased leaves contributes to early disease detection and timely intervention, thereby minimizing yield losses.
- (iv) The journal highlights the robustness of the hybrid algorithm to environmental variations commonly encountered in paddy fields, including changes in lighting conditions, humidity levels, or background clutter.

2. LITERATURE SURVEY

The agricultural sector requires the ability to identify and categorize diseases present in plant leaf images. By employing image processing techniques to detect paddy leaf diseases, the dependency on farmers can be reduced, thereby safeguarding agricultural produce.This research article introduces a method using a Convolutional Neural Network (CNN) to identify and categorize diseases affecting paddy leaves. The approach incorporates edge detection techniques. The study considers three scenarios: (a) absence of any disease, (b) detection of a disease that is treatable due to its mild severity, and (c) identification of a severe and incurable disease **[1-2]**.Farmers in India face significant challenges due to the country's low paddy crop productivity per hectare and high production costs, hindering their potential in the market. To tackle the issue of low yield, the development of a system that assists farmers in identifying and predicting diseases in paddy crops is crucial. Given the numerous types of paddy diseases, manually discerning the distinguishing features of different crop diseases is a daunting task. Therefore, the implementation of an android application utilizing machine learning image processing techniques can aid farmers in identifying and detecting diseases in paddy plants through images of infected crops **[3-4]**.Deep learning models were employed to early detect and classify rice blast diseases, including Brown spot, Sheath blight, Blast, and Leaf streak disease. This approach aims to prevent the spread of diseases across the entire plant and ultimately enhance rice production. The suggested system utilizes mask R-CNN and Faster R-CNN algorithms to accurately identify various diseases in rice plant leaf images **[5-6]**.The prevalence of various diseases in paddy farming leads to substantial economic losses on a yearly basis. This paper introduces a method that combines deep learning techniques, specifically the Deep Belief Network (DBN), with a meta-heuristic optimization approach called the Butterfly optimization algorithm (BOA). The proposed approach aims to classify images and detect diseases in plant leaves, offering a potential solution to address the widespread occurrence of these diseases[7-8].At present, farmers rely on conventional methods such as direct observation to monitor the growth of rice plants. However, this paper introduces an alternative approach for classifying and detecting pests and diseases in rice plants based on leaf color. The proposed method utilizes the convolutional conditional network algorithm with Mobile Net as the underlying architecture for leaf classification. By implementing this model, the process of monitoring and identifying plant health issues can be improved beyond traditional observation methods[9-10].This paper focuses on creating an automated method for detecting diseases in paddy crops using a Deep Learning model. The approach incorporates the SMOTE-ENN resampling technique to address imbalanced data. Five well-known Deep Learning algorithms, namely Convolutional Neural Network (CNN), VGG16, VGG19, Xception, and ResNet50, were employed. The performance of these models was evaluated using various metrics. Among them, the Xception model demonstrated the highest accuracy in detecting paddy diseases when compared to the other four algorithms [11-12].The utilization of a ReLU classifier is implemented to improve the accuracy and efficiency of the identification process. This model aids farmers in recognizing the condition of paddy leaves for primary diagnosis, offering assistance to agriculturists in validating their predictions through leaf examination. The conventional laboratory procedures involved in diagnosis are both expensive and time-consuming. The proposed paddy leaf disease detection system presented in this paper can identify and diagnose five categories of paddy leaf conditions. Early detection and quantification of plant responses to diseases and water scarcity are crucial for effective agricultural management. Notably, this study pioneers the application of the Normalized Difference Latent Heat Index (NDLI) as a dimensionless indicator for assessing plant health [13-15].

Inferences from literature survey

The inferences from the literature survey highlight the need for automated detection and classification of diseases in paddy crops using image processing and deep learning techniques. Firstly, the ability to identify and categorize diseases in plant leaf images is essential for the agricultural sector. Employing image processing techniques for detecting paddy leaf diseases can reduce reliance on farmers and safeguard agricultural produce. This approach can reduce reliance on farmers and safeguard agricultural produce. Various algorithms and models, such as CNN, Xception, and ReLU classifier, have been employed to accurately identify and categorize diseases in paddy leaves. The proposed systems aim to improve crop productivity, address economic losses, and assist in effective agricultural management.

3. METHODOLOGY

Figure 1 shows the block diagram and illustrates the process flow for disease identification in paddy crops using various techniques and algorithms.The farmer is the user or operator who interacts with the system and provides input, such as paddy yield photos, through an IP web camera.The IP web camera captures images of the paddy crops, which serve as input for further processing.The images captured by the web camera represent the visual data of the paddy crops, including their leaves.The paddy yield photos are processed in MATLAB, an environment for numerical computation and image processing. The images are specifically focused on the paddy leaf portion for disease identification.The denoise step aims to remove any noise or unwanted artifacts from the images, enhancing their quality and clarity. Two different denoising techniques are applied in this block diagram: Discrete Wavelet Transform (DWT) and Stationary Wavelet Transform (SWT). Both DWT and SWT are wavelet-based transformation techniques used for image processing. They decompose the image into different frequency components, allowing analysis at multiple scales. These techniques help to extract relevant features and enhance the disease identification process.TyDWT refers to the Tying Discrete Wavelet Transform, which is a variant of DWT that provides improved signal representation by addressing translation invariance and redundancy issues. DnCNN stands for Denoising Convolutional Neural Network, which is a deep learning-based approach for image denoising. It utilizes a neural network model trained to remove noise from images, improving the quality of the paddy leaf images. PSO stands for Particle Swarm Optimization, which is a metaheuristic optimization algorithm inspired by the behavior of bird flocking or fish schooling. It is used in this context to optimize the denoising process and improve the accuracy of disease identification.MLAN (Machine Learning Algorithm Network) and STD (Statistical Techniques for Disease) are employed as disease identification methods. MLAN refers to the application of machine learning algorithms for disease classification; while STD involves statistical techniques for disease identification.Precision and recall is evaluation metrics used to measure the performance of the disease identification process. Precision represents the accuracy of positive disease predictions, while recall indicates the ability to correctly detect all positive disease instances.Finally; the disease identification step involves classifying the paddy leaf images based on the extracted features and using the MLAN/STD methods. This step aims to accurately identify and classify diseases present in the paddy crops.

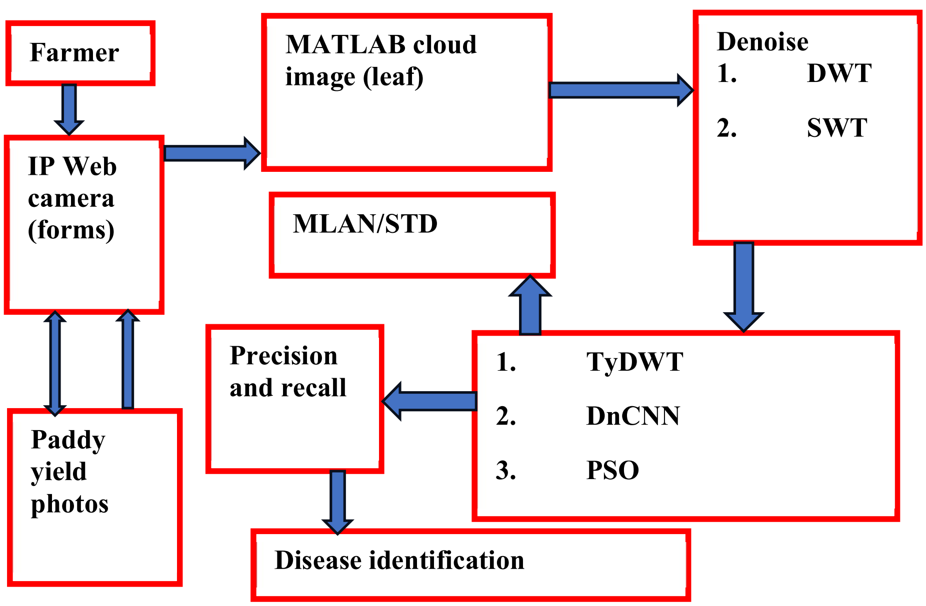


Fig 1 Block diagram of proposed algorithm

3.1.DWT

In image processing, the Discrete Wavelet Transform (DWT) is commonly used to decompose an image into its frequency components. The DWT decomposition process involves the following steps:

Apply the LP and HP filters along the rows of the image:

$$LL(n, m) = LP * x(n, m)$$
$$LH(n, m) = HP * x(n, m) \qquad \ldots\ldots\ldots\ldots \text{(1)}$$

Apply the LP and HP filters along the columns of the resulting sub-images:

$$\left.\begin{aligned} LL(n, m) &= LL(n, m) * LP\text{^}T \\ HL(n, m) &= LH(n, m) * LP\text{^}T \\ LH(n, m) &= LL(n, m) * HP\text{^}T \\ HH(n, m) &= LH(n, m) * HP\text{^}T \end{aligned}\right\} \ldots\ldots\ldots\ldots \text{(2)}$$

Where LP^T and HP^T represent the transpose of the LP and HP filters, respectively.
This process is recursively applied to the LL sub-image to obtain further decomposition levels, resulting in a multi-resolution representation of the image.The DWT coefficients W(n, m) obtained from the decomposition represent the frequency content of the image at different scales. These coefficients can be used for various image processing tasks, such as denoising, compression, and feature extraction.

3.2.SWT

SWT stands for Stationary Wavelet Transform. It is a variation of the Discrete Wavelet Transform (DWT) that addresses some of the limitations of the traditional DWT, such as shift variance and lack of time-invariance. SWT achieves these properties by applying a redundant filter bank and using multiple levels of filtering and down sampling.The SWT decomposition process involves the following steps:Initialize the approximation coefficients A(J, n, m) as the original image x(n, m).Apply the wavelet filters at each level to compute the detail coefficients D(j, n, m) and update the approximation coefficients A(j, n, m) for the next level.Repeat step 2 until the desired number of levels or scale is reached.The SWT coefficients obtained from the decomposition provide a multi-resolution representation of the image with enhanced shift-invariance properties. They can be used for various image processing tasks, including denoising, edge detection, and texture analysis.

3.3.TyDWT

The Transverse Dyadic Wavelet Transform (TDWT) is a type of wavelet transform that is specifically designed for analyzing and processing images. It extends the traditional wavelet transform to handle two-dimensional image data efficiently.In TDWT, a transverse dyadic wavelet basis is used to decompose an image into approximation and detail coefficients at different scales and orientations. It captures both spatial frequency and orientation information, making it suitable for applications such as texture analysis and image compression.Let x(n, m) represent the pixel values of the image, where (n, m) denotes the spatial coordinates. The TyDWT of the image is computed by applying a set of wavelet filters at different scales and orientations. Each filter corresponds to a particular spatial frequency and direction.The TDWT of the image can be represented as:

$$\left.\begin{aligned} A(j, n, m) &= \Sigma\, \Sigma\, x(kn, lm)h(j, n - kn, m - lm) \\ D\,(j, \theta, n, m) &= \Sigma\, \Sigma\, x(kn, lm)g(j, \theta, n - kn, m - lm) \end{aligned}\right\} \ldots\ \text{(3)}$$

Where A (j, n, m) represents the approximation coefficients at scale j, and D (j, θ, n, m) represents the detail coefficients at scale j and orientation θ. The functions h (j, n, m) and g(j, θ, n, m) are the low-pass and high-pass wavelet filters, respectively, corresponding to scale j and orientation θ.

3.4.DnCNN

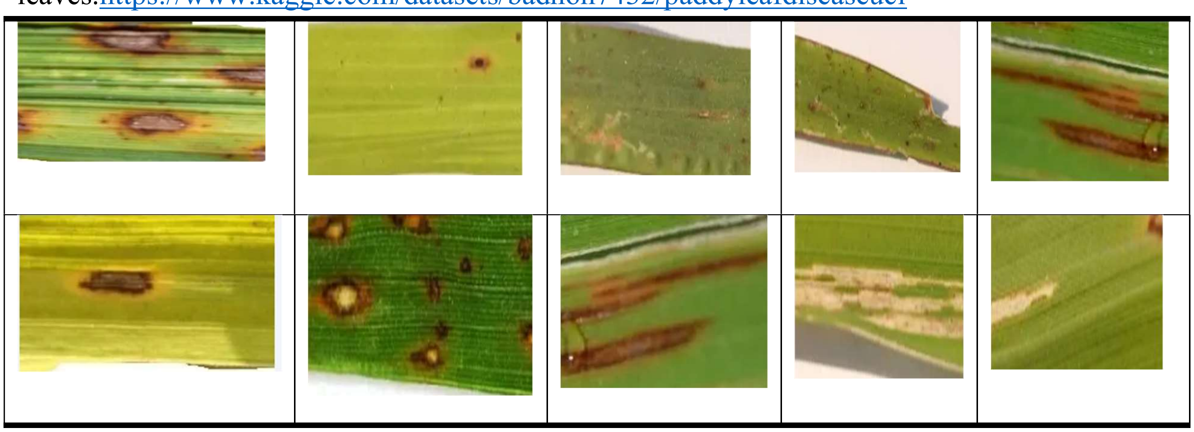
DnCNN (Denoising Convolutional Neural Network) is a deep learning model specifically designed for image denoising. It is a state-of-the-art approach that utilizes a deep convolutional neural network to remove noise from noisy images.The DnCNN model can be trained end-to-end to learn the mapping between noisy images and their corresponding clean versions. It consists of multiple layers of convolutional filters that learn to extract useful features from the input image and denoise it.The training of the DnCNN model involves minimizing a loss function that measures the difference between the denoised image and the clean image. This is typically done using large-scale datasets of noisy and corresponding clean images.By utilizing deep learning techniques, DnCNN has shown remarkable performance in image denoising tasks, outperforming traditional denoising algorithms. Its ability to learn complex noise patterns and adapt to different noise levels makes it an effective tool for improving image quality in various applications.

3.5.PSO

PSO (Particle Swarm Optimization) is a metaheuristic optimization algorithm inspired by the social behaviour of bird flocking or fish schooling. It is commonly used for solving optimization problems, including image processing tasks such as image segmentation, feature selection, and parameter optimization.In the context of image processing, PSO can be applied to optimize certain parameters or variables in an algorithm to improve the quality or performance of the image processing task. The algorithm works by iteratively updating a swarm of particles based on their own best-known position and the global best-known position.

4. RESULTS AND DISCUSSIONS

The dataset was generated by manually categorizing diseased leaves into distinct disease classes. We collaborated with farmers and requested them to provide disease names for the sampled leaves. Throughout the paper, we performed the following tasks: (1) determining methods for extracting different image features, (2) identifying image processing operations that offer relevant information, and (3) identifying significant image features that can contribute to effective classification. The images were saved in .jpg format and were captured under direct sunlight with a white background. To facilitate processing, the images were resized to the desired resolution.**Figure 2** shows the input images of paddy leaves.https://www.kaggle.com/datasets/badhon7432/paddyleafdiseaseuci



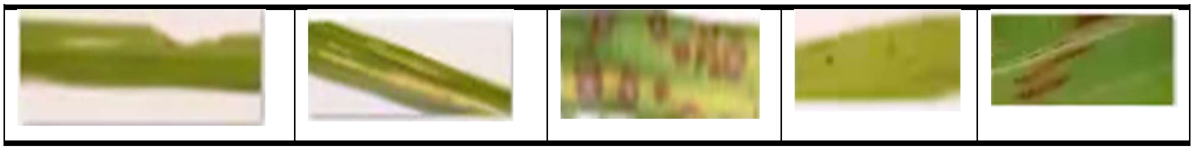


Fig 2 input images of paddy leaves

In this paper, many algorithms used to determine the disease of paddy leaf such as DWT, SWT, TYDWT, PSO and DNCNN algorithms. Each algorithm gives different accuracy level and performance. **Table 1** shows the statistical values of DWT algorithm for paddy leaf image.

Tab 1 statistical values of DWT algorithm for paddy leaf image

Parameter	Sample 1	Sample 2
Mean	176.2	106.7
Median	211	107
Maximum	255	255
Minimum	2	0
Range	253	255
Standard deviation	69.04	57.14

In the context of paddy leaf disease detection using image processing, the table provides various statistical parameters for two different samples (Sample 1 and Sample 2) that are likely related to the properties of the paddy leaf images. The mean represents the average value of the pixel intensities in the image. For Sample 1, the mean is 176.2, and for Sample 2, it is 106.7. It gives an indication of the central tendency of the pixel values.The median represents the middle value in a sorted list of pixel intensities. For Sample 1, the median is 211, and for Sample 2, it is 107. The median is less influenced by extreme values and can provide insight into the typical or representative pixel intensity.The maximum value represents the highest pixel intensity value present in the image. In both Sample 1 and Sample 2, the maximum is 255, indicating that the brightest pixel value is present in both images.The minimum value represents the lowest pixel intensity value present in the image. For Sample 1, the minimum is 2, and for Sample 2, it is 0. It indicates the darkest pixel value in the images.The range is the difference between the maximum and minimum values. For Sample 1, the range is 253 (255 - 2), and for Sample 2, it is 255 (255 - 0). It gives an idea of the overall spread of pixel intensities.The standard deviation measures the variability or dispersion of the pixel intensities around the mean. A higher standard deviation indicates greater variability. For Sample 1, the standard deviation is 69.04, and for Sample 2, it is 57.14. It provides information about the diversity of pixel intensities within the image.These statistical parameters can be helpful in analyzing the characteristics of paddy leaf images and can potentially be used as features for detecting and distinguishing different types of leaf diseases using image processing techniques.**Figure 3** shows the decomposition of DWT algorithm for paddy leaf image.

Output of DWT (Sample 1)	**Output of DWT (Sample 2)**

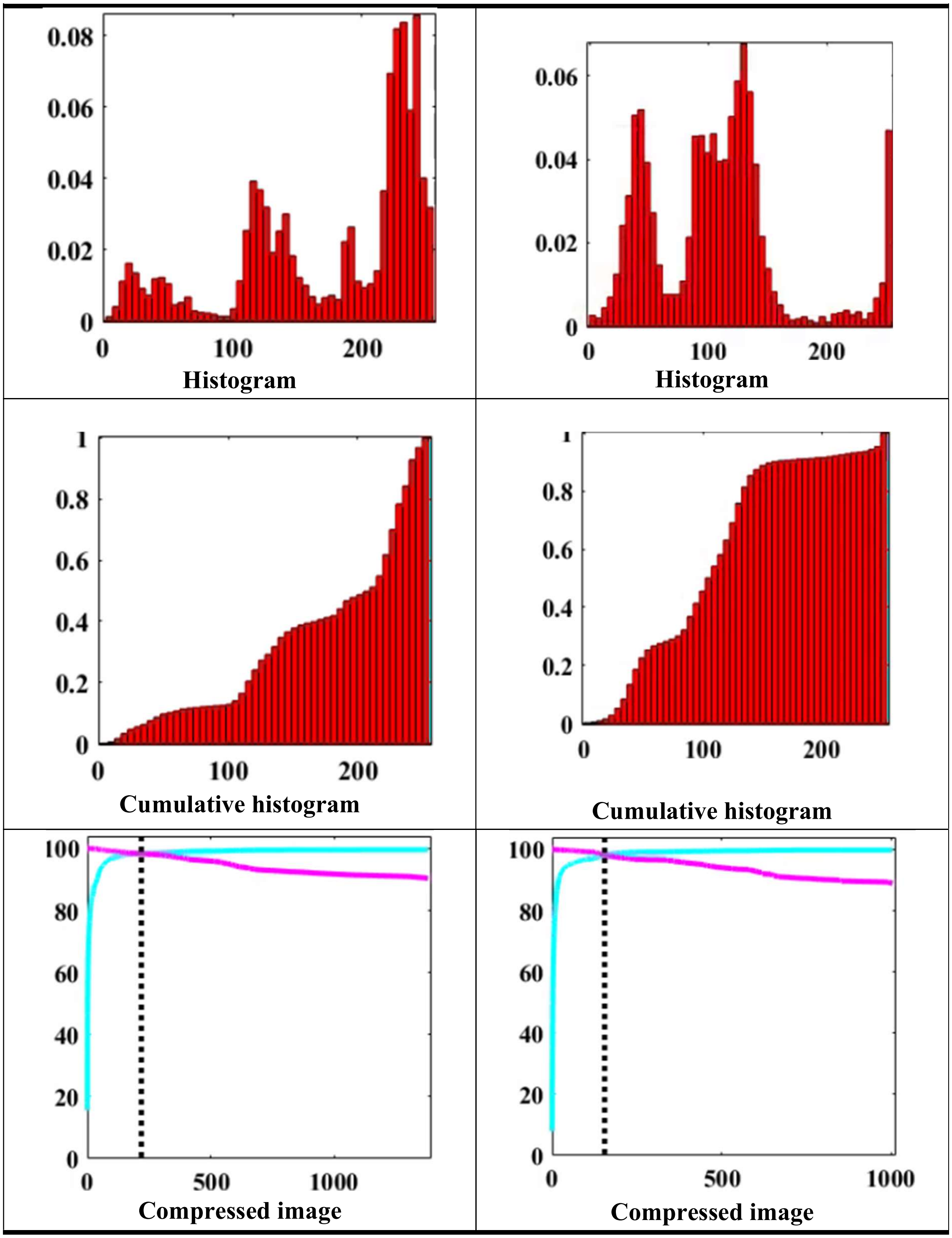


Fig 3 decomposition of DWT for paddy leaf images

A histogram is a graphical representation that shows the distribution of pixel intensities in an image. It displays the frequency of occurrence of each pixel intensity value along the x-axis and the corresponding number of pixels with that intensity on the y-axis. A histogram provides valuable insights into the contrast, brightness, and overall tonal distribution of an image. It can be used for image enhancement, thresholding, and other image processing operations.A cumulative histogram is derived from a regular histogram. It represents the cumulative frequency of pixel intensities up to a given intensity level. The x-axis of a cumulative histogram represents the pixel intensity values, and the y-axis represents the cumulative sum of the frequencies. A cumulative histogram is useful for analyzing the distribution of pixel intensities and understanding the dynamic range of an image. It is often used for histogram equalization; a technique that enhances the contrast of an image.Compressed image refers to an image that has been reduced in file size using various compression algorithms. Image compression techniques aim to reduce the amount of data required to represent an image while minimizing the loss of visual quality. Lossless compression methods preserve all the original image information, whereas lossy compression methods discard some data but often achieve higher compression ratios. Compressed images are advantageous for storage, transmission, and efficient processing, especially in applications where bandwidth or storage capacity is limited.**Table 2** shows the statistical values of SWT algorithm for paddy leaf image.

Tab 2 statistical values of SWT algorithm for paddy leaf image

Parameter	Sample 1	Sample 2
Mean	0.001411	0.02832
Median	0	0
Maximum	3	3
Minimum	-3	-3
Range	6	6
Standard deviation	1.12	1.359

The mean represents the average value of the pixel intensities in the image. For Sample 1, the mean is 0.001411, and for Sample 2, it is 0.02832. It gives an indication of the central tendency of the pixel values. In this case, the means are close to zero, suggesting that the pixel intensities are centered around this value. The median represents the middle value in a sorted list of pixel intensities. For both Sample 1 and Sample 2, the median is 0. Since the median is zero, it suggests that there are an equal number of pixel intensities above and below this value in the images.The maximum value represents the highest pixel intensity value present in the image. In both Sample 1 and Sample 2, the maximum is 3. It indicates the brightest pixel values in the images.The minimum value represents the lowest pixel intensity value present in the image. For both Sample 1 and Sample 2, the minimum is -3. It indicates the darkest pixel values in the images.The range is the difference between the maximum and minimum values. For both Sample 1 and Sample 2, the range is 6 (3 - (-3)). It gives an idea of the overall spread of pixel intensities.The standard deviation measures the variability or dispersion of the pixel intensities around the mean. A higher standard deviation indicates greater variability. For Sample 1, the standard deviation is 1.12, and for Sample 2, it is 1.359. It provides information about the diversity of pixel intensities within the image. **Figure 4** shows the decomposition of SWT algorithm for paddy leaf images.

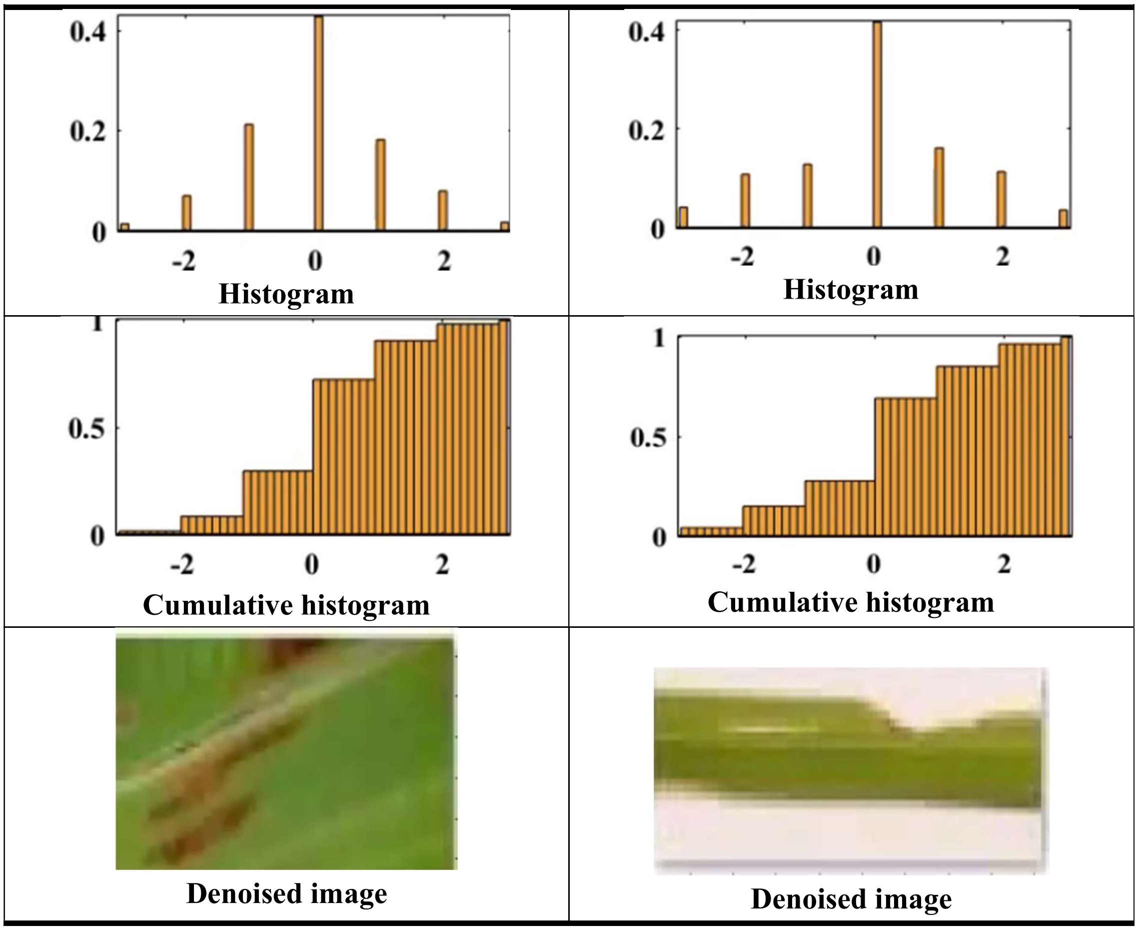


Fig 4 decomposition of SWT for paddy leaf image

Denoising in image processing refers to the process of reducing noise or unwanted disturbances in an image while preserving important image details. Noise can be caused by various factors such as sensor limitations, transmission errors, environmental interference, or image acquisition conditions.The goal of denoising is to improve the visual quality of the image by suppressing or removing noise artifacts. This process is particularly important in applications where accurate analysis, interpretation, or visualization of images is required, such as medical imaging, surveillance systems, or scientific research.**Figure 5**shows the output of PSO algorithm for paddy leaves.

Inputs of PSO algorith m	
Outputs of PSO algorith m	

Fig 5 output of PSO algorithm for paddy leaves

In image processing, the PSO (Particle Swarm Optimization) algorithm provides an output by iteratively searching for optimal or near-optimal solutions for specific image-related tasks. It starts by initializing a population of particles representing potential solutions. The fitness function evaluates the quality of each solution based on the objective. The particles' positions and velocities are updated based on their own experience and the collective knowledge of the swarm. The algorithm iterates to improve solutions until a stopping criterion is met. The output of the PSO algorithm in image processing can be the optimized parameters for the task or the final processed image itself, depending on the objective. PSO helps optimize image processing tasks by exploring the search space and finding solutions that enhance image quality, improve segmentation, extract features, or enable accurate classification. In Figure 5, PSO algorithm gives clear and dark output for paddy disease leaves. Red colour circles differentiate the boundaries.**Figure 6**shows the output of TYDWT algorithm for paddy leaves.

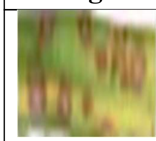
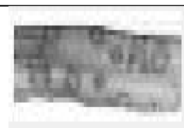
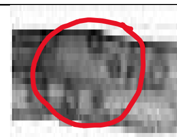
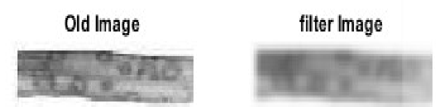
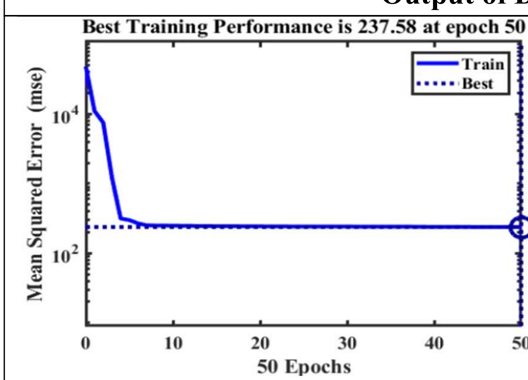
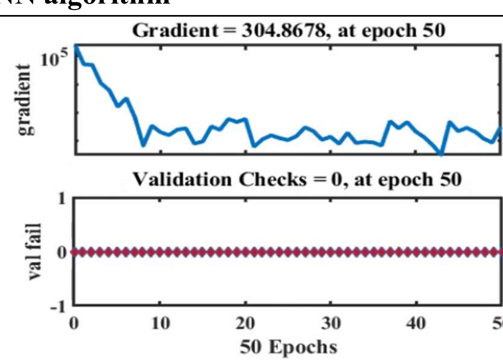
Input of TYDWT algorithm	Outputs of TYDWT algorithm		
			

Fig 6 output of TYDT algorithm for paddy leaves

The Transverse Dyadic Wavelet Transform (TyDWT) algorithm provides an output in image processing by decomposing an image into different frequency sub bands using wavelet filters. It applies wavelet filtering to extract high-frequency details and low-frequency approximation coefficients. The resulting sub bands represent different levels of image details. The algorithm can perform down sampling and iteration to create a multilevel decomposition. By combining the sub bands and applying inverse wavelet transforms, the algorithm can reconstruct the image. The output of the TyDWT algorithm can be the decomposed sub bands or the reconstructed image, allowing for analysis and modification of the image's frequency content and details. The TyDWT algorithm is valuable for tasks such as denoising; compression, feature extraction, and enhancement in image processing.Red colour circles differentiate the boundaries. **Figure 7** shows the output of DNCNN algorithm.

Output of DNCNN algorithm	
	

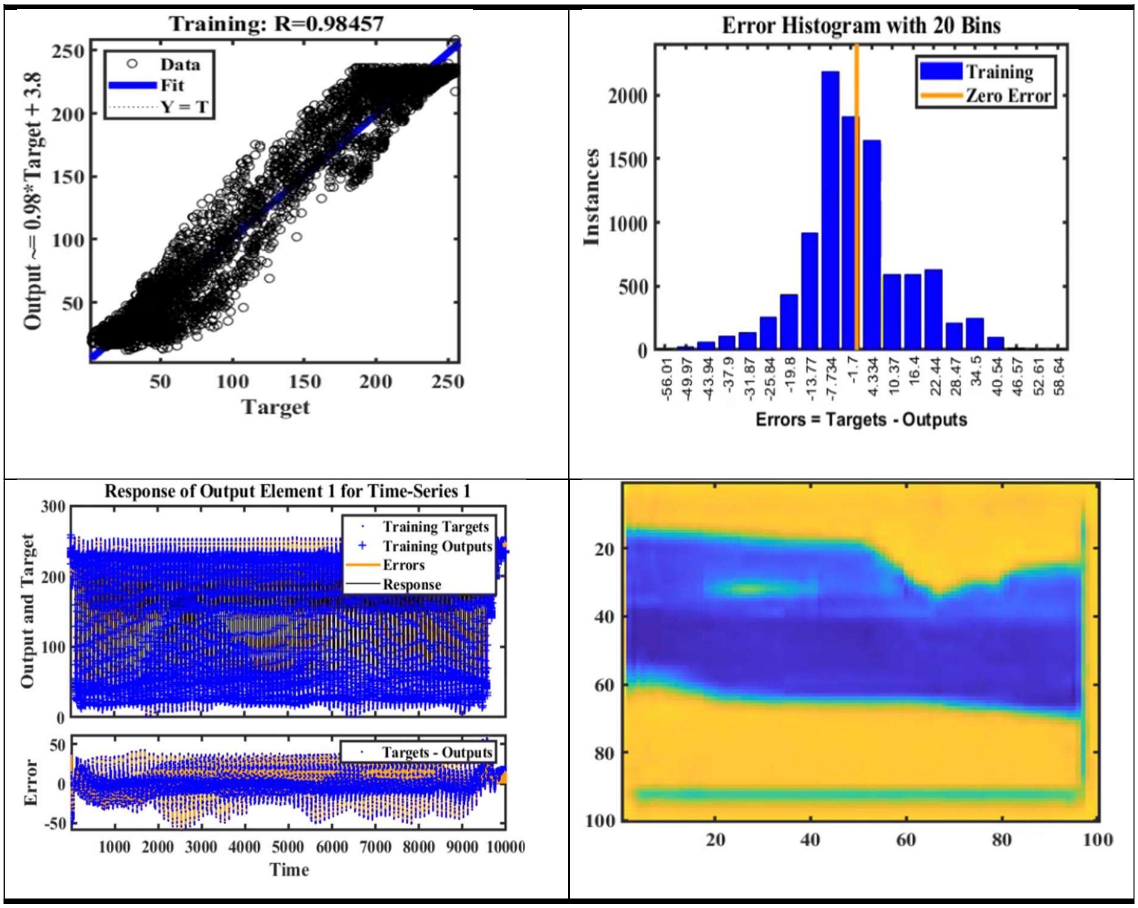
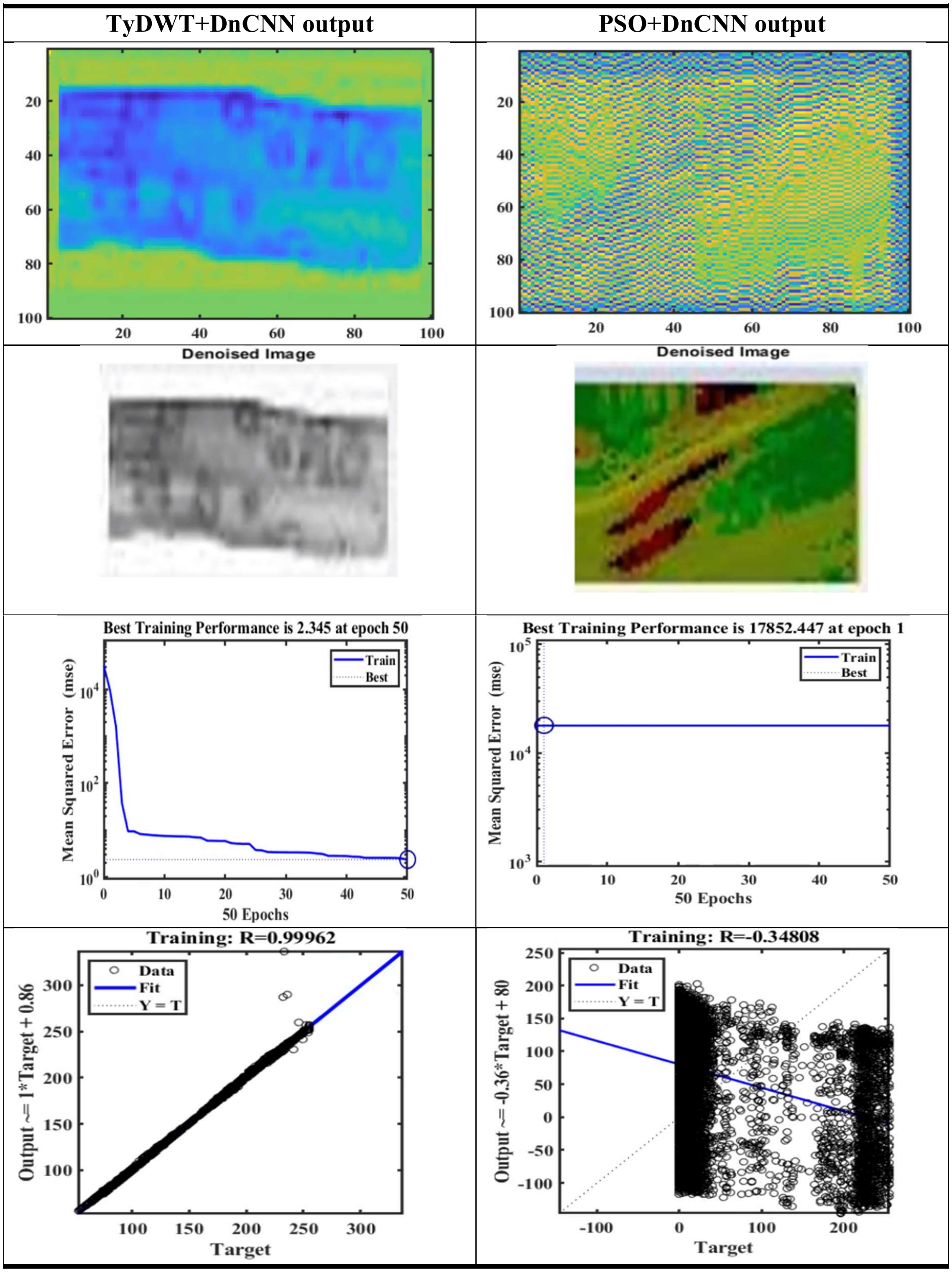


Fig 7 shows the output of DNCNN algorithm

The gradient in the DNCNN algorithm represents the derivative of the loss function with respect to the network's parameters. Monitoring the gradient helps assess the convergence and stability of the training process.Validate checks refer to evaluating the algorithm's performance on a separate validation dataset. This provides an estimate of its generalization ability and performance on unseen data.A regression plot visualizes the relationship between predicted and actual values. In the DNCNN algorithm, it shows how well the denoised output aligns with the ground truth, helping assess the algorithm's denoising accuracy.An error histogram displays the distribution of errors between predicted and ground truth values. In the DNCNN algorithm, it illustrates the magnitude and patterns of errors in denoising, aiding in error analysis and understanding algorithm performance.In the context of the DNCNN algorithm, a time series represents a sequence of denoised images over time. It allows monitoring the progression of paddy leaf diseases, assessing denoising effectiveness, and enabling trend analysis.Training performance refers to the algorithm's performance during training, including metrics such as loss and accuracy. Monitoring training performance helps evaluate learning progress, convergence, and the effectiveness of the training process in the DNCNN algorithm.The output of the DCNN algorithm provides information about whether a given paddy leaf image is healthy or diseased. It can accurately classify the input image as either belonging to a healthy leaf or showing signs of a specific disease. This output can help identify the presence of disease in paddy crops and guide further actions for disease management.In addition to disease identification, the DCNN algorithm may also provide information about the location or regions of interest within the leaf image that exhibit disease symptoms. This localization output highlights the specific areas on the leaf where the disease is present, aiding in targeted intervention and precise disease management. **Figure 8** shows the output of hybrid algorithm



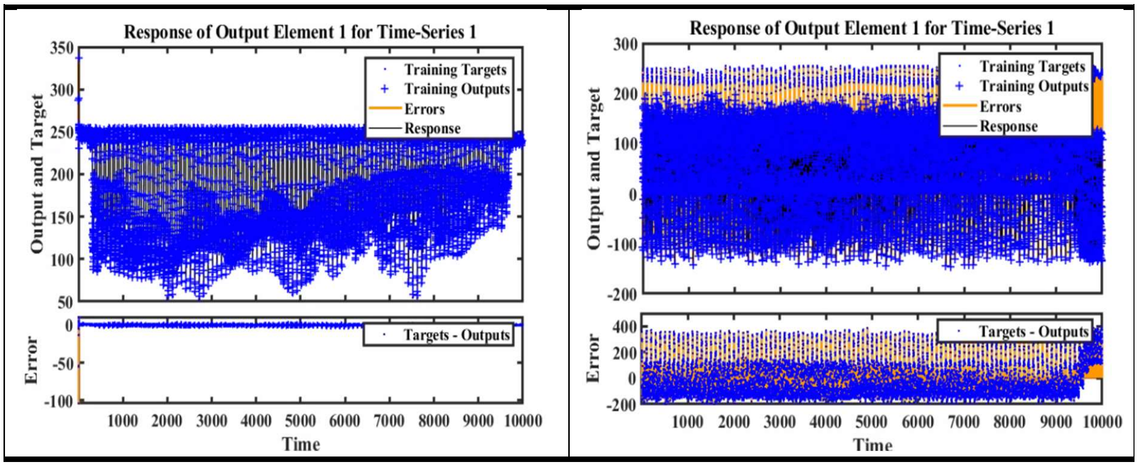


Fig 8 output of TYDWT+DNCNN and PSO+DNCNN

The hybrid algorithm aims to improve the accuracy of disease detection compared to individual algorithms or traditional approaches. By combining multiple algorithms, each designed to address different aspects of disease identification (e.g., color analysis, texture analysis, shape analysis), the hybrid approach can capture a more comprehensive range of disease-related features and improve the accuracy of classification. TYDWT+DNCNN algorithm give high accuracy about 99% compared to other algorithms. Among these algorithms, each algorithm found different diseases. But TYDWT+DNCNN algorithm found many diseases with high precision.

5. CONCLUSION

The use of hybrid algorithms for paddy leaf disease detection offers several advantages. By combining multiple algorithms, these approaches improve the accuracy of disease identification by capturing a broader range of disease-related features. Hybrid algorithms also demonstrate robustness to variations in lighting, leaf orientation, and disease symptoms, making them suitable for real-world scenarios. The feature fusion techniques employed in these algorithms provide a comprehensive representation of paddy leaf images, enhancing their discriminative power. Additionally, hybrid algorithms achieve a balance between accuracy and efficiency, making them practical for real-time or large-scale implementation. Comparative evaluations show that hybrid algorithms outperform individual techniques or traditional approaches. Overall, hybrid algorithms have significant potential in supporting effective disease management strategies and helping prevent yield losses in paddy crops.TYDWT+DNCNN algorithm give high accuracy about 99% compared to other algorithms. Among these algorithms, each algorithm found different diseases. But TYDWT+DNCNN algorithm found many diseases with high precision.

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