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Explainable AI for Multi-Granular Paddy Disease Identification and classification via a Superb Fairy-Wren Optimized Shuffle Transformer

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Abstract

Significant obstacles are presented by the recent increase in paddy leaf diseases, highlighting the necessity of targeted study and quick adoption of an AI method for crop leaf disease detection. Paddy, a staple meal for more than half of the world's population and a major component of many different cuisines, has many health advantages but is hampered by conditions like brown spot and blast disease. Accurate classification is necessary for managing paddy leaf disease effectively. Therefore, in this research we introduced a novel research framework for accurate predictions and classification of multiple plant leaf disease. In this proposed methodology there four phases, preprocessing, segmentation, feature selection and optimized detection and classification. Initially the raw input images are fed into the preprocessing phase to perform some initial phases. After the completion of preprocessing the, the affected portions are segmented. With the help of TransU-Net approach the segmentation is performed. The essential features are selected using Sine-Cosine Harris Hawks Optimization (SCHHO) algorithm. Finally the multiple paddy leafs are classified using a novel shuffle transformer. To enhance the prediction performance even more the classification approach parameters are fine-tuned using Superb Fairy-wren Optimization Algorithm (SFOA). These findings demonstrate the model's ability for real-time implementation in agricultural applications, offering small-scale farmers a dependable and effective option. This study provides a framework for tackling different crop diseases and emphasizes the importance of combining thermal imaging and deep learning to improve crop disease management.

Keywords: *Paddy Leaf Disease, Transu-Net, Sine-Cosine Harris Hawks Optimization (SCHHO) Algorithm, Shuffle Transformer, Superb Fairy-Wren Optimization Algorithm (SFOA).*

Introduction

One of the most difficult issues facing the agricultural industry is the early identification of pests and diseases that affect crops. In India, rice accounts for 93% of total grain yield production and 70% of total crop production [1]. In order to maintain India's staple crop yield, it is crucial for the country to detect illnesses in paddy plants early. The biggest obstacle in the realm of agriculture is still identifying and classifying pests and illnesses of plants [2]. Insects harm crops at practically every stage, which lowers agricultural yield.Because of the many linkages and intricate construction in the birth of various species, classifying insects that harm crops is a laborious task. To prevent lower yield and significant crop damage, it is imperative to identify, classify, and minimize insect infections that harm crops, mostly through the employment of biological systems and efficient pesticides [3-5].

Crop production is often impacted by a small number of elements, such as meteorological conditions, such as temperature and moisture, aberrant fertilization, unfavorable circumstances, including stress, and an imbalance in soil nutrients [6]. Furthermore, if crops are harvested too soon and piled up, or if they are harmed by natural events like cyclones or strong winds, which can cause panicle collisions and pest attacks during the grain production process, these circumstances may cause the grains to become discolored [7-9]. In image categorization, deep learning (DL) approaches have

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raised high expectations.These techniques work by using tagged training datasets to learn features [10]. Furthermore, the illnesses that harm apples, tea, grapes, tomatoes, pears, and peaches have already been identified using these techniques. Typically, the techniques use photos of leaves to identify the illnesses [11]. For this investigation, photographs from a homogeneous setting are used in this background. Additionally, the information is available online from a variety of sources [12, 13].

Each disease has unique characteristics. The color, shape, and size of illness symptoms can be used to identify a disease based on how it affects the host, which is the plant. Certain plant illnesses cause the plant to display similar colors but different shapes, while other diseases cause the plant to display different colors but similar shapes [14]. Because of these variations, farmers may become perplexed and neglect to choose the right insecticide. Taking pictures of diseased leaves, determining the illness's information, and implementing preventative or remedial actions to combat the disease are some strategies to prevent crop loss brought on by disease infection.Cameras can be positioned at precise distances around the fields to periodically take pictures as an automated solution to these issues [15]. The primary disease analysis system can receive this image and use it to determine the disease and provide information regarding the choice of insecticides and disease prevention strategies. These systems automatically identify the diseases that previously happened according to their training expertise [16, 17]. Given this context, the study's goal is to show how Machine Learning (ML) techniques can be applied to other domains, such as agriculture.Selecting outstanding characteristics is one of the most important aspects of ML field deployment [18]. Only when the non-disease and disease sections have been segmented can disease-based features be extracted. Since many crops have green leaves, it is imperative that the primary focus of this study be the extraction of leaf portions from the diseased area. This is a significant step in assessing the feature's quality [19, 20]. Therefore in this research we introduced a novel proposed framework.

The key contributions of this research are as follows,

- With the help of TransU-Net approach the segmentation is performed. The affected regions are segmented.
- The essential features are selected using Sine-Cosine Harris Hawks Optimization (SCHHO) algorithm.
- Finally the a novel framework is introduced for multiple paddy leafs classification, Optimized shuffle transformer is employed.
- To enhance the prediction performance even more the classification approach parameters are fine-tuned using Superb Fairy-wren Optimization Algorithm (SFOA).
- To simulate and evaluate the performances proposed approach was compared with existing approaches, proposed approach gain a superior performances.

Related Works

An automated method for precisely identifying and categorizing illnesses from a given image was presented by Haridasan et al. [21]. In order to protect paddy crops from diseases that commonly afflict Indian rice fields, the suggested system for the identification of rice plant diseases takes a computer vision-based approach that makes use of image processing, machine learning, and deep learning techniques. This lessens the need for traditional methods. To identify and categorize particular types of paddy plant diseases, convolutional neural networks and a classifier based on support vector machines are combined.

By detecting selective lesion traits, Salamai et al. [22] introduced a lesion-aware visual transformer for the precise and trustworthy diagnosis of rice leaf diseases. To capture a contextual local and global representation of illness traits at various scales and channels, a multi-scale contextual feature extraction network is introduced. In order to identify distinguishing lesions in paddy leaves that give the model discriminative leaf regions that can direct the ultimate categorization decision, a weakly supervised Paddy Lesion Localization (PLL) unit was then introduced. In order to improve the spatial exchanges among the visual semantics of paddy leaves, a characteristic tuning unit is proposed that empowers modeling the interactions among both local and global latent spaces.

Bharabidharan et al. [23] presented a method known as a filter-based feature transformation strategy to process the thermal pictures of paddy leaves and improve the accuracy of identifying different paddy illnesses using machine learning approaches. Every thermal image has seven statistical characteristics and seven Box-Cox transformed statistical features extracted. Four machine learning methods—the K-Nearest Neighbor classifier, Random Forest classifier, Linear Discriminant Analysis classifier, and Histogram Gradient Boosting classifier are then tested.

Padhi et al. [24] presents a hybrid Deep Learning method for the early and accurate diagnosis of rice diseases of the leaves that combines model hybridization and thermal imaging. This innovative application of thermal imaging improves the practicality and effectiveness of diagnosing illnesses. Utilizing transfer learning, 18 Convolutional Neural Network (CNN) models were assessed; statistical evaluation employing Duncan's multiple range test (DMRT) revealed that Darknet53 was the top-performing model.

PLDC-RBFNN-SSA is a suggested radial function neural network optimized using the Salp-Swarm technique for rice leaf disease segmentation was suggested by Raja et al. [25]. Regions of interest (ROI) for rice leaf disease are then segmented using Black Widow's k-means clustering algorithm on these preprocessed output images. An adaptive grayscale co-occurrence matrix windowing technique (GLCMWAA) is then used to extract radiation characteristics from the segmented output image.

Venkatraman et al. [26] suggested a hybrid deep learning (DL) algorithm that was created by adding a channel attention mechanism and the Swish ReLU activation function to the Squeeze-and-Excitation network architecture. During extraction of features and selection, our suggested model's channel attention mechanism determines which characteristics of channels are most crucial for categorization. The Swish ReLU activation function is used to alleviate the dying ReLU issue, and the Squeeze-and-Excitation blocks enhance cross-channel communication and information transmission.

A deep learning model to identify leaf illness automatically was introduced by Dubey and Choubey [27]. The first step is to transform the paddy leaf photos into an RGB color model. The noise in the green band is then eliminated using the median filter. The green band's texture and color characteristics are then taken off. Important characteristics are chosen following the extraction of features by using machine learning and optimization algorithms. First, an adaptive rain optimization algorithm (ARO) and support vector machine-recursive feature elimination (SV-RFE) are used to choose the features. The common features are then chosen. To determine if an image is a normal image, a Tungro image, a Bacterial Leaf Blight disease image, or a Blast illness image, the adaptive bi-long short-term memory (ABi-LSTM) algorithm is fed the chosen features.

Research Gap

The traditional techniques for identifying leaf diseases are based on human vision. In these situations, it takes a lot of time and money to get professional guidance. The methods that rely on human eyesight have numerous shortcomings. The hired person's or expert's eyesight determines how accurate and precise the human vision approach is. A machine learning-based approach makes it possible to recognize the many kinds of diseases, choose the best course of action, and choose the optimal treatment. The fact that machine learning-based approaches complete jobs more reliably than human specialists is one of its benefits. Therefore, a novel machine learning-based classification methodology is required to address the shortcomings of traditional methods.The subject of plant leaf disease detection using machine learning techniques has seen very few recent advancements, and the detection and categorization of paddy leaf diseases is the rarest of these.

Proposed Methodology

Diseases have a major impact on the quality and productivity of rice harvests, resulting in large yield losses and lower farmer incomes. Rice leaf diseases must be identified early and accurately in order to reduce their impacts, enhance rice quality, and guarantee higher farmer profits. Farmers have always relied on manual illness detection and classification, which is labor-intensive and prone to mistakes. Therefore in this research we introduced a novel framework for multiple paddy leaf disease classification. The below subsections are explained the proposed framework in detail. Figure 1 shows the overall proposed framework.

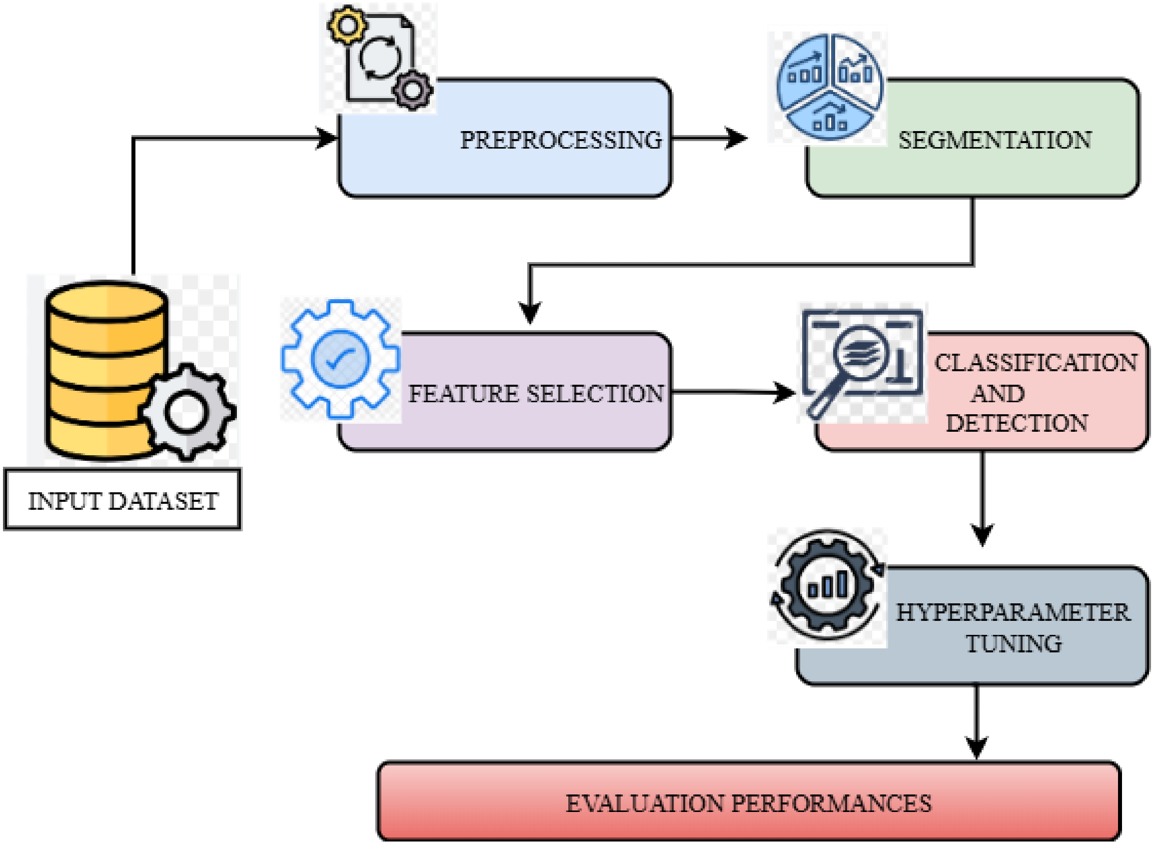


Figure 1: Overall Proposed Framework

Preprocessing

In image processing for crop disease identification, RGB images must first be converted to grayscale and then to thermal images. By concentrating on various facets of the image, every phase improves the analysis. By eliminating color information and leaving simply differences in intensity, grayscale conversion makes the image simpler. Spots, lesions, and unusual textures all of which are critical markers of diseases are highlighted in this way. Grayscale photos also lessen the processing load, allowing for a quicker and more effective examination.By recording temperature changes in the crop, which frequently correspond with disease-related stress reactions, thermal imaging provides an additional layer of vital information. Temperature variations between diseased and healthy plant components can provide an early diagnosis method even before outward symptoms show up. Because of this, thermal imaging adds a dimension to visual data, improving the accuracy of crop disease identification. Better crop management results from the strong, diversified approach to disease identification made possible by simulated thermal imaging. Sample preprocessed image is shown in figure 2.

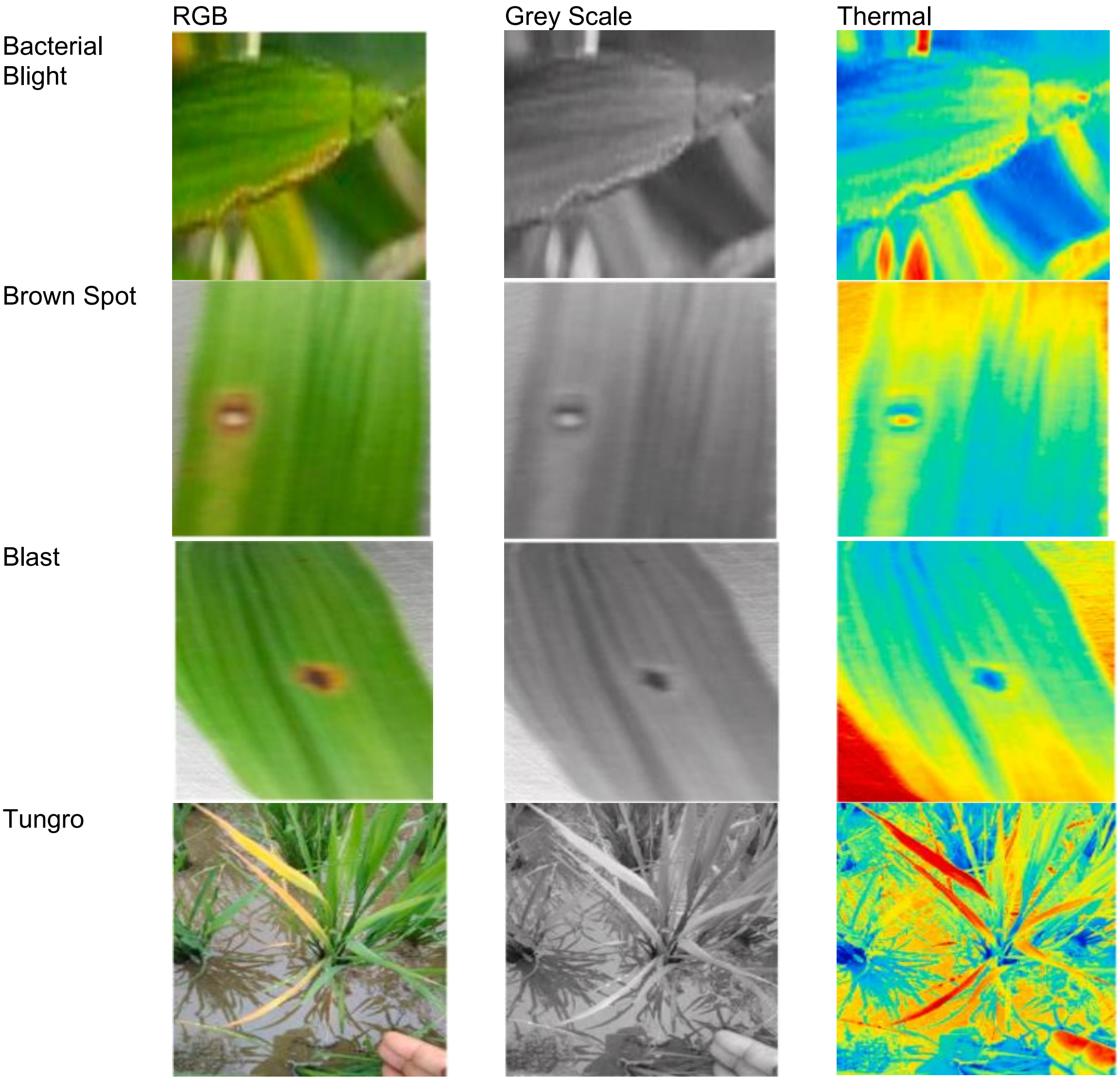


Figure 2: Samples of Preprocessing Images

Segmentation using TransU-Net

For segmenting the affected portions we used TransU-Net approach. The CNN encoder, CNN decoder, Transformer encoder and Transformer decoder are the four parts that make up TransUNet. Additionally, we construct the TransUNet framework in three different configurations, as described below, in order to perform a comprehensive analysis of the Transformer encoder and Transformer decoder and investigate their best implementation within U-Net topologies.

Only Encoder-Based

In order to create a map of features for the inputs, CNN is initially utilized as a method for extracting features in a CNN-Transformer hybrid encoder. Feature modifications are subjected to patch embedding rather than raw images. We employ a conventional U-Net decoder for the decoding stage. Because (1) it enables us to utilize the intermediate high-resolution CNN map of features in the decoding path, and (2) we discover that the ensemble CNN-Transformer encoder outperforms a pure Transformer as the encoder, we have chosen this architecture. A hybrid segmented loss that combines dice loss and pixel-wise cross entropy loss will be used to train the encoder-only strategy.

Only the Decoder

For the encoding stage in this setup, we employ a standard CNN encoder. In the segmentation model, we employ a CNN-Transformer ensemble decoder for the decoding stage. At first, the organ inquiries are set to zero. They are supplemented with accessible positional embeddings in accordance with Eq. (1) prior to processing by the Transformer decoder. P will be decoded again into the full-resolution segmentation map after being progressively improved based on the U-Net features. In accordance with earlier research, we train the network using the Hungarian matching loss to upgrade the organ queries across the decoding layers. Matching couples among predictions and ground-truth segments is the goal of this loss. For every segmented prediction, it combines binary mask loss and pixel-wise classification loss:

$L=\lambda 0Lce+Ldice+\lambda 1Lcls$

While binary cross-entropy loss and dice loss are indicated by the pixel-wise classification losses Lce and Ldice correspondingly. For every candidate region, the cross-entropy loss instantiates the classification loss. The hyper-parameters λ0 and λ1 are used to balance the mask categorization loss and the per-pixel segmentation loss. Additionally, we use deep supervision, applying the training loss to the output at every TransUNet decoder stage.

Encoder + decoder

In this case, we incorporate the Transformer encoder and Transformer decoder into the U-Net framework. The entire network is then trained using the Hungarian matching loss, just like in the decoder-only model. Histogram equalization of the segmented images are shown in figure 3.

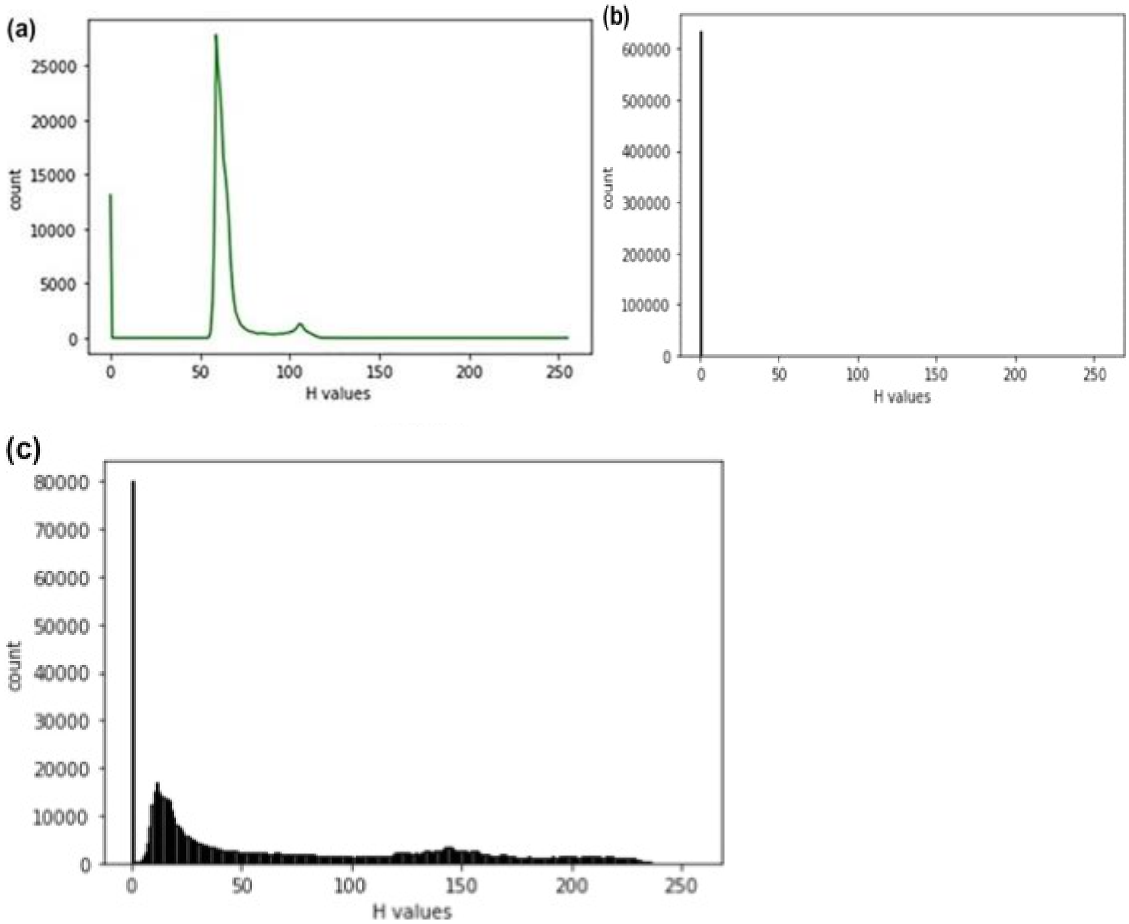


Figure 3: (a) Hue part histogram (b) Background removed blast impacted portion histogram (c) The backdrop histogram's normal section was eliminated.

Sine-cosine Harris hawks optimization (SCHHO) algorithm for selecting features

Here is an explanation of how the suggested SCHHO algorithm is applied to the feature selection problem. The procedure consists of three steps:

Setting up: The suggested technique begins by initializing N candidate solutions at random. Every xi is meant to represent a subset of characteristics based on its binary representation xi,jbin, which is accomplished using:

$x_{i,j}^{bin}=1$ if $x_i>0.5$ 0 otherwise (1)

Wherein a characteristic or dimension of a potential solution x_i is denoted by $x_{i,j}^{bin}$. Keep in mind that 0 indicates that a feature in the dataset is deselected; otherwise, it indicates that it is selected. For instance, if a dataset has five characteristics, then the issue dimension is also five. This means that a potential solution might keep values xi = [0.4, 0.6, 0.1, 0.7, 0.9], which would appear to be xi,jbin = [0,1,0,1,1] when transformed to binary.According to xbini, the method of learning should only be used to assess the second, fourth, and fifth attributes.Therefore, using Eq. (1), the intention function evaluates the fitness function of the i^{th} solution after every potential solution has determined the subset of characteristics:

$f_i=w_1\times\in_i+w_2\times d_iD$, $w_i=0.99$, $w_2=1-w_1$ (2)

Wherein the amount of characteristics chosen by the optimization technique, in this instance SCHHO, and the error $\in_i$ produced by the algorithm for learning are balanced by using the weights w1 and w2. The overall amount of characteristics in the initial dataset is denoted by D.

Updated solutions: This is where the primary SCHHO solution updating procedure is carried out, which includes exploitation and exploration. The optimal solution xprey is identified when the updated potential solutions are assessed using the fitness function. Until the termination criteria the maximum number of iterations in this study are satisfied, this process is repeated.

Classification The dataset is reduced by applying the chosen subset of characteristics that SCHHO was able to retrieve. Here, the hold-out technique is applied, in which the dataset is split into training and testing sets at random with an 80%:20% partition ratio. The k-NN algorithm is employed to classify results; for fair comparison, the algorithm is executed 30 times with random initialization.

Shuffle Transformer

A convolutional neural network (CNN) called the Shuffle Transformer uses three parts to identify local and global links among feature mappings in an image. The first modules is the window-based multi-head self-attention module (WMSA), which employs self-attention over the rows and columns to identify long-range dependencies among various image elements after converting the feature maps into a 2D grid. The following module, called the Neighbour Window Connection Module (NWC), captures local interactions and reduces computational complexity by connecting the feature maps of nearby pixels inside a tiny window.

After applying self-attention, the channels are shuffled using the shuffle window-based multi-head self-attention module (shuffle-WMSA), which enhances the network's capacity to identify difficult features by capturing a variety of information from the feature maps. These three modules work together to give the Shuffle Transformer cutting-edge picture categorization capabilities. The Shuffle Transformer can effectively and precisely capture complex elements in images by utilizing channel shuffling algorithms and a combination of global and local information. The Shuffle-Transformer's architecture is shown in Figure 4.

Superb Fairy-wren Optimization Algorithm (SFOA)

In order to address the optimization problem, the processes involved in implementing the suggested excellent fairy-wren method are first mathematically represented in this section.

Motivating

Superb fairy-wrens are little birds that weigh 8–13 g and are 14 cm long. The plumage of females and chicks is yellow-brown, but that of males is blue-black and gray. They are frequent resident birds that live mostly in damp forests in southeast Australia. They have slender bodies, pointed tails, and broad undersides. Through migration, these birds educate their young how to hunt and breed, and the young adults may go on to lead the new flock or protect the other chicks in the original flock from predators. Males exhibit wooing activities, such as spreading their bodies and presenting petals, throughout the spring to summer breeding season. They also impart "codes" to hatchlings through unique cries that aid in chick identification.

Excellent fairy-wrens use a cooperative reproductive approach, with groups of up to five individuals, comprising a pair of females and extra male helpers, defending their area all year long. Some men profit from supporting closest relatives because of the uneven sex ratio, which has fewer females. Although they also eat seeds, flowers, and fruit, their primary food source is insects. With a broad abdomen and a long, thin beak, they can hunt flexibly, but they are also susceptible to predators.

They use certain sounds and behaviors to alert their friends to danger. The creation of algorithms for optimization for superb fairywrens that replicate their natural behavior has been motivated by these habits and behavioral traits, which are essential for individuals reproduction.

Initialization

The suggested SFOA strategy utilizes a individuals-based approach that efficiently resolves the optimization problem of the real environment. The work that is listed in the search space will be used by each SFOA member to calculate the amount for the problem decision variable.In the meantime, the equation (3) will be used to initialize every SFOA member at the principal location at the start of the algorithm.

X=X1⋮Xi⋮XN=x1,1…x1,d⋮⋱⋮xi,1…xi,d…x1,D⋱⋮…xi,D⋮ ⋱ ⋮⋱⋮xN,1…xN,d…xN,D (3)

X=ub-lb×rand0,1+lb (4)

while r represents a random integer in the interval [0,1], N provides the amount of global members, Xi represents the ith SFOA member. The decision variables' upper and lower bounds are denoted by ub and lb, accordingly.

SFOA Mathematical Framework

The suggested SFOA approach's architecture updates the population members' locations in the problem-solving space by simulating the natural behavior of adults and juveniles of magnificent fairywrens.

Stage of Growth of Young Birds

The placements of individuals are modified during the SFOA growth phase using dynamic simulations, which necessitate extensive expertise for the development of young birds. Training from experiences is a sequence of process motions designed to cause broad shifts in SFOA members' positions, enhancing the global search algorithm's capacity for exploration. To get a better goal function, SFOA will use formula (5) to decide each member's location.

Xnewi,j=Xi,jt+lb+ub-lb×rand, r>0.5 (5)

Stages of Breeding and Feeding

By mimicking the magnificent fairy-wren's teaching mechanisms during breeding and nursing, the roles of individuals were modified in the subsequent phase of SFOA. The wrens will begin breeding when the risk criterion is low, and they will employ special paternity testing during egg incubation to stave off alien species invasion. Equation (6) illustrates how hazard thresholds are calculated.

s=r1*20+r2*20 (6)

Both of them, r1 and r2, are normally distributed random numbers. Owing to the cooperative reproduction traits of SFOA, several birds nurture eggs throughout the year in order to implement identification instruction. Each SFOA moves around during this cycle (m), taking turns feeding and instructing. By simulating this event, SFOA members' locations are somewhat altered, which increases the algorithm's use for local searches.Develop a factor p that grows as the length of the instructional cycle decreases. The corresponding member is then substituted if the objective function's value increases with the new spot.

Xnewi,j=XG+XbXi,jt×p, r<0.5 and s<20 (7)

XG=Xb×C (8)

Whereas C represents a constant with an integer value of 0.8 and Xb is the current ideal location.

p=sinub-lb×2(ub-lb)×m (9)

m=FEsMaxFEs×2 (10)

The present amount of assessment is indicated by FEs, while the maximum amount of analyses is indicated by MaxFEs.

Avoiding the Stage of Natural Enemies

The location of individuals in the population is modified during the predator reduction phase of SFOA based on the magnificent fairywren's defensive mechanism against predator assault.

When a predator spots the amazing fairy-wren, it dashes away, continuously flapping its wings to block the predator's line of sight. To notify other SFOA members, a warning sound is simultaneously played. In this scenario, a predator's target SFOA will swiftly flee, resulting in a minor shift in the member's position whose modes of motion are explained by a numerical equation (12).

Xnewi,j=Xb×Xi,j×l×k, r<0.5 and s>20 (11)

Simultaneously, Xb was included to regulate the birds' motion direction in order to stop them from heading in the direction of the bad position, which would have wasted evaluation time.

k=0.2×sinπ2-w (12)

w=π2×FEsMaxFes (13)

In order to avoid predators during flight, w represents the sound frequency value, which serves as a sign of trouble.

Result and Discussion

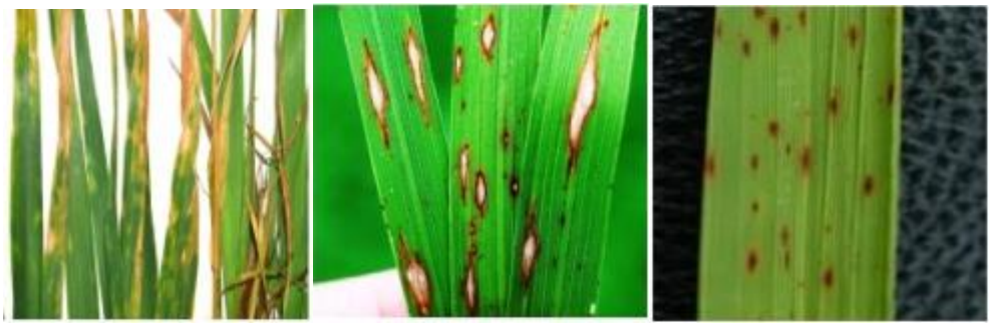
In this section we analyze the performances of proposed approach. Additionally we compare the proposed approach with existing approaches to show the effectiveness of the proposed framework. Along with sample images are also illustrated. Table 1 shows the parameters and their values.

Table 1: Parameter Setup

Parameter	Values
Batch size	64
Learning rate	0.001
Epoch	200
Momentum	10^{-9}
Optimizer	SFOA

Data Gathering

The procedure of gathering the photos utilized in this study is known as picture acquisition. We used a high-resolution digital camera to take pictures of the rice plant leaves from the actual farm field. All of the photos that were taken are then transferred to the computer where the process of execution will be completed in order to identify disorders. Images of leaves with varying degrees of disease spread are included in the dataset. The data set was gathered in the rural areas of Tamilnadu's Tirunelveli District, specifically in Ayikudi and Panpoli.A total of 650 photos are taken, of which 95 are of normal condition, 125 are of bacterial blight, 170 are of blast, 110 are of sheath rot, and 150 are of brown spots. See Fig. 2 for a selection of the example photos.



Bacterial Blight Blast Brown spot

Tungro

Figure 4: Sample Images

Evaluation Criteria

The effectiveness of the model is assessed using a number of other measures that are frequently employed in machine learning, in addition to accuracy. The confusion matrix is essential for measuring these metrics and provides a thorough understanding of how well the model differentiates between the various disease classifications. Eqs. (14)–(17) provide the mathematical expressions for the various performance measurements that are computed from the confusion matrix entries.

Accuracy=TpTp+Tn+Fp+Fn (14)

Precision=TpTp+Fp (15)

F1-Score=2×Precision×recallPrecision+Recall (16)

Recall=TpTp+Fn (17)

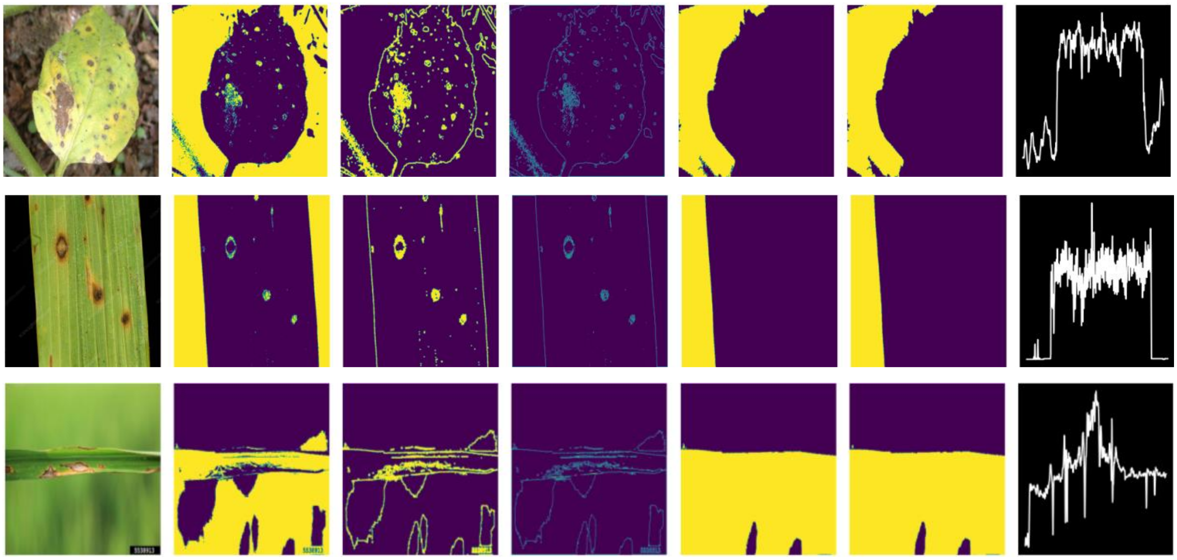


Figure 5: Sample Segmented Outcomes

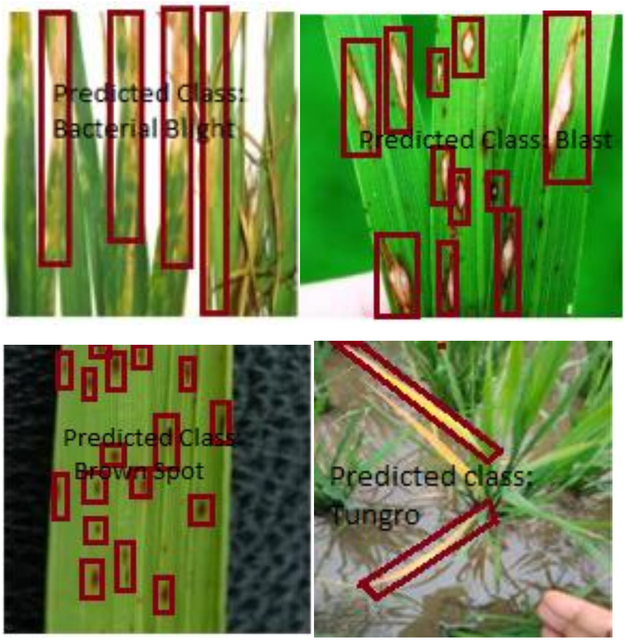


Figure 6: Sample Classified and Detected Images

Samples from segmented and classified images is shown in figure 5 and 6.

Table 2: Class Wise Performance

Metric	Bacterial blight	Blast	Brown spot	Turgro
Accuracy	97.2	99.3	96.8	94.7
F1-score	91.5	98.4	88.6	93.8
Precision	85.2	95.6	88.0	80.4
FDR	14.8	4.4	12.0	19.6
FPR	3.2	1.1	2.8	3.6
FNR	8.5	3.2	5.0	6.4
TPR	91.5	96.8	90.0	85.6
TNR	94.2	98.7	96.3	97.2
NPV	96.7	98.9	95.4	97.5

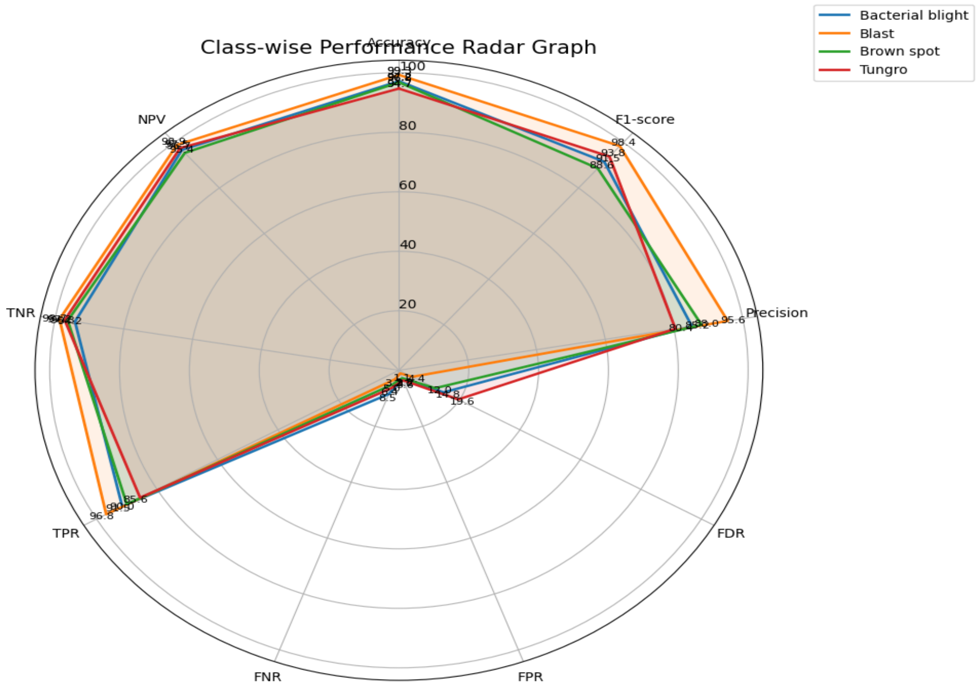


Figure 7: Differentiation of Class Wise Performances

Table 2 and figure 7 shows the differentiation of class wise performances. While comparing with existing approaches proposed approach gain a superior performances.

Table 3: Overall Performance Comparison

S.No	Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
1	DCNN	88.84	89.22	88.84	88.81
2	MobileNet	92.42	92.63	92.42	92.39
3	VGG16	93.19	93.42	93.19	93.20
4	Xception	96.58	96.61	96.58	96.57
5	ResNet34	97.50	97.52	97.50	97.50
6	Proposed	98.20	98.35	98.10	98.20

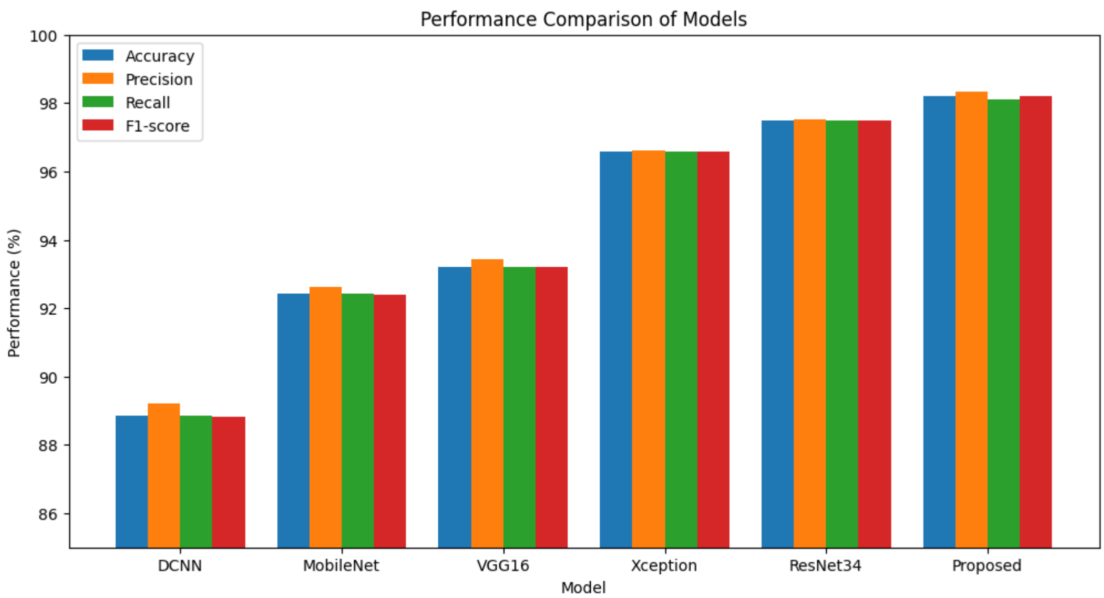


Figure 8: Overall Performances

Table 3 and figure 8 shows the overall performances of proposed approach. Differentiating with existing approaches, proposed approach obtain high performances.

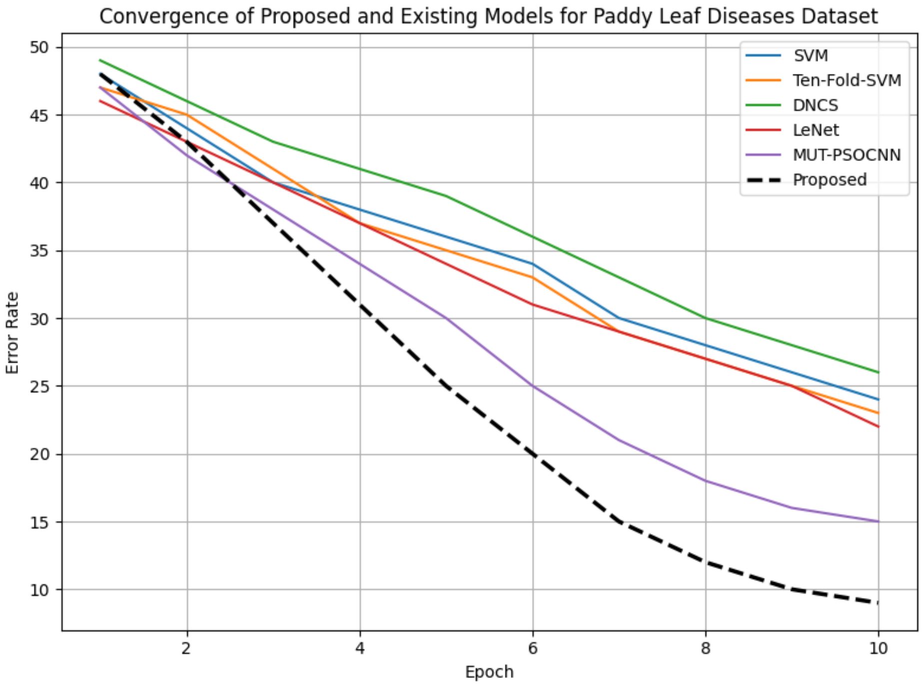


Figure 9 Shows the Convergence Graph.

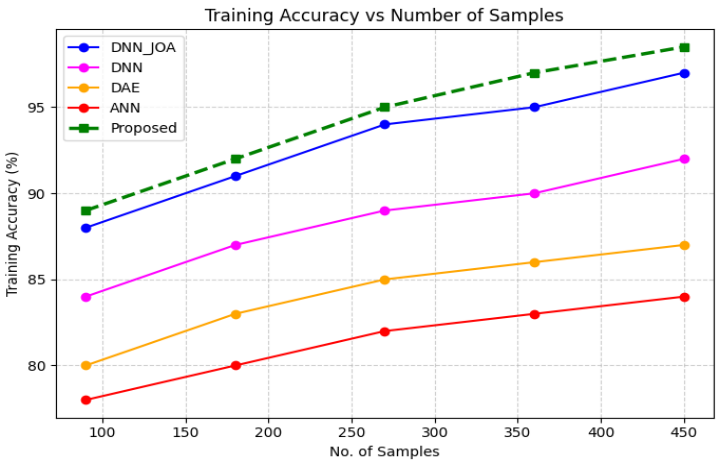


Figure 10 Shows the Training Accuracy Over Existing Approaches.

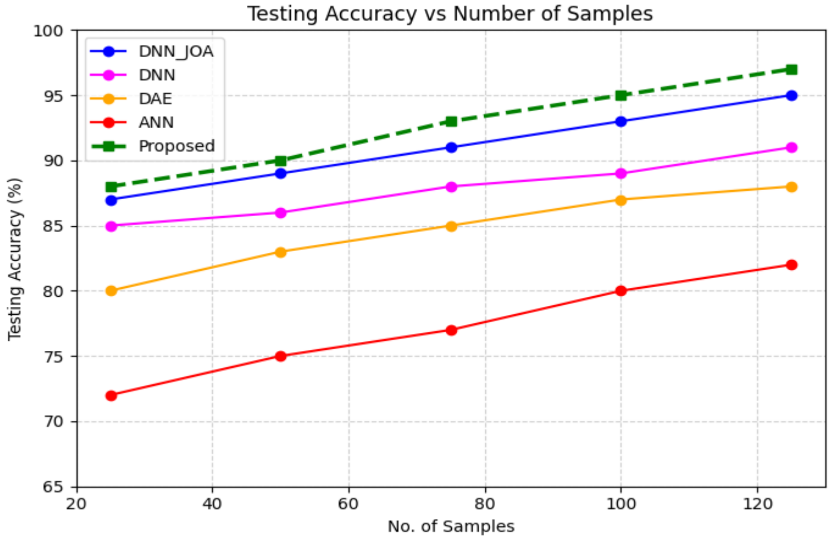


Figure 11: Testing Accuracy

Testing accuracy of proposed with existing approaches is shown in figure 11.

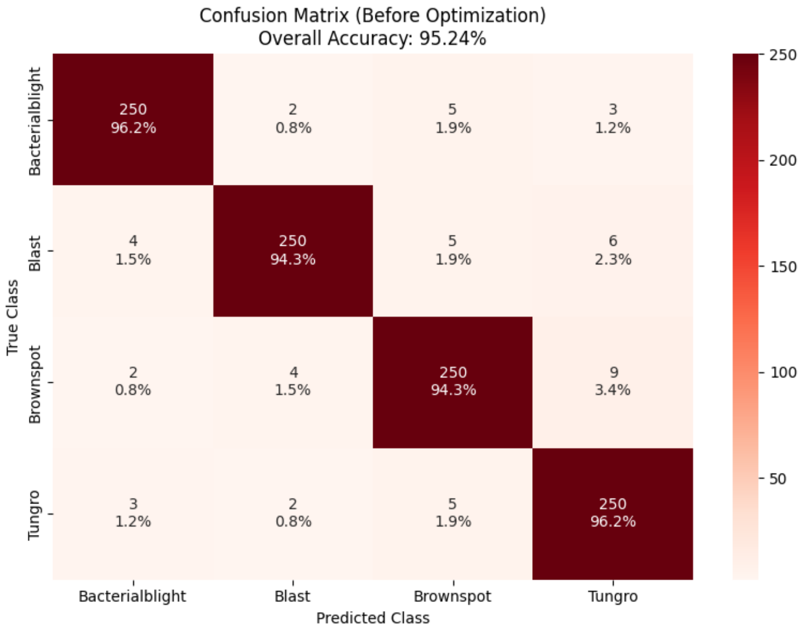


Figure 12: Confusion Matrix Before Optimization

Figure 12 shows the confusion matrix before optimization. Before optimization proposed approach perform less efficacy.

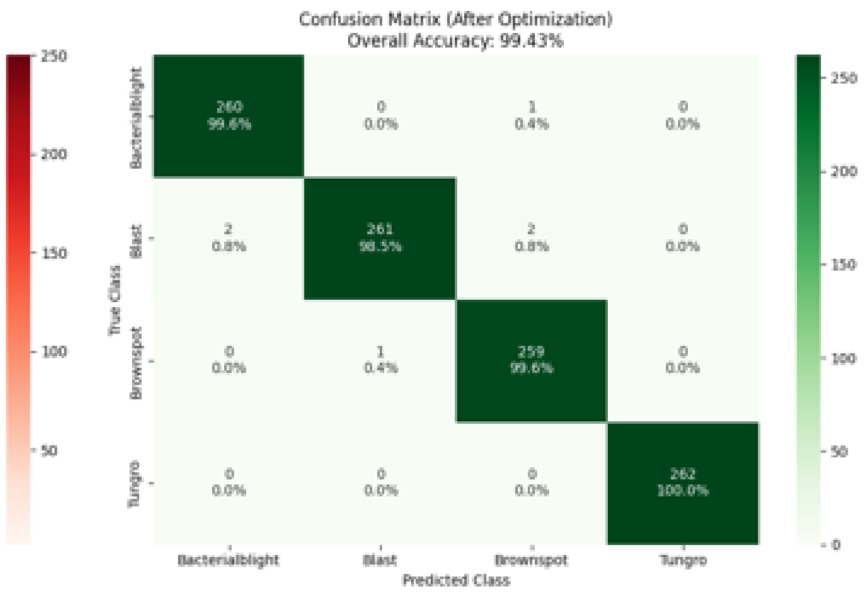


Figure 13: After Optimization

After optimization proposed approach performs higher effectiveness which is shown in figure 13.

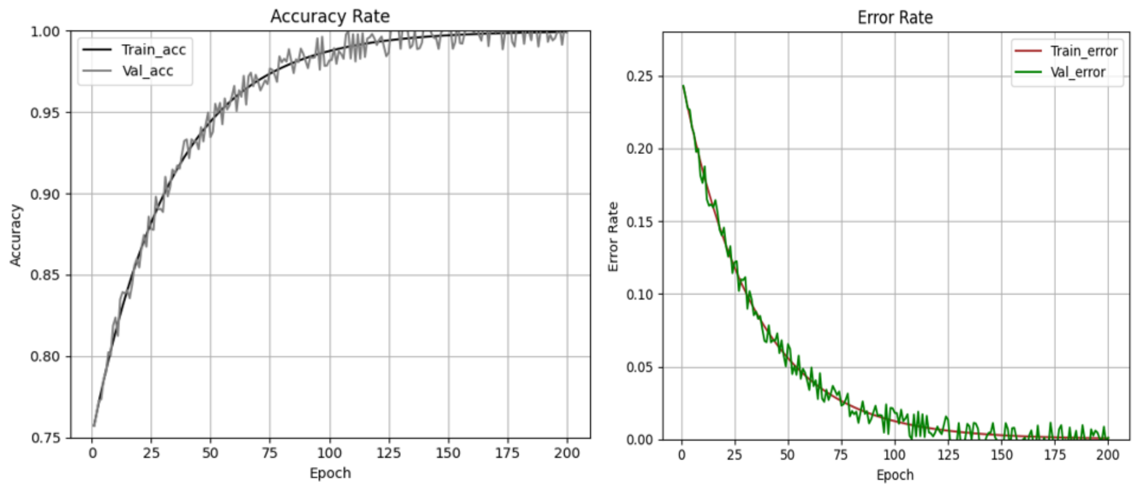


Figure 14: Learning rate 0.1 epoch 200

Figure 14 shows the learning rate 0.1.

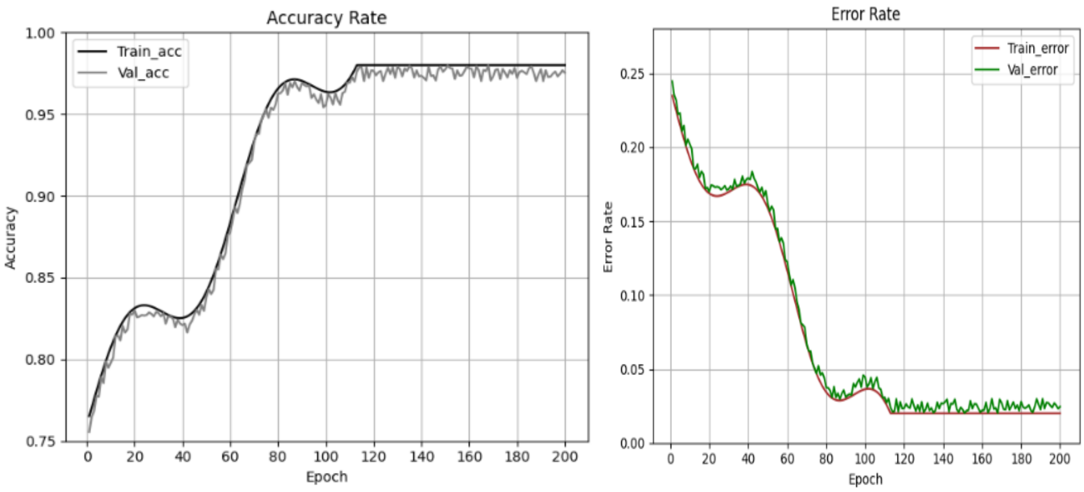


Figure 15: Learning Rate 0.01 Epoch 200

Figure 15 shows the accuracy and error rate while setting learning rate 0.01.

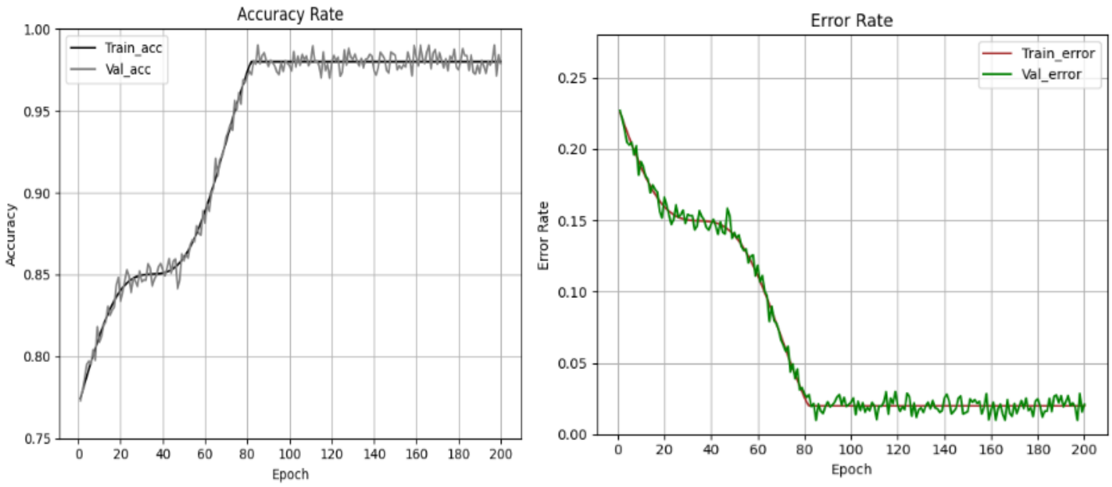


Figure 16: Learning Rate 0.001 Epoch 200

Figure 16 shows the accuracy and error rate while setting learning rate 0.001.

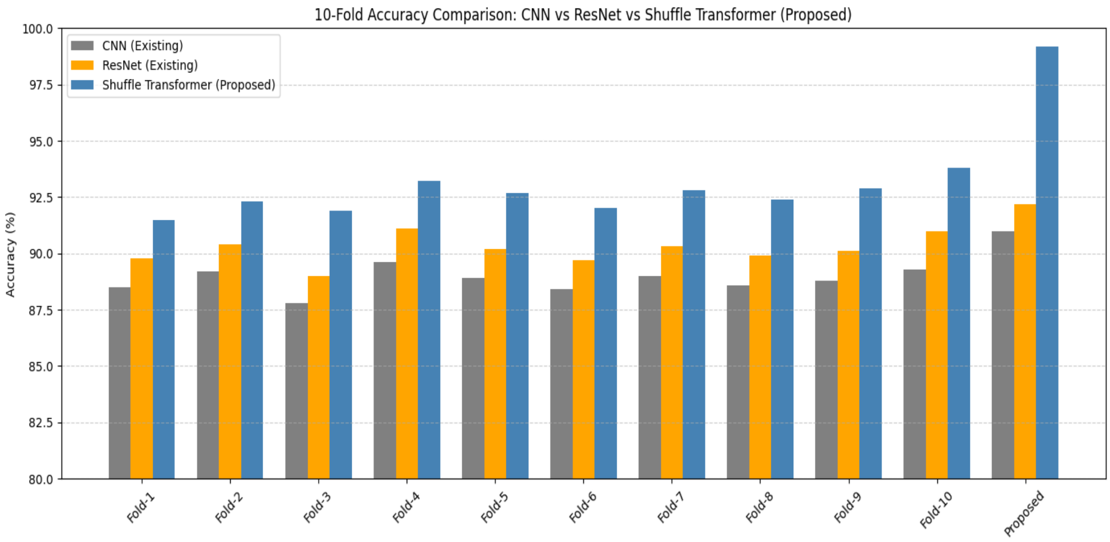


Figure 17: K-Fold Cross Validation

Figure 17 shows the k-fold cross validation analysis.

Conclusion

By using a hybrid deep-learning strategy that combines sophisticated classification algorithms with thermal rendering, this study offers a substantial advancement in the diagnosis of rice leaf disease. The model's capacity to detect diseases before outward symptoms appear is improved by the innovative technique of transforming natural images to thermal images, which enables early disease diagnosis based on temperature fluctuations.To complete some preliminary steps, the preprocessing stage first receives the raw input images. The impacted sections are divided once the preprocessing is finished. The segmentation is carried out with the aid of the TransU-Net technique. The Sine-Cosine Harris Hawks Optimization (SCHHO) algorithm is used to choose the key features. Lastly, a new shuffle transformer is used to classify the various paddy leaves. The Superb Fairy-wren Optimization Algorithm (SFOA) is used to fine-tune the categorized approach parameters in order to further improve the prediction performance. In addition to improving disease detection accuracy, the suggested framework supports sustainable agriculture practices by giving small-scale farmers a useful tool. This study makes a substantial contribution to precision agriculture by showing how crop management and disease monitoring can be advanced by integrating Deep Learning and conventional machine learning techniques.

Compliance with Ethical Standards

Conflict of Interest

The authors declare that they have no conflict of interest.

Human and Animal Rights

This article does not contain any studies with human or animal subjects performed by any of the authors.

Informed Consent

Informed consent does not apply as this was a retrospective review with no identifying patient information.

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Availability of Data and Material

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Code Availability: Not applicable

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