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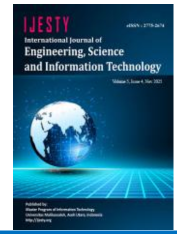

Vision Transformer-Based Multi-Head Self-Attention for Early Recognition and Classification of Paddy Leaf Diseases in Rice Fields

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Abstract

Rice has become an essential food source for a large portion of the world's population, greatly enhancing global food security. One of the fundamental staple crops, paddy, is especially susceptible to diseases primarily caused by bacteria and viruses. The source of the rice blast, Magnaporthe oryzae, poses a severe danger to the world's rice supply, mainly in South India. Both yield and quality are at risk due to the continuous threat of different diseases. However, a few diseases can drastically lower crop yields and quality, making agricultural productivity extremely vulnerable. Therefore, it is crucial to detect diseases at an early stage to effectively manage these risks. Scalable and effective solutions are required because conventional approaches are laborious, expensive, and frequently inaccessible to smallholder farmers. Data-driven strategies like machine learning (ML) and deep learning (DL), can assist in addressing these issues and increasing agricultural sustainability and crop yield. This study presents a new Vision Transformer-based hyperparameter optimization approach for the classification and detection of paddy leaf diseases in rice crops field (VTMHSA-RCPRF). The VTMHSA-RCPRF model comprises data preprocessing, ViT multi-head self-attention-based feature extraction, MLP-based Focal Loss for classification and detection, and Population-Based Training (PBT) as hyperparameter tuning. A wide range of experiments have been carried out to exhibit the promising performance of the VTMHSA-RCPRF method. The simulation outcomes highlighted that the VTH-RCPFRF approach reaches better performance over its recent approaches in terms of distinct measures.

Keywords: *Vision Transformer, Paddy Leaf Disease Detection, Multi-Head Self-Attention, Hyperparameter Optimization, Deep Learning.*

1. Introduction

As a main source of food production and the foundation of many economies around the world, Agriculture contributes significantly to the GDP (about 17%) of nations like India. Therefore, increasing crop yields and guaranteeing food security are important issues [1]. Environmental and biotic issues are among the difficulties facing modern agriculture. Plant roots, stems, leaves, flowers, and panicles are all impacted by biotic diseases, which are caused by bacteria, fungi, and pests. To determine the type of disease using traditional methods, professionals are required [2]. The obstacles to increasing crop productivity can be overcome by technological developments and innovative solutions. Based on the report of FAO (Food and Agriculture Organization), over 50% of people worldwide rely on rice (Oryza sativa L.) as their main food source. However, a wide range of diseases, including bacteria, viruses, and fungi, can seriously harm rice crops [3].
As the most vital staple crop, Rice provides sustenance to over half of the world's population. India ranks as the second-largest producer of both paddy and wheat [4]. Diseases like sheath blight, rice blast (a fungal disease that affects every part of the rice plant), bacterial blight (a fungal disease caused by Oryzae species), brown spots (Chochliobolus miyabeanus), flax spots, tungro, and leaf smut (a fungal disease that causes black spots) frequently affect the rice crop [5]. About 80% of rice crops are at risk due to these diseases, which can affect many plant components and spread quickly throughout the field. This might result in catastrophic famine as well as significant economic, social, and environmental losses.

The most destructive disease of rice (Oryza sativa L.) is rice blast, which is brought on by Magnaporthe oryzae [6]. It causes 10% of yearly crop losses worldwide and exacerbates food instability. Paddy is susceptible to a few diseases that can drastically lower its ideal and high-quality yield. Effective disease control depends on the prompt diagnosis and detection of plant diseases. To detect crop diseases, agricultural professionals have always relied on visual inspections. However, this method can cause delays in diagnosis and treatment because it is frequently expensive, time-consuming, and prone to human error [7].

The yield of the paddy was affected by diseases like bacterial leaf streaks, brown spots, rice blasts, and fake smut [8]. Early disease detection will enable farmers to take further measures to avoid crop loss, output loss, and financial loss. For a long time, farmers have visually assessed paddy plants for illnesses using their knowledge and crop management strategies, which may have resulted in mistakes. Utilizing cutting-edge technology to develop a model for monitoring plant disease, detecting the type of disease affecting paddy plants, and taking preventative measures to reduce crop loss [9].

Recently, crop imagery and computer-aided diagnostic techniques have become the most popular tools for monitoring leaf diseases and pests. Current developments in machine learning, deep learning, and image processing techniques have made automatic leaf disease detection seem like a promising tool that could improve the quantity and quality of rice production [10]. The demand for rice increases with population growth. Thus, disease control is essential in rice farming, and prompt detection of rice illnesses is necessary for efficient control and timely pesticide application. The purpose of this study is to develop and suggest a novel DL-based automated model for the classification and diagnosis of paddy leaf diseases.

In this work, we introduce a new Vision Transformer-based hyperparameter optimization approach for classification and recognition of paddy leaf diseases in rice fields (VTMHSA-RCPRF). The VTMHSA-RCPRF model comprises data preprocessing, Vision Transformer (ViT) multi-head self-attention-based feature extraction, MLP-based Focal Loss for classification and detection, and Population-Based Training (PBT) as hyperparameter tuning. A wide range of experiments has been carried out to exhibit the greater achievement of the VTMHSA-RCPRF method.

2. Literature Review

Identify different rice plant diseases like bacterial blight, brown spot, and blast using Convolutional Neural Networks (CNNs) and deep learning techniques. Images of various plant illnesses are used to the CNN model training, and multiple models are assessed to find the best one for identifying the disease [11]. The results of this study will help farmers manage diseases in a timely and efficient manner by advancing automated paddy disease diagnostics. In terms of classifying paddy diseases, the different models obtained varying degrees of accuracy.

Present a new hybrid DL approach for the early and accurate diagnosis of rice leaf diseases that combines model hybridization and thermal imaging [12]. Simulated thermal images were added to capture temperature changes that are suggestive of early stress reactions before symptoms become apparent. Transfer learning was used to evaluate CNN models. Duncan's multiple range test (DMRT) was used for analysis of statistics, and Darknet53 was found to be the best-performing model. Significant performance improvements were obtained by hybridizing Darknet53 by substituting a Support Vector Machine (SVM) for its dense layer. These findings demonstrate the model's efficiency for real-time implementation in agricultural applications, offering small-scale farmers a reliable and effective solution. This study provides a framework for tackling different crop diseases and emphasizes the importance of combining DL model and thermal imaging to improve the management of crop disease.

Develop and suggest a novel DL-based automated model for the classification and diagnosis of paddy leaf diseases. K-means clustering is used to group the data after it has been pre-processed by selecting the ROIs, labeling, enhancing, and segmenting it using adaptive thresholding [13]. Color, shape, and texture information were extracted using the MobileNetV3 model, a pre-trained transfer learning technique. The hybrid Genghis Khan Shark Optimization (GKSO) with Simulated Annealing (SA) model is used to choose the key features. In order to classify diseases, the selected features are then given to the CatBoost. Metrics including accuracy, sensitivity, and F1-score have been used to validate the system's performance as the DL methods for disease detection and classification.

Provide an effective and suitable method for identifying diseases in rice leaves using a DL approach. To meet the algorithmic requirements, images of rice leaf diseases were collected and processed [14]. 32 pretrained models were first used to extract features. Next, we used a variety of ML and ensemble learning classifiers to categorize the images of rice leaf diseases, including bacterial blight, rice blast, and brown spot, and compared the outcomes. The suggested process is more effective than the existing approaches. The model EfficientNetV2B3 with ET and HGB classifiers achieves better outcome even after the segmentation phase.

3. Methods

In this paper, an innovative VTMHSA-RCPRF method is presented for rice blast leaf disease classification. The VTMHSA-RCPRF technique has different kinds of procedures, such as data preprocessing, ViT-based feature extraction, MLP-based Focal Loss using classification and health detection, and Population-Based Training (PBT) for the hyperparameter tuning process. The overall working procedure of the VTMHSA-RCPRF algorithm is given in Figure 1.

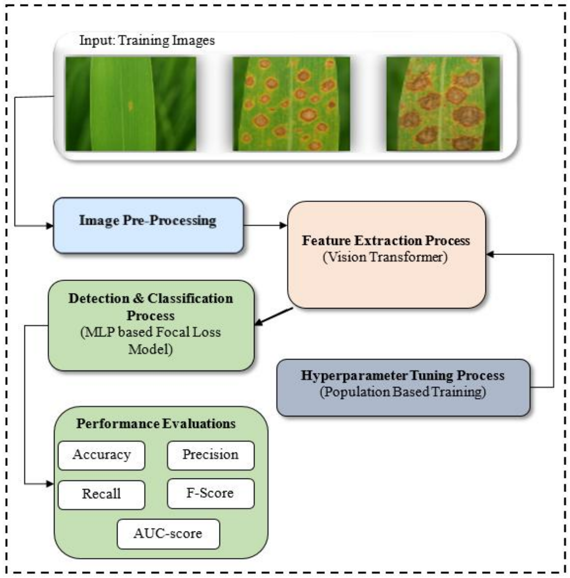

Fig 1. Overall working procedure of the VTMHSA-RCPRF technique

3.1. Data preprocessing

The first step is data preprocessing, which improves quality, normalizes values, and eliminates noise from raw rice leaf photos before they are analysed [15]. The key phases in DL are data preprocessing. A model's performance will be improved, and the output will be positively impacted if raw data is prepared correctly using necessary approaches. The suggested VTMHSA-RCPRF technology initially undergoes a WF-based image preprocessing step to eliminate the noise. As a linear filter, the WF reduces the mean square error (MSE) between the original and filtered signals. Its goal is to enhance images that have been deteriorated by additive noise. By modifying the filter's parameters, the WF strikes a balance between lowering noise and maintaining significant visual features. Eqs. (1), (2), and (3) provide a mathematical representation of WF.

$$\hat{S}(u,v) = G(u,v)X(u,v) \quad (1)$$

$$G(u,v) = \frac{H * (u,v)P_S(u,v)}{|H(u,v)|^2 P_S(u,v) + P_n(u,v)} \quad (2)$$

$$G(u,v) = \frac{H * (u,v)}{|H(u,v)|^2 + \frac{P_n(u,v)}{P_S(u,v)}} \quad (3)$$

The power spectrum of the signal and noise operations is indicated here by $P_S(u,v)$ and $P_n(u,v)$, respectively. P_s in Eq. (2) is divided to obtain Eq (3).

The contrast of an image is then improved using CLAHE (Contrast Limited Adaptive Histogram Equalization). In order to achieve this [16], CLAHE first divides the image into patches, and then, while maintaining the noise amplification limitation, equalizes the histograms of the patches. Local contrast will rise as a result, particularly in low-visibility regions, but noise will also be amplified, particularly in areas with low contrast or homogeneity. Although it is typically used in combination with other techniques to attain better outcomes, this increases the efficacy of CLAHE in image visibility enhancement over basic denoising.

3.2. Feature Extraction Using Vision Transformer (ViT)

By focusing on disease-relevant areas throughout the entire image, the Vision Transformer (ViT) multi-head self-attention-based feature extraction approach automatically learns both local and global leaf patterns [17]. As a variant of Neural Network model architecture, ViT processes visual input, particularly images, using a Transformer technique. ViT operates by converting the input images into small patches, each of which will be represented in vector form, as opposed to conventional techniques, which frequently employ convolutional layers for image processing. The Transformer model uses these patch vectors as input after they have been flattened into a one-dimensional sequence. To maintain the image's spatial context, positional information (position embedding) is added to each patch vector. This sequence is subsequently processed by the Transformer encoder, which includes a MLP and multiple self-attention layers. This enables the model to recognize the intricate relationships between various image components. The classification layer then receives the Transformer encoder's output and uses it to create class predictions.

3.3. Self-Attention

A crucial part of the Transformer architecture of ANN, the self-attention mechanism allows the model to concentrate on and assess the importance of different interactions between elements in a data sequence [18], like words in text or patches in an image. The fundamental steps of the self-attention mechanism are as follows:

Query, Key, and Value Representation: These representations are used for every image patch that undergoes a linear transformation.

Image Division: Like "words" or "tokens" in natural language models, images are divided into discrete parts. Every patch in the image is regarded as an entity that is treated with self-attention.

Normalization and Weighting: A SoftMax function is used to normalize the suitability scores, producing weights that highlight the patches that are most pertinent to the query patch. The values of the image patches are then multiplied by these weights to create a new weighted representation for each patch that considers how it relates to the other patches in the image.
Conformity Score Calculation (Dot Product): The conformity score (dot product) of each patch in the key image is queried with each other patch. The relevance of the patch-query to the patch-key is indicated by this score.
Integration and Output: The output of self-attention at the level of the entire image is created by combining the weighted representations of each patch. This output is subsequently used in further stages of the ViT model. The model can understand the relationship between each element in the data sequence and assess its significance with respect to other elements. With a stack of self-attention layers, this configuration develops into multi-head attention, which increases the model's efficiency to identify diverse relationships in the data.

3.4. MLP-based Focal Loss Model for Disease Detection

After that, the MLP-based Focal Loss model was employed to accurately classify and identify both healthy and blast-infected rice leaves [19]. A focal 1oss-based MLP classifier processes the feature-selected training data. The process of correctly classifying the data into the appropriate activity labels can be handled by this classifier. When it comes to addressing complicated datasets where linear models are inadequate, MLP's ability to capture non-linear correlations between features and target variables offers distinct advantages over conventional ML techniques. Furthermore, foca1_1oss enables the MLP to focus more on learning from difficult instances, including hard -to-distinguish or minority class samples, by lessening the influence of well-classified examples. This becomes more resilient to noise, outliers, and variations in the distribution by prioritizing the accurate classification of difficult instances.
The foca1_1oss function $L_{focal}(p,y)$ can be described by:

$$L_{focal}(p,y) = -(1-p)^{\gamma} \cdot \log(p) \cdot y - p^{\gamma} \cdot \log(1-p) \cdot (1-y) \quad \ldots (4)$$

Where y characterizes the actual label, which can be either 0 or 1, the predicted probability of the accurate class is, p and the focusing parameter that modifies how much weight is given to easier samples can be denoted as γ.
By down-weighting easy examples according to the value of γ, this approach highlights examples that are hard to classify. The model can focus more on cases that have been misclassified when $\gamma > 0$ since it lessens the loss related to correctly classified examples (where $p \approx 0$ or $p \approx 1$). The focal nature of the loss function is attributed to the increasing effect of down-weighting as γ grows.

3.5. Population-Based Training (PBT) based Hyperparameter Tuning

Lastly, the process of hyperparameter tuning for better disease classification performance is carried out using Population-Based Training (PBT). As a genetic algorithm, the PBT aims to increase the effectiveness of hyperparameter optimization [20]. The main concept of PBT is to gradually grow a population of models by enabling them to explore with various hyperparameter configurations and share data so that the optimal configurations can be exploited. When compared to conventional techniques, this dynamic and adaptive approach frequently yields faster convergence to optimal or nearly optimal solutions. Like the random search process, the hyperparameters are chosen randomly. For a few rounds, the models learn in parallel, but they never converge. After evaluating each model, the framework identifies the model that performs better. There are two ways to externally update each weight and hyperparameters during the PBT process.
Exploitation: Uses randomly chosen individuals from the upper quantile to replace the weights and hyperparameters of the poorest individuals in the lower quantile.
Exploration: Offers suggestions for extra hyperparameters to thoroughly investigate and analyze the solution space. Until the iteration for the hyperparameter change is finished, this step is repeated. The PBT can be expressed mathematically as follows:

Initialization of the Population: Hyperparameters are assigned at random from predetermined ranges to generate a population.

$$P = \{\theta_i, \gamma_i\})i = 1, N \quad \ldots (5)$$

Where N represents the population size, and θ_i and $1'i$ stands for the model's parameters and hyperparameters, correspondingly.
Model Training: Each model $\{\theta_i,)^{\prime i \}}$ is trained for a certain number of steps S, producing updated parameters:

$$\theta_i \leftarrow \mathrm{Train}(\theta_i, \gamma_i, S) \quad \ldots (6)$$

The ML technique and dataset being used determine which training function is used.
Performance Evaluation: Evaluate the model performance (F) on a validation dataset using a performance metric.

$$F_i = \mathrm{Evaluare}(\theta_i) \quad \ldots (7)$$

Selection and Exploitation: Arrange the models based on the metric's performance evaluation. Identify which models are underperforming. Replace underperforming models with modified copies of models that perform better.

$$(\theta_p)1'_p) \leftarrow (\theta_b, 1'_b) + \mathrm{Pe\pi urb}(1'_b) \quad \ldots (8)$$

Where $\mathrm{Perturb}$ is a function that modifies the hyperparameters $1'b$ in a modest way, and θ_b, γ_b is a high-performing model.

Perturbation of Hyperparameters (Exploration): Slightly mutate or perturb the selected models' hyperparameters:

$$\gamma_p \leftarrow \gamma_b + \delta \quad \ldots (9)$$

A minor random change is represented by the symbol δ. Until the iteration process has been completed or the convergence conditions are met, the process should be repeated.

The algorithm for PBT model is given below:

Algorithm: PBT approach

Initialize population $P = \{\theta_{i,r_i}\}, i = 1, N$

While not converged, do

for $each\theta_i, \gamma_i \in P$

$\theta_i \leftarrow Train(\theta_{ir_i}, S)$

$F_i = Evaluate(\theta_i)$

Sort models according to F_i

Replace the model that performs poorly

Perturb hyperparameters of selected models

End for

End while

4. Results and Discussion

In this study, the experimental validation outcomes of the VTMHSA-RCPRF method are examined utilizing the Kaggle dataset [21] includes 10431 annotated rice leaf images that were gathered from South Indian paddy fields between 2021 and 2024. The dataset includes both healthy and rice blast-infected plants, such as mild, moderate, and severe. Figure 2 shows the sample images of paddy leaf disease.

Table 1. Details on the database

Classes	No. of Images
Healthy	5869
Mild	3131
Moderate	885
Severe	556
Total No. of Images	**10431**

(a) Normal (b) Mild (c) Moderate (d) Severe

Fig 2. Sample images of Paddy Disease (a) Normal (b) Rice Blast (c) Moderate (d) Severe Leaf

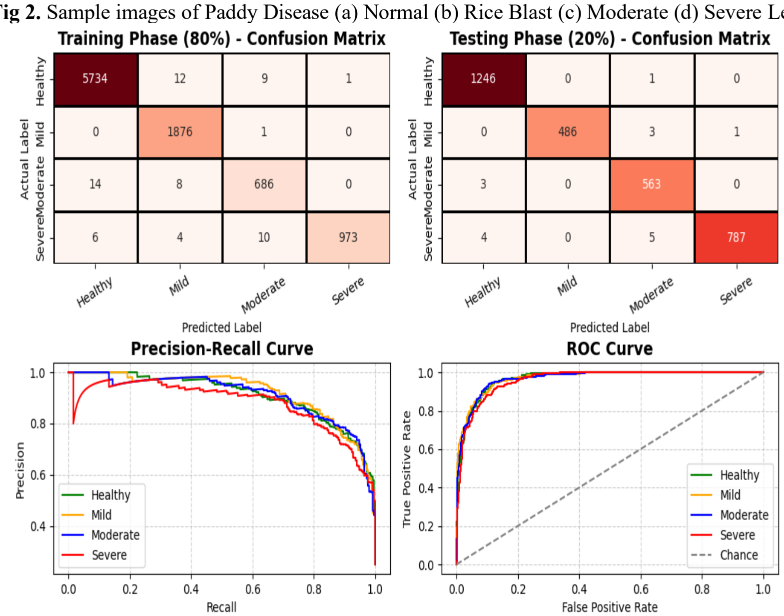

Fig 3. Rice-Blast Detection outcome of (a-b) 80% and 20% confusion matrices and (c-d) PR and ROC curves

Figure 3 demonstrates the Rice-Blast recognition findings of the VTMHSA-RCPRF method under the testing dataset. Figures. 3a-3b symbolizes the confusion matrices produced by the VTMHSA-RCPRF approach on 80:20 of TRPH/TSPH. The experimental analysis implied that the VTMHSA-RCPRF approach has familiar and classified all class labels exactly. Also, Figure. 3c validates the PR curve of the VTMHSA-RCPRF technique. The outcome stated that the VTMHSA-RCPRF method has increased maximum efficiency of PR under all classes. Lastly, Figure. 3d displays the ROC cruve of the VTMHSA-RCPRF technique. The result signified that the VTMHSA-RCPRF algorithm has resulted in effective performances with highest ROC values under various classes.
In Table 2 and Figure. 8, the Rice-Blast classifier outcomes of the VTMHSA-RCPRF method with 80:20 TRPH/TSPH. The experimental analysis designate that the VTMHSA-RCPRF system accurately classified distinct stages. With 80%TRPH, the VTMHSA-RCPRF model offers average 98.25%, $accu_y$ 97.36% $prec_n$, 98.16% $reca_l$, 99.72% F_{score}, and 98.27% AUC_{score}. Afterward, with 20%TSPH, the VTMHSA-RCPRF technique gets average 97.78% $accu_y$, 96.56% $prec_n$, 98.02% $reca_l$, 97.12% F_{score}, and98.32% AUC_{score}.

Table 3. Rice blast outcome of VTMHSA-RCPRF technique with 80:20 TRPH/TSPH

Class	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}	AUC_{score}
TRPH (80%)					
Healthy	97.20	97.89	99.34	97.61	98.50
Mild	96.66	96.30	99.43	99.86	97.66
Moderate	98.89	97.56	97.84	97.70	96.64
Severe	96.91	95.92	98.78	97.84	98.80
Average	**98.25**	**97.36**	**98.16**	**98.24**	**99.72**
TSPH (20%)					
Healthy	99.84	97.77	98.97	98.87	98.78
Mild	98.70	96.47	97.64	95.05	96.87
Moderate	97.96	98.44	96.88	97.15	95.13
Severe	96.94	97.79	95.25	98.52	98.49
Average	**97.78**	**96.56**	**98.02**	**97.12**	**98.32**

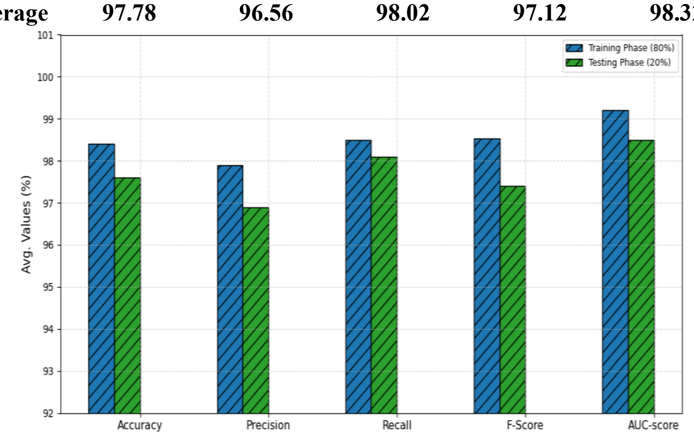

Fig 4. Average of VTMHSA-RCPRF method on 80:20 TRPH/TSPH

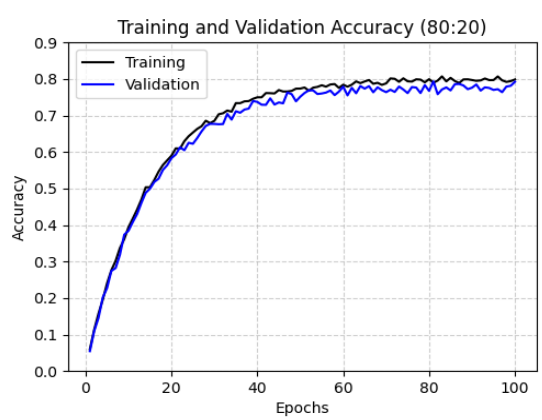

Fig 5. $Accu_y$ curve of VTMHSA-RCPRF method at 80:20 TRPH/TSPH

In Figure. 5, the training accuracy (TRAC) and validation accuracy (VLAC) outcomes of the VTMHSA-RCPRF model are demonstrated on 80:20 TRPH/TSPH. The TRAC and VLAC is evaluated over a range of 0-100 epoch counts. The figure emphasizes that the TRAC and VLAC values illustrate a rising tendency, which reports the skill of the VTMHSA-RCPRF approach with remarkable outcomes over various iterations. Besides, the TRAC and VLAC remain close over the epochs, which specifies low insignificant overfitting and exhibits improved performance of the VTMHSA-RCPRF method, assuring constant prediction on unseen samples.

In Figure. 10, the training loss (TRLS) and validation loss (VLLS) graph of the VTMHSA-RCPRF model is shown under 80:20 TRPH/TSPH. The TRLS and VLLS values are computed over a range of 0-100 epochs. It is signified that the TRAC and VLAC values explain a declining tendency, notifying the effeceincy of the VTMHSA-RCPRF approach to balance a tradeoff between data fitting and generalization. The steady decline in loss values further promises the greater efficiency of the VTMHSA-RCPRF method and tunes the prediction outcomes over time.

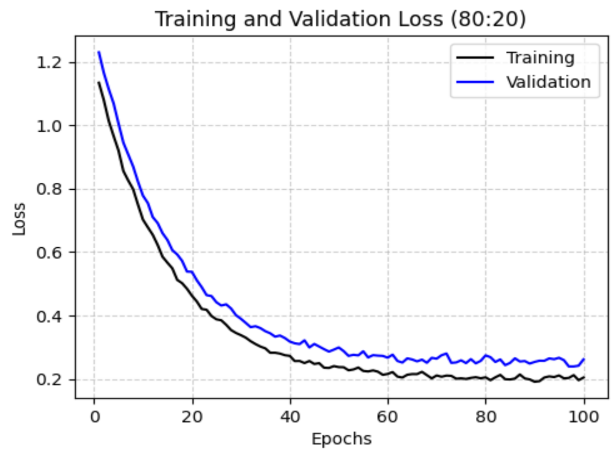

Fig 6. Loss curve of VTMHSA-RCPRF method at 80:20 TRPH/TSPH

To demonstrate the improved efficiency of the VTMHSA-RCPRF method, a brief comparison analysis is demostrated in Table 3 and Figure 7. The experimental study showed that the CNN and VGG19-SVM methods had poorer classification performance. The DenseNet-ISVM and ResNet-50 methods have attempted to get somewhat more accurate classification results in the interim. However, the VTMHSA-RCPRF technique demonstrates promising performance with 98.82% $accu_y$, 97.87% $prec_n$, 98.27% $reca_l$, and 99.07% F_{score}.

Table 3. Comparative study of VTMHSA-RCPRF with other technqiues

Classifiers	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}
VTMHSA-RCPRF	98.82	97.87	98.27	99.07
DenseNet-SVM	97.13	96.82	97.18	96.70
ResNet-50	97.13	96.42	98.98	95.70
CNN	97.96	98.18	95.46	96.32
VGG19-SVM	96.13	95.26	96.34	97.80

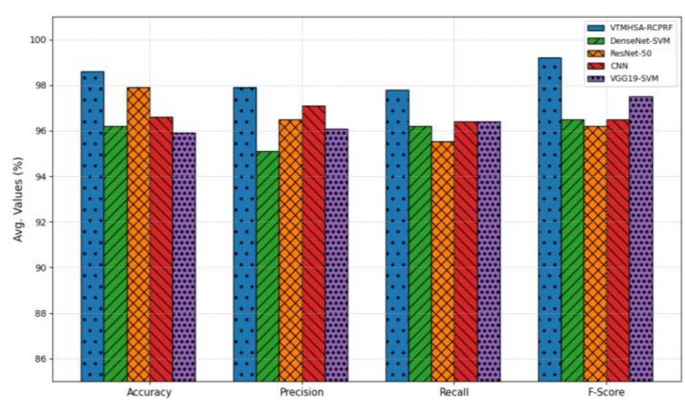

Fig 7. Comparative outcome of VTMHSA-RCPRF technique with other existing models

5. Conclusion

In this article, we present a new Vision Transformer-based hyperparameter optimization method for earlier recognition and classification of paddy leaf diseases in rice field (VTMHSA-RCPRF). The VTMHSA-RCPRF technique has different kinds of procedures such as data preprocessing, ViT-based feature extraction, MLP based Focal Loss using classification and detection of healthy and Population Based Training (PBT) for hyperparameter tuning process. A wide range of experiments have been carried out to exhibit the remarkable performance of the VTMHSA-RCPRF technique. The results highlighted that the VTH-RCPFRF technique reaches better performance over its recent approaches in terms of distinct measures.

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