

# VISION TRANSFORMER WITH PATCH ATTENTION FOR FINE-GRAINED BLACK GRAM LEAF DISEASE IDENTIFICATION AND SEVERITY ESTIMATION

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## ABSTRACT

Black gram, commonly known as urad bean, is a crop that is popularly cultivated and has substantial economic value in India, particularly in the southern and central regions. But black gram is vulnerable to several leaf diseases, and farmers face significant crop losses and financial difficulties. One of the most prevalent leaf diseases in black gram is yellow mosaic disease (YMD), which hinders healthy production and causes significant economic losses to local farmers. The quality and quantity of black gram are drastically decreased by this disease. Therefore, early and correct diagnosis is needed to control the disease appropriately and promptly. Plant leaf disease classification and identification have recently undergone a revolution thanks to deep learning-based pre-trained models. To resolve these problems, the study developed a Vision Transformer with Patch Attention for Fine-Grained Black Gram Leaf Disease Identification and Severity Estimation (VTPA-BGLDI) Model. To increase the number of image samples, data augmentation approaches were used at the initial phase for effective training. In the second phase, we designed a VT-driven classification model specifically tailored for Blackgram disease identification in analyzing yellow mosaic disease imagery. Before processing, the Vision Transformer (VT) splits the input image into smaller patches, which are then fed sequentially to the model in a manner similar to word embeddings. Lastly, the input images are classified into the appropriate class using a Multi-Layer Perceptron (MLP). The BPLD dataset comprises five distinct classes of plant disease images. Based on the experimental findings obtained from the BPLD dataset, we determined that the proposed VTPA-BGLDI technique outperforms existing approaches in classifying Yellow Mosaic Disease in Blackgram.

**KEYWORDS:** Blackgram, Agricultural sector, Plant Leaf Diseases, Deep Learning, Vision Transformer, Multi-Layer Perceptron.

## 1. INTRODUCTION

The agricultural sector serves a vital and indispensable role in sustaining the rapidly growing global population by ensuring the availability of essential food resources [1]. The continuous growth of the human population presents a significant challenge in maintaining and strengthening global food security [2]. However, the stability and productivity of agricultural systems are directly threatened by various factors, including the lack of arable land, the appearance of crop diseases, and climate change. A major obstacle to achieving food security is crop diseases, which are caused by several pathogens, such as bacteria, viruses, fungus, and other microbes. Crop productivity and quality can drop significantly as a result of these dangerous chemicals. To alleviate future damage in agricultural productivity and to enable the application of efficient disease management strategies, it is essential to quickly identify and accurately categorize these leaf plant diseases [3].

One important pulse crop with substantial nutritional and commercial value is the black gram (*Vigna mungo*). A legume cultivated in south India, *Vigna mungo* is otherwise called as black matpe, mash kalai, urad bean, uzhunnu parippu, urid bean, minapa pappu, ulundu paruppu, uddu, or black gram. Similar to its close relative, the mung bean, it has been taxonomically reclassified from the *Phaseolus* genus to the *Vigna* genus. Nonetheless, the crop is still vulnerable to a number of diseases that have a major influence on its growth and productivity, containing Yellow Mosaic, Anthracnose, Leaf Crinkle, and Powdery Mildew. Yellow Mosaic Disease (YMD), a serious production bottleneck for the black gram crop, cause yield reductions of up to 100%. The virus, which is transmitted by whiteflies, is a member of the family Geminiviridae and the genus Begomovirus (*B. tabaci* Gennadius). Rapid and accurate disease detection is crucial for managing Black Gram Plant Leaf Diseases (BPLD) effectively.

Traditional disease diagnosis techniques might be inaccurate and time-consuming. Consequently, incorporating deep learning (DL)-based disease categorization approaches have become a feasible way to enhance agricultural disease detection. The classification and identification of diseases in the agriculture industry has been revolutionized as a result of the development of DL technology. DL models make use of advanced neural networks that can handle enormous quantities of data and automatically recognize complex patterns and attributes. Accordingly, these models have proven to be highly reliable in distinguishing between diseased and healthy leaf plants. They have consequently developed into essential tools for contemporary agriculture, providing significant assistance in ensuring enhanced agricultural productivity and managing crops.

Ultimately, the effective implementation of DL-based disease detection methods holds great promise for improving food security. These systems have the potential to reduce crop losses and boost overall agricultural output by facilitating prompt disease diagnosis and making well-informed decisions black gram agriculture and beyond. Consequently, the goal of this research is to significantly advance the sustainable growth of global food system and agriculture. In this context, understanding the impact of these diseases on blackgram and exploring effective disease management strategies are essential for safeguarding this important crop and promoting sustainable agricultural productivity in the long term.

This study explores the various diseases that impact blackgram and their effects, highlighting the importance of research initiatives and disease prevention strategies in preserving the health and yield of this vital crop. It also seeks to harness the capabilities of deep learning techniques to accurately classify diseases affecting black gram leaves. To accomplish this objective, a comprehensive BPLD dataset comprising diverse disease samples is utilized for model training and evaluation. Through a systematic comparison of multiple DL approaches, the study aims to determine the most effective approach for disease identification, thereby contributing to improved agricultural management and productivity.

## 2. RELATED WORK

Talasila et al [1] present a unique Deep CNN (DCNN) for the categorization of Blackgram disease. To solve this problem, the first step is to use DeepLabv3 + layers with MobileNet-V2 as a feature extractor to separate the leaf region from every image in the dataset. Then, the proposed model undergoes noise injection augmentation, rotation, mirror symmetry, lighting correction, and random shifting. Finally, a DCNN model was developed for the detection and categorization of leaf diseases in black gram plants, taking into account a depth, wide range of parameters, and size of the contemporary CNN models. The segmented leaf regions from the BPLD dataset, collected directly from real agricultural fields, were utilized to train and evaluate the proposed DCNN framework. The performance of the model in disease recognition was assessed using 5-fold cross-validation. The experimental results demonstrate that the proposed DCNN outperforms existing advanced CNN models in classifying BPLD and shows strong potential for deployment in real-time applications.

Harika et al [2] introduce an image based-technique for identifying Blackgram Crop Disease (DBCD) based on images. In India, the black gram plant, commonly known as "Vigna mungo," is frequently referred to as "urad." This research focuses on four major diseases that adversely affect black gram yield: yellow mosaic, anthracnose, leaf crinkle, and powdery mildew. The BPLD dataset was employed to perform classification of these black gram crop diseases. For comparative evaluation, two DL models and three ML algorithms were implemented. The DL approaches include a CNN and an artificial neural network (ANN), while the ML techniques comprise random forest (RF), k-nearest neighbor (KNN), and decision tree (DT) algorithms. These methods were applied to accurately diagnose BGCN. Here, different classification methods are compared by measuring accuracy, precision, and recall. According to the analysis, CNN performs better than other classification models with a better accuracy rate.

Prasanth et al [3] propose a DL-based technique that uses support vector machines (SVMs), local binary patterns, and CNNs with 50 layers to correctly recognize and classify leaf diseases in blackgram leaf plants. Initially, a database of images of blackgram leaves was collected with yellow mosaic virus, leaf blight, and leaf spot. To improve the appearance of the image, data processing is performed. After that, we trained a CNN architecture to extract disease classification features from the plant leaf images with fewer parameters and lower LBP. By using SVM as a classifier on the CNN with the output features of the LBP model, the presented technique improves the accuracy of our model and reduces the amount of incorrect classifications. The simulation outcomes demonstrate that the presented approach outperforms other existing techniques. Finally, we demonstrate that BLPD can be accurately identified and categorized using deep learning techniques, particularly CNN and SVM.

Hridoy and Rakshit [4] suggested Black Gram CNN (BGCNN) for the identification of these diseases; BGCNN's performance has been evaluated against the most advanced DL models, including InceptionV3, AlexNet, and VGG16. The original dataset, which contained 2830 images, was used to train all the models. An enlarged dataset, which included 16,980 images created using image augmentation, considerably improved the testing accuracy. For both the enlarged and original datasets, BGCNN accomplishes accuracy rates of 82.67% and 97.11%, respectively. However, for the enlarged dataset, InceptionV3, AlexNet, and VGG16 have obtained accuracy rates of 93.78%, 95.49%, and 96.67%, correspondingly. The results obtained the effectiveness of BGCNN in identifying YMD.

Raman [5] suggests "Improved InceptionV3 Transfer Learning based Crossover Honey Badger (ITL-CHB)," an automated approach for detecting and classifying BPLD. There are five categories of plant disease images in the BPLD dataset. To boost the data diversity and address the problem of data imbalance, the BPLD dataset undergoes an augmentation procedure, including intensity leveling, scaling, and grayscale conversion. The CHB approach is used by the pre-trained InceptionV3 model to extract features with precisely determined hyperparameter values. As a result, the suggested ITL-CHB method accurately predicts and categorizes images of diseased and healthy leaves. Several performance measures are used to assess the efficiency of the suggested models. The comparison outcome shows that the ITL-CHB method was more successful in identifying and categorizing BGLD than other methods currently in use, including EfficientNet, SVM, CNN, and ResNet50, with better accuracy rate.

## 3. PROPOSED METHODOLOGY

In this work, preprocessing the data and training the VT model for BPLD classification are the two primary stages of the suggested methodology. Figure 1 illustrates our suggested VTPA-BGLDI framework, and the data augmentation is described in the following section.

### 3.1 Image Preprocessing

In the initial stage, the preprocessing is done to enhance the image quality of leaf plants and make them appropriate for the technique used [16]. The black gram leaf images are resized to  $320 \times 240$  pixels while maintaining their original aspect ratio. Because the images were collected directly from agricultural fields under uncontrolled conditions, they display variations in lighting, such as shadows and uneven illumination. To increase the quality of blackgram leaf images, histogram equalization is applied. Because the RGB color model does not clearly distinguish intensity components, the images are transformed into the HSV color space. HSV represents color information in a manner that better corresponds to human visual perception, allowing improved separation of color and brightness features.

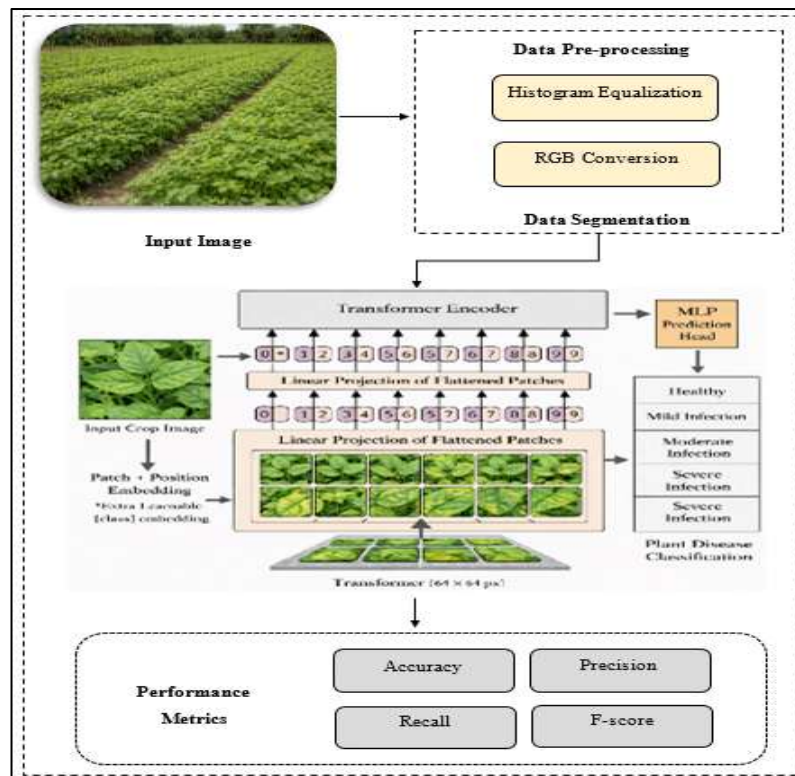


Fig. 1. Working process of the VTPA-BGLDI model

### 3.2. Image Segmentation

To determine the region of interest (ROI), the leaf images are segmented. Its goal is to split the disease-affected region. However, image segmentation is a difficult operation that is impacted by complicated backgrounds and fluctuating illumination. Through the segmentation procedure, unnecessary details are removed from the background of the images of blackgram leaves. To segment the ROI and the background, a leaf image mask is created using a variety of different colors. Morphological operations are subsequently applied to generate a leaf image with a black background. Following this, the color channels are converted into black and white intensity values to produce the final background-free image.

### 3.2 VT-based Disease Classification

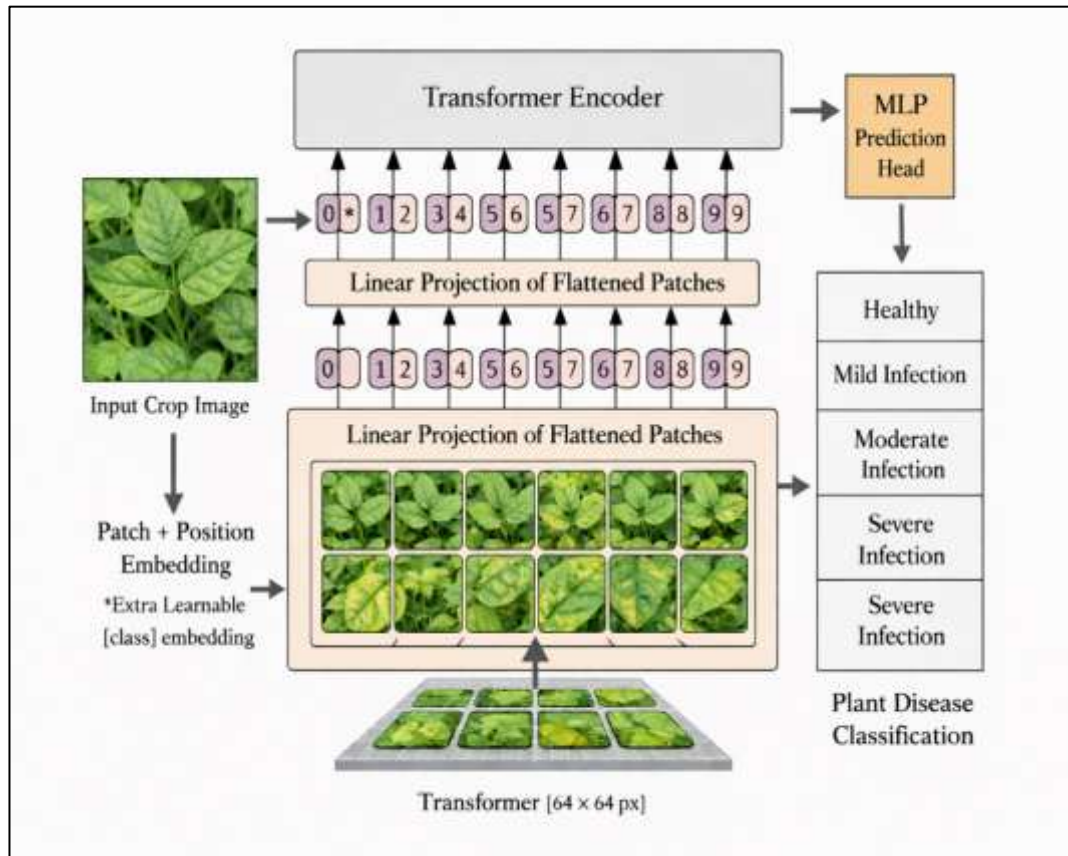
Vaswani et al. [17] proposed the transformer architecture, an encoder-decoder unit that transforms a given sequence of components into a different sequence. Enabling parallel data processing is the main idea behind the transformers. In this study, we investigated a VT architecture for BLPD classification, as illustrated in Figure 2, in which an image of 72 by 72 pixels is fed into the VT architecture as input data. The input image is first transformed into patches. The amount of patches that VT supports varies depending on the underlying scenario. The supplied image was divided into nine patches. Similar to word embeddings, the image  $X \in \mathbb{R}^{(H \times W \times C)}$  is transformed into a sequence structure when dealing with 2D images and fed into the transformer's input 2D patches  $X_p \in \mathbb{R}^{N \times (P^2 \cdot C)}$ , where  $(P, P)$  denotes the image patches' resolution and  $(H, W)$  denotes the original image's resolution. The effective length of the sequence of the transformer is  $N = HW/P^2$ . These patches were handled by the transformer similarly to how natural language processing tokens are handled.

Each layer of the transformer has a fixed width, and each vectorized path is mapped to the  $D$  model dimension using a trainable linear projection, the result of which is known as patch embeddings. The following is a description of the embedding, encoder, and classifier layers that make up the VT:

**Embedding Layer:** Each patch is processed as a separate token by the transformer, which then uses a learnable linear projection  $E$  to map to dimensions  $D$ . The learnable class token  $U_{class}$ , which is essential to perform the classification task, is fused with the embedding projections. To categorize the actual image, each patch's arrangement is tracked and maintained using the positional embedding  $E_{pos}$  as shown below.

$$Z_0 = [U_{class} \cdot X_p^1 E, X_p^2 E, \dots, X_p^N E] + E_{pos} \quad (1)$$

**Encoder Layer:** This stage involves receiving a set of embedded patches  $Z_0$  via the transformer encoder. After the VT generates  $L$  encoder blocks, these blocks are split into MLP and MHSA subcomponents.



**Fig. 2.** VT-based BPLD classification

The key constituent of the transformer encoder is the MHSA block, which has concatenation and self-attention layers. The input for the self-attention is  $x = x_1, x_2, \dots$ . As stated in Equation (2),  $X_n$ , the transformer, is in charge of performing an attention action concurrently on a set of queries ( $Q$ ) with all ( $K$ ) keys and ( $V$ ) values.

$$Atten(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{D}}\right)V \quad (2)$$

Now the weight matrices,  $W^Q$ ,  $W^K$ , and  $W^V$  must be learned in order to achieve the weights on the value, and a self-attention is represented as  $Atten$ . After scaling by the square root of  $D$ , the dot product between the query ( $Q$ ) and all keys ( $K$ ) is calculated, and the Softmax function is employed to obtain normalized attention weights. The transformer then performs multi-head attention by executing scaled dot-product attention in parallel across multiple heads, each with distinct learnable weight parameters. The final output is created by fusing all of these attention heads, as stated in Eq. (3).

$$MHSA(Q, K, V) = conc(Atten1, \dots, Attenh)W^O \quad (3)$$

The learning parameter matrices in Eq. (3) are  $W_i^Q$ ,  $W_i^K$ ,  $W_i^V$  and  $iV^O$ , while MHSA represents the combined attention heads. Eqs. (4) and (5) demonstrate that the encoder portion is made up of similar layers since  $L$ . The blocks are made up of  $GeLU$  activation and two dense layers. The encoder uses a skip connection, and layer normalization (LN) comes before the output.

$$z'_l = MHSA(LN(Z_{l-1})) + Z_{l-1}, \text{ where } l = 1, 2, 3, \dots, L \quad (4)$$

$$z_l = MLP(LN(z'_l)) + z'_l, \text{ where } l = 1, 2, 3, \dots, L \quad (5)$$

**Classification layer:** To predict the encoder's final layer for classification, the sequence's initial item,  $Z_l^0$ , is obtained and fed into an external head classifier is given as follows:

$$y = \text{Layer Normalization}(Z_l^0) \quad (6)$$

In this case,  $Z_l^0$  is the first item considered for the decision, and  $y$  is the model's output. The training and testing of the VT model are given in Algorithm 1.

**Algorithm 1** Pseudocode the VT architecture

Input: Dataset of BLPD images  
 Dataset split: Training, Validation, and Testing  
 Output: predicted labels(Healthy, Mild, Moderate, Severe)  
 Training: Model parameters,  $P$ : 9, Mini-batch size: 32, Optimizer: AdamW, Image size: (224, 224, 3),  $N$ , number of samples, Learning rate: 0.0001, Loss function: Cross-Entropy

Set the number of mini-batches as:  $N_b = \frac{N}{b}$

For fold = 1 to 5

For iteration = 1: number of epochs

For batch = 1, number of mini-batches

- Perform Image augmentation
- The obtained augmented training batch is fed to the VT encoder
- Add position encoding
- Passs through MHSA block
- Extract classification tokens (CLS token)
- Feed CLS token to the MLP classifier
- Compute Softmax output probabilities
- Calculated Cross-Entropy loss
- Perform Lossbackpropagation
- Update model parameters using AdamW optimizer

Model testing:

1. Feed the input image into the trained VT model
2. Extract CLS token representation
3. Calculate the predicted label ( $\hat{y}$ ) using Softmax output
3. Experimental Outcomes

#### 4. EXPERIMENTAL RESULTS

In this study, the stimulation outcomes of the VTPA-BGLDI algorithm are tested under the BPLD dataset [18] with 6437 samples and four classes collected under natural field conditions, as shown in Table 1. A publicly available dataset obtained from Mendeley Data was utilized for the classification of blackgram leaf conditions. The images were carefully annotated and categorized into four classes based on severity levels: Healthy, Mild, Moderate, and Severe infection stages of YMD. The sample image of the blackgram is shown in Figure 1.

The dataset was collected to develop an automated leaf disease recognition and severity estimation framework using advanced computer vision and DL approaches. The images capture variations in illumination, background complexity, and symptom progression, making the dataset suitable for real-world agricultural applications.

State-of-the-art DL approaches were performed to classify disease severity with high accuracy. A comprehensive performance comparison was conducted using multiple evaluation metrics to evaluate the effectiveness, robustness, and generalization ability of each model. The experimental results provide valuable insights into automated disease recognition and severity grading, contributing to precision agriculture and improved crop disease management strategies.

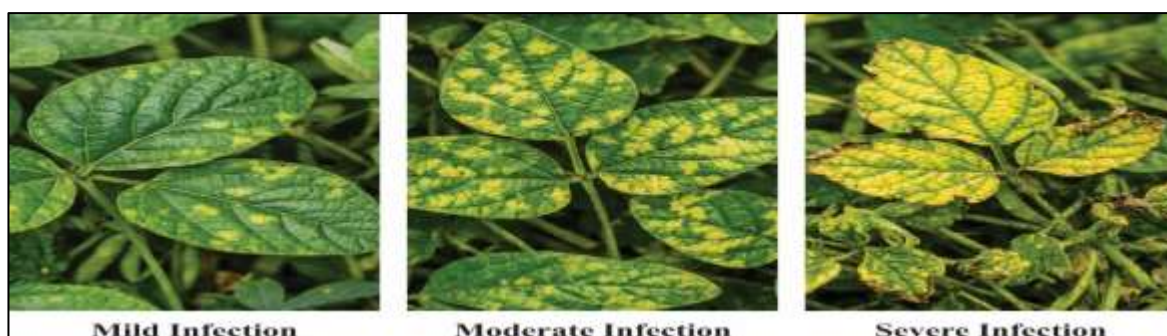


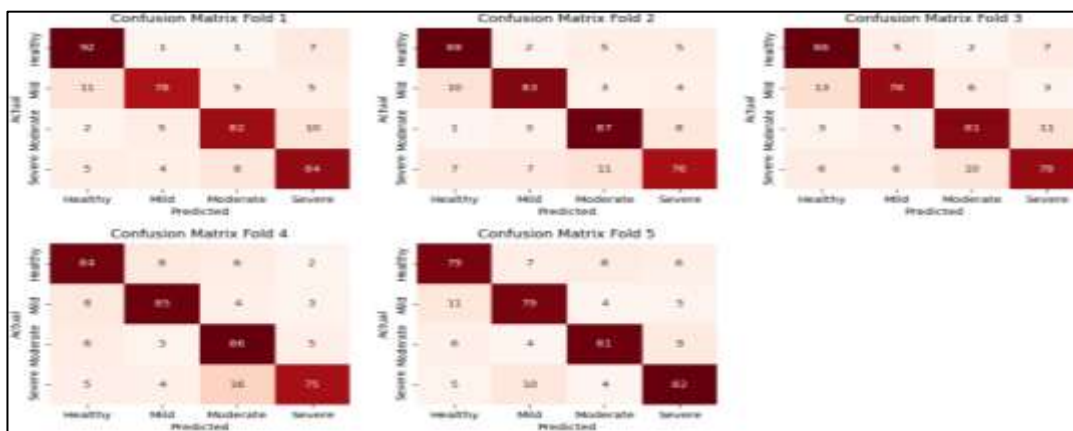
Fig. 3. Sample images of YMD in Blackgram

Table 1. Details on the dataset

Classes	No. of Samples
Healthy	3406
Mild	1843
Moderate	786
Severe	312
<b>Total No. of Samples</b>	<b>6437</b>

The confusion matrices produced by the VTPA-BGLDI method under TRAPH/TESPH are demonstrated in Figure. 3. The experimental value shows the detection and classification of five classes. The confusion matrix presented above represents the averaged classification results obtained using stratified 5-fold cross-validation. The dataset was divided into four equal subsets, used for the training phase (TRPH) and one fold for the testing phase (TSPH). This process was repeated five times, ensuring that each sample was used once for validation. The final confusion matrix was computed by averaging the outcomes across all five folds to ensure robustness and reduce bias caused by a single data split.

The diagonal elements of the matrix indicate correctly classified samples for each class (Healthy, Mild, Moderate, and Severe), while the off-diagonal elements represent misclassifications between severity levels. Higher diagonal values demonstrate the strong discriminative capability of the proposed model across different disease severity stages. The confusion matrix also reveals the model's capability to differentiate between adjacent severity levels (e.g., Mild vs. Moderate), which is typically more challenging due to similar visual symptoms. Minimal misclassification among severity stages indicates effective feature extraction and reliable classification performance. Overall, the averaged confusion matrix confirms the stability, consistency, and generalization ability of the proposed framework across multiple validation folds.

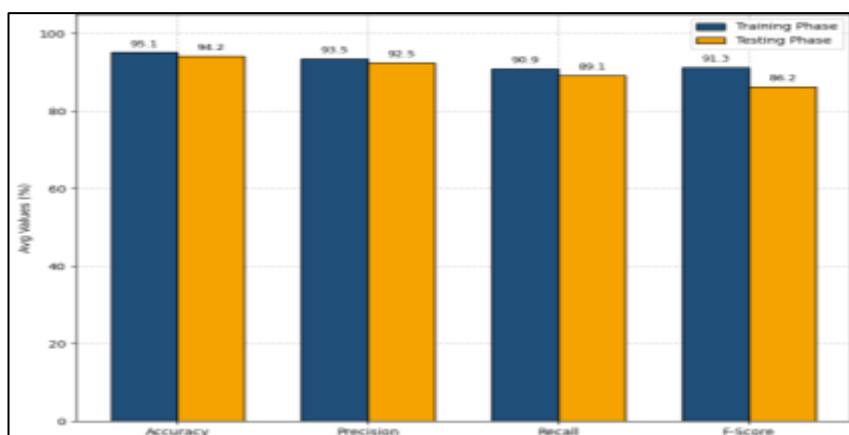


**Fig. 4.** Confusion matrix of the VTPA-BGLDI method under TRPH/TSPH

Table 2 and Figure 4 demonstrates the intrusion detection outcome of the VTPA-BGLDI method is examined under TRPH/TSPH. The outcomes highlighted that the VTPA-BGLDI method effectively identified five types. With TRAPH, the VTPA-BGLDI technique achieves average  $accu_y$ ,  $prec_n$ ,  $reca_l$ , and  $F_{score}$  of 95.13%, 93.51%, 90.01%, and 91.30%, respectively. Followed by TSPH, the VTPA-BGLDI method attained average  $aaccu_y$ ,  $aprec_n$ ,  $areca_l$ , and  $af_{score}$  of 94.24%, 92.52%, 89.10%, and 86.24%, correspondingly.

**Table 2.** Classification outcomes of the VTPA-BGLDI method under TRPH/TSPH

Classes	$Accu_y$	$Prec_n$	$Reca_l$	$F_{score}$
Healthy	94.65	95.19	87.60	99.64
Mild	95.32	96.61	90.81	93.28
Moderate	95.27	97.78	90.77	94.74
Severe	95.29	79.05	90.86	77.56
<b>Average</b>	<b>95.13</b>	<b>93.51</b>	<b>90.01</b>	<b>91.30</b>
Healthy	93.73	90.15	86.55	95.23
Mild	94.45	95.61	89.96	88.80
Moderate	94.38	96.97	89.90	90.18
Severe	94.42	77.38	89.98	70.74
<b>Average</b>	<b>94.24</b>	<b>92.52</b>	<b>89.10</b>	<b>86.24</b>

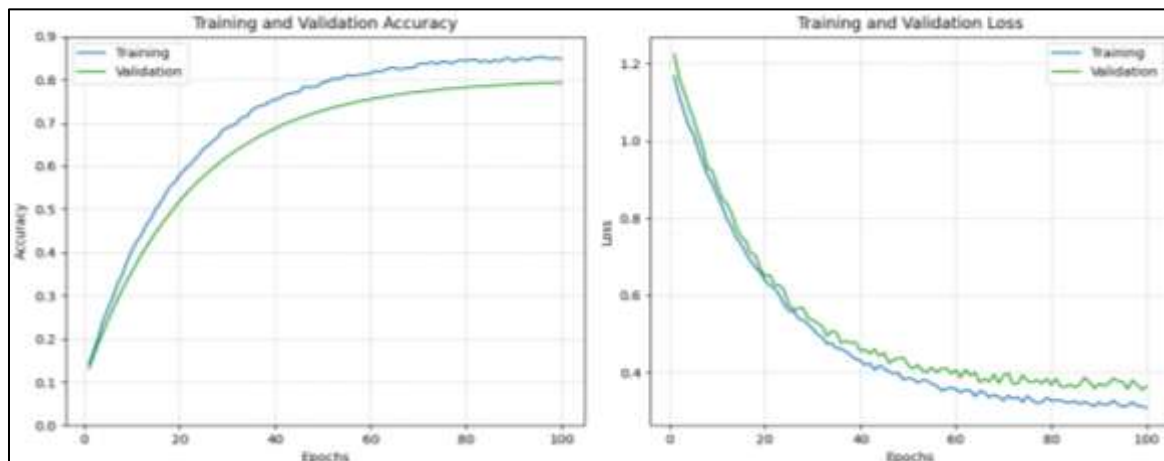


**Fig. 5.** Average of the VTPA-BGLD technique under TRPH and TSPH

Figure 5 illustrates the performance of the VTPA-BGLD technique on the TRPH and TSPH datasets using training accuracy (TRAC) and validation accuracy (VLAC) curves. The results offer clear insight into the model's learning progression and its ability to generalize across epochs. As the number of training epochs increases, both TRAC and VLAC exhibit a consistent upward trend. This pattern reflects the capability of the VTPA-BGLD model to effectively capture underlying patterns. Furthermore, the continuous rise in the VLAC curve demonstrates that the model not

only fits the training data well but also sustains strong predictive performance on unseen samples, confirming its robust generalization ability.

Figure 5 offers a comprehensive analysis of the training loss (TRLS) and validation loss (VALS) of the VTPA-BGLD technique on the TRAPH and TESP datasets across different epochs. The gradual decline in training loss indicates that the model effectively updates its weights, thereby reducing classification errors on both datasets. These results reflect the strong learning interaction between the VTPA-BGLD model and the training (TR) data, highlighting its capability to extract meaningful patterns. Moreover, the continuous decrease in loss values demonstrates that the model consistently refines its parameters to minimize the gap between predicted outputs and actual training class labels.

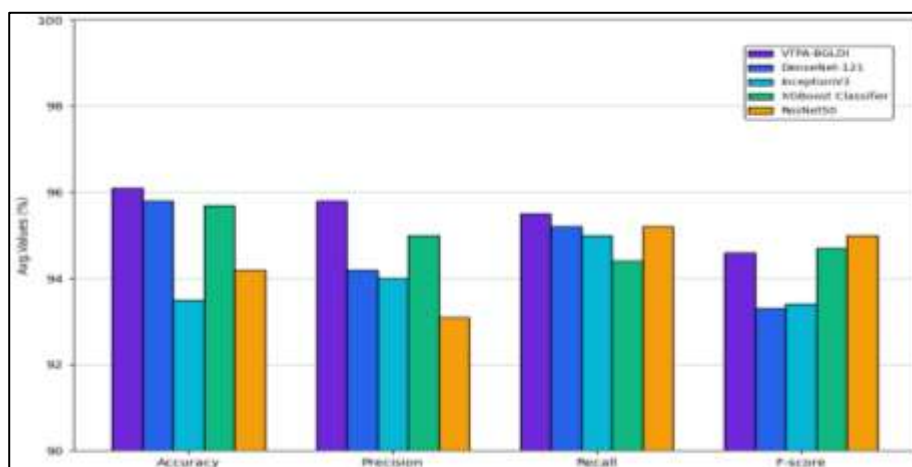


**Fig. 6.** Accuracy and loss curve of the VTPA-BGLD method under TRPH and TSPH

Table 4 and Figure 6 present a comparative evaluation of the VTPA-BGLD technique against several existing models. The results indicate that VTPA-BGLD achieves the superior performance, recording an  $acc_y$  of 96.20%,  $prec_n$  of 95.80%,  $reca_l$  of 95.40%, and an  $F_{score}$  of 94.70%. While DenseNet-121 and the XGBoost Classifier also perform well, their metrics are slightly lower, with accuracy around 95.70–95.80%. InceptionV3 and ResNet50 show relatively lower results, particularly in terms of accuracy and precision. These observations confirm that VTPA-BGLD provides more robust and reliable classification compared to the other methods evaluated.

**Table 4.** Comparative outcomes of the VTPA-BGLDI approach with other algorithms

Methods	$Accu_y$	$Prec_n$	$Reca_l$	$F_{score}$
VTPA-BGLDI	96.20	95.82	95.40	94.70
DenseNet-121	95.82	94.35	95.14	93.31
InceptionV3	93.54	94.24	94.70	93.52
XGBoost Classifier	95.71	95.25	94.55	94.80
ResNet50	94.30	93.12	95.22	95.12



**Fig. 7.** Comparative outcomes of the VTPA-BGLDI technique with other algorithms

## 5. CONCLUSION

In this study, we developed Vision Transformer with Patch Attention for Fine-Grained Black Gram Leaf Disease Identification and Severity Estimation (VTPA-BGLDI) Model. To increase the number of image samples, data augmentation approaches were used at the initial phase for effective training. In the second phase, we designed a VT-driven classification model specifically tailored for Blackgram disease identification in analyzing yellow mosaic

disease imagery. Before processing, the VT model splits the input image into smaller patches, which are then fed sequentially to the model in a manner similar to word embeddings. Lastly, the input image is classified into the appropriate class using a MLP. The BPLD dataset comprises five distinct classes of plant disease images. Based on the experimental findings obtained from the BPLD dataset, we determined that the proposed VTPA-BGLDI approach outperforms existing techniques in classifying YMD in Blackgram.

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