International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
IJISAE
ISSN:2147-6799 www.ijisae.org Original Research Paper

Optimization-Based Auto-Metric Graph Neural Network Framework for Rice Leaf Disease Classification

Veeramreddy Rajasekhar[1], Gnanasekaran Arulselvi[2], K. Suresh Babu[3]

Submitted: 10/02/2023 **Revised:** 11/04/2023 **Accepted:** 09/05/2023

Abstract: Plants play an imperious concern for all kinds of life. Out of which, rice plant is considered as a main agricultural crop. These rice plant leaves are furthermore suffered from the disease. The early stage of recognition of disease can overcome the spreading of disease all over rice crops. Several existing methods of Rice Leaf Disease Classification (RLDC) are utilized with Machine Learning (ML), but it does not accurately classify the rice leaf disease, and also it takes high computation time. To overcome these issues, a Vulture-based Auto-metric Graph Neural Network proposed (VAGNN) for RLDC. At first, the input rice leaf images are taken from the Rice Leaf Disease Image Samples dataset. Then the input rice leaf images are pre-processed using Anisotropic Diffusion Filter Based Unsharp Masking and Crispening (ADF-USMC). Then these pre-processed rice leaf images are given to Bayesian Fuzzy Clustering (BFC) for segmentation. Then the segmented image is given into VAGNN to classify the rice leaf disease image namely i) bacterial blight, ii) brown spot, iii) blast and iv) tungro. Finally, the attained outcomes of the designed model are validated with other prevailing models in terms of accuracy, sensitivity, precision, and so on.

Keywords: *Rice Leaf Image, Anisotropic Diffusion Filter Based Unsharp Masking and Crispening, Bayesian Fuzzy Clustering, Vulture Optimization, Auto-Metric Graph Neural Network.*

1. Introduction

A major source of revenue and a means of subsistence in India is agriculture. Rice is the main crop grown in India's major geographical regions. Typically, one of the most significant sources of income for people is agriculture [1]. According to the ecological state and needs of the land, farmers gather various food plants [2]. Crop yields significantly influence domestic and global economies. India's primary economic activity is agriculture. Indians rely on agriculture for almost 70% of their income. Most Indians choose rice as their main food source [3, 4]. For the Indian economy, the rice production crops and the agricultural products that go with them are crucial. Numerous elements, such as the characteristics of the soil, the climate, irrigation, the terrain, the choice of seeds, and biological factors, can influence the progress and potential growth of the rice crop [5]. Plant disease is one of the most important biological factors that severely lower the productivity of rice crops. However, there are many problems in agriculture that farmers must deal with, like a lack of water, natural disasters, plant diseases, etc. [6]. Fungus and bacteria are the main sources of disease in plants. Serious rice diseases reduce India's rice production by 10% to 15% [7].

Plant disease is one of the most important biological factors that severely lowers the productivity of rice crops. The well-known diseases brown spot, leaf smut, and bacterial leaf blight substantially affect crops and lower yields. Recognizing plant diseases is one of the most important subjects in agriculture [8, 9]. Recognizing plant diseases and increasing crop output is crucial for preventing quantity losses [10]. Monitoring plant health and disease can be extremely harmful to sustainable agriculture. Plant diseases are typically very challenging to track the process due to manual processes' lengthy processing times, large workloads, and the need for knowledge of plant diseases [11, 12]. Therefore, plant diseases are identified using image processing techniques. Image capture, image pre-processing, image segmentation, feature extraction, and classification procedure are all processes in the image processing process for diagnosing diseases [13]. In general, manual plant disease detection is challenging because it takes a lot of time, is challenging to process, is expensive on large farms, and results in mistakes when identifying the disease type [14].

It has been discovered that diseases significantly harm rice crops, causing considerable costs for the agricultural

[1] Research Scholar, Department of Computer Science and Engineering Faculty of Engineering and Technology, Annamalai University, Chidambaram, Tamil Nadu, India.
rajasekhar.v86@gmail.com
[2] Associate Professor, Department of Computer Science and Engineering Faculty of Engineering and Technology, Annamalai University, Chidambaram, Tamil Nadu, India.
arulselvi_ag2004@yahoo.com
[3] Professor & Principal ,Department of Computer Science and Engineering,Siddhartha Institute of Technology & Sciences(SITS),Narapally, Korremula Road, Ghatkesar Mandal, Peerzadiguda, Hyderabad, Telangana 500088.
Sureshbabu.kunchala@gmail.com

sector. To accurately and reliably diagnose the disease that affects rice plants, plant pathologists are searching [15, 16]. One successful application of ML in crop remote sensing is the classification of agricultural illnesses [17]. The identification of agricultural diseases is currently a major field of research for Deep Learning (DL). The advancement of dynamic ML and artificial intelligence approaches has provided a mechanism to accurately detect rice leaf disease to get around these problems [18]. Based on DL, rice leaf disease detection is quick, automated, affordable, and appropriate for application right now. The categorization of rice leaf disease is done using a variety of existing methods; however, this takes a long time to compute and does not accurately classify the disease [19, 20]. These issues require some solutions to be put up to be overcome. These problems served as the inspiration for our study project.

The major contributions of this manuscript are summarized as follows,

- Vulture-based Auto-metric Graph Neural Network (VAGNN) for RLDC is proposed in this manuscript.
- At first, the input rice leaf disease images are taken from the Rice Leaf Disease Image Samples dataset.
- Then the input rice leaf images are pre-processed using Anisotropic Diffusion Filter Based Unsharp Masking and crispening.
- Then these pre-processed rice leaf images are given to Bayesian fuzzy clustering for segmentation.
- Then the segmented image is given into VAGNN for classifying the rice leaf disease images such as i) bacterial blight, ii) brown spot, iii)blast, and iv) tungro.
- The proposed VAGNN method is implemented in python and the efficiency is estimated with the help of several performance metrics such as f-measure, accuracy, sensitivity, specificity, and False Positive Rate (FPR).
- Then the performance of the proposed VAGNN method is analyzed and it was analyzed with the existing methods.

The remainder of the manuscript is explained as follows: Section 2 reviews the literature survey, Section 3 explains the proposed technique, Section 4 displays the results and discussion, and Section 5 completes the manuscript.

2. Literature Survey

In this part, some of the most current studies on RLDC employing DL were reviewed,

Deep neural networks (DNN) with transfer learning were used by Krishnamoorthy, N et al. [21] to predict rice leaf diseases in 2021. The leaf photos are first subjected to the pre-processing stage. In the pre-processing stage, all of the photos were shrunk to 224x 224x3 pixels and had their pixel values scaled from 0 to 1. The image enhancement method was used to increase the size of the initial dataset of training images. Next, it was proposed to use a pre-trained InceptionResNetV2 model for the feature extraction and classification task. Low F-Score and excellent accuracy are achieved.

The Identification and categorization of rice leaf diseases using the Optimized DNN of the Jaya algorithm was presented by Ramesh et al. in 2020 [22]. To separate the input photos into regions with and without disease, the rice leaf images were first pre-processed utilizing the conversion of RGB images into HSV images based on hue and saturation components binary images. The DNN was then used to classify these previously processed images, and the Jaya Optimization Algorithm was used to optimize the weight parameters of the DNN. A high F-Score in this computation led to an increase in computation time.

Rice illnesses detection and classification using attention-based neural networks (AbNN) and Bayesian optimization(BO) were presented by Wang et al. in 2021 [23]. Here, the MobileNet structure-based AbNN model and the augmented attention mechanism were used. Additionally, the BO approach is used to adjust the model's hyperparameters. It has a lower accuracy but a higher F-Score.

Using an improved DNN, Nalini et al. [24] revealed the identification of Rice leaf disease in 2021. To reduce classification mistakes, the weights of the DNN model are tuned using the crow search algorithm (CSA). After pre-processing the pictures of rice leaves, a k-means clustering method was used to extract the areas that were disease-indicative. Finally, experimental verification of the suggested DNN-CSA method's classification efficiency and effectiveness showed short computation time with decreased F-Score.

3. Proposed Methodology

In this section, the Vulture-based Auto-metric Graph Neural Network (VAGNN) for RLDC is discussed. Here, the classification of rice leaf diseases is developed for testing and training the classifier with five stages. The four stages include image acquisition, image pre-processing, image segmentation, and image classification. The block diagram of the proposed

VAGNN methodology is given in Fig. 1. The detailed description of each stage is given below,

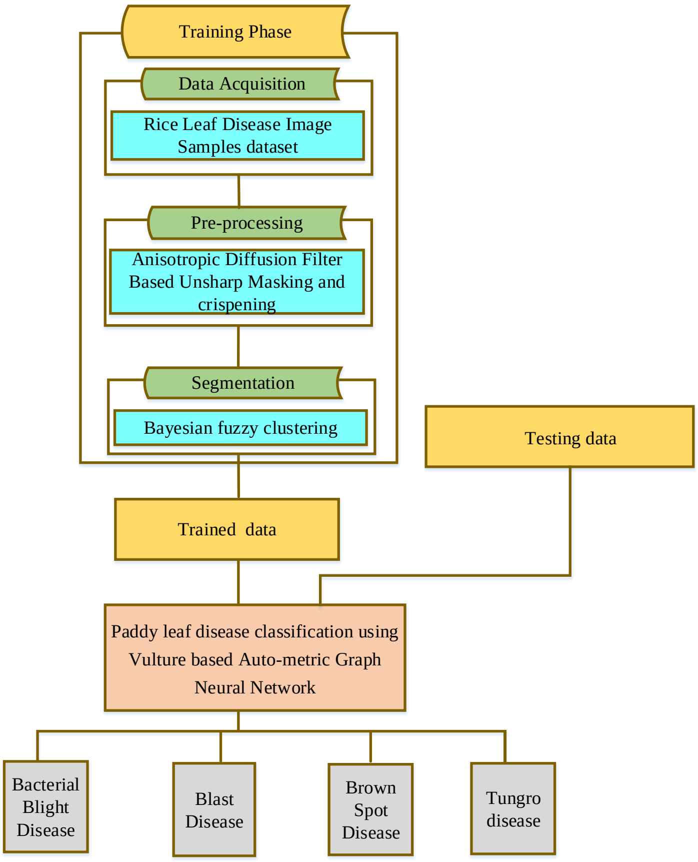

Fig. 1 Overall workflow of the proposed VAGNN method

3.1 Image acquisition

To classify the leaf illness in this stage, the input rice leaf image is collected from the dataset of Rice Leaf Disease Image Samples. The collection consists of 5932 pictures of rice leaves with illness. It includes the four types of rice leaf diseases known bacterial blight, blast, brown spot, and tungro.

3.2 Pre-processing method

The primary purpose of pre-processing in image processing is to improve the picture data by removing unneeded inaccuracies from the image. Anisotropic Diffusion Filter Based Unsharp Masking and Crispening (ADF-USMC) is used in this classification of rice leaf diseases. The input rice leaf photo $image(a,b)$ are first gathered from the database and are noisy; therefore, the ADF-USMC approach is suggested to reduce the noise from the input rice leaf images. Here, the ADF-USMC method provides edge rice leaf images $image_{edge*}$ from input rice leaf images that can be expressed in Eqn. (1),

$$image_{edge*} = image(a,b) - image_{smoothening}(a,b) \quad (1)$$

From Eqn. (1), $image(a,b)$ represents the input rice leaf image, which is the 2nd derivative of an image taken in a and b directions, $image_{smoothening}(a,b)$ and specifies smoothening image form of the input rice leaf image. Then, the overall Unsharp masking operator is arithmetically expressed in Eqn. (2), (2)

From Eqn. (2), SC specifies the scaling constant as $SC > 0$. The practical values of SC varies from 0.2 to 0.8, with the highest value of SC increases the capacity of sharpening. The gradient function for smoothening the image of rice leaf is expressed in Eqn. (3), then the smoothening form of the rice leaf image is arithmetically expressed in Eqn. (4),

$$\frac{\partial_{image}}{\partial_t} = \frac{image_{smoothening}}{\Delta SF} = \left\|\nabla_{image}(a,b)\right\|^2$$

(3) (4)

From Eqn. (3) and (4) Δ_{image} represent the edge image of Edge Anisotropic Diffusion filter regularization, ΔSF representing the stability factor and it is varying between *0* to *1/7* for stability purposes and the diffusion coefficient is arithmetically expressed in Eqn. (5),

$$d\left\|\nabla_{image}(a,b)\right\| = \frac{1}{1+\left(\frac{\nabla_{image}(a,b)}{R}\right)^2} \qquad (5)$$

From Eqn. (5), $d\left\|\nabla_{image}(a,b)\right\|$ represents the gradient function, d represents the diffusion rate control that is selected as the gradient function to reserve the rice leaf images, constantly R regulating the edge sensitivity of a rice leaf image that fluctuates from 1 to 1.5. Substitute Eqn. (4) in Eqn. (1), and it provides Eqn. (6).

$$image_{edge^*} = image(a,b) - \left\{ image(a,b) + \Delta SF\left[\nabla(d\left\|\nabla_{image}(a,b)\right\|)\nabla_{image}(a,b)\right]\right\} \qquad (6)$$

Finally, the ADF-USMC-based filter is formulated in Eqn. (7),

$$image_{sharpening} = image(a,b) + SC \times image_{edge*} \qquad (7)$$

From Eqn. (7) it clearly shows that the ADF-USMC method removes noise and enhances the quality of the input rice leaf image. Then, these pre-processed images are given to the segmentation process.

3.3 Segmentation process

With the aid of Bayesian Fuzzy Clustering (BFC), the ROI region of a plant leaf disease image is segmented in this section. It provides the pieces for extracting ROI region features from rice leaves. The term "Bayesian model" refers to the overall probability of the information points and the attributes. By applying the following Eqn. (8), the Bayesian Fuzzy clustering is evaluated.

$$p\left(\mathrm{Im}age_{pre}^{j}, Cl^*, \mathrm{GPD}^*\right) = p\left(\mathrm{Im}age_{pre}^{j} / Cl^*, \mathrm{GPD}^*\right) p\left(GPD_*\right) \overline{p}\left(Cl_* \mid GPD_*\right) = ROI\ \ region \qquad (8)$$

Where $p\left(GPD^*\right)$ is represented as the Gaussian Prior Distribution (GPD), $\overline{p}\left(Cl_* \mid GPD_*\right)$ is represented as the Fuzzy Cluster Prior (FCP), $p\left(\mathrm{Im}age_{pre}^{j}, Cl^*, \mathrm{GPD}^*\right)$ is represented as the Fuzzy Data Likelihood (FDL). The Bayesian Fuzzy clustering method based on FDL is assessed, with the help of Eqn. (9)

$$p\left(\mathrm{Im}age_{pre}^{j}, Cl^*, \mathrm{GPD}^*\right) = \prod_{i=1}^{g} FDL\left(k_i \mid \mathrm{c}_i, \mathrm{GPD}\right) \qquad (9)$$

Where $\mathrm{Im}age_{pre}^{j}$ specifies pre-processed rice leaf image, Cl^* specifies fuzzy relationship, GPD^* is represented as the cluster prototypes, g is represented as the measure of the segmented data points in the cluster GPD, k_i is represented as the number of segmented ROI region points. The outlook of data is associated with the development of GPD^* and normal likelihoods are represented in terms of FDL. Hence, the gatherings are prepared and shared means ethics are clustered and it is called the cluster model. The cluster models are given in Eqn. (10)

$$p\left(\mathrm{Im}age_{pre}^{j}, Cl^*, \mathrm{GPD}^*\right) = \prod_{i=1}^{g}\left\{\frac{1}{Y\left(c_i, n, \mathrm{GPD}\right)}\right\}\prod_{m=1}^{x} N\left(\mathrm{k}_i \mid \mu = g_m, \mathrm{z} = c_{im} * \mathrm{Im}age\right) \qquad (10)$$

Where $Y\left(c_i, n, \mathrm{GPD}\right)$ is represented as the normalization constants, GPD is represented as the cluster, the total number of the clusters is represented as x, the cluster number is represented as m, and the fuzzifier is represented as n. FCP is exploited to mock fuzzy C-means (FCM) performance by using the Bayesian model. It is assessed with the help of Eqn. (11-12).

$$\overline{p}\left(Cl_* \mid GPD_*\right) = \prod_{i=1}^{g} FCP\left(c_i \mid \mathrm{GPD}^*\right) \qquad (11)$$

Where FCP comprise three aspects, such as $Y\left(c_i, n, \mathrm{GPD}\right)$, $\prod_{m=1}^{x}\left(h_{im}^{\frac{nx}{2}}\right)$ and Dirichlet $\left(c_i \mid \mu\right)$

$$\overline{p}\left(Cl_* \mid GPD_*\right) = \prod_{i=1}^{g} Y\left(c_i, n, \mathrm{GPD}\right)\prod_{m=1}^{x}\left(h_{im}^{\frac{nx}{2}}\right) Dirichlet\left(c_i \mid \mu\right) \qquad (12)$$

Where, the membership of the data point in the group m is represented as h_{im} and the factor of mean is represented as the μ. The initial factor castoffs FDL equilibrium is persistent. The subsequent inspiration to offer high member-ship reverences. The third factor is represented by Enthusiasm. It distributes additional manipulability and expertise for the clustering practice. The GPD is assessed with the help of Eqn. (13).

$$p\left(GPD^*\right) = \prod_{m=1}^{x} N\left(q_m \mid \mu_q, \sum_{q}\right) \qquad (13)$$

Where μ_q is represented as the mean of the dataset and it is determined with the help of Eqn. (14)

$$\mu_q = \frac{1}{g}\sum_{k=1}^{g} k_i \qquad (14)$$

Where $\sum_q$ is represented as the data covariance and it is determined with the help of Eqn. (15)

$$\sum_z = \frac{\chi}{g}\sum_{i=1}^{g}\left(k_i - \mu_q\right) * \left(k_i - \mu_q\right)^T \qquad (15)$$

Where χ is represented as the user-recognized constriction which interrupts the strong point. These elements help determine the combined possibility of the data and parameters. The image of rice leaf disease with the collected ROI region is then used as the classification input. Moreover, input, preprocessed, and segmented images of the developed model are shown in Fig.2.

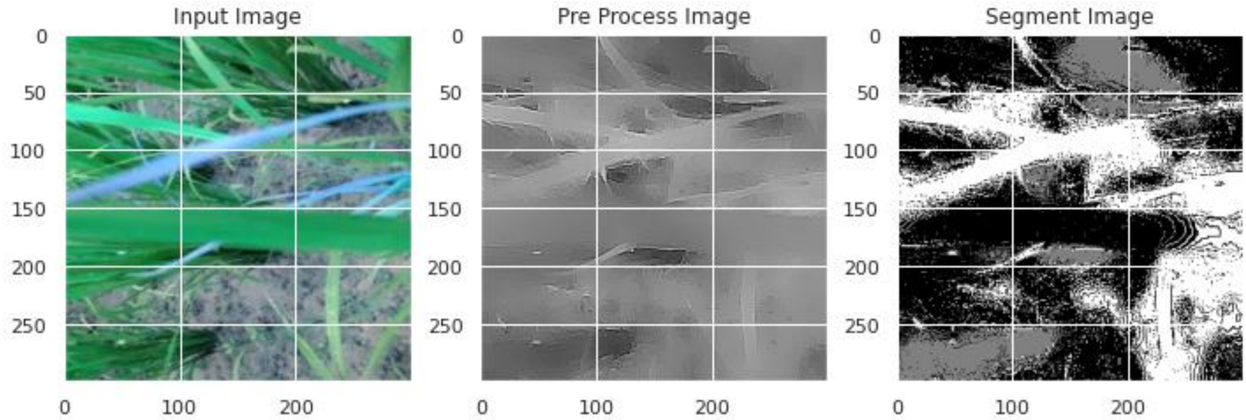

Fig. 2 Input, preprocessed, and segmented images

3.4 Classification using AGNN

In this stage, the Auto-metric Graph Neural network [29] classifier's vulture fitness is updated. The meta-learning approach used in the proposed VAGNN model is intended to categorize rice leaf disease. Here, the proposed VAGNN is trained using the node classification of a tiny graph that was produced using a random sample selection from the training set. Additionally, the proposed VAGNN involves initializing the graph structure, structuring the layer, defining the loss function, and identifying plant leaf disease using a meta-learning training process. This categorization of the rice leaf diseases into Bacterial Blight Disease, Blast Disease, Brown Spot Disease, and Tungro Disease are done directly using the proposed VAGNN.

To identify the rice leaf, the extracted characteristics of the picture are first randomly chosen from the dataset and used as input for the VAGNN model. Here, the segmented features of the rice leaf image are denoted as $(Feature)$, which is represented in Eqn. (16),

$$Feature = \left((e^1 l^1, e^2 l^2 ......, e^{n-1} l^{n-1}, e^n l^n\right) \qquad (16)$$

Where, e denotes the segmented features with a label (disease or non-disease) (l). Here, the rice leaf images in the graph are randomly selected for each category with a disease or non-disease label. Here, the nodes are randomly selected for each category with a disease or non-disease label. Moreover, the graph structure $graph = \left(Node, EPM, Weight\right)$ is initialized, where node set implies $(Node)$, edge probability matrix is (EPM), weights are mentioned as $(Weight)$. Additionally, the features of a node $Node_i$ are calculated using Eqn. (17),

$$Node_i = \left[l_i, \eta_i, cs_i \quad feature_i\right] \qquad (17)$$

Where, the risk factor is mentioned η_i, label encoding is l_i, the cognitive score is cs_i and the features are represented as $feature_i$. Here, l represents the zero vectors for the node with unknown labels. Additionally, the setup of the graph results in a completely linked network, meaning that the weights and edge probability matrices for each member are both set to 1.

This is provided to the VAGNN layer input via frequency constraint after graph structure configuration. The dataset's unknown node label (rice leaf disease) is obtained in this case by updating the node features by passing data across the nodes. Based on the risk factor, the likelihood of the edge matrix is calculated, and the weight matrix is automatically recognized by characteristics. Moreover, the calculation of the probability matrix with risk factors $(\eta_1, \eta_2, \eta_3 ....\eta_N)$ is mentioned as Eqn. (18),

$$EPM_{a,b}^{RF} = \begin{cases} 1; & if \quad \left|\eta_a^{RF} - \eta_b^{RF}\right| \le \zeta \\ 0; & otherwise \end{cases}$$

(18)

Where, the edge weights among nodes l_i and l_j belongs to [0,1], the element $(EPM_{a,b})$ is mentioned as

$$EPM_{a,b} = \frac{1}{\left(RF + 1 - \sum_{RF=1}^{RF} EPM_{a,b}^{RF}\right)}, (RF)$$

denoting the number of risk factors, and the threshold value is mentioned as (ζ) that is used for measuring the similarity of risk factor features among two different nodes, which is mentioned as $(fs_1, fs_2, fs_3 ....fs_N), fs \in IS^{\dim}$ where $IS^{\dim}$ is the feature dimension. Additionally, the weights matrix between nodes with features is calculated using Eqn. (19),

$$Weight_{a,b}^{(l)} = CNN_\theta \left(abs(fs_a - fs_b \right)$$

(19)

Where, $Weight_{a,b}^{(l)}$ weights between nodes in the network use absolute differences abs and fs_a, fs_b represent the feature set between the nodes. Subsequently, the nodes in the network are updated for attaining accurate outcomes using Eqn. (20),

$$NUF\left(Node_i\right) = Leaky - \mathrm{Re}\,LU\left(\sum_{B^l} B * Node^l * \theta_B^l\right)$$

(20)

Where, NUF is the node updating factor, $Node_i$ is the overall count of nodes on (l) the number of network layers, $Leaky - \mathrm{Re}\,LU$ denotes the non-linear activation function, and θ_B^l denotes the training parameters used for changing the dimension of features of every node. Moreover, the outcome of this model is concatenated $Node_i$ to preserve the input node features and the attained outcome of the VAGNN layer is mentioned in Eqn. (21),

$$Node^{(l+1)} = \left[Node^l, NUF(Node^l) \right]$$

(21)

Instead of being coupled to the input nodes for the last layer, the output of the Rice leaf disease is directly injected into the Softmax layer after the feature dimension has been changed to normalize the output.

3.4.1 Vulture optimization

The Vulture Optimization (VO) [30] is a Meta-Heuristics algorithm that simulates the two primary behaviors of the Egyptian Vulture, which are the capacity to roll objects with twigs and the ability to toss stones.

Pebble tossing: The egg is repeatedly smashed by two or three Egyptian Vultures until the stones break, and they do this to identify the egg's weak spots or cracks. This method is used in this meta-heuristics to introduce new solutions at random locations in the solution set, and potentially, when a new solution enters the set, it may lead to four different outcomes depending on the possibility and the purpose of enabling parameters for carrying out the operations and choosing the extension of the performance.

Roll with twigs: The ability of the Egyptian Vulture to roll objects with twigs is another amazing capability. They can use this ability to move an object, find its position or weak areas, or even merely peer over the side that is facing the ground. This behavior of the Egyptian Vulture is referred to as the rolling of the solution set for shifting the variables' locations to modify the signification and maybe produce new solutions that produce better fitness values and better paths when it comes to multi-objective optimization.

The fitness function of the vulture is used for the accurate classification of rice leaf diseases and enhances the performance of the designed model with better prediction and classification accuracy. Additionally, the parameters are given in the Eqn. (22), are updated using the VAGNN model's loss function computation.

$$l\left(PPR^*, PPR\right) = -\sum_{type} e_{type}\left(V(f)\log EPM\left(PPR^* = e_{type} / IS\right)\right)$$

(22)

Where, PPR denotes the prediction outcome of the Rice leaf disease, PPR^* is the label of rice leaf disease, $V(f)$ is represented as the vulture fitness function, (IS) denotes input data, $(types)$ denotes the count of classes. The initialized graph structure, GNN layer, and loss function serve as the foundation for the proposed VAGNN model. To generate the graph structure that is provided to the layer, in which the information is passed among the network nodes and updated by the VAGNN model, the sample data is extracted in this case. Rice leaf disease is categorized here. Additionally, the network parameters are modified by the model's loss function, which is provided in Eqn. (23).

$$FP_{(t+1)} = GDA(\ell_t, FP_{(t)}) \qquad (23)$$

Where, GDA denotes the gradient descent algorithm for updating final parameters FP based on loss function ℓ_t with training epoch (t).

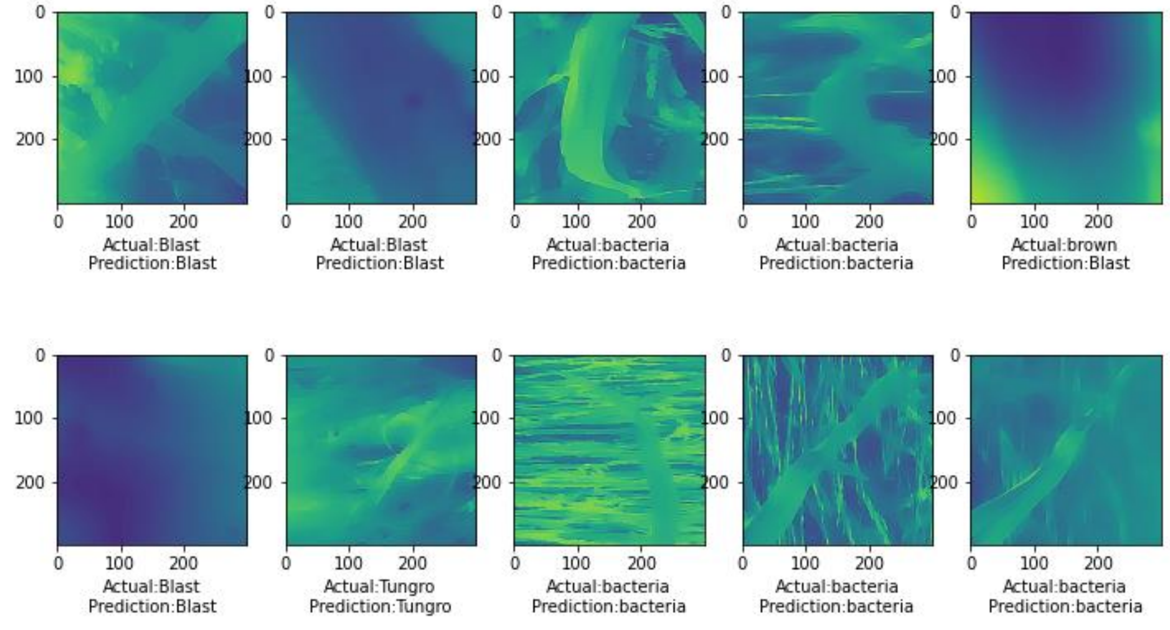

Fig. 3 Output result of the proposed VAGNN method

After performing the training epoch, the parameters are updated, and obtain the outcome which is utilized to categorize the rice leaf disease namely i) Bacterial Blight Disease, ii) Blast Disease, iii) Brown Spot Disease and iv) Tungro Disease. The output result of the proposed VAGNN method is given in Fig. 3.

4. Result and Discussion

The experimental findings of the suggested VAGNN approach are detailed in this section. The simulations are performed on a computer running Windows 11, an Intel Core i3, and 8GB of RAM. The proposed approach is simulated using Python. To evaluate the performance of the suggested method, performance metrics including accuracy, F-Score, sensitivity, specificity, precision, and FPR are examined. The training accuracy and training loss of the developed model is shown in Fig.4.

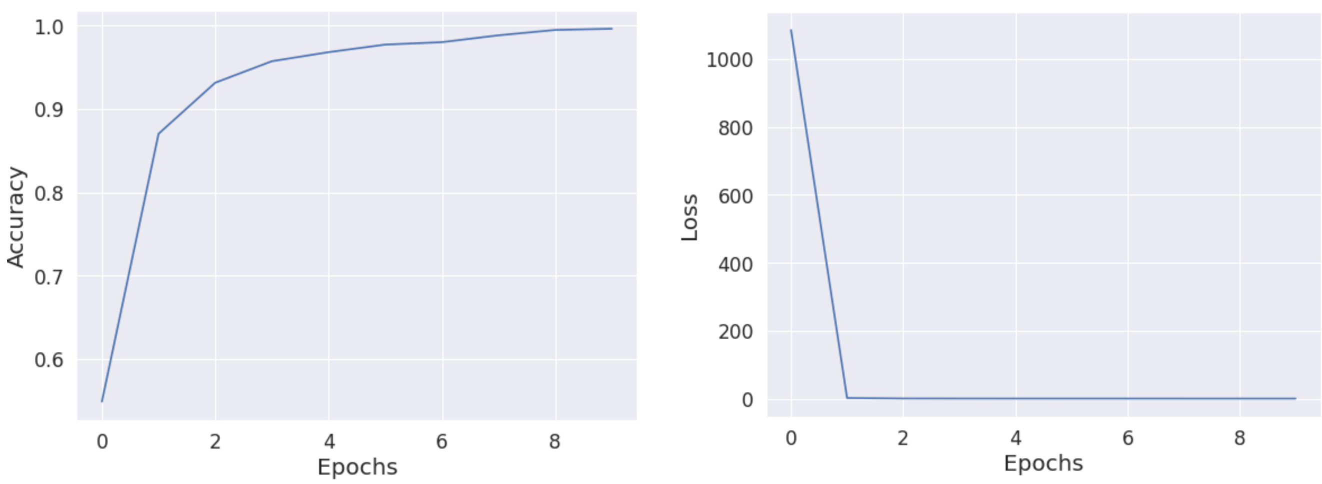

Fig. 4 Training accuracy Vs. training loss

The acquired results are then evaluated using the currently available methodologies such as Deep convolutional neural network (DCNN) [25], CNN-transfer learning (CNN-TL) approach [26], CNN-support vector machine (CNN-SVM) [27], and Visual Geometry Group Network-16 (VGG16) [28] respectively.

4.1 Dataset description

The Rice Leaf Disease Image Samples Dataset contains information about rice leaf disease. The dataset has 5932 records about rice leaf disease. It includes the four types of rice leaf diseases known bacterial blight, blast, brown spot, and tungro. 80% of the data on rice leaf disease are used for testing, and 20% are utilized for training.

4.2 Performance measures

This is a crucial step for choosing the optimal classifier. To verify the performance, the performance metrics accuracy, sensitivity, specificity, precision, F-score, and False positive rate (FPR) are examined. It is decided to use the confusion matrix to scale the performance measures. The True Positive, True Negative, False Positive, and False Negative values are required to scale the confusion matrix. The confusion matrix of the developed model is shown in Fig.5.

- True Positive (TP): Count of samples in which the predicted class label is positive, and then the real class label is correct.
- True Negative (TN): Count of samples in which the predicted class label is negative, and then the real class label is correct.
- False Positive (FP): Count of instances in which the predicted class label is positive, and then the real class label is incorrect.
- False Negative (FN): Count of instances in which the predicted class label is negative, and then the real class label is incorrect.

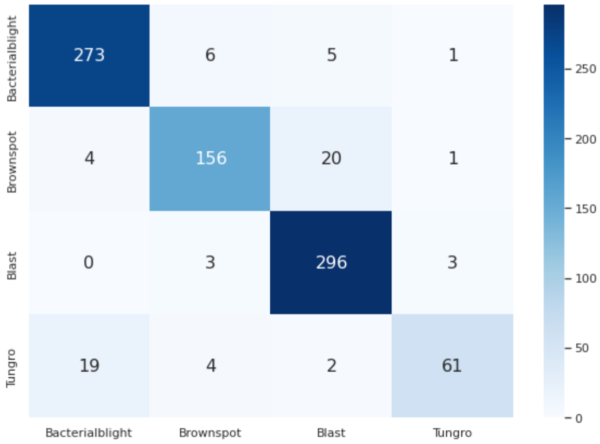

Fig.5 Confusion matrix

4.3 Simulation Analysis

The proposed VAGNN method's performance analysis is shown in Fig. 6-11. The suggested VAGNN approach is then analyzed and evaluated against the DCNN [25], CNN-TL [26], CNN-SVM [27], and VGG16 [28] existing methods, respectively.

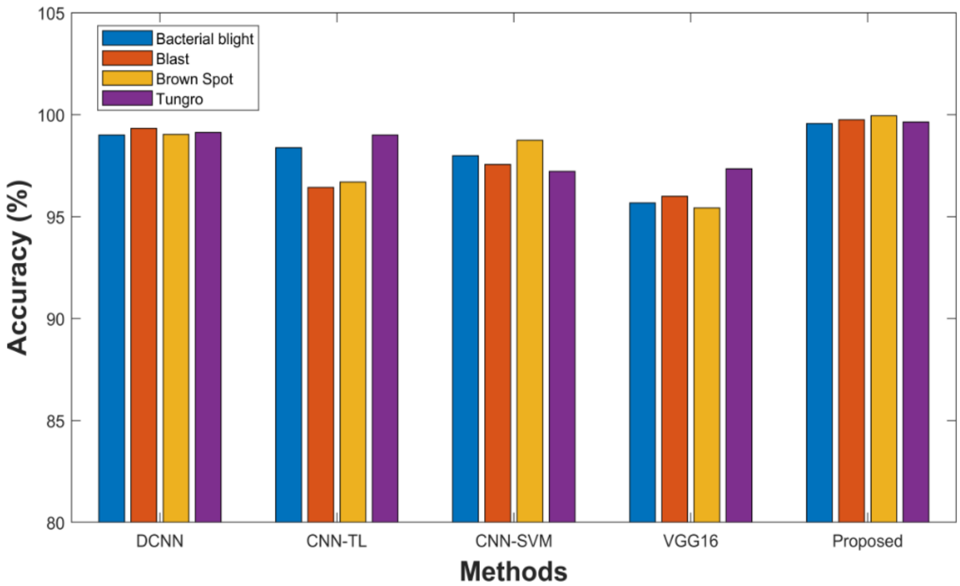

Fig. 6 Accuracy analysis

Fig. 6 depicts the Accuracy analysis. Here, the proposed VAGNN method attains 9.77%, 14.31%, 28.05%, and 15.61% higher accuracy for Bacterial Blight Disease; 6.74%, 15.54%, 19.46%, and 7.91% higher accuracy for Blast Disease; 5.23%, 8.29%, 18.09%, and 20.43% higher accuracy for Brown Spot Disease; 12.85%, 4.89%, 7.83%, and 8.80% higher accuracy for Tungro Disease compared with an existing method like DCNN [25], CNN-TL [26], CNN-SVM [27], and VGG16 [28] existing methods, respectively.

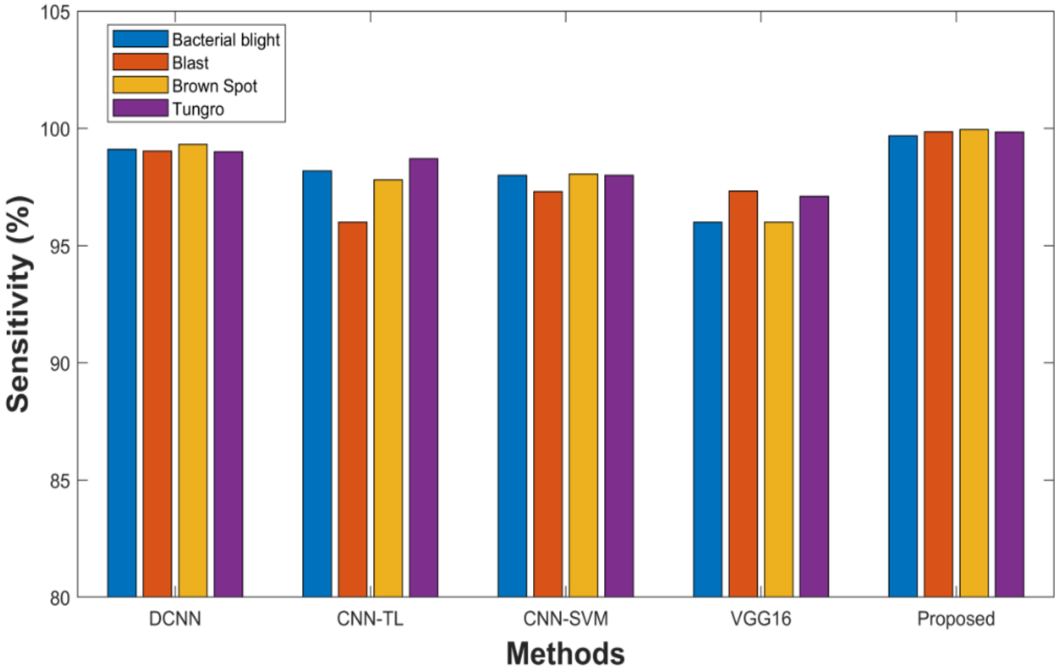

Fig. 7 Sensitivity analysis

Fig.7 depicts the sensitivity analysis. Here, the proposed VAGNN method attains 10%, 11.01%, 18.5%, and 20.53% higher sensitivity for Bacterial Blight Disease; 8.04%, 11.8%, 7.4%, and 10.9% higher sensitivity for Blast Disease; 6.13%, 8.29%, 7.19%, and 12.43% higher sensitivity for Brown Spot Disease; 10.8%, 6.19%, 11.03%, and 7.80% higher sensitivity for Tungro Disease compared with an existing method like DCNN [25], CNN-TL [26], CNN-SVM [27], and VGG16 [28] existing methods, respectively.

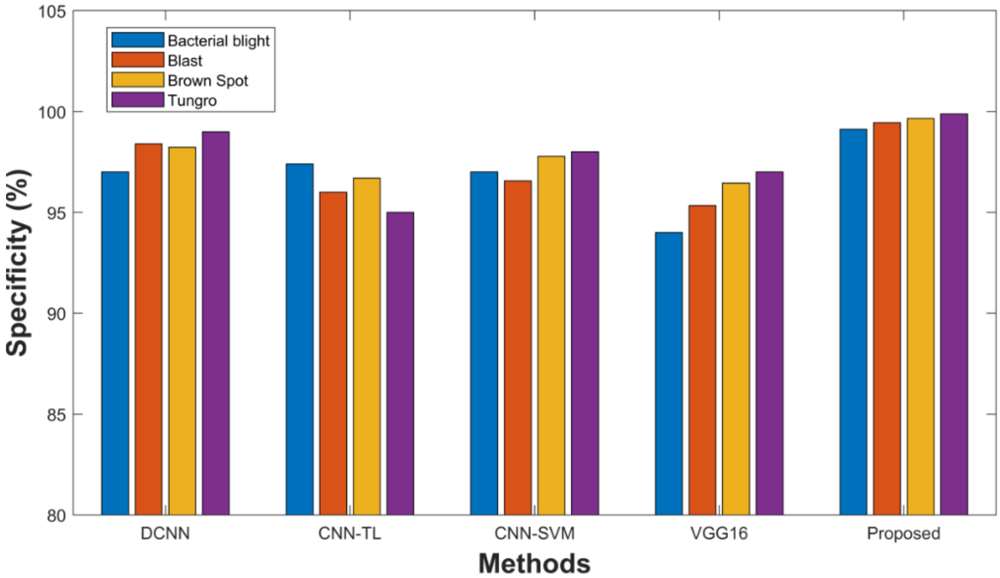

Fig. 8 Specificity analysis

Fig. 8 depicts the Specificity analysis. Here, the proposed VAGNN method attains 10.77%, 11.31%, 8.05%, and 5.61% higher specificity for Bacterial Blight Disease; 16.74%, 5.54%, 9.46%, and 10.9% higher specificity for Blast Disease; 8.23%, 4.29%, 13.09%, and 17.43% higher specificity for Brown Spot Disease; 6.85%, 12.89%, 9.83%, and 8.80% higher specificity for Tungro Disease compared with an existing method like DCNN [25], CNN-TL [26], CNN-SVM [27], and VGG16 [28] existing methods, respectively.

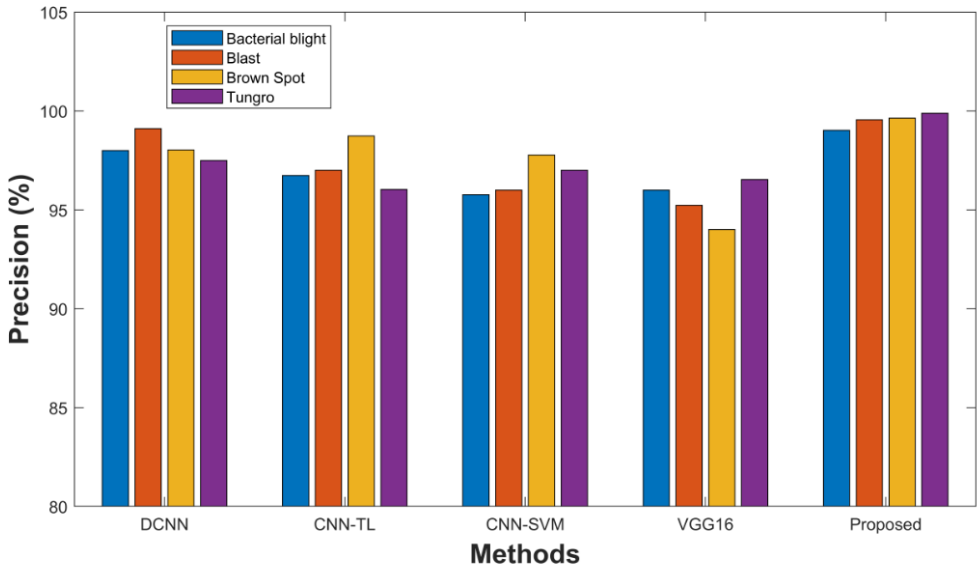

Fig. 9 Precision analysis

Fig. 9 depicts the precision analysis. Here, the proposed VAGNN method attains 7.8%, 5.01%, 8.5%, and 10.53% higher precision for Bacterial Blight Disease; 8.04%, 16.8%, 17.4%, and 7.9% higher precision for Blast Disease; 16.13%, 8.29%, 10.19%, and 9.43% higher precision for Brown Spot Disease; 10.8%, 6.19%, 9.03%, and 11.80% higher precision for Tungro Disease compared with an existing method like DCNN [25], CNN-TL [26], CNN-SVM [27], and VGG16 [28] existing methods, respectively.

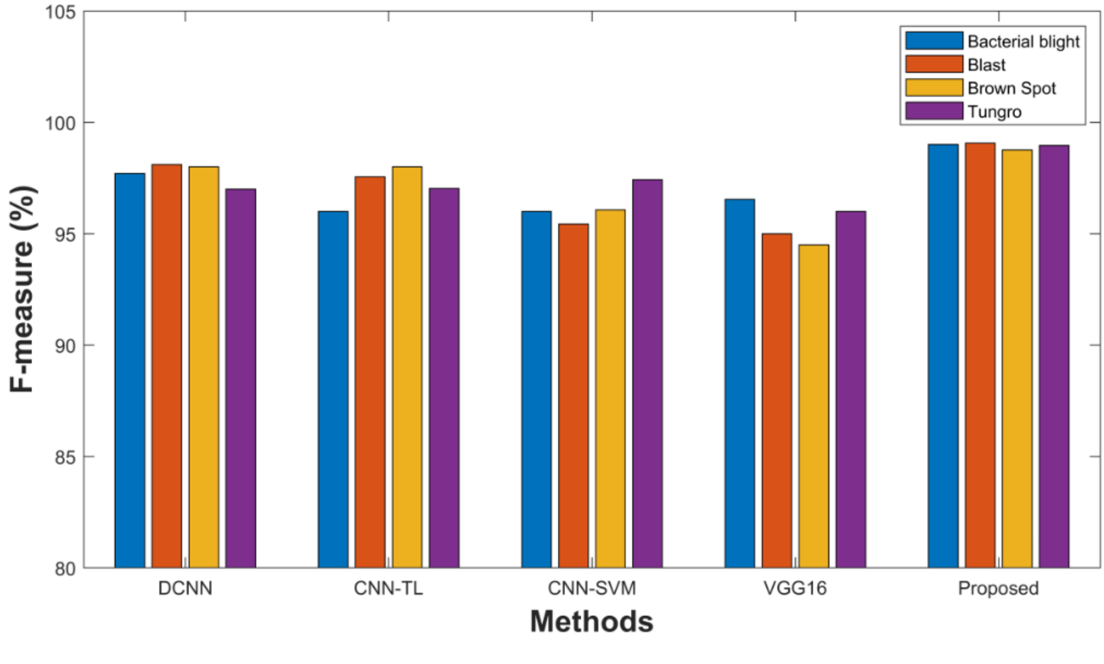

Fig. 10 F-measure analysis

Fig. 10 depicts the F-Score analysis. Here, the proposed VAGNN method attains 28.15%, 17.41%, 22.37%, and 12.643% higher f-Score for Bacterial Blight Disease; 18.515%, 16.63%, 22.229%, and 9.67% higher f-Score for Blast Disease; 15.45%, 14.340%, 19.252%, and 9.63% higher f-Score for Brown Spot Disease; 13.46%, 7.18%, 19.48%, and 8.615% higher f-Score for Tungro Disease compared with an existing method like DCNN [25], CNN-TL [26], CNN-SVM [27], and VGG16 [28] existing methods, respectively.

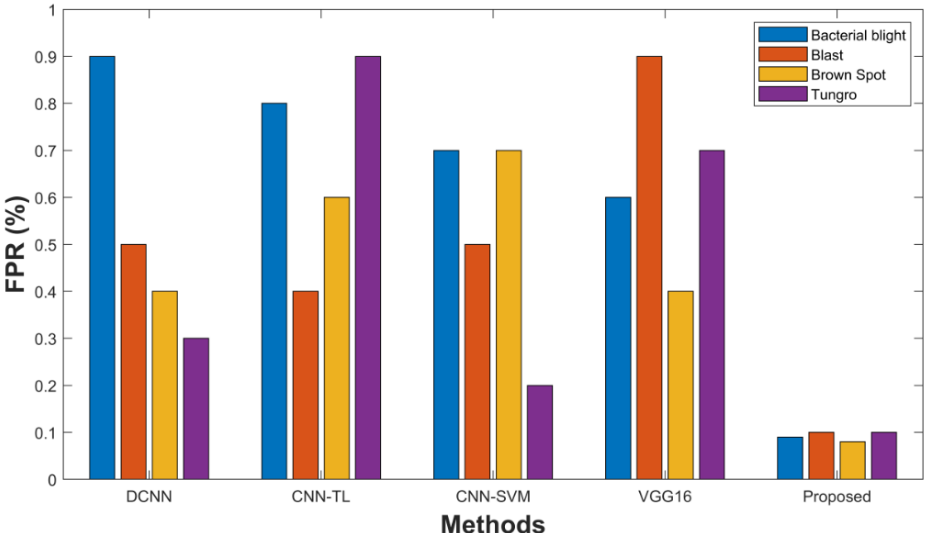

Fig. 11 FPR analysis

Fig. 11 depicts the FPR analysis. The proposed VAGNN method attains 7.26%, 2.169%, 4.94%, and 2.806% lower FPR values compared with existing methods like DCNN [25], CNN-TL [26], CNN-SVM [27], and VGG16 [28] existing methods, respectively.

5. Conclusion

In this study, VAGNN was successfully used to classify photos of the diseases Bacterial Blight, Blast, Brown Spot, and Tungro. Python is used to implement the suggested VAGNN approach, and several performance metrics, including f-measure, sensitivity, specificity, precision, accuracy, and FPR, are used to determine its efficiency. Then the performance of the proposed VAGNN method attains 99.56% accuracy, 99.68% sensitivity, 99.12% specificity, 99.02% precision, 99% F-measure, and 0.009% FPR for bacterial blight diseases. Also, attains 99.75% accuracy, 99.85% sensitivity, 99.45% specificity, 99.55% precision, 99.06% F-measure, and 0.01% FPR for blast diseases. Additionally, attains 99.94% accuracy, 99.46% sensitivity, 99.65% specificity, 99.64% precision, 98.76% F-measure, and 0.008% FPR for brown spot diseases. Finally, attains 99.64% accuracy, 99.84% sensitivity, 99.78% specificity, 99.88% precision, 98.96% F-measure, and 0.01% FPR for Tungro diseases. The attained outcomes show the efficiency of the designed model and the developed model can categorize the rice leaf diseases accurately. In the future, hybrid optimization improves the performance of identifying and classifying rice leaf diseases accurately with their hybrid fitness function.

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