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A Feature-Based Machine Learning Framework for Plant Disease Recognition Using Color and Texture Analysis

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ABSTRACT

One of Tamil Nadu's staple crops, paddy guarantees a sufficient supply of food for millions of farmers and promotes socioeconomic prosperity in the Chidambaram area of the Cuddalore district. Nevertheless, it has been discovered to be extremely vulnerable to a number of diseases, including bacterial leaf blight, blast, and brown spot, which can significantly reduce yield and quality.Since the conventional methods of diagnosing these diseases are extremely time-consuming, laborious, and prone to human error, early and accurate detection are crucial for prompt intervention and treatment. In order to develop an effective, scalable, and efficient solution, this study proposes a revolutionary categorization of paddy disease utilizing image analysis and deep learning approaches based on cutting-edge developments in artificial intelligence. In this work, we introduced a Feature-Based Machine Learning Framework for Plant Disease Recognition Using Color and Texture Analysis (FBMLF-PDRCTA) Technique. First, a Sobel operator is used to segment the lesion's edge after the sample picture has been smoothed using median filtering and histogram equalization. This greatly lowers background information and enhances image quality. Next, using color and texture features, the image's matching feature parameters are retrieved. Finally, Support Vector Machine is one of the most commonly used machine learning methods for categorisation. According to the study findings, when the total amount of node in the concealed layer is changed to 98, the FBMLF-PDRCTA's detection rate may reach up to 95.8%. The recognition technique developed with an SVM, having good accuracy, may effectively address the drawbacks of manual categorisation using the colour and textural features of a rice sheath blight image.

1. INTRODUCTION

Over fifty percent of the world's population relies mostly on rice, based on the Food and Agriculture Organisation (FAO), and crop damage causes farmers all over the world to suffer significant losses.

Food security, initiatives to reduce poverty, and sustainable development are all impacted by these losses, which can have detrimental effects on the economy, society, and environment. Furthermore, rice diseases can lower yields by up to 80%, based by the International Rice Research Institute (IRRI) [1]. This would lead to lower agricultural revenues, fewer food available, and higher consumer expenditures.It leads to the usage of dangerous chemicals and pesticides, which may have detrimental effects on both the environment and human health. Sheath blight, brown spot, and false smut are among the major fungal diseases that are posing a growing danger to rice farming in the Chidambaram area of the Cuddalore district [2]. These diseases are getting worse due to climate change. One of the most common diseases in the growing of rice is rice sheath blight, which is brought on by Rhizoctoniasolani.

In order to ensure sustainable growing of rice and availability of food for millions of people worldwide, effective control of rice diseases of the leaves is essential. The amount and propagation of the infection across the leaf surface area are often indicators of the disease's severity in rice plants [3]. Less than 10% leaf surface damage is indicative of a mild form of the disease, but over 10 percent damage is indicative of a severe case. It is important because it directly affects rice crop growth, development, and yield.Furthermore, identifying this rice disease by hand is laborious and does not offer early disease identification, which might result in large production losses. With machine training and deep learning methods, crop diseases can be accurately and quickly identified and categorised, increasing agricultural output and quality. It lowers labour expenses while also making the process more precise overall.

In this work, we introduced a Feature-Based Machine Learning Framework for Plant Disease Recognition Using Color and Texture Analysis (FBMLF-PDRCTA) Technique. First, a Sobel operator is used to segment the lesion's edge after the sample picture has been smoothed using median filtering and histogram equalization. This greatly lowers background information and enhances image quality. Next, using color and texture features, the image's matching feature parameters are retrieved. Finally, Support Vector Machine is one of the most commonly used machine learning methods for categorisation. The results of the experiment show that the FBMLF-PDRCTA's recognition accuracy can reach its maximum when the number of nodes in the hidden layer is set to 98.

2. RELATED WORKS

Creates a multi-class dataset of rice diseases that includes one class of healthy leaves and eleven rice diseases. This work incorporated weights that had been trained from the large-scale, multiple-class ImageNet data set into the trials in light of the current fascination with transfer learning.We created a rice disease detection software that offers a straightforward and effective diagnosis of rice diseases based on a transfer learning-based RegNet model.

uses a large-scale database of annotated photos covering six common rice diseases—bacterial stripe, false smog, leaf blast, neck damage, sheath blight, and brown spot—to present a deep machine learning-based automated detection method for rice leaf diseases. Using a variety of performance indicators, such as precision, recall, and general diagnostic accuracy, we assessed seven sophisticated deep learning designs: MobileNetV2 [4], GoogLeNet, EfficientNet, ResNet-34, DenseNet-121, VGG16, and ShuffleNetV2. When it came to lowering class confusion and increasing diagnostic accuracy, GoogLeNet, DenseNet-121, ResNet-34, and VGG16 outperformed the rest.To guarantee complimentary feature extraction capabilities, these models were chosen using a variety of architectural considerations. A simple average fusion technique was then used to merge the four high-performing networks into an ensemble model [5],This offered reliable, scalable diagnostic capabilities appropriate for use in actual agricultural settings and dramatically decreased misclassification rates.Independent test data gathered in a variety of environmental settings was used to further confirm the model's performance.

Aggarwal uses a variety of deep learning techniques to provide an appropriate and efficient approach for rice leaf disease prediction. To meet the algorithmic requirements, pictures of rice diseases of the leaves were collected and processed. Initially, attributes were extracted using 32 models that had been trained.Next, we used a variety of machine machine learning and ensemble-based classifiers to classify the photos of rice leaf diseases, including bacteria blight, fire, and brown spot, and compared the outcomes.The suggested process is more effective than existing approaches. Along with additional performance parameters including precision, recollection rate, F1-score, Matthews's coefficient, and Kappa statistics, it achieves 90–91% accurate identification on a common data set.For the framework EfficientNetV2B3 with ET and HGB classifiers [6], the value reaches 93–94% even after segmentation. With a 94% accuracy rate, the suggested model effectively detects rice leaf diseases. The experimental findings demonstrate the validity and efficacy of the suggested method for detecting rice illnesses.

Kokila suggests an automated method for rice leaf disease identification based on deep learning. Using a publicly accessible rice illness dataset, three cutting-edge models—YOLOv5, DenseNet-201, and ResNet-101—were assessed. The Google Colab platform was used for training and testing each model [7]. The goal of this study was to determine which model would work best in the actual world. The findings demonstrate that YOLOv5 provided a reliable and scalable approach for real-time disease identification, outperforming DenseNet-201 and ResNet-101 in detection accuracy. By facilitating early diagnosis and well-informed decision-making, this effort advances precision agriculture, ultimately enhancing crop health and encouraging sustainable farming methods.

3. PROPOSED MODEL

In this work, we introduced a FBMLF-PDRCTA Technique [8]. First, a Sobel operator is used to segment the lesion's edge after the sample picture has been smoothed using median filtering and histogram equalization. This greatly lowers background information and enhances image quality. Next, using color and texture features, the image's matching feature parameters are retrieved. Finally, Support Vector Machine is one of the most frequently used machine learning methods for categorisation.The overall working process of FBMLF-PDRCTA model is demonstrated in Figure 1 [9].

3.1. Image Preprocessing

Numerous elements, including noise and illumination, have an impact on the standard of the obtained images, which will negatively impact border detection. Image smoothing effectively reduces noise or image distortion to mitigate this problem. Mean and median filtering are common processing techniques. The idea behind mean filtering is to use an area of the picture as a template, then average the data inside that area and assign it to the region's centre. On the other hand, median filtering has become more popular.In order to make surrounding pixel values near the true value and lessen the impact of isolated noise points, The fundamental idea behind the use of median filters is to substitute the actual value of a point in an imagesequences with the mean value of all the nearby points. Thisenhancement of images is used to improve the contrast of grey at the edges, reinforce the contoured edge and highlight data within the image [10], and make information analysis easier.We can significantly improve the image's quality and recognisability for better display by using image enhancement. Histogram equalisation and grey change enhancement are popular techniques for improving images. By only altering the grey image's light and dark contrast, grey change enhancement improves the image's clarity.
One technique to improve the contrast of an image is histogram equalisation. The primary goal is to improve the contrast of an image by transforming its histogram distribution into a roughly uniform distribution.

3.2. Feature Extraction

To identify the inherent qualities (i.e., aspects) of objects in photographs, feature extraction is used. These retrieved features are crucial for identifying the classes and providing a mathematical description of the key information. To categorise rice plant leaf diseases, characteristics such as colour, texture, and shape are retrieved. These characteristics are used to differentiate between rice disease kinds.
The illness region is identified using colour characteristics based on different values55. An object's surface description in an image is called image texture56. Texture features can be extracted using a variety of methods [11], including Gabor texture features. This work uses the colour correlogram approach to extract colour features and LBP to extract colour texture-based features. But this research is unusual in that it uses a multilayer feature representation strategy to apply LBP to multiple blocks of the image rather than the entire image^64,65. By increasing picture attributes, these multi-blocks aid in the effective classification of rice plant diseases. The next subsection provides a thorough explanation of multi-block image representation.

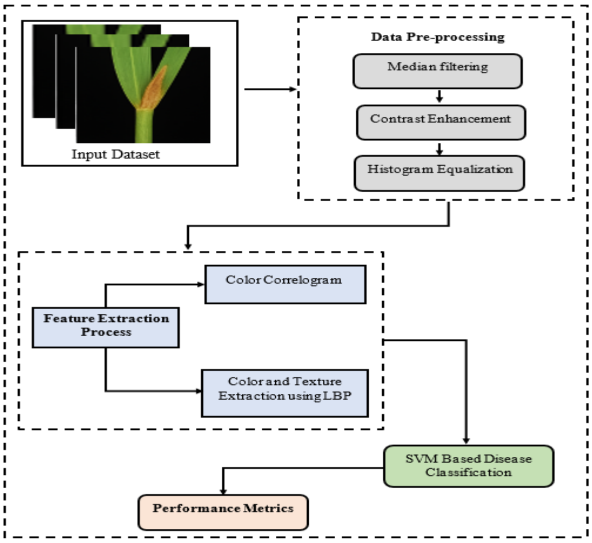

Figure 1. Working Strategy of the Proposed FBMLF-PDRCTA Model

Color Correlogram

Colour Unlike the colour histogram, which solely takes the colour representation from an image without taking into account any spatial information, the correlogram approach shows the spatial association of colour shifts with respect to the distance change66. An image's colour correlation distribution is shown by a colour correlogram. Content-based photos are retrieved using it.
Correlogram of colour (CC) CC generally illustrates how the spatial relationship of colour pairings is impacted by distance [12]. The CC of a picture is a table indexed by colour pairings, where the probability of finding a pixel of colour c_jj at a distance D from the pixel of colour c_ii in this image is set by the D entry in row (c_ii, c_jj). The calculation of CC is shown in Equation 9.

$$\gamma^{(D)}_{c_{ii},c_{jj}} = Pr_{p1\in I_{c(ii)},p2\in I}[p_2 \in I_{c(jj)}||p_1 - p_2| = D] \quad (9)$$

where I denotes the set of image pixels, and I_(c(ii)) represents the set of pixels of colour c_ii. The colours in I are quantised into m colours, c_1, c_mMultilevel multi-block as a standard grid of fixed size^ is the most widely used technique for feature representation.Equation 10 provides a mathematical formulation of the ML representation process. Let L be a +ve integer representing the stage amount such that L is greater than 0.

$$N = L^2$$

$D_{t\ \mathrm{Log}} = \bigcup_{n=1}^{N} B_n$ (10)

where B_-n denotes the nth bricks at a given level L, and N is the total amount of bricks at level L. The multilayer feature representation method's fundamental concept is shown in Figure 5.

Using LBP to extract colour and texture

Features related to colour and texture offer crucial information for identifying and categorising rice plant illnesses. An essential technique for obtaining features and content analysis in image research is texture. It describes how the pixels in an image of rice are arranged spatially [13].

If a neighbor's grey level is greater than the value of the centre pixel in a predetermined patch, a value of unity is assigned; if not, a value of zero is assigned. The block number is represented by N, and the level number is represented by L.

A 3 x 3 patch, or the pixels around an 8-digit binary number, is taken into account by the standard LBP. After labelling every pixel, a 256-bin histogram and LBP feature map are produced. Because each bin is regarded as a single feature, this LBP histograms is used as a vector of features for the categorisation procedure [14]. A case study of the LBP extraction of features procedure described in Eq. 11 is shown in Fig. 6 [14].

$LBP(x, y) = \sum_{p=0}^{N} 2^p \ (g(B_p - B(x_c, y_c$ (11)

where the LBP features at the xc, yc centre pixel are represented by LBP (xc,yc). The centre pixel's value is B(xc,yc), and the neighbouring pixel's value is B_p. The neighbour pixel index is denoted by the index p. The function g(x) will equal zero if x is less than zero and one otherwise.

The majority of studies focus on traditional LBP descriptors, while greyscale picture preprocessing has made use of their variations. The demand for photos of coloured rice on the World Wide Web, which is utilised in numerous applications, is growing. Thus, color-texture features from coloured rice photos have been extracted using LBP descriptors.

3.3. Rice disease classification Based SVM

Images of rice plants are divided into several classes and categories using the classification system. There are two steps in the categorisation process. In order to describe a predefined set of categories and comprehend the data, the classifier is first trained using classification methods.The second step involves evaluating the learnt classification model using a subset of data. Each coordinate is represented by the associated features. Every class's extracted features are represented by each point. Following that, it is discovered that the hyperplane distinguishes between classes. The hyperplane with the greatest distance between classes is found using training vectors.

Support Vector Machines (SVM) and other binary classification algorithms are frequently extended to solve multiclass classification issues using the One-Against-All (OAA) technique. If you have K classes, this method has trained K different binary SVM classifiers. Every predictor m has been trained to differentiate class m among the total of every other class. Each classifier uses a linear kernel to make decisions, and a hyperplane is a collection of linearly separated data. As in Eq. 1, by decreasing the desired function, the goal is to determine the ideal hyperplane derived from a weight vector w_m and bias term b_m for each class m.

$$\min \frac{1}{2}\|w_m\|^2 + C\sum_{i=1}^{l} \xi_i^m$$

Constraints to $(w_m)^T FE_i + b_m \geq 1 - \xi_i^m$ for $y_i = m,$ (14)

$(w_m)^T FE_i + b_m \leq -1 + \xi_i^m$ for $y_i \neq m,$

$$\xi_i^m \geq 0, i = 1,2, \ldots, l.$$

And the characteristics obtained for the i-th data point are denoted by FE_i. Each data set's goal labels are represented by y_i. A weight vector associated with class m is called w_m. The bias term b_m is connected to class m. The slack variables that enable sof margin classification are ξ_i^m. The regularisation parameter C is used to balance the margin size and classification error SVMs have employed the following kernel function:

$K(x_i, x) = x_i^T x$ (16)

The point product among the two input vectors x_i and x in the initial feature space is shown here as K(x_i,x). Since the information is linearly separable, this kernel technique has been applied.

4. Experimental Results

The experiments of proposed FBMLF-PDRCTA technique have produced positive classification results, with the maximum average classification accuracy. The classification results show that the suggested FBMLF-PDRCTA models performed nearly as well as the outcomes reported in recently published works. The proposed method has greater potential for classifying many forms of rice diseases with more variety of symptoms than prior studies carried out by other researchers; therefore the overall classification performance is satisfactory. The values of the parameter of FBMLF-PDRCTA technique is shown in Table 1.

Table 1. Values of the parameters of FBMLF-PDRCTAtechnqiue

Parameters	Parameters Values
No. of Layers	24
Learning Rate	0.001
Dropout	0,5
Validation Threshold	20
Epoch	10(min), 20(max)

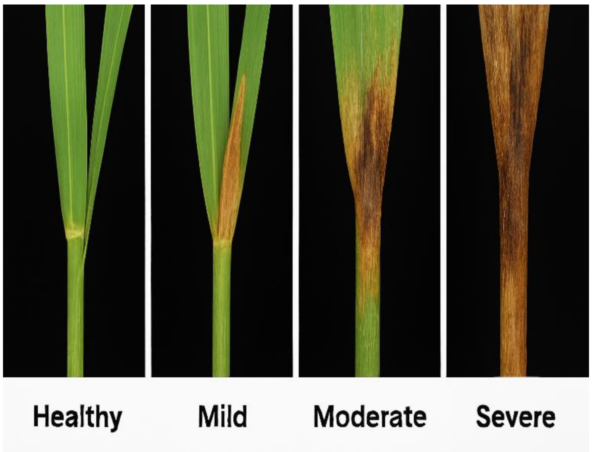

Figure 2. Sample Images of Rice Sheath Blight

The training accuracy and verification accuracy outcomes of the FBMLF-PDRCTA models utilised in this investigation are displayed in Figures 3 and 4 [15]. The results demonstrate that FBMLF-PDRCTA was more appropriate than the others due to its high accuracy. Figure 5 compares the overall outcomes, with FBMLF-PDRCTA at the top of the chart.

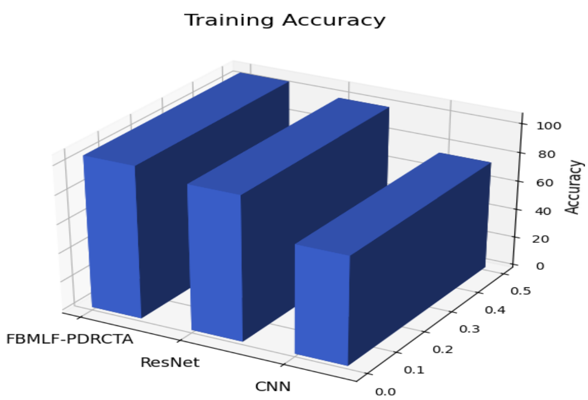

Figure 3. Traning Accuracy of FBMLF-PDRCTA technique with other existing models

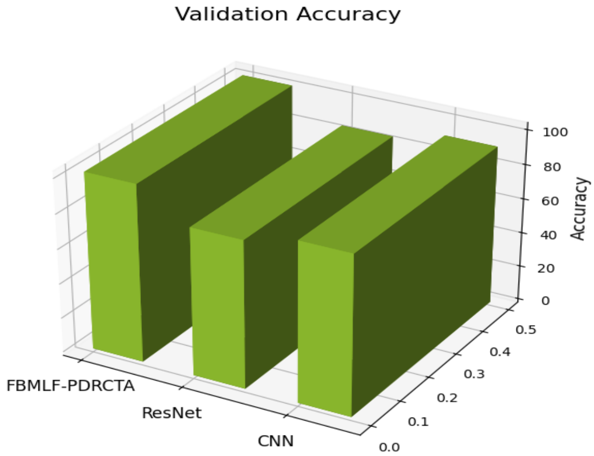

Figure 4. Validation Accuracy of FBMLF-PDRCTA technique with other existing models

Figure 4 illustrates how the results of the recommended FBMLF-PDRCTA methodology compare to state-of-the-art publications [16]. The literature describes research on identifying diseases impacting rice leaves using a variety of image analysis and machine learning techniques. However, the current work uses state-of-the-art deep learning models with new datasets and combinations to classify rice disease symptoms. A limited handful of disease forms found on rice leaves are the focus of most of the literature. The dataset has a greater diversity of rice-related illnesses with a larger spectrum of symptoms than an earlier study conducted by other researchers.

The proposed method considers automated identification of rice illnesses that impact rice leaves, such as brown spot & bacterial blight. Even while training from scratch, or baseline training, outperforms transfer learning, the outcomes are still inadequate. The accuracy of both models is less than 85%. FBMLF-PDRCTA utilises a set of kernel matrices as a local attribute extractor to extract regional features in order to find sets of the kernel to recover good discriminative features.

In the suggested model, the hyperparameter has to be changed. In order to achieve model accuracy of less than 95%, other methods like CNN and ResNet classifiers are also used. This approach also helps identify diseases by collecting data on rice leaves. The Results of deep extraction of features and transfer learning using ResNet. The high validation accuracy standard deviation is another sign of low precision.

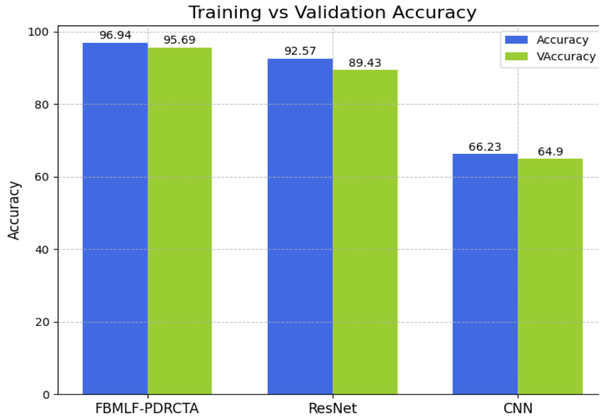

Figure 5. Average Comparisionof FBMLF-PDRCTA technique with other existing models

5. CONCLUSION

In this study, we introduced a Feature-Based Machine Learning Framework for Plant Disease Recognition Using Color and Texture Analysis (FBMLF-PDRCTA) Technique. First, a Sobel operator is used to segment the lesion's edge after the sample picture has been smoothed using median filtering and histogram equalization. This greatly lowers background information and enhances image quality. Next, using color and texture features, the image's matching feature parameters are retrieved. Lastly, one of the most used machine learning techniques for classification is Support Vector Machine. The experimental outcomes demonstrate that when the number of hidden layer nodes is set to 98, the recognition accuracy of the FBMLF-PDRCTA can reach up to 95.8%. The recognition method built using an SVM has good accuracy and can successfully overcome the shortcomings of manual recognition based on the color and texture attributes of the rice sheath blight image.

REFERENCES

[1] Ahmad, N., Asif, H. M. S., Saleem, G., Younus, M. U., Anwar, S., &Anjum, M. R. (2021). Leaf image-based plant disease identification using color and texture features. *Wireless Personal Communications*, *121*(2), 1139-1168.

[2] Hayit, T., Endes, A., &Hayit, F. (2024). KNN-based approach for the classification of fusarium wilt disease in chickpea based on color and texture features. *European Journal of Plant Pathology*, *168*(4), 665-681.

[3] Fan, X., Luo, P., Mu, Y., Zhou, R., Tjahjadi, T., &Ren, Y. (2022). Leaf image based plant disease identification using transfer learning and feature fusion. *Computers and Electronics in agriculture*, *196*, 106892.

[4] Ifty, R. A., Irfan, A. H., Dipta, T. R., Rabby, M. S. M., & Ismail, M. (2024, December). A Novel Image-Based Machine Learning Approach for Feature-Driven Plant Disease Detection. In *2024 27th International Conference on Computer and Information Technology (ICCIT)* (pp. 693-698). IEEE.

[5] Wani, J. A., Sharma, S., Muzamil, M., Ahmed, S., Sharma, S., & Singh, S. (2022). Machine learning and deep learning based computational techniques in automatic agricultural diseases detection: Methodologies, applications, and challenges. *Archives of Computational methods in Engineering*, *29*(1), 641-677.

[6] Munjal, D., Pandey, M., & Singh, L. (2025). HyFPlantNet: hybrid feature-based plant disease classification network. *Iran Journal of Computer Science*, 1-11.

[7] Hayit, T., Endes, A., &Hayit, F. (2024). KNN-based approach for the classification of fusarium wilt disease in chickpea based on color and texture features. *European Journal of Plant Pathology*, *168*(4), 665-681.

[8] Sood, A., & Reddy, P. V. (2024). Integrating Color and Texture Features for Automated Plant Health Classification Using K-Means Clustering.

[9] Li, Y., Chen, X., Yin, L. and Hu, Y., 2024. Deep Learning-Based Methods for Multi-Class Rice Disease Detection Using Plant Images. *Agronomy*, *14*(9), p.1879.

[10] Ahmed, I., &Yadav, P. K. (2023). Plant disease detection using machine learning approaches. *Expert Systems*, *40*(5), e13136.

[11] Aggarwal, M., Khullar, V., Goyal, N., Singh, A., Tolba, A., Thompson, E.B. and Kumar, S., 2023. Pre-trained deep neural network-based features selection supported machine learning for rice leaf disease classification. *Agriculture*, *13*(5), p.936.

[12] Alsakar, Y. M., Sakr, N. A., &Elmogy, M. (2024). An enhanced classification system of various rice plant diseases based on multi-level handcrafted feature extraction technique. *Scientific Reports*, *14*(1), 30601.

[13] Vishnoi, V. K., Kumar, K., & Kumar, B. (2022). A comprehensive study of feature extraction techniques for plant leaf disease detection. *Multimedia Tools and Applications*, *81*(1), 367-419.

[14] Rajpal, N., Yadav, J., &Mondal, K. K. (2024). Multi-resolution analysis and deep neural network architecture based hybrid feature extraction technique for plant disease identification and severity estimation. *Evolutionary Intelligence*, *17*(2), 1163-1183.

[15] Ahmad Loti, N. N., Mohd Noor, M. R., & Chang, S. W. (2021). Integrated analysis of

machine learning and deep learning in chili pest and disease identification. *Journal of the Science of Food and Agriculture*, *101*(9), 3582-3594.

[16] Rajpal, N., Yadav, J., &Mondal, K. K. (2024). Multi-resolution analysis and deep neural network architecture based hybrid feature extraction technique for plant disease identification and severity estimation. *Evolutionary Intelligence*, *17*(2), 1163-1183.