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AUTOMATED DISEASE DETECTION IN RICE PLANT LEAVES USING A WALD STATISTICAL PIECEWISE REGRESSIVE EXTREME LEARNING CLASSIFIER

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ABSTRACT

Agriculture plays a very important role in the Indian economy, global food security, and environmental sustainability. Rice plants are affected by diseases due to various fungi, bacteria, viruses, as well as non-infectious factors. Early plant leaf disease recognition is a crucial part in agriculture to significantly improve crop yield as well as superiority. Conventional methods unable to perform accurate rice leaf diseases without increasing time complexity. Therefore, a novel technique called Wald Statistical Piecewise Regressive Extreme Learning Machine (WSPRELM) is introduced for improving the accuracy of plant leaf disease detection with minimal time. Numbers of rice plant leaf images are gathered as of database. Afterward input image are preprocessed to enhance the image quality. Then the ROI segmentation and feature extraction is performed using Russel–Rao indexive statistical region merging technique. Finally, the leaf image diseases are correctly classified into Healthy, Brown Spot, Hispa, and Leaf Blast using Wald statistical piecewise regression by analyzing extracted feature with ground truth features. Experimental results of proposed WSPRELM technique achieve high accuracy (93.26%), precision (0.942), recall (0.948) and F1-score (0.944) with low disease identification time (132.66ms). These results suggest that WSPRELM has the potential to be a robust solution for rice plant leaf disease detection.

Keywords: *Rice Plant Leaf Disease Detection*, *Extreme Learning Machine, Russel–Rao Indexive Statistical Region Merging Technique, Wald Statistical Piecewise Regression*.

1. INTRODUCTION

Agriculture acts as a fundamental part at meeting food requirements and ensuring food safety for ever-mounting worldwide population. Plant diseases significantly minimize food manufacture and impact crop yield. Deficit of proper detection of plant diseases is leading cause of crop defeat at numerous countries. Therefore, there is a high recommendation for automatic recognition as well as diagnosis of plant diseases. Early diagnosis of plant diseases as of images remains demanding because of elevated error rates and so on. Timely as well as effectual observing of diseases is mainly significant for enhancing crop's yield.

A light weight dCNN was designed [1] with the aim of achieving higher accuracy in rice leaf disease detection, but failed to address the time complexity of dCNN. A CNN Model for Maize, Rice, and Wheat (MRW-CNN) was presented [2] for identifying leaf diseases with superior accuracy. But the model failed to detect disease severity levels and multiple diseases on the same leaf images.

An improved method for classifying rice diseases was developed in [3], which integrates a CNN through BiGRU to achieve higher accuracy at minimal cost. However, it failed to leverage additional samples to enhance the model structure in complex scenarios. A custom CNN architecture was developed [4] for identifying as well as categorizing common diseases at rice plants with maximum accuracy. However, the reliability and robustness of the models were not enhanced. A transfer learning approach was introduced in [5]. But it failed to accurately identify crop micronutrient deficiency symptoms.

A fine-tuned deep learning model was developed in [6] for real-time plant disease detection. However, it failed to accurately detect and classify multiple diseases on the same leaf. A CNN-based deep learning architecture was introduced in [7] for rice disease classification,

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for making rapid decisions to improve the agricultural yields and quality. However, the rice disease classification was not performed within a constrained time. DL and transfer learning methods were designed in [8] to accurately identify as well as categorize rice leaf diseases. But, the models failed to achieve elevated accuracy and efficiency in disease diagnosis. A robust new deep ensemble model was developed in [9] for plant disease detection. However, early diagnosis of plant disease detection with minimal time was a major challenging issue. A new multimodal data fusion framework was developed in [10] to diagnose rice diseases for agricultural IoT. However, it failed to focus on segmenting the infected portions of the leaf images. Additionally, the severity levels of the diseases remained unaddressed.

Adapted Lemurs Optimization Algorithm-basis of feature transformation was developed in [11] to enhance the accuracy of identifying different paddy diseases. However, it failed to incorporate efficient classifiers for accurately addressing the rice leaf disease detection problem. A lightweight federated deep learning model was introduced in [12] for accurate categorization of rice leaf diseases. But, it failed to differentiate between different types of rice leaf diseases.ML and DL models were designed [13] with the aim of early detection of multi-scale rice diseases. However, it did not achieve further accurate recognition of rice diseases across different kinds. Two deep learning approaches based on the autoencoder method were developed in [14] for the automatic recognition of diseases from multispectral images. SVM-based probabilistic NN was developed in [15] to classify images for plant disease recognition. But it failed to improve classification results.

The main purpose of the study is to address the difficulties in early rice plant leaf disease detection and discover the suitable solutions plan leaf disease detection based on accurately extracting features classify them into different classes. To achieve this, an automated mechanism is introduced based on deep learning algorithm to enhance the early detection of plant leaf diseases.

1.1 Major contribution of paper

The key contributions of WSPRELM technique are listed below,

- A new WSPRELM has been developed to improve accuracy of rice plant leaf disease identification by including several processes, namely preprocessing, segmentation, and feature extraction in the extreme learning machine classifier.
- To minimize the rice plant leaf disease identification time, the Russell-Rao index-based statistical region merging technique is employed for ROI segmentation from the image, based on pixel similarity measures.
- To improve accuracy and precision of rice plant leaf disease identification, Wald statistical piecewise regression is employed to analyze the extracted features with ground truth features. Based on this analysis, precise plant leaf disease identification is performed.
- To estimate result of WSPRELM, inclusive experimentation is performed with different assessment parameters.

1.1 Organization of paper

Remainder of manuscript is structured as follows: Section 2 provides appraisal of literature review. In Section 3, WSPRELM described in detail. Section 4 presents experimental evaluation with dataset description. Experimental analysis along with a quantitative analysis is discussed in section 5. Lastly, Section 6 gives conclusion of manuscript.

2. LITERATURE REVIEW

Deep learning model was designed in [16] for crop disease prediction. However, it failed to improve the accuracy rate of crop disease prediction. A DCNN was designed [17] for detection as well as recognition of rice plant diseases. However, it failed to enhance categorization effectiveness as well as efficacy of disease severity classification methods.

A DCNN transfer learning method was introduced in [18] for precise recognition as well as categorization of rice leaf diseases. However, it failed to diagnose the rice leaf diseases accurately. Faster R-CNN was presented [19] for detecting major diseases affecting rice. However, it failed to improve the model performance for plant leaf disease detection within minimal time. An effective IoT-based plant disease recognition method was developed in [20] based on semantic segmentation. However, the precision performance during plant disease recognition was not improved. An Artificial Neural Network was introduced in [21] with the aim of improving the accuracy of paddy disease classification.

A lightweight neural network was developed in [22] for crop disease identification with the aim of minimizing processing time while maintaining high accuracy. However, it failed to improve the accuracy of disease recognition. New DL model was designed [23] to attain superior accuracy at plant disease recognition. The Dense Higher-Level Composition Feature Pyramid Network was introduced in [24] for effectively detecting plant diseases. Convolutional neural network (CNN) models were developed in [25] to achieve higher classification results with maximum average accuracy.

A dual generative adversarial network (GAN) was designed in [26] for generating high-quality rice leaf disease images. The Hydra framework was introduced in [27] based on an ensemble deep learning model for the recognition of plant diseases. However, it failed to increase the robustness of models when dealing with large datasets.CNN model was designed [28] for accurately detecting as well as managing rice leaf image diseases. CNN method was developed in [29] specifically designed to enhance the accuracy of rice leaf disease categorization, but it did not improve the accuracy or training speed. A custom CNN architecture was designed in [30] for detecting and classifying general diseases from rice plant images. However, the reliability and robustness of the models was not improved.

From the above all related works this research identifies the following research gap. The major problem is it failed to accurately classify the rice plant leaves for early disease detection with minimum time. Also, larger number of samples unable to achieved elevated performance of lead disease detection. The detection and classification of multiple diseases was not attained effectively and thus reduces precision of disease identification. In addition, diseases severity levels were not addressed by means of accurately segmenting the diseased portion of the plant leaf images. To overcome these problem this manuscript, a novel technique is needed for enhancing the early detection of plant diseases. Therefore, this study proposed a WSPRELM technique for automated rice plant leaves disease detection. This technique provides better quality images and subjected to ROI segmentation and feature extraction to get best segmentation results with high accuracy. Also, proposed technique provides high training for improving the accuracy of classification.

Research focused on rice plant leaves disease detection using WSPRELM technique is significant for developing more efficient, accurate, and scalable solutions, enabling farmers to avoid crop losses, improve yields, and reduce reliance on harmful pesticides. This research is critical for ensuring sustainable agriculture, particularly in developing regions where rice farming is a vital source of livelihood.

3. PROPOSAL METHODOLOLOGY

Plant diseases considerably impact agricultural productivity and leading to economic losses worldwide. Among various plant parts, leaves are mainly vulnerable to a wide range of diseases caused by fungi, bacteria and viruses. Premature recognition as well as precise diagnosis of these diseases is essential for effectual disease administration with crop defense. Conventional techniques of disease recognition are time-utilizing, susceptible to error. However, a novel WSPRELM is introduced particularly in the fields of image processing, for automated plant leaf disease detection with minimal time as well as error. The different processes of proposed WSPRELM are illustrated in below figure 1.

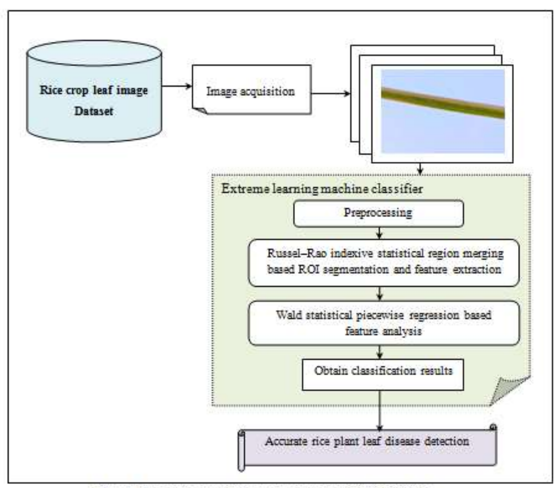

Figure 1 Architecture diagram of proposed WSPRELM

Figure 1 depicts structural design of WSPRELM for accurate rice plant leaf disease detection. First, number of sample plant leaf images $SI = \{SI_1, SI_2, \dots, SI_N\}$ are collected from the image dataset in acquisition phase. After collecting the input images, the image quality is enhanced to facilitate ROI segmentation using the Russell-Rao index-based statistical region merging technique, and to extract significant features. Then, the Wald statistical piecewise regression is applied to analyze the extracted feature vectors with either the ground truth feature vectors or the testing feature vectors, thus enabling the classification of images into Healthy, BrownSpot, Hispa, and LeafBlast categories with higher accuracy and minimal time consumption.

3.1 Wald statistical Piecewise Regressive Multilayer Extreme Learning Machine

The Multilayer ELM is ML method that belongs to the type of feedforward neural networks. The main objective of Extreme Learning Machine is computational efficiency and fast training due to the absence of an iterative process. The multilayer extreme learning machine architecture includes the cascade of numerous processing layers.

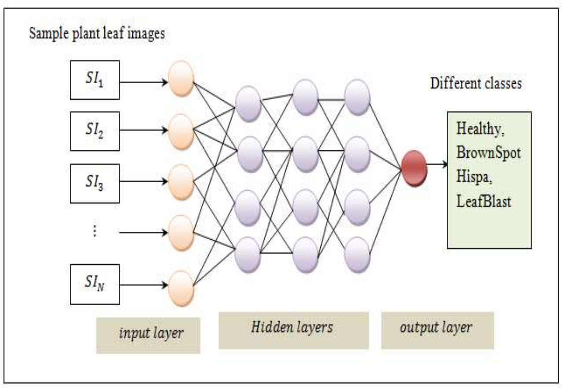

Figure 2 structure of multilayer Extreme Learning Machine

Figure 2 portrays a construction of multilayer ELM comprises of input layer, two hidden layers, as well as output layer. Designed structure did not employ some back-propagation. Structural design comprises training samples $\{S_i, Y_i\}$ where S_i denotes a training samples images $SI = \{SI_1, SI_2, \dots, SI_N\}$and Yrepresents the preferred output. Each layer consists of neurons to transmit input as of single layer to another. Activity of neurons is computed as below,

$$Q = \sum_{i=1}^{n} [SI_i * \vartheta_{ih}] + B_{ih} \quad (1)$$

Wherever, activity of neurons at input layer 'Q', 'SI_i' indicates sample plant rie leaf images, ϑ_{ih}represents weight matrix among input as well as hidden layer, bias function 'B_{ih}'

$$\vartheta_{ih} = \begin{bmatrix} \vartheta_{11} & \vartheta_{12} & \cdots & \vartheta_{1n} \\ \vartheta_{21} & \vartheta_{22} & \cdots & \vartheta_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ \vartheta_{m1} & \vartheta_{m2} & \cdots & \vartheta_{mn} \end{bmatrix} \quad (2)$$

$$B_{ih} = \begin{bmatrix} B_{11} & B_{12} & \cdots & B_{1n} \\ B_{21} & B_{22} & \cdots & B_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ B_{m1} & B_{m2} & \cdots & B_{mn} \end{bmatrix} \quad (3)$$

Afterward input is transmitted to initial hidden layer wherever noisy pixels removed from the rice leaf images. By applying this process, noisy pixels are effectively removed from rice leaf images, resulting in cleaner and more accurate images for further analysis.

In the second hidden layer, ROI segmentation involves extracting the regions corresponding to the leaves in image processing for further analysis or processing. The ROI segmentation is performed using Russel–Rao indexive statistical region merging. It is an algorithm used for image segmentation to evaluate the pixel values within a regional based on the merging criteria. The merging criterion typically refers to the conditions used to combine similar pixel intensity. This criterion ensures that regions with similar pixel intensity characteristics are grouped to provide a segmentation results. Let us consider the number of pixel intensity represented by $PI = \{PI_1, PI_2, \dots, PI_K\}$ and measure the Russel–Rao index to merge the similar pixel intensity.

$$RRI = \frac{PI_i \cap PI_j}{K} \quad (4)$$

Where, RRI denotes a Russel–Rao index measure the similarity between the two pixel intensity 'PI_i' and'PI_j' , K indicates a number of pixels within the images. The statistical region method verifies the similarity through 'TH' as below,

$$SO = \begin{cases} RRI > TH, & 1 \\ RRI < TH, & 0 \end{cases} \quad (5)$$

From the above equations (5), SO denotes a segmentation output. If the Russel–Rao index is better than 'TH', segmentation provides output as '1'. Otherwise, the segmentation provides output as '0'. Therefore, the similarity greater than the threshold function 'TH' is merged and to form a region. In this way, image segmentation is performed.

After the image segmentation, the feature extraction process is performed in third

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hidden layer. The significant dominant color features are extracted for quantifying the brightness and intensity of pixels in segmented ROI image. The color moments such as mean and standard deviation across all pixels in the image is computed as given below,

$$\mu_{PI} = \frac{1}{K} \sum_{h=1}^{K} PI_h \quad (6)$$

$$\sigma_{PI} = \sqrt{\left(\frac{1}{K}\sum_{h=1}^{K}(PI_h - \mu_{PI})^2\right)} \quad (7)$$

Where, μ_{PI} denotes a mean value of pixels 'PI within the ROI image' and Kindicates the number of pixels within the ROI image, μ_{PI} indicates a mean value of pixels, σ_{PI} denotes a standard deviation of pixels 'PI.

Texture feature is extracted and it provides the spatial correlation between the pixels' within the ROI image.

$$TF = \frac{1}{D_h * D_K} \sum_h \sum_K (PI_h - \mu_{Ph})(PI_K - \mu_{PK}) \quad (8)$$

Where 'TF' denotes a texture feature,PI_h denotes a pixel, PI_K denotes a neighboring pixels, μ_{Ph} and μ_{PK}specifies a mean of the pixels and neighboring pixels, D_h and $D_K$indicates a deviation of the pixels and neighboring pixels respectively.

Finally, the extracted features are matched with the ground truth image features or testing features in third hidden layer. It is used to assess the classification of the diseases from the image using Wald statistical piecewise regression. It is ML techniques in which association among independent variable (i.e. extracted features vector) and dependent variable (i.e. testing features vector) is measured based on Wald Statistical Test. Based on the statistical test, partitioned or classify the image into different classes.

$$PR = WST\ (FV_E, FV_T) \quad (9)$$

$$WST\ (FV_E, FV_T) = \frac{(FV_E - FV_T)^2}{var(FV)} \quad (10)$$

Where PR designates piecewise regression outcome,$WST\ (FV_E, FV_T)$ denotes a Wald statistical test between an extracted feature vector 'FV_E' and testing feature vector 'FV_T', $var(FV)$ designates a variance between two features vector. Therefore, the extracted feature vector closest to the testing feature vector is utilized to classify the images as Healthy, Brown Spot, Hispa, and Leaf Blast. Output of hidden layer is linear permutation of dissimilar functions, as follows.

$$H = \sum \alpha\ (\vartheta_{ho}\, SI + B_{ho}) \quad (11)$$

Where,H' indicates hidden layer output, αdenotessigmoid activation function of hidden neuron, 'ϑ_{ho}' represent weight between the hidden and output layer neuron. Finally, classified results are obtained at output layer. In this way, accurate plant leaf disease detection is performed. The algorithm of Wald statistical Piecewise Regressive Extreme Learning Machine is given bellow.

// Algorithm 1: Wald statistical Piecewise Regressive Extreme Learning Machine
Input: Dataset 'DS', Sample rice crop leaf images '$SI = \{SI_1, SI_2, \ldots, SI_N\}$'
Output: Increase the leaf detection accuracy
Begin
Step 1: **Collect** the number of Sample rice crop leaf images '$SI = \{SI_1, SI_2, \ldots, SI_N\}$'**--input layer**
Step 2: **for each input image** SI **—hidden layer 1**
Step 3: Assign weight matrix and bias using (1)
Step 4: Preprocess the image
Step 5: Segment ROI image using (4) (5) **—hidden layer 2**
Step 6: Extract color features using (6) (7)
Step 7: Extract texture features using (8)
Step 8: **for each** feature vector FV_E **—hidden layer 3**
Step 9: **for each** testing vector FV_T
Step 10: **Measure** Wald statistical test using (9) (10)
Step 11: Classify the images into different classes
Step 12: **End for**
Step 13: **End for**
Step 14: **End for**
Step 15: Obtain the accurate classification results -- **output layer**
End

Algorithm 1 outlines the process of predicting rice crop leaf disease using the Wald Statistical Piecewise Regressive Extreme Learning Machine. Initially, rice crop leaves images are collected from the dataset are given into the neural network's input layer for disease prediction. Subsequently, the input leaf images undergo preprocessing in the first hidden layer to enhance image quality. In the second hidden layer, the image segmentation process is executed to extract the ROI as of input image. Following this, color and texture aspects are extorted as of ROI input image. Extracted aspects are then forwarded to third hidden layer. The Wald statistical test is employed to analyze extracted as well as testing feature vectors. Based on outcomes of the statistical test, disease classification results are obtained at the output layer.

4. EXPERIMENTAL SETUP

WSPRELM, with conventional techniques, dCNN [1] and MRW-CNN [2] are implemented in python programming language. In order to conduct the experimentation, the multi-image rice plant leaf database obtained as ofhttps://www.kaggle.com/datasets/shayanriyaz/riceleafs. The database comprises the image collection of four rice diseases and the dataset is divided to training as well as validation. Each folder contains four types of categories are presented such as BrownSpot, healthy, hispa and LeafBlast. For experimental purposes, sample images 200 to 2000 are selected from the dataset.

5. COMPARATIVE PERFORMANCE ANALYSIS

Comparative study of WSPRELM with conventional methods is presented. The performance analysis employs various metrics. Result of every method in these metrics is demonstrated during tables as well as graphical depictions.

Rice plant leaf disease identification accuracy: it refers to the ratio of correctly detected plant leaf diseases from the total number of sample images in the dataset. It is given below,

$$Acc = \frac{TP+TN}{TP+TN+FP+FN} * 100 \quad (12)$$

Where, Acc' denotes a accuracy 'Acc' , TP denotes a true positive cases, TNindicates true negatives cases, FPrepresents false positive, false negative 'FN'. It s calculated in percentage (%).

Precision: it defined to the percentage ratio of properly forecasted positive values to total number of positive values respectively. The formula for precision is give below,

$$Pre = \frac{TP}{TP+FP} \quad (13)$$

Where, Pre denotes a precision rate is measured depend on 'TP' and 'FP' rate respectively.

Recall: It refers to the ratio of precisely forecasted positive values to actual positive class. It computed as follows,

$$Rec = \frac{TP}{TP+FN} \quad (14)$$

Where, 'Rec' denotes a recall rate, TPrepresents true positive and'FN' indicates false negative rate.

F1-score: it refers to the harmonic mean of precision as well as recall to estimate result of categorization method. The F-measure calculated using the following formula:

$$F1 - score = 2 * \frac{Pre * Rec}{Pre + Rec} \quad (15)$$

Where Pre denotes a precision, Rec' denotes a recall rate.

Rice plant leaf disease identification time: it calculated as amount of time taken through method to detect rice plant leaf disease. It is measured using formulates as below.

$$DD_{time} = \sum_{i=1}^{N} S_i * Time\ (DD) \quad (16)$$

Where, DD_{time}denotes a disease detection time, 'S_i' denotes a number of sample images, and the actual time consumed in disease detection '$Time\ (DD)$'. It is calculated in milliseconds (ms).

Table 1 comparison of accuracy versus sample images

Sample images	Accuracy (%)		
	WSPRELM	dCNN	MRW-CNN
200	94	89	86
400	95.36	91.05	87.65
600	96.1	90.65	88.05
800	95.23	89.56	87.11
1000	94.1	91	89.05
1200	92.36	90.65	88.11
1400	91.2	89.05	87.05
1600	90.36	88.2	85.25
1800	94.32	90.05	87.14
2000	93.23	89.1	86.52

Table 1 illustrates result outcomes of rice plant leaf disease recognition accuracy. The performance outcomes of CIKF-AISR were compared to outcomes of conventional methods. Overall comparison results prove that WSPRELM increased accuracy by 4% compared to [1] and 7% compared to [2]. This improvement is achieved due to WSPRELM's utilization of a Wald statistical piecewise regressive extreme learning machine to analyze color and texture features extracted as of ROI input image. The extorted aspects are matched with testing feature vector using the Wald statistical test to detect different classes of plant leaf images such as BrownSpot, healthy, hispa, and LeafBlast.

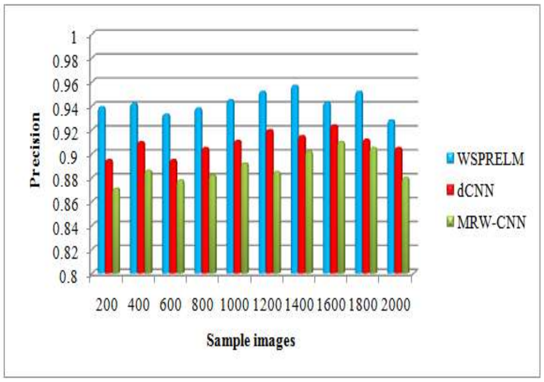

Figure 3 performance analysis of precision

Figure 3 illustrates a performance study of Prein rice crop disease detection. WSPRELM demonstrates superior precision performance than the two conventional methods. This enhancement is attained by integrating Wald statistical piecewise regression into an extreme learning classifier with higher true positives and minimized false positives. WSPRELM improves precision performance by 4% compared to [1] and by 6% compared to [2].

Table 2 comparison of recall versus sample images

Sample images	Recall		
	WSPRELM	dCNN	MRW-CNN
200	0.955	0.911	0.886
400	0.953	0.9	0.893
600	0.948	0.895	0.875
800	0.95	0.91	0.885
1000	0.948	0.905	0.875
1200	0.946	0.903	0.892
1400	0.944	0.895	0.876
1600	0.951	0.903	0.882
1800	0.947	0.911	0.896
2000	0.942	0.902	0.887

Table 2 portrays performance study of $Rec$with number of sample images. The comparison results showed that the recall performance using WSPRELM was enhanced by 5% and 7% compared to [1] and [2], respectively. This improvement is achieved by applying Extreme Learning Network, which accurately classifies plant crop images, thereby improving the accuracy of outcomes.

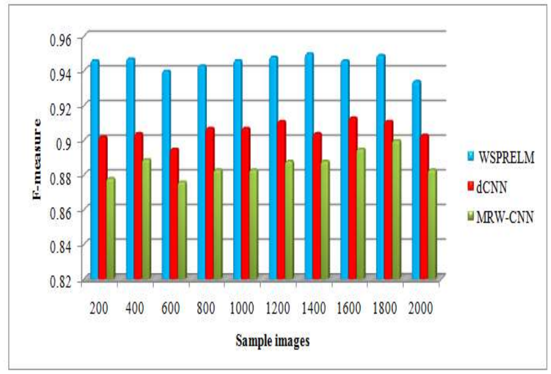

Figure 4 performance analysis of F1-score

The graphical analysis presented in Figure 4 illustrates the performance analysis. The results clearly demonstrate that employing WSPRELM yields a higher F1-score compared to other methods. This enhancement is particularly beneficial in extreme learning classifiers, where accurate classification is paramount. The overall performance results indicate a 4% improvement in the F1-score compared to [1] and a 7% improvement compared to [2], respectively.

Table 3 depicts the graphical representation of DD_{time}in relation to number of rice crop leaf images. However, DD_{time}using WSPRELM is minimized than the conventional techniques.

Table 3 comparison of Rice plant leaf disease identification time versus sample images

Sample images	Rice plant leaf disease identification time (ms)		
	WSPRELM	dCNN	MRW-CNN
200	58	66	84
400	73.8	89.6	98.6
600	82.2	113.2	126.5
800	96.8	128.9	138.3
1000	114.3	145.6	159.5
1200	136.2	157.8	175.1
1400	149.5	189.6	208.2
1600	165	206.2	223.5
1800	205.3	224.3	255.6
2000	245.5	273.6	296.6

This enhancement is attained by utilization of the Russell-Rao index-based statistical region merging technique for ROI segmentation and feature extraction. From this analysis, the plant leaf disease identification time using WSPRELM was found to be minimized by 18% and 26% compared to [1] and [2], respectively.

5.1 Difference from Prior Literature

This study provides nuanced insights into the plant leaf disease detection by effectively classify the rice plant leaves. Though prior work [1; 2] identified rice leaf diseases, this research finds the severity of the disease by categorizing the leaf images into Healthy, Brown Spot, Hispa, and Leaf Blast. Furthermore, contrary to studies [3; 4] that combined CNN to achieve minimal cost, this investigation demonstrates the reliability and robustness of the technique by training larger or additional samples, resulting in enhanced crop yield. Also, this research segment the disease affected region and extract the most contributed primary features to get improved disease detection results with lesser complexity in contrast to research [8; 18].

6. CONCLUSION

In this paper, a novel WSPRELM is developed to achieve the declared purpose of improving plant leaf disease detection by addressing problems such as accuracy and time complexity. This can be performed by preprocessing, ROI and feature extraction and classification process. First, preprocessing is employed to improve image excellence. With this, quality of the image is enhanced. The ROI is segmented by using Russell-Rao index-based statistical region merging technique to minimize the problem of time consumption of disease detection. Following this, extract color as well as features as of leaf images. With extracted feature vector, Wald statistical piecewise regression is applied for classifying the different diseases with higher accuracy. Comprehensive performance analysis is conducted using different metrics. Comparative results also prove that the presented WSPRELM achieves higher accuracy as 93.26% in rice plant leaf disease identification. There also notable improvement in precision as 0.942, recall as 0.948 and f1-score as 0.944. Moreover, rice plant leaf disease detection time is also minimized as 132.66 ms compared to existing methods.

As the rice is a vital crop for global food security, the paper on rice plant leaf disease detection is extremely interesting or relevant to an international audience. Diseases affecting rice have important economic and environmental impacts. By introducing automatic mechanism for rice plant leaf disease detection, the paper gives benefit for agricultural systems globally. Its potential applications in improving crop health, particularly in regions greatly based on rice production, make it of specific interest to researchers, agricultural experts, and technologists working toward sustainable farming solutions on a global scale.

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