International Journal of Informatics and Communication Technology (IJ-ICT)
Vol. 14, No. 2, August 2025, pp. 405~415
ISSN: 2252-8776, DOI: 10.11591/ijict.v14i2.pp405-415

Automated rice leaf disease detection using artificial intelligence deep learning

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Article Info

Article history:

Received Sep 8, 2024
Revised Nov 19, 2024
Accepted Dec 15, 2024

Keywords:

Artificial intelligence
Deep neural network
Kernel attention
Rice plant disease
Semantic batch normalization

ABSTRACT

As one of the top five rice-producing countries, India relies heavily on rice for both economic management and food needs. To ensure healthy rice plant growth, early detection of diseases and timely treatment are essential. Since manual disease detection is time-consuming and labor-intensive, an automated approach is more practical. This work presents a deep neural network (DNN)-based artificial intelligence (AI) method for recognizing rice leaf diseases. The method detects three common diseases: leaf smut, bacterial leaf blight, and brown spot, as well as healthy images. The approach uses an AI-based attention network and semantic batch normalized DeepNet (AN-SBNDN) combined with a channel attention mechanism to improve disease detection accuracy. Experiments with rice leaf datasets and comparison with conventional networks like residual attention network (Res-ATTEN) and dynamic speeded up robust features (DSURF) validate the effectiveness of the method. Key performance metrics include average accuracy, time, precision, and recall, achieved at 21%, 44%, 26%, and 31%, respectively.

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1. INTRODUCTION

Agricultural competence is influenced by several considerations like increasing population globally the consequences on crops spawned by paramount weather imbalances and numerous pandemics taking place on an extreme level also have an impact on the food security. The farmers would only take measures at the time when it is behind time for the disease to cease from proliferating owing to the reason that it will cost too much for the farmers to instrument the crop preservation assessments during the early inception of the diseases that emerges in very minimal advantages. Attention-aware features were evaluated by the residual attention network (Res-ATTEN) on disease identification from four distinct plant types was proposed in [1]. With the aid of the ResNet-18 architecture, attention learning was integrated that in turn aided in the overall system accuracy. In addition, several residual attention units were joined with the purpose of forming a single architecture. Upon comparison with the conventional attention network architectures that concentrated on single type of attention, mixed type of attention learning, combining both the spatial and channel attention with improved accuracy was said to be arrived at. Over the recent few years, crop is getting affected owing to the presence of fungi and bacteria due to the rapid climatic changes and soil temperature. Owing to the fungi-bacterial crop, food quality is reducing gradually. A modified deep neural network and dynamic speeded up robust features (DSURF) method was designed [2] forenhancing overall detection procedure. Here, artificial intelligence (AI) techniques were employed for identifying and classifying plant diseases for both fungus and bacteria. The reality that the plant leaf disease diagnosis procedure is deliberate to carry out manually and another reality that the opulence of diagnosis arecomparable to the pathologist's potentialities makes the automatic diagnosis issue a very good application domain for computer-aided diagnosis. Utila *et al.* [3], EfficientNet deep learning architecture was presented in plant leaf illness diagnosis categorization showed an improved accuracy using transfer learning. Best artificial neural network was identified initially and then with the obtained shape and color disease diagnosis was made in [4] accurately. Rice is cultivated globally, with a particular emphasis on Asian countries, where it constitutes a significant portion of the diets of approximately half of the world's population. In spite of this fact, farmers and planting experts still come across with numerous continuous hurdles for innumerable years, inclusive of rice diseases. Rathore *et al.* [5] focus was made on constructing lightweight deep learning method for detecting rice plant diseases in a further precise manner, therefore minimizing the computation cost and complexity. A survey of rice crop disease identification for expanding rice conception was investigated in [6]. Different plant disease has a crucial influence on food crop yield and upon improper recognition would spread the disease widely. However, with the lack in identification of minute plant lesion features compromised the precision. To address on this issue, Chen *et al.* [7], deep learning techniques using ensemble convolution network was applied with the purpose of enhancing the overall potentiality for identification of minute plant lesion features. However, error rate was not focused. Vallabhajosyula *et al.* [8], an ensemble neural network based on the transfer learning mechanism was designed to plant leaf disease detection. Here with a loss function of gradients error factor was addressed, therefore ensuring early disease detection. Yet another deep transfer learning mechanism for intelligent support system was designed in [9]. Here, pathogen damage was ensured in an accurate manner. Aappraisal of sophisticated deep learning techniques for plant disease recognition was investigated in [10]. Motivated by the above issues, like, precision, recall and accuracy in rice plant leaf disease recognition, an AI-based attention network and semantic batch normalized DeepNet (AN-SBNDN) is designed using channel dot product attention (DPA) network-based preprocessing and semantic region of interest (ROI) logits and batch normalized DeepNet feature engineering. Rest of the manuscript is structured as given below. In section 2 gives the related works on the rice plant leaf disease detection for rice images. Section 3 displays conciseexplanation of AI-based AN-SBNDN. After that, section 4 introduces experimental outcomes, as well as section 5 describes implementation details. Section 6 introduces a comprehensive evaluation analysisamong AN-SBNDN method and other conventional methods using table, graphical representation. Lastly, section 7 concludes manuscript.

2. LITERATURE SURVEY

Rice is an essential food source globally with the most rice being produced and consumed in Asia. However, in the presence of fungi, bacteria and other microbial diseases pose a negative influence on the plant's health and crop yield. Manual diagnosis of these diseases is said to be demanding specifically in areas with a scarcity of crop preservation specialists. Automation of disease identification and bestowing effortlessly accessible decision-support mechanisms are prerequisite for ensuring efficient rice leaf protection measures and reducing rice crop losses concurrently. Despite several methods involved in disease diagnosis still no reliable method has been recognized that converge these requirements. A survey on several disease detection methods employing deep learning was investigated in [11]. Yet another comprehensive review on precision agriculture was presented in [12]. Here several machine learning techniques were investigated along with its advantages and disadvantages involved in disease detection. In spite ofenhancementexamined inprecision and accuracy, losses incurred in analysis were not considered. For concentrating on this aspect, a lightweight federated learning technique was presented in [13] that by extracting features from pre-trained model and selecting efficient features laid mechanism for accurate detection. Disease is the principal component that influences the germination and rice evolution. Due to rice diseases huge amount of loss are said to incur in grain yield. But, diagnosis of disease and therapy specifically necessitate specialized skills that farmers frequently don't possess, hence causing a delay of treatment while waiting for specialists in diagnosing and treating the disease owing to misdiagnosis. An automated disease diagnosis mechanism employing modern deep learning framework called, U-Net architecture was designed in [14]. By employing this type of design accurate disease detection was ensured with minimum loss. Yet another Bayesian optimization mechanism with attention-based neural network was proposed in [15] to focus on the accuracy aspect. A holistic review on image processing techniques for leaf disease identification was investigated in [16]. A convolutional neural network based deep learning framework was designed in [17] that employed preprocessing and semantic segmentation for detecting leaf disease. A hybrid mechanism involving three machine learning techniques, convolution neural network (CNN), support vector machine (SVM) and random forest (RF) classifier was proposed in [18]. With this type of hybrid mechanism early action can be taken to safeguard the crops from disease. Computer vision and machine learning methods were used in [19] to focus on accuracy aspects of leaf disease detection. An ensemble of deep learning techniques were introduced in [20]-[25] that first accumulated the extracted features and then ensemble categories were generated to determine the output in an accurate manner. With the effort to focus on the early detection of rice plant leaf disease that can identify different cases involved in rice images, an AI-based AN-SBNDN is proposed in this work.

3. METHOD

Agriculture plays major role in aiding the increasing population and providing as an indispensable source of energy. Rice plant leaf diseases pose a serious threat to both the quality of crop and corresponding yield that has an influence on agricultural development. The conventional method for rice plant leaf disease remains in manual observation that is found to be both laborious and time consuming. To make certain higher standard or characteristic, volume and rice production, it is essential to diagnose rice leaf disease in its premature stage in interest of decreasing the pesticide utilization in agriculture that in turn circumvents environmental harm. Researchers have acknowledged the utilization of AI techniques based deep learning for identifying or detecting the diseases affecting rice leaves. The process flow steps of the proposed method AI-based AN-SBNDN are shown in Figure 1.

As illustrated in the above figure, the rice plant leaves images obtained as of images across the internet and the dataset is created. Image dimensionality is reduced by eliminating the background pixels in the preprocessing step. The next step is the feature engineering in which semantic ROI logits and batch normalized DeepNet feature engineering model is applied to identify the normal portion (i.e., healthy images) and the diseased portion (i.e., brownspot, hispa and leafblast) respectively.

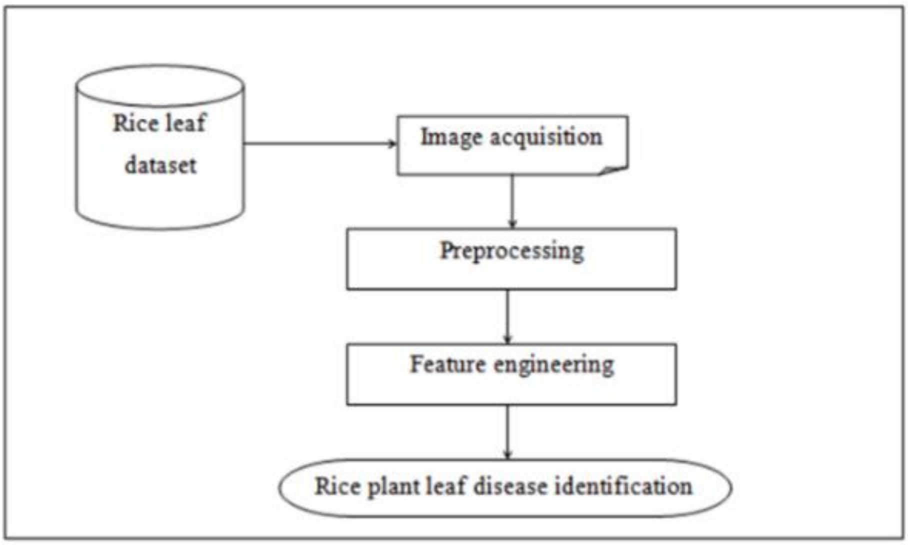

Figure 1. Structure of AI based AI-SBNDN

3.1. Acquisition of images

Despite the requirement for accessing huge number of images for rice plant leaves diseases are indispensable to create complete experiment further genuine or well-grounded. In this work, one rice plant leaf disease dataset from https://www.kaggle.com/datasets/shayanriyaz/riceleafs is used to observe potentiality of the proposed technique in precisely recognizing healthiness of rice plant leaves. Some samples of the healthy and three types of diseased images are depicted in Figure 2.

As stated earlier than, all the rice leaf images giventhrough rice leaf dataset encapsulated under unconstrained environmental circumstances. As a consequence, in the majority of cases, images hold in custody unsolicited details which unfavorably and straightly influence disease detection accuracy. As presented in the above figure, it is comprehensible that the part in the image is not associated to the disease detection problem. Hence, the rice plant leaves require to be detected and secluded from the background prior to the application of the image disease detection process.

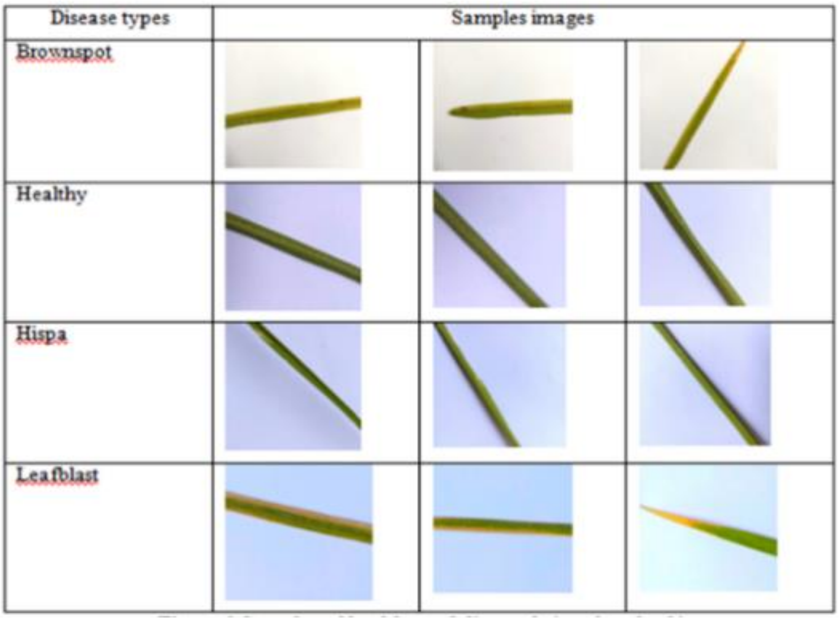

Figure 2. Sample of healthy and diseased leaf images of rice plant

3.2. Channel dot product attention network-based preprocessing

Owing to the complication involved in field environment and resemblance of rice plant leaf diseases, recognition errors give rise to proliferation of plant diseases. As a consequence, rice plant leaf disease recognition accuracy cannot congregate prerequisites of accuracy in agriculture. Depend on these outcomesin straight line, directly implementing deep neural learning to rice plant leaf disease recognition not significant. Consequently, improving NNs preprocessing capacity and improving feature engineering aspects using AI techniques contain become two importantdemands for precision agriculture to use AI-based deep learning in rice plant leaf disease recognition field. In this section, channel DPA network-based preprocessing model is designed to focus on removing noisy soil area pixels and retaining actual rice crop images. Channel attention network (CAN) employs neighborhood cross-channel exchange technique without dimensionality reduction. This technique makes certain which the data or details from neighboring channels (i.e., features) is correlated devoid of losing image data, addressing correlation issue of information included in rice plant leaf disease images. To summarize, the CAN caneruditethrough employing DPA framework. Given the sample images (i.e., input feature maps into distinct channels) '$SI = \{SI_1, SI_2, \dots, SI_n\} \in R^{N*C}$' the DPA framework produces sample image matrix 'SIM', key matrix 'KM' as well as value matrix 'VM' with 'N' and 'C' representing the sample input size of raw rice leaf images and the corresponding input channels respectively.

$$SI = \begin{bmatrix} BS_1 & BS_2 & \dots & BS_N \\ HI_1 & HI_2 & \dots & HI_N \\ H_1 & H_2 & \dots & H_N \\ LI_1 & LI_2 & \dots & LI_N \end{bmatrix} \tag{1}$$

Then, the DPA for each raw sample images is mathematically represented as (2)-(4).

$$SIM = SIW_{sim} \in R^{N*D_k} \tag{2}$$

$$KM = KW_{km} \in R^{N*D_k} \tag{3}$$

$$VM = VW_{vm} \in R^{N*D_k} \tag{4}$$

From the (2)-(4), with the aid of three matrices, DPA is generated according to the rice plant leaf image dimensions 'D'. Moreover, with the sample image matrix '$SIM \in SI$' and key matrix 'KM' possessing similar pixel intensities of raw rice plant leaf images, to measure the similarity between the '$i-th$' sample matrix vector 'SI_i^T' and the '$j-th$' key matrix vector 'KM_j^T', we used the softmax normalization function '$softmax(SI_i^T KM_j^T)$'. Owing to the reason that the sample matrix vector and the key matrix vector are produced often by different neighborhood pixels of raw rice plant images, the correlations between '$softmax(SI_i^T)$' and '$softmax(KM_j^T)$' are commonly skewed. The DPA calculate pixel value at location 'i' throughcarrying out weighted sum covering everypositions, where all position's value feature is allocated weight depend on its similarity to every other locations. Using the Kernel-induced SoftMax normalization function, the '$i-th$' row of sample matrix vector with respect to the '$j-th$' key matrix vector 'KM_j^T' employing Kernel attention individually attend to crucial pixel features (i.e., discarding the noisy background portions) therefore ensuring accurate AI-assisted rice plant leaf disease identification.

$$D(SIM, KM, VM)_i = \frac{\sum_{j=1}^{N} e^{SIM_i KM_j VM_j}}{\sum_{j=1}^{N} e^{SIM_i KM_j}} \tag{5}$$

From the (5), 'i' denotes the iteration identifier for the corresponding dimensions 'D' of the dot product 'SIM', 'KM', and 'VM' respectively. Then, the degree of similarity between 'SIM_i' and 'KM_j' using Kernel-induced SoftMax normalization function is stated as (6).

$$Res = \frac{\sum_{j=1}^{N} Sim(SIM_i, KM_j) VM_j}{\sum_{j=1}^{N} Sim(SIM_i, KM_j)} \tag{6}$$

From the above (6) results, the noisy background portions are removed or discarded retaining the normalized foreground rice plant leaf images. The channel attention employing global pooling function to arrive at the preprocessed resultant images is formulated by fusing global average as well as global max pooling as (7).

$$PI = G(Res) = G_{avg}(Res) + G_{max}(Res) \tag{7}$$

By performing global pooling as given (7), original multidimensional input '$SIM * KM * VM$' is transformed to one dimensional matrix '$PI * 1 * 1$' (i.e., weighted feature maps) employed for effective cross-channel information fusion operation (i.e., identification of three types of disease), therefore ensuring good visual interpretation. Here high weighted feature map results are said to be the foreground leafy image whereas low weighted feature map results are said to be the background noisy or surface portions. The pseudo code representation of channel DPA network-based preprocessing is given in Algorithm 1.

Algorithm 1. Channel DPA network-based preprocessing

Input: Dataset 'DS', sample images '$SI = \{SI_1, SI_2, \dots, SI_N\}$'
Output: computationally-efficient noise-eliminated preprocessed rice plant leaf images
Step 1: **Initialize** 'N', channel 'C'
Step 2: **Begin**
Step 3: **For** each Dataset 'DS' with Sample Images 'SI'
Step 4: Obtain sample images as given in equation (1)
Step 5: Perform Dot Product Attention (DPA) for each raw sample images as given in equations (2), (3) and (4) to return sample image matrix, key matrix and value matrix
Step 6: Perform Dot Product Attention (DPA) for the resultant formulated sample image matrix, key matrix and value matrix as given in equation (5)
Step 7: Measure degree of similarity using Kernel-induced Softmax Normalization function as given in equation (6)
Step 8: **If** '$Res \geq 0.5$ *and* $Res < 1$'
Step 9: **Then** high correlation exists between 'SIM_i' and 'KM_j' with respect to 'VM'
Step 10: Restore the foreground rice plant leaf image
Step 11: Return preprocessed image 'PI'
Step 12: **End if**
Step 13: **If** '$Res < 0.5$'
Step 14: **Then** low correlation exists between 'SIM_i' and 'KM_j' with respect to 'VM'
Step 15: Discard the background portions
Step 16: **Go to** step 4
Step 17: **End for**
Step 18: **End**

3.3. Semantic ROI logits and batch normalized deepnet feature engineering for disease detection

The procedure of changing preprocessed data into a set of significant characteristics that can be utilized for AI-based deep learning tasks is referred to as feature engineering. Feature engineering is a technique employed in several fields, including AI, to identify significant patterns or representations in input data. This feature engineering procedure aids in ease in process and improve the subsequent modeling tasks. In our work, semantic ROI logits and batch normalized DeepNet feature engineering for disease detection are presented. The feature engineering process here consists of ROI configuration and the disease detection. In this process, fiirst, in the ROI configuration process, the base distance '(α, β)' is quantized into 'l' non-adjacent distance annotated bounding boxes making use of coarse-grid spacing discretization. With the objective of minimizing training losses in RoIsbymaximum distance values as well as enhance precision depend on network forecast distance of adjacent pixels, by splitting specified distance annotated bounding boxes in a coarse-grid discretized manner. Ground truth residual 'Res_{dis}' is measured for distance of ground truth 'GT_{dis}' whichappears in annotated bounding boxes 'i' as (8).

$$Res_{dis} = \frac{(\log(GT_{dis}) - loc_i)}{\log(t_{i+1}) - \log(t_i)} \tag{8}$$

From in (8), ground truth residual resultant pixels are obtained 'Res_{dis}' also, the locus 'loc_i' for a distance of ground truth 'GT_{dis}' is measured as (9).

$$loc_i = \frac{\log(t_{i+1})}{2} \tag{9}$$

Following which the left edge of the '$i - th$' distance annotated bounding boxes '$\log(t_i)$' and the right edge of the '$i - th$'' distance annotated bounding boxes '$\log(t_{i+1})$' is mathematically evaluated as (10).

$$x_i = \log(t_i) = \exp\left[\log + \frac{\log\left(\frac{\beta}{\alpha}\right) * i}{l}\right];\ \log(t_{i+1}) = 1 - \log(t_i) \tag{10}$$

The distance index '$i \in \{1,2, \ldots, l\}$' is provided to pixel if ground-truth distance is 'GT_{dis}'. Following which the second process called Batch normalization Neural Network model is performed with the purpose of obtaining engineered features for accurate identification of plant leaf disease in rice crop. Batch Normalized NN model integrated through ROI configuration extract lesion features of diseased rice leaves, therefore improving recognition accuracy significantly. Let us consider 'SB' to represent a small batch of size 'u' of the entire preprocessed training set. Then, the experimental mean and variance of small batch 'SB' is formulated as (11) and (12).

$$\mu_{SB} = \frac{1}{u} \sum_{i=1}^{u} x_i \tag{11}$$

$$\sigma_{SB}^2 = \frac{1}{u} \sum_{i=1}^{u} (x_i - \mu_{SB})^2 \tag{12}$$

With the above experimental mean and variance obtained from (11) and (12) of small batch 'SB', for a layer of network with '$d - dimensional$' input '$x = \left(x^{(1)}, x^{(2)}, \ldots, x^{(d)}\right)$' each ROI configured input is normalized individually as given below.

$$x_i^{(k)} = \frac{x_i^{(k)} - \mu_{SB}^{(k)}}{\sqrt{\left(\sigma_{SB}^{(k)}\right)^2 + \epsilon}}, where\ k \in [1, d] \&\ i \in [1, u] \tag{13}$$

Finally, with the above obtained per dimension mean '$\mu_{SB}^{(k)}$' and per dimension standard deviation '$\sigma_{SB}^{(k)}$', the batch normalized output (i.e., the engineered features identification of plant leaf disease in rice crop) provides with the precise disease detection with minimum error. The batch normalization function is formulated as (14).

$$BN_{y_i^{(k)}} = \gamma^{(k)} x_i^{(k)} + \beta^{(k)} \tag{14}$$

From (14), '$\gamma^{(k)}$' and '$\beta^{(k)}$' represents results learned in the optimization process (i.e., the engineered features) whereas '$x_i^{(k)}$' denotes the normalized output (i.e., plant leaf disease in rice crop) respectively. The pseudo code representation of semantic ROI logits and batch normalized DeepNet feature engineering for disease detection is given in Algorithm 2.

Algorithm 2. Semantic ROI logits and batch normalized DeepNet feature engineering

Input: Dataset 'DS'
Output: precise rice leaf disease detection
Step 1: **Initialize** 'N', preprocessed image 'PI', small batch 'SB'
Step 2: **Begin**
//Region-of-Interest configuration
Step 3: **For** each Dataset 'DS' with preprocessed image 'PI'
Step 4: Evaluate ground truth residual values as given in equations (8)
Step 5: Measure locus 'loc_i' for a distance of ground truth 'GT_{dis}' as given in equation (9)
Step 6: Evaluate left and right edge distance annotated bounding boxes as given in equation (10)
Step 7: **End for**
//Feature engineering-based disease detection
Step 8: **For** each small batch 'SB'
Step 9: Evaluate experimental mean and variance as given in equations (11) and (12)
Step 10: Perform normalization of ROI configured input separately as given in equation (13)
Step 11: Return engineered features '$\gamma^{(k)}$' and '$\beta^{(k)}$' as given in equation (14)
Step 12: Return normalized output (i.e., plant leaf disease in rice crop) '$x_i^{(k)}$' as given in equation (14)
Step 13: **End for**
Step 14: **End**

With the objective of focusing on both the quality (i.e., precision) and quantity (i.e., recall) aspects, two different procedures, i.e., ROI configuration and feature engineering for rice plant leaf disease detection is designed. First, with the obtained preprocessed image 'PI' as input, a small batch 'SB' is considered for testing and subjected to semantic logits function to retrieve ROI configurations for further processing. This with the aid of left and right edge distance annotated bounding boxes obtains exact region of interest, therefore ensuring precise detection. Second, with the configured ROI features as input, feature engineering process is applied. Here, batch normalization function is applied to make training faster and stable via normalization by means of re-centering and re-scaling, therefore obtaining relevant instances in a significant manner.

4. EXPERIMENTAL SETUP

Comparison analysis is imparted to evaluate performance of three different deep learning methods, AI-based AN-SBNDN, Res-ATTEN [1], and deep neural network and dynamic speeded up robust features (DSURF) [2] in solving the multi-image rice plant leaf disease identification problems using rice leaf dataset obtained from https://www.kaggle.com/datasets/shayanriyaz/riceleafs. In the multi-image rice plant leaf disease identification task, performance of selected three deep learning methods is assessed or estimated using estimating mean values of four metrics by testing set, comprising rice plant leaf disease identification accuracy, rice plant leaf disease identification time, precision and recall.

5. DISCUSSION

In this section a detailed analysis of four distinct performance metrics, rice plant leaf disease identification time, accuracy, precision and recall is made by making elaborate comparisons between proposed AI-based AN-SBNDN and existing methods, Res-ATTEN [1] and deep neural network and dynamic speeded up robust features (DSURF) [2] using table and graphical representations.

5.1. Performance measure of rice plant leaf disease identification time

In this section rice plant leaf disease identification time is measured. Early the disease detection made precautionary steps can be made by limiting the spread. The plant leaf disease identification time is measured using formulates as (15).

$$DD_{time} = \sum_{i=1}^{N} S_i * Time\ (DD) \tag{15}$$

From (15), disease detection time 'DD_{time}' is measured by taking into consideration the samples involved in simulation process 'S_i' and actual time utilized in disease detection '$Time\ (DD)$'. It is measured in milliseconds (ms). Statistical analysis of rice plant disease detection time is shown in Table 1.

Table 1. Statistical analysis of rice plant disease detection time using AN-SBNDN, Res-ATTEN [1], and DSURF [2]

Sample images	Rice plant disease detection time (ms)		
	AN-SBNDN	Res-ATTEN	DSURF
200	70	94	116
400	85.35	110.25	130.35
600	105.25	135.35	165.35
800	125.55	155.85	199.35
1,000	165.35	190	215.35
1,200	190.45	215.45	235.55
1,400	205.25	240	280.35
1,600	245.35	275.35	315.35
1,800	280	325.35	355.55
2,000	315.55	350.15	400.25

5.2. Rice plant leaf disease identification accuracy

Rice plant leaf disease identification or detection accuracy refers to ratio of properly anticipated observations to every observation is what calculates this. It is most inherent metric and it is percentage ratio of properly forecasted sample images to every images present in dataset. It is expressed as (16).

$$Acc = \frac{TP+TN}{TP+TN+FP+FN} \tag{16}$$

From the (16), the accuracy 'Acc' result is arrived at, depend on = true positive 'TP', (i.e., prediction of positive cases as positive), true negative 'TN' (i.e., forecast of negative cases as negative, false positive 'FP' (i.e., forecast of negative cases as positive cases) and false negative 'FN' (i.e., forecast of positive cases as negative cases). Precision refers to ratio of properlyforecasted observations to every positively predicted observation. Table 2 compares the rice plant disease detection accuracy using AN-SBNDN, Res-ATTEN [1], and DSURF [2] respectively.

Table 2. Statistical analysis of rice plant disease detection accuracy or accuracy using AN-SBNDN, Res-ATTEN [1], and DSURF [2]

Sample images	Accuracy (%)		
	AN-SBNDN	Res-ATTEN	DSURF
200	91.5	90.37	74.5
400	92.35	91.15	72.55
600	95	92	83.35
800	93.15	89.35	80
1,000	92	86	78.45
1,200	88.45	84.35	76
1,400	85	82	75
1,600	88.45	84.15	77.85
1,800	90.35	85	80
2,000	85.25	80	75

5.3. Performance measure of precision

To be more specific, precision measurement of algorithms defines to percentage ratio of properly forecasted positive values to total number of positive forecasted values. It is expressed as (17).

$$Pre = \frac{TP}{TP+FP} \tag{17}$$

From (17), precision 'Pre', rate is measured depend on true positive 'TP' and false positive 'FP' rate respectively. Table 3 provides the comparison between three methods with respect to precision.

5.4. Performance measure of recall

Recall evaluates how many properly anticipated positive observations there were compared to every of actual class observations. In other words, it is percentage ratio of precisely forecasted positive values to actual positive class. It is estimated as (18).

$$Rec = \frac{TP}{TP+FN} \tag{18}$$

From (18), recall rate 'Rec' is measured by taking into consideration 'TP' and 'FN' rate. Lastly, Table 4 lists the recall rate using three methods.

In a similar manner as precision, a decreasing trend was initially observed followed by which an increasing trend was then observed for the remaining samples. Also, simulations performed with 200 sample images, false and negative results were obtained for 7 sample images using AN-SBNDN, 15 sample images as well as 21 sample images using [1], [2] respectively. With this overall recall rate using the three methods were observed to be 93.45% using AN-SBNDN, 85.71% using [1], and 79.20% using [2].

Table 3. Statistical analysis of precision using AN-SBNDN, Res-ATTEN [1], and DSURF [2]

Sample images	Precision (%)		
	AN-SBNDN	Res-ATTEN	DSURF
200	90.9	81.81	72.72
400	85.25	78.15	70.45
600	82.15	75.35	68.35
800	78.35	72	65
1,000	80	74	66.45
1,200	82.35	75.35	68
1,400	85	77	70
1,600	88.15	78.35	72.45
1,800	85.35	76	70
2,000	82	74	68.35

Table 4. Statistical analysis of recall using AN-SBNDN, Res-ATTEN [1], and DSURF [2]

Sample images	Recall (%)		
	AN-SBNDN	Res-ATTEN	DSURF
200	93.45	85.71	79.2
400	90.25	83.15	77.45
600	88	81	75
800	86.35	80	74
1,000	85	78.25	72.25
1,200	85.15	77	70
1,400	87	79.45	72.55
1,600	87.35	81	74
1,800	89	83.25	75.35
2,000	90	85	77

6. CONCLUSION

An AI-based system that utilizes a channel DPA network-based preprocessing and semantic ROI logits and batch normalized DeepNet feature engineering for rice plant leaf disease detection is proposed. With preprocessing section being analytical and is straight forward using noise handling via DPA and Kernel-induced SoftMax normalization function. Obtained images are fed into the semantic ROI logits and batch normalized DeepNet feature engineering for rice plant leaf disease detection. Here two processes, i.e., ROI construction and feature engineering for disease detection in rice crop were designed. Semantic logits for configuring the ROI for further processing and feature engineering was performed using batch normalized DeepNet. Finally, with the aid of the results learnt in the optimization process, the normalized output (i.e., disease detection) was obtained. The quantitative analysis and validation confirm that the proposed AN-SBNDN method was better than state-of-the-art methods, i.e., Res-ATTEN and DSURF method in terms of precision, recall, rice plant leaf disease identification time and accuracy.

FUNDING INFORMATION

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

AUTHOR CONTRIBUTIONS STATEMENT

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Suhaila M. P.	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓				
Hemalatha S.							✓	✓	✓	✓	✓	✓	✓	✓

C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflicts of interest regarding the publication of this paper.

DATA AVAILABILITY

The datasets used and analyzed during the current study are available from the corresponding author on reasonable request.

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