DEEP LEARNING AND METAHEURISTIC ALGORITHM FOR EFFECTIVE CLASSIFICATION AND RECOGNITION OF PADDY LEAF DISEASES

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ABSTRACT

One of the most recent agricultural research topics is the recognition and classification of diseases from a plant leaf. With the exponential advancement of smart farming, plant disease detection becomes digitalized and data-driven, allowing advanced decision support, smart examination, and preparation. The detection of agricultural plant diseases using machine learning techniques would reduce the dependence on farmers to preserve agricultural goods. This paper proposes a deep learning-based metaheuristic algorithm of paddy leaf disease detection and recognition that enhances accuracy, generality, and training performance. This paper describes field images of various kinds of paddy leaf diseases: normal, bacterial blight, brown spot, and blast diseases. In this paper, the input image is assigned to pre-processing to remove artifacts and noise from the image. The Optimized Deep Convolutional Neural Network with Cuckoo Search (DCNN-CS) Algorithm is then used to classify leaf diseases by using the pre-processed image. During both the basic pre-training and fine-tuning phases of the DCNN approach, weights and biases are optimized using a cuckoo search algorithm (CS) to reduce classification errors. This DCNN-CS technique allows the application of simple statistical optimization methods with a reduced computing workload, resulting in high classification accuracy. Finally, the proposed DCNN-CS model's classification accuracy and efficiency were evaluated and compared to other Classification Techniques.

Keywords: *Paddy Leaf Diseases, Deep Convolutional Neural network, Cuckoo Search, Classification.*

1. INTRODUCTION

Early detection of plant disease symptoms is extremely beneficial to agriculture. However, owing to a deficiency of embedded computer vision developed for smart agriculture, this challenge remains difficult [1]. Leaves play an important part in crops because they provide knowledge about the quantity and type of horticultural yield. Climate change, the presence of weeds, and soil infertility are all factors, which affect food production. Also, the production of various agricultural products as well as economic harm caused by plant or leaf diseases are major hazards [2]. Agricultural yields are also affected by a variety of factors which includes lack of water, plant disease [3]. Early detection, treatment, and prevention of plant diseases, particularly in their early phases of development, is therefore crucial for increased productivity [4]. Hence, several works have addressed the problems with successful early phase diagnosis and classification of plant diseases related to particular restrictions.

Many research [5] have used traditional image processing and machine learning (ML) algorithms to execute agricultural activities. However, deep learning (DL), a subset of machine learning (ML), has recently proven to be remarkably efficient for real-world object identification, recognition, and classification [6]. As a result, the agricultural study aims to contribute toward Deep Learning-based approaches. The Deep Learning techniques have generated cutting-edge findings in the agricultural sector such as crop discrimination [7], fruit harvesting [8], and plant identification [9]. Likewise, current research focuses on another important agriculture-based problem, the detection of plant diseases.

Manual seed analysis, for example, is inefficient since it takes time and is labour intensive. As a result, image-processing approaches for disease identification and prediction based on physical properties of plant leaves have been developed [10]. These strategies have been used to classify widespread paddy leaf diseases such as bacterial blight, brown spot, sheath rot, and blast diseases [11]. Image processing depends on segmentation findings to remove characteristic disease attributes like color, scale, and shape. However, helps to determine these characteristics as specific disease forms are challenged by the wide range of plant effects. In some instances, a single disorder manifests as yellow frameworks, while in others, it manifests as brown frameworks [12]. In one particular plant type, the disease can also lead to identical forms and colors while some can induce opposite colors, but different shapes. While specialists can quickly diagnose picture-based plant diseases, human diagnosis is unnecessarily time-consuming and costly for providing agriculture solutions [13]. As such, the human system is often inaccurate because it is strongly influenced by personal bias and practice [14]. As a result, current disease inspection procedures often produce incorrect classification outcomes, minimizing paddy yields in recent decades [15].

On large farms, manual detection of plant diseases is normally done by scientists using their naked eyes, which takes more time and costs more money. [13]. It's difficult to achieve, and it can lead to a mistake when selecting the disease category [14]. Paddy yield has decreased in recent years due to a lack of awareness about appropriate management for identifying paddy leaf diseases [15]. To address this, an effective and fast detection system for paddy leaf disease is required. As a result, this paper proposes a novel approach for identifying paddy plant diseases using images. Brown spot, Leaf blast, and Bacterial blight are the most common rice plant diseases involved in this paper (Figure 1). This paper offers a new DCNN for the classification of paddy leaf diseases. By a cuckoo search algorithm (CS), a search tool simulating improved results, the error had been minimized. In normal pre-training and fine-tuning stages, optimization was performed to build the DCNN-CS structure which allows simple statistical training, computer workload reduction, and precision in classification. Paddy images have been pre-processed for the first time. Several attributes, including texture, shape and color were derived from previously diseased fields. Finally, the proposed technique was proposed for the classification of paddy leaf disease detection. Under multiple cross-validations, the DCNN-CS outperformed another machine learning algorithm.

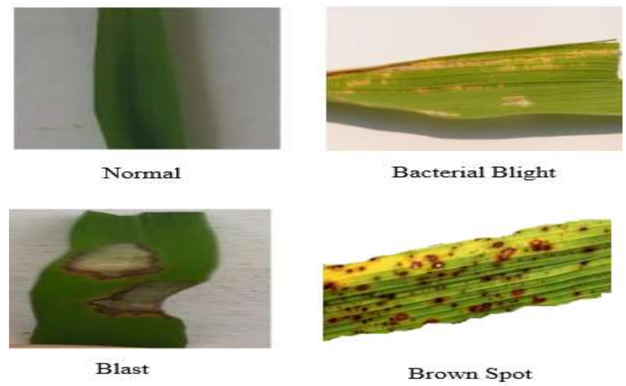


Figure 1: Sample Paddy Leaf (Normal & Diseased Leaf).

The remaining of this paper is organized as follows: Section 2 includes the most recent works on Paddy leaf disease classification. Our proposed approach is presented in Section 3. The experimental study is shown in Section 4. Section 5 is the conclusion section.

2. RELATED WORK

The following are some of the most recent studies on the recognition and classification of paddy leaf diseases.

Yang Lu et al. [16] created a novel rice plant disease identification technique based on a deep convolutional neural network. They used a dataset of 500 images of diseased and uninfected paddy leaves. 10 popular rice diseases are used to classify them. They demonstrated that their solution outperformed the standard machine learning system in terms of accuracy. The experimental reports demonstrated the efficacy and feasibility of their suggested system. Gittaly Dhingra et al. [17] proposed a segmentation strategy for ROI assessment based on neutrosophic reasoning adapted from the fuzzy package. For segmentation, they used three objective features. Feature subsets based on segmented fields are addressed for confirming whether the leaf was infected or not. The experiment featured several classifiers, and the random forest version outperformed the others.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

They used a dataset of 400 leaf images, 200 of that were diseased and 200 of which were not.

D.Nidhis et al. [18] used image processing methods to create a tool for identifying the disease type caused by leaves in paddy. The magnitude of the disease was performed by calculating the percentage of the diseased area. Insecticides are used based on the type of the diseases for the brown spot, bacterial blight and paddy explosion that are major diseases affecting the paddy yield and its production. Taohidul Islam et al. [19] proposed a new approach for identifying and classifying rice plant diseases. In their work, they detected and classified diseases by image processing method based on the percentage of RGB value of the diseased component. They used the Naive Bayes classifier that is a basic classifier, to categorize disease. Using only one element, they were able to identify and classify three different kinds of paddy leaf diseases. As a result, it was a faster approach that took less computing time.

Gayathri Devi and Neelamegam [20] devised a method for automatically detecting diseases in paddy leaves by using the image processing method. For feature extraction, they used a hybridized greyscale cooccurrence matrix, SIFT and DWT. Following feature extraction, the infected and normal leaves were classified using classification methods such as SVM, KNN, Neural Networks and Naive Bayes. Aydin Kaya et al. [21] analysed on four publicly available datasets for deep neural network-based plant categorization about the role of four alternative transfer learning approaches. Transfer learning would improve low-performance plant categorization systems and bring significant benefits for automatic plant recognition, according to their findings.

The author Alessandro et al. [22] employed CNN to identify weeds in soybean yield photos and classify the weeds as broadleaf or grass. A database of over 15,000 photos of soybean, soil, grass weeds, and broadleaf was developed. The CNN used in this paper reflected a DL approach that has seen considerable accomplishment in image recognition. Zhou et al. [23] for computing the azimuth angle, developed a skeleton extraction tool for defining and counting maize seedlings. The RGB images were converted to greyscale images before being pre-processed for threshold segmentation. Threshold optimization is used to segment the images, and the technique's effectiveness was validated by analysing automatic measurements of plant shapes. To overcome the challenges associated with the extraction of plant skeletons, the technique used external pressure method-skeleton-debarring methodology relies on the saliency logic framework. The system calculated the seedling rate accurately and provided valuable analytical methodology for the agronomic study. Furthermore, an approach struggled to assess the utility of data collected by a series of applications.

Chouhan et al. [24] created a Bacterial foraging optimization-based RBFNN for automatically detecting and classifying plant diseases. A Bacterial foraging optimization was employed to define optimal weight to the radial basis classification in this instance. An approach improved network performance by looking for and combining seed values for the feature extraction operation. For the study, the approach took cedar apple rust, leaf spot, and rusts into account. Zhang et al. [25] created a neural network for predicting disease in leaves. The system used 2 templates to train DCNN by modifying parameters, pooling layers, and incorporating dropout operations. By improving model training and recognition reliability, the approach increased accuracy and reduced optimization iterations. But the system does not take fair decisions on the diagnosis of a disease. Parameters must also be defined, in particular, batch sizes, which are crucial in the deep learning approach.

Tetila et al. [26] used images restricted by the aerial vehicle model to create a basic linear iterative clustering system for monitoring soybean foliar diseases in yield. An approach was constructed on segmentation and utilized the clustering technique to analyze plant leaves in images and describe the features using foliar physical characteristics such as gradient, texture, and color. If the layers of the CNN are expanded, the system fails. Furthermore, the method did not make use of higher resolution cameras. Barbedo [27] created a deep learning approach and data augmentation for the classification of plant diseases. Though, the approach encountered dataset limitations in terms of sample types, preventing the mechanism for plant disease classification from being created. Due to insufficient data access, this approach generated flawed findings. Sharma et al [28] created a

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Spider monkey optimization method for repairing the important attributes produced by the subtractive pixel adjacency method. By evaluating the characteristics of leaves, the selected features are taken to help vector machines for the classification of healthy and diseased plants. However, the system failed to identify plant disease groups, resulting in the multi class dilemma.

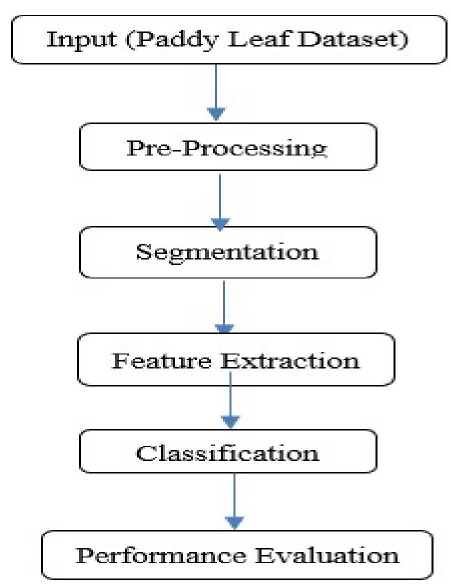
Chuanlei et al. [29] implemented a leaf disease identification system for predicting plant diseases. The process employed changed the colour transition structure in the red, green, and blue systems to Hue, Saturation, and Intensity and grey techniques. The correlation and combined genetic algorithm-based feature filtering were utilized in this study to pick the features, which improved the accuracy of leaf disease recognition. Finally, the SVM classifier was used to identify the diseases. The method had yet to process the images of diseased leaves. Shen et al. [30] suggested a clustering strategy based on sub-modular optimization for improved segmentation in images. First, a limited number of suitable trajectories are selected, and each initial trajectory is then separated into fragments with the proper trajectories that are referred to as fragment centres. Finally, fragments are hybrid as clusters by a 2-phase bottom-up clustering process.

Dong et al. [31] suggested a special hyperparameter optimization method that could evaluate the best hyperparameters for a given sequence using the action prediction network controlled by Continuous Deep Q-Learning. Dong et al. suggested a quadruplet DNN to notices possible interactions with training instances, to achieve an efficient representation, and constructed a mutual network with four branches linked by loss function composed of triplet-loss and pair-loss. Wang et al. [32] created a two-branch neural network for aesthetics evaluation (AA) and attention box prediction (ABP). The AA network determines the final cropping, while the ABP network determines the initial cropping. Wang et al suggested a novel data amplification approach that involves video training data from a surviving dataset with an annotated image, allowing the network to research the diverse saliency details while preventing overfitting due to the limited no. of. training videos.

Human vision-based techniques are used to diagnose leaf diseases in the traditional system. Finding specialized advice in these situations is both time-consuming and costly. Human vision-based approaches have many challenges. A machine learning-based approach allows the identification of disease types, the creation of smart decisions, and the selection of appropriate diagnoses. One advantage of employing a machine learning based technique is, it completes jobs more reliably than human experts. As a result, a modern machine learning-based classification methodology is needed to solve the problems of existing approaches. There have been very few recent advances in the field of plant leaf disease finding using an ML technique, and this is particularly significant for paddy leaf disease classification and detection.

3. PROPOSED METHODOLOGY

Pre-processing, image segmentation, feature extraction, and feature classification are the four phases of the proposed method. The paddy leaf images were gathered, and the data was gathered as a result of agricultural productivity. In the pre-processing phase, the image parameters are decreased and the backdrop is removed. The image is then segmented using a k-mean clustering approach to separate the healthy and sick parts of the image. Then the DCNN CS approach is used to classify diseases. The process of recognized and classifying the proposed paddy leaf diseases is seen in Figure 2.



ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Figure 2: Proposed DCNN-CS System Model

In real-time use, a digital camera is used to take images of paddy leaves. The research method included a data collection containing images from both normal and diseased leaves [33]. These details have been further split into training and testing sets.

3.1. Pre-processing

In pre-processing, the data set images will be resized and cut to 300 * 450 pixels for minimizing memory and power computation. A vital thing at this stage is to remove the image background by adding a fusion based on hue factors. In the RGB model, the image is first converted to HSV. Because it exceeds white, the S attribute is considered for the method in the HSV method. The image is transformed to a binary image based on the threshold value 90 and is merged with the original RGB image for the development of a mask. Based on many tests, the threshold value is chosen. By assigning pixel values to 00s, the phase of fusion removes the background. In the RGB form, the pixel value 0 is black.

3.2 Segmentation

The K-means clustering approach is used for the segmentation of the image. Clustering is the method by which the image is grouped into clusters. This clustering extracts the diseased part from image datasets. In an image, clusters for the non-diseased and the diseased image are predicted in the application of this cluster. This methodology is implemented to the hue of the background image framework of the HSV.

The hue part only contains the pure color; it does not contain any data such as lightness and obscurity. Based on the histogram analyses of the hue variable centroid value, perfect segments are generated to solve the randomness issue of the cluster. Also, the undesirable green element is removed from the diseased portion cluster. A histogram is created from the background extracted image for the hue portion. After that, the hue rates and counts for each bin are taken from the histogram that has been constructed. Differentiate between normal and diseased portions based on diseased images and histogram. The highest value in the normal and diseased portions of the hue factors is chosen for the centroid selection of each cluster. In the clustering procedure, the black color value and the center values are defined.

3.3 Feature Extraction

In this section, both texture and color features were extracted. The color characteristics involve the extraction of mean values and default values, while the textures involve GLCM characteristics like contrast, homogeneity, power and correlation.

3.3.1 Extraction of Color Feature

The elements R, G, and B for the diseased part are first removed and measured the average value and standard deviation. The HSV method is used to remove elements H, S, and V and approximate the mean value. Elements L, A, and B are derived from the LAB color model and the average value is determined.

The following methods were used to measure the mean and standard deviation.

$$M_n = \frac{1}{k} \sum_{i=1}^{k} Q_{ni} \tag{1}$$

$$S_n = \sqrt{\frac{1}{k} \sum_{i=1}^{k} (Q_{ni} - M_n)^2} \tag{2}$$

where k is the total no. of. pixels and Q_{ni} is the pixel rates.

3.3.2. Texture Features Extraction

The GLCM records the texture of the image using the spatial relationship among the pairs of grey pixel strength. Correlation, contrast, and energy are the structures derived from the GLCMs for the defined displacements homogenous. Normalization is used to standardize the characteristic values once the color features and texture characteristics have been retrieved. Min-Max is used to standardize values between 0 and 1 for this standardization system. The following are the formulas for these characteristics.

$$h_n = \sum_{i=0}^{k} \frac{Q_{ni}}{1+(n-i)^2} \quad (3)$$

$$c_{nn} = \sum_{i=0}^{k} Q_{ni} \, (n-i)^2 \quad (4)$$

$$c_{on} = \sum_{i=0}^{k} Q_{ni} \frac{(n-M)(i-M)}{S_n} \quad (5)$$

$$e_n = \sum_{i=1}^{k} (Q_{ni})^2 \quad (6)$$

where h_n stands for homogeneity, c_{nn} for contrast, c_{on} for correlation, e_n for energy, k for a total number of pixels, Q_{ni} for pixel values, M_n for mean, and S_n for standard deviation.

This technique will remove attributes like contrast, combination, strength, and identity as well as texture. Furthermore, extracted texture characteristics were utilized to calculate the hue and prominence of the clusters.

3.3.3. Shape Features Extraction

The shapes derived from binary images obtained through pre-processing have been focused on the analysis of disease (blobs) which have been formed irregularly. In specific, these blobs were used for detecting image areas representing various things. Therefore, a key part of the blob estimation method is to determine the number of diseases.

3.4 Deep Learning-based Classification

The DCNN model consists of an input layer with 3 layers of hidden units, N input neurons, and a classification output layer [18]. The DCNN was learned using a two-stage DL methodology: pre-training and fine-tuning. Network weights were frequently initialized during the pre-training phase, and the framework was trained using the training sets. The methodology was then fine-tuned to see how well it can be applied to various plant species datasets. The training images are split into 2 groups, t_1 and t_2, for this reason. The output layer, input layer, and hidden layers are three major elements of DCNN's structure. Figure 3 shows the DCNN architecture that has been proposed.

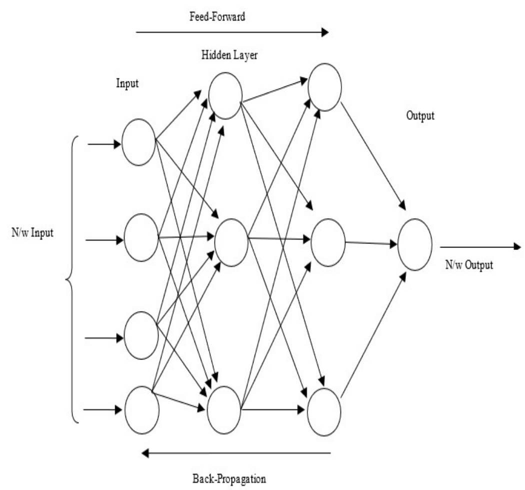


Figure 3: DCNN Architecture

Two hidden layers are supplied to the DCNN for learning mapping relations between output and input and detecting a preference for weight fitness. Throughout the training phase, DCNN employs the CS to iteratively alter the weight of nodes in hidden layers. As training iterations pass, this neural network continues to match the labelled training data's decision boundary. Two hidden layers are designed to improve the DCNN's training pace and classification accuracy. The total number of nodes in the hidden layer is calculated using Eq. (7).

$$K = \sqrt{x+y+z} \quad (7)$$

where x represents the number of input layer nodes, y represents the number of output layer nodes, k represents the number of hidden layer nodes, and z represents a constant value between 1 to10.

$$F = \frac{1}{1+a^{-i}} \quad (8)$$

The mapping function M_f activates the network's input data, which is referred to as 'a'.

$$M_f = \text{Sig}(w_n i + \beta_n) \quad (9)$$

here, f and w are the bias and weight matrix s between the hidden and output layers, respectively.
It implements various supervised loss functions for DNN to match the illustration space of hidden

neurons with human interaction. We want to use the data sample labels, which reflect human principles, in this instance. The loss form for a hidden layer could be calculated using a functionally labelled data sample (i, v).

$$F(w_f, b_f, \text{i, v}) = \frac{1}{2k} \sum_{p=1} ||h_p\left(w_f, b_f;\ \text{i}\right) - v_p||_2^2 \quad (10)$$

w_f and b_f are bias subsets, and k is the number of neurons in the hidden layers.
DCNN's loss function is cross-entropy, which is used to prepare for testing and training. The employ of cross-entropy losses significantly enhanced the sigmoid and soft-max output models' accuracy. Eq. (11), determines the cross-entropy loss.

$$L_f = \frac{1}{i} \sum_{n=1}^{i} [b_n \log \hat{b}_n + (1 - b_n) \log(1 - \hat{b}_n)] \quad (11)$$

Where n denotes the number of training samples, b_n denotes the nth real output of the training set, and $\hat{b}_n$ denotes the nth predicted output of the testing set. For the optimum weight selection of the DCNN network, we use the CS algorithm.

The primary objective of the CS Algorithm is to improve the fitness value of each solution in the population. This algorithm attempts to move the fitness value into the right solution by changing the values. After that, the latest and existing solutions are evaluated, and then the better solutions are chosen for the next iteration. It has a significant advantage over other optimization strategies in terms of computational complexity, time, and convergence speed.
Fine-Tuning: Backpropagation (BP) was used to fine-tune network weights that were implemented by the network weights obtained during the pre-training process. Once a minimal error rate was reached, the better network weights were acquired in the testing process spending training results.

DCNN-CS Algorithm

The algorithm shows specific stages in the suggested DNN-CSA framework. This method was implemented to increase classification accuracy thereby lowering the error rate.
Input: Weight (ω), population (f), bias (β), awareness probability (p) and total no. of. iterations (i_{max}) are all variables to include.
Output: The best network model (N_n) for reducing classification error.

i. Use the image dataset t_1 to pre-train N_n.
ii. Using the k-means clustering algorithm, segment the images in t_1.
iii. Extract features.
iv. In the d-dimensional search space,
v. initialize the N individual cuckoo positions with: $n^{c,i}$ (c=1,2,…,F; i=1,2,…., i_{mx})
vi. For each position, test the fitness function f $(*)$.
vii. Let Y as the memory value.
viii. The following steps should be used to choose random positions:
    For i=1 to F do
    Choose the p and the random solution.
    Make z_g), a random number generator.
    If $(z_g > p)$ then: $n^{c,i} + z_c * hv^{c,i} * (y^{z,i} - n^{c,i})$,
    else
    select a random section.
    end if
    end for
ix. Consider f $(*)$ for all positions and analyze the probability of the new solution.
x. If $h(n^{c,i}) < y_i\ or\ i = i_{max}$, then go to Step 10:
    else
    update *Y* and go to Step 7.
xi. Fine-tune all parameters in N_n with rates obtained after pre-training and features derived from t_2 image datasets.

4. EVALUATION RESULTS AND ANALYSIS

The proposed method's findings are reported, and the method's efficiency is shown by a comparative evaluation using the accuracy, sensitivity, and specificity metrics. During the training and testing phases, the proposed DNN-CS Algorithm provided Paddy Leaf disease classification results that were comparable to those of an SVM algorithm.

Accuracy: The accuracy measures how often a plant disease can be detected, and it's calculated as follows:

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

$$\text{Accuracy} = \frac{TN + TP}{TN+FN+TP+FP}$$

The true positive is denoted by TP. The true negative is denoted by TN. False-positive is referred to as FP, and false negative is referred to as FN.

Sensitivity: Using a sample of inputs defined by the classification outcomes, sensitivity identifies the right portion of plant disease. True positive rates are another name for sensitivity or recall, which is described as,

$$\text{Sensitivity} = \frac{TP}{FN+}$$

Specificity: During plant disease detection, the specificity detects the incorrect section. The specificity, also referred to as the false positive rate, is calculated as follows:

$$\text{Specificity} = \frac{TN}{TN + FP}$$

The efficiency of our proposed system, DCNN-CSA, is calculated and compared to existing classifiers like ANN, RF, and SVM. Normal, brown spot, bacterial blight, and blast disease are among disease types that are compared. A total of 70% of the images in the dataset are used for training, 20% for testing, and 10% for validation. The DCNN-CS method's classification efficiency is shown in Table 1. The highest accuracy of 99.3% is achieved using the DCNN-CS classifier for the bacterial blight-affected leaf image. The differences between the normal, Blight, blast, and brown spot is given clearly after result analysis criteria.

Table 1:. Performance of Paddy Leaf Diseases based on Classification

Performance Metrics / Leaf Type	Normal	Bacterial Blight	Blast	Brown Spot
Accuracy	91.34	99.3	97.4	92
Specificity	75	79.8	91.7	80
Sensitivity	74.3	90.6	89.4	81.5

The confusion matrix for the proposed system is indicated in Figure 4. True Positive, True Negative, False Positive, and False Negative values can all be predicted using this confusion matrix. From this confusion matrix, the normal image's TN, TP, FP, and FN values are 110, 20, 1, and 1 correspondingly; the brown spot's TN, TP, FP, and FN values are 103, 26, 2, and 1 correspondingly; bacterial blight's TP, TN, FP, and FN values are 28, 100, 3 and 1 correspondingly; and the blast influenced image's TP, TN, FP, and FN values are 27, 98, 1 and 1. Performance Metrics such as accuracy, precision, and loss function are represented graphically.

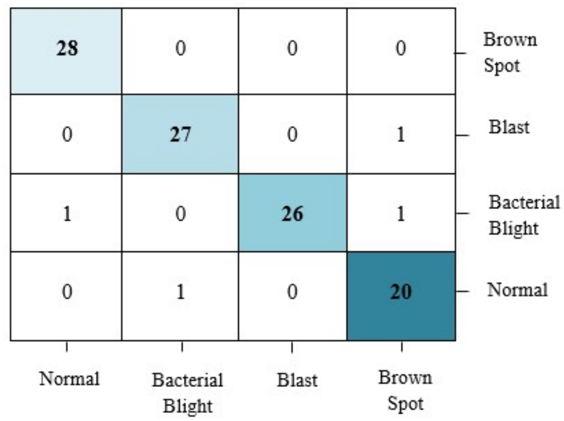


Figure. 4. Confusion matrix of Proposed DCNN-CS

The accuracy comparative graph for the four classes, that involves the proposed and existing classifiers, is seen in Fig.5. Using our recommended system DCNN-CS, we were able to achieve 91.34 percent normal image accuracy, 99.3 percent bacterial blight accuracy, 97.4 percent blast accuracy, and 92 percent brown spot accuracy. The graph compares the precision of the four classes in relation to the four classifiers (including the existing and proposed classifiers) is shown in Fig. 6. The precision rate of the normal images is 75, bacterial blights are 79.8, blasts is 91.7, brown spots are 80 by using our suggested system DCNN-CS Techniques. The comparative graph of Recall or Sensitivity for the 4 classes with esteem to the four classifiers (including existing and suggested classification techniques) is shown in Fig.7. The True Positive rate of the normal leaf is 74.3, blast is 89.4, bacterial blight is 90.6 and the brown spot is 81.5 by using our suggested DCNN-CS system.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

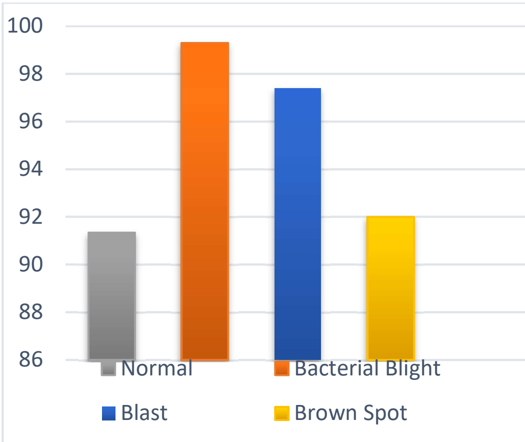


Figure 5: Analysis of DCNN-CS based on Accuracy

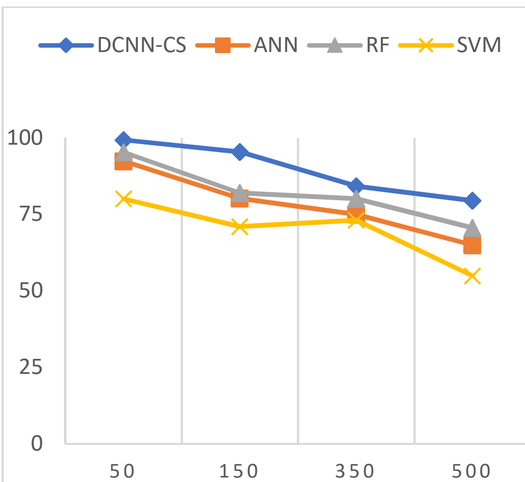


Figure. 6. Specificity of proposed DCNN-CS

The training and testing accuracy analysis graph is seen in Figures 8 and 9. The number of samples included for the training phase is 500, while the number of samples included for the testing process is 150. When the number of samples termed improves, so does the training and testing precision. By comparing both the training and testing accuracy, the DCNN CS approach achieves 99.3 percent training accuracy with 500 samples and 97.4 percent testing accuracy with 150 samples. The accuracy of training is higher than that of testing, as seen in the chart.

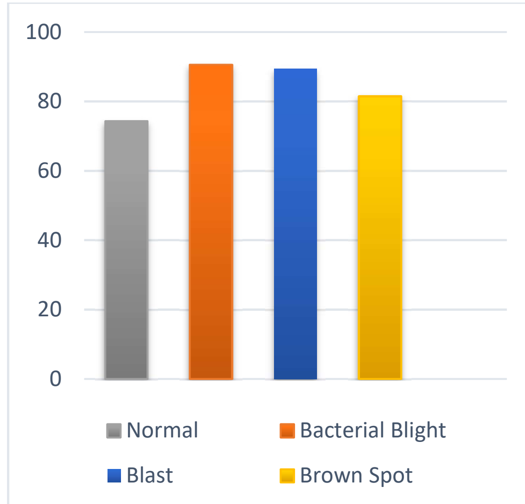


Figure 7: Sensitivity of Proposed DCNN-CS

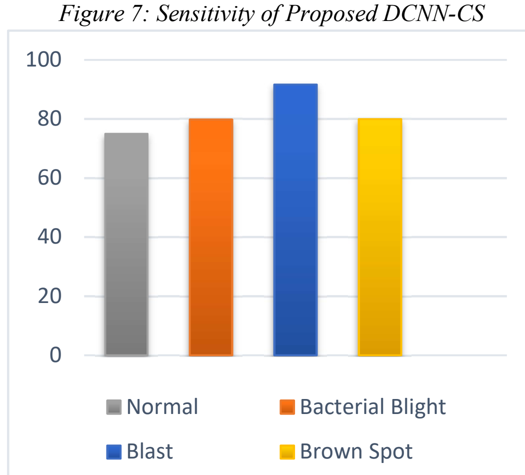


Figure 8: Comparison Graph of Training Accuracy

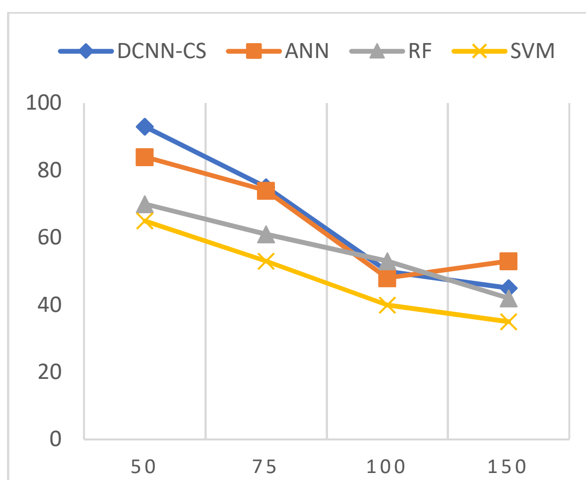


Figure 9: Comparison Graph of Testing Accuracy

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

5. CONCLUSIONS

This paper proposed a novel DCNN-CS classification algorithm for the identification of leaf diseases in paddy datasets to overcome a limitation of embedded computer vision approaches effective for smart agriculture. Classification errors were reduced by using the CSA to optimize weights and biases in the DCNN method during both the normal pre-training and fine-tuning phases, resulting in proposed DCNN-CS techniques. RGB images are converted to HSV images and hue component masking is used to remove the background in pre-processing. A clustering procedure is used to segment the diseases and normal sections. Disease classification is carried out using the proposed DCNN-CS system, with the best weights chosen by the CS. To fine-tune the stability of our system, we developed a feedback loop. The accuracy, specificity, and sensitivity of the experimental effects were tested and compared to ANN, RF, and SVM. As compared to other classifiers, the DCNN CS system had a high accuracy of 99.3 percent for bacterial blight, 97.4% for the affected blast, 92 percent for brown spot, and 91.34 percent for the normal leaf image. When contrasting testing accuracy and training accuracy, the DCNN-CS classifier achieved the highest testing accuracy of 99 percent, followed by the ANN classifier at 90 percent, the RF classifier at 90 percent, and the SVM classifier at 91.4 percent. Moreover, my further studies in this track can be proved to be the better one than the values which are systemized at present.

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