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IMPROVED DETECTION AND CLASSIFICATION OF PESTS, DISEASES, AND NUTRIENT DEFICIENCIES IN PADDY CROPS USING OPTIMIZED DEEP BELIEF NETWORKS WITH BIDIRECTIONAL LONG SHORT-TERM MEMORY

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Abstract

A significant percentage of the world's population relies on paddy, or rice, as their main source of sustenance. But it is vulnerable to a number of pests, illnesses, and nutrient shortages, which may have a negative effect on the yield and quality of the crop. Effective pest management and crop protection depend on the early and precise detection of these problems. In this manuscript present an Improved Detection and Classification of Pests, Diseases, and Nutrient Deficiencies in Paddy Crops using optimized Deep Belief Networks with Bidirectional Long Short-Term Memory (PCDC-DBN-BLSTM). Initially, the input paddy crop images are taken from the dataset. Then by using the proposed preprocessing technique as Anisotropic Guided Filtering (AGF), the input data is cleaned and normalized to make it suitable for classification. Hence the preprocessed images are provided to adaptive and concise empirical wavelet transform for feature extraction. Then the extracted color and shape features are fed to Deep Belief Networks with Bidirectional Long Short-Term Memory (DBN-Bi-LSTM) for Paddy Crops Disease Classification. Generally, DBN-Bi-LSTM doesn't reveal any adaption of optimization technique for Paddy Crops Disease Classification. Therefore, in this manuscript proposed a hybrid optimization technique like Slime Mould Optimization and Golden Eagle Optimization (SMO-GEO) for optimizing the weight parameter of DBN-Bi-LSTM. The proposed method is implemented in MATLAB. Here the performance of proposed method is assessed using performance metrics like accuracy, sensitivity, computational time and ROC. The proposed method provides 23.43%, 17.99%, 36.71% higher accuracy and 33.98%, 12.54%, 19.21%, 13.44% higher AUC compared with existing methods like Bi-LSTM, DBN, CNN and MLP respectively.

Keywords: *Paddy Crops Disease, Bidirectional Long Short-Term Memory (Bi-LSTM), Slime Mould Optimization (SMO), Golden Eagle Optimization (GEO).*

1. Introduction

Economic, social, and ecological damages are brought on by plant maladies and vermin. To stop these losses, early plant disease diagnosis is required. These activities typically involve the diagnosis of plant illnesses by specialists like agricultural engineers or botanists, which results in high overhead costs, lost time, and ineffectiveness [1] [2]. Important studies in the field of object identification have recently made it possible to detect such diseases and pests with great efficiency, in short timeframes, and without the assistance of professionals [3] [4]. For the agriculture industry, identifying plant diseases and pests as quickly as possible presented substantial challenges. Plant ailments in agriculture have a negative effect on productivity. We want to draw attention to how tightly linked agriculture and food production are [5]. On the basis of effective plant disease prevention and control, reliable forecasts were found. To produce agricultural products, their management and decision-making functions are essential. In India, a variety crop variety have been created to act as hosts for a variety of diseases and pests [6] [7]. Subtropical climates dominated Indian agriculture because they are better suited than tropical ones for the establishment of pest insects [8]. However, the disease is automatically and programmed detected by looking for signs on plant leaves, making it easier and less expensive [9] [10]. Additionally, it aids in visual processing for control, evaluation, and supervision [11] [12]. According to a study, the first crop to be farmed in Asia was probably rice [13]. These categories include grain pathogens, foliar pathogens, leaf sheath infections, and diseases of the seeds [14] [15]. Nanotechnology and precision farming have the potential to reduce the cost of these illnesses on future generations [16]. By using inputs linked to soil, crop, and weather variables, precision agriculture enables farmers to detect and eradicate crop illnesses early. If farmers take into account the inputs, a larger yield will follow [17]. Innovations for identifying these diseases are incorporated into integrated agriculture, therefore they must be thorough enough to inform farmers to take any necessary action when a disease is discovered [18]. The issue with CNN is that it requires enormous quantities of training data to be effective. Therefore, gathering photos of the crop that are unhealthy can be difficult. Transfer learning will help to get over this restriction [19]. There are numerous illnesses that can affect rice plants. Different types of infections than those that infected other plants were responsible for infecting rice plants. Sesame leaf spots and Cochliobolus miyabeanus are two fungus-related disorders in addition to brown spots. The majority of instances are in West Bengal, Orissa, Andhra Pradesh, and Tamil Nadu. Symptoms: Affects both primary fields and nurseries. Blight affects seedlings; the patches, which range in size from 0.5 to 2.0 mm, are correlated with one another. The panicle's neck also develops a brown-colored infection; in extreme situations, the yields are reduced by 50%. Because of their potent phototaxis, they were once observed and managed using light traps. Since stem borers are the worst pests for rice cultivation anywhere in the globe, they attack immature plants all the way up to maturity. These insects pose a serious threat to rice plants, which will reduce their ability to produce as much as possible. In a deep learning model, flies were trained to identify the diseases that rice plants might contract based on the images they recorded [20].

Several existing approaches suggested in [21-30] they are unable to differentiate between the appropriate conditions, and occasionally they misidentify the disorders, which has a negative impact on crop output. Since different illnesses require different treatment approaches, inaccurate disease detection results in incorrect plant disease management. Therefore, despite the treatment of sickness, plants' health does not become better. This results in a significant loss of crop in addition to financial and labor losses. Currently, farmers identify diseases either by using reference materials or by drawing on their personal experiences. Farm owners and employees must constantly focus on the illness of the plant whenever it is affected by the disease. This method of disease diagnosis is ineffective and time-consuming. The decision-making process now used for disease detection includes subjectivity, which is an issue. A variety of plant disease detection models have been developed by many academics using pattern recognition, computer vision, and digital image processing to provide precise and quick findings. In contrast, they are time-consuming to compute and do not provide adequate illness identification precision. These encourage us to conduct research in this area.

The following constitutes this manuscript's primary contribution,

- In this manuscript present an improved Detection and Classification of Pests, Diseases, and Nutrient Deficiencies in Paddy Crops using optimized Deep Belief Networks with Bidirectional Long Short-Term Memory (PCDC-DBN-BLSTM).
- Initially, the input paddy crop images are taken from [31-33].
- Then the input images from the dataset are cleaned by using Anisotropic Guided Filtering (AGF) technique.
- Then the most discriminating features from the preprocessed images are extracted using Adaptive and Concise Empirical Wavelet Transform.
- Then the extracted features are fed to Deep Belief Networks with Bidirectional Long Short-Term Memory (DBN-Bi-LSTM) for Paddy Crops Disease Classification.
- Generally, DBN-Bi-LSTM doesn't reveal any adaption of optimization technique for Paddy Crops Disease Classification. Therefore, in this manuscript proposed a hybrid optimization technique like Slime Mould optimization and Golden Eagle optimization (Hyb-SMO-GEO) for optimizing the weight parameter of DBN-Bi-LSTM.

Section 2 of the manuscript outlines the associated work section, Section 3 analyzes the recommended approach, Section 4 presents the findings and conclusions, while Section 5 brings the manuscript to a close.

2. Literature Survey

Several studies have been done on the classification of paddy disease. This section examines some of the most current scientific projects,

In 2022, Karunanithi, *et.al*., [21] illustrated research in the literature on the creation of enhanced hybrid neural networks in order to recognize and categorize diseases in paddy crops. The authors discuss the significance of prompt diagnosis and precise disease categorization in paddy crops for successful crop management and yield optimisation. They explore the drawbacks of conventional disease detection techniques and provide an alternative: improved hybrid neural networks. The creation of a novel hybrid neural network architecture termed "CoAtNet" This article's key addition to the understanding of rice crop disease is its classification. The CoAtNet model, which combines convolutional neural networks (CNNs) and attention processes to improve disease recognition accuracy, is designed and configured according to the authors' descriptions.

In 2019, Geetharamani, *et.al*., [22] concentrate on creating a system that employs deep learning to identify plant leaf diseases. Implementing a nine-layer deep CNN for the precise and effective detection of plant leaf diseases is the focus of this article's literature review. In order to ensure crop health and productivity, the authors stress the significance of early and accurate detection of plant leaf diseases. They talk about the difficulties associated with manual inspection and the limitations of expert knowledge in conventional methods of disease identification. They draw attention to the promise of CNNs and other deep-learning techniques for automated and accurate disease detection. This article's main contribution is the design of a nine-layer deep CNN architecture for identifying plant leaf diseases.

In 2020, Panigrahi, *et.al*., [23] focus on using harm maize leaves, use machine learning approaches. The literature review in this article focuses on the application of machine learning methods to precisely identify and classify different diseases affecting maize plants. To preserve crop health and maximize productivity, the authors stress the importance of early detection and efficient management of maize leaf diseases. They talk about the limitations of manual disease diagnosis techniques and the possibilities for automating the process with machine learning techniques. This study's main contribution is the application of machine learning techniques for categorizing and identifying maize leaf diseases.

In 2021, Chen, *et.al*., [24] have presented the lightweight attention networks to identify illnesses in rice plants. In this used the MobileNet-V2 pre-trained on ImageNet as the backbone network and added the attention mechanism to understand the significance of inter-channel relationship and spatial points for input features in order to improve the learning potential for minute lesion features. In the interim, the transfer learning was carried out twice for model training, and the loss function was optimized. Comparatively speaking, the proposed strategy performs better than other cutting-edge approaches. On the public dataset, it achieves an average identification accuracy of 99.67%.

In 2020, Li, *et al*., [25] illustrate a body of literature that focuses on the creation of a method for employing deep convolutional neural networks (CNNs) to recognise pests and diseases affecting rice plants in videos. To preserve the health and productivity of rice crops, the authors discuss the significance of early diagnosis and treatment of diseases and pests in rice plants. They talk about the drawbacks of conventional manual inspection techniques and suggest using deep CNNs for quick and accurate detection. The invention of a recognition technique using deep CNNs for video-based identification of pests and illnesses of rice plants is the main contribution of this study. The CNN model used by the authors to learn and categorise various disease and pest patterns in rice plants using video data is described in terms of its architecture and configuration.

In 2023, Abd Algani, *et.al*., [26] have suggested identification and classification of leaf diseases using enhanced deep learning. Ant Colony Optimization with Convolution Neural Network (ACO-

CNN), a deep learning approach for disease detection and classification, is presented in this. Ant colony optimization (ACO) was used to examine the efficacy of disease diagnosis in plant leaves. The CNN classifier is used to remove color, texture, and plant leaf arrangement geometry from the input photos. A few of the metrics for measuring effectiveness that were used to analyze and suggest a way show that the suggested strategy outperforms existing techniques with a rate of accuracy concert measures are employed for the execution of these approaches. The stages of disease detection include photo capture, image separation, removing the nose, and classification.

In 2021, Jain, *et.al*., [27] have presented Crop disease detection system feature selection using a memetic salp swarm optimization algorithm. In this describes an algorithm for automatically detecting diseases that makes use of image segmentation, feature extraction, optimization, and classification techniques. It suggests a binary version of the memetic salp swarm optimization algorithm (MSSOA), which searches for the ideal number of characteristics that provide the best classification accuracy. In comparison to the UCI benchmark datasets, the proposed feature selection algorithm performs better than five metaheuristic feature selection algorithms (BSSA, BPSO, BMFO, BCOA, and IBHHO). The findings show that the suggested approach works better than the other algorithms in terms of good classification accuracy and feature size reduction.

In 2022, Hassan et al., [28] have introduced the using deep features as well as artificial intelligence classifiers, plant disease detection. The authors discuss the importance of precise and effective plant disease detection for disease management and crop protection. They talk about the drawbacks of conventional techniques and suggest using deep features and machine learning classifiers to analyse plant pictures to find diseases. The main innovation presented in this paper is the use of deep learning algorithms to extract relevant features from plant pictures and then input those features into machine learning classifiers. The authors explain how they went about extracting deep features and training a machine learning classifier. The authors run trials using a dataset of plant photos with various diseases to assess the effectiveness of their approach.

In 2022, Turkoglu, *et al*., [29] suggested that the creation of PlantDiseaseNet, a Convolutional neural network (CNN) ensemble for plant pest and disease detection. The authors emphasise the significance of timely and precise plant disease and pest identification for successful crop management and yield preservation. They talk about the drawbacks of conventional techniques and suggest using CNN ensembles as a workaround. The creation of PlantDiseaseNet, a collection of CNN models intended to identify and categorise plant illnesses and pests, is what this article's main contribution. The ensemble, which combines the predictions of various CNN models to improve accuracy and robustness, is described by the authors along with its architecture and setup.

In 2021, Muppala, *et.al*., [30] have presented the four-layer deep neural network with search and rescue optimization (DNN-SAR) approach to identify leaf folders and yellow stemborers. Insects in the paddy field are attracted by light traps, and the photos of the captured insects are then evaluated using the suggested detection method. The DNN-SAR uses the deer hunting algorithm to contrast-enhance images, the rapid average group filter to reduce impulsive noise, and social ski-driver optimization to segment data. The deep neural network's optimal weights are chosen using the search and rescue optimization algorithm, which has increased convergence rates, decreased learning complexity, and increased detection accuracy.

3. Proposed Methodology

In this section, an improved Detection and Classification of Pests, Diseases, and Nutrient Deficiencies in Paddy Crops using optimized Deep Belief Networks with Bidirectional Long Short-Term Memory (PCDC-DBN-BLSTM) is discussed. The overall block diagram of proposed PCDC-DBN-BLSTM methodology is shown in figure 1. The detailed discussion regarding the proposed PCDC-DBN-BLSTM methodology is discusses as follows,

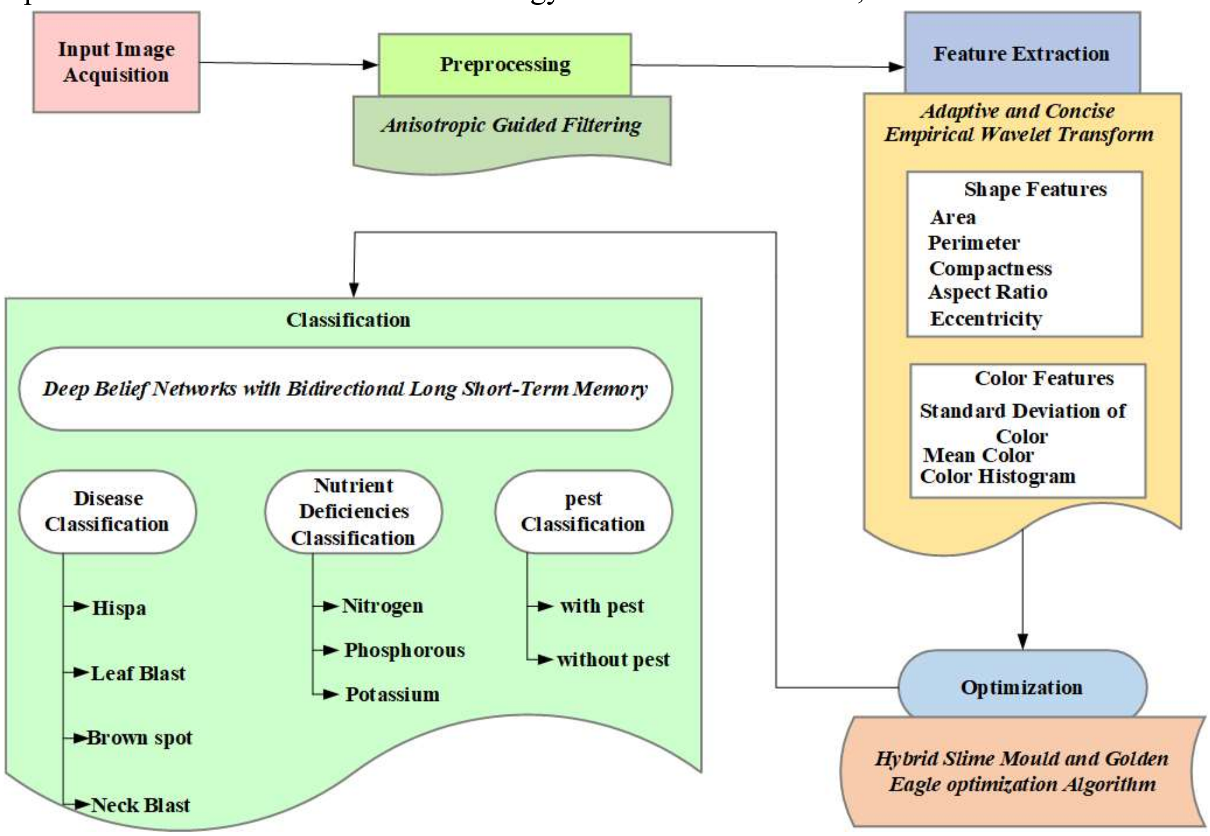

Figure 1: Block Diagram of proposed PCDC-DBN-BLSTM Methodology

3.1. Image Acquisition

The proposed experiments are first carried out using input images from the [31-33] dataset.

3.2. Preprocessing using Anisotropic Guided Filtering

Input images from the dataset are pre-processed using the proposed Anisotropic Guided Filtering (AGF) technique [34]. In this section, preprocessing is carried out in two specific ways as converting the image to grayscale and reducing noise. Initially, the input RGB image is converted into grayscale using equation (1) as follows,

$$Gray = 0.299 * R + 0.587 * G + 0.114 * B \quad (1)$$

Where, R, G and B indicates the red, green, and blue values of each pixel in the input RGB image. For each pixel in the RGB image, apply the above equation (1) to obtain the corresponding grayscale pixel value. The resulting grayscale image will have the same width and height as the original RGB image but only one channel (intensity). Then for noise reduction, proposed Anisotropic Guided filter is applied to the grayscale image. The pre-processing stage of the proposed AGF approach includes operations for scaling, background removal, and cropping. To ensure the accuracy of the acquired image features, pre-processing can be done using the anisotropic guided filtering (AGF) technique. Initially, create a vector out of the pixel values y_i given a patch from the input image that is indexed with the subscript i. This patch matches a different patch that was identical to the position in the reference photo and vectorized to be called g_i. The averaging steps in equation (2) low-pass filter these values, whereas the formulation for b_i correctly adjusts the level of diffusion to reserve strong edges, thus nullifying these measurements. Due to weak diffusion when is little or excessive diffusion when is large, depending on the technique, details close to edges are either preserved or the edges dissolve. In order to obtain scaled images with dimensions, the resizing technique is first conducted to the input rice leaf image samples it is demonstrated as follows in equation (2),

$$b_i = \frac{1}{n} \sum_{j \in N(i)} b_j \tag{2}$$

Where, $N(i)$ indicates the neighbourhood of pixel i, n denotes the number of pixels in the patch. In order to improve background removal, regularize the average step rather than b_i which is represented in equation (3),

$$\tilde{b}_i = \sum_{j \in N(i)} w_{ij} b_j \tag{3}$$

Where, w_{ij} denotes the importance attributed to a neighbourhood situated at j the area around the pixel's centre, which is at i. The objective in creating these weights is to accomplish maximum image cropping while maintaining distinct edge boundaries in the input image, which improves the input image's visual quality and is expressed as follows in equation (4),

$$\arg\min_{w_i} \ \tilde{b}_i^2 + \mu \sum_{j \in N(i)} \left\| w_{ij} \Delta_j \right\|_2^2 \tag{4}$$

Where, w_{ij} indicates how much weight is given to the neighbourhood pixel j and Δ_j represents the neighbourhood's gradients are contained in a vector that is positioned at in the reference image. Finally, the pre-processed images are provided for the feature extraction process.

3.3. Feature extraction using Adaptive and Concise Empirical Wavelet Transform

An adaptable and condensed empirical wavelet transform is a feature of the article's portion of the pre-processed images. Technique for feature extraction using (ACE-WT) [35]. Here the features such as, shape, color features are extracted using the proposed ACE-WT approach. Through the scale-space representation, the suggested ACE-WT technique extracts the most pertinent information. The ACE-WT technique that has been presented may effectively extract various features from pre-processed images. The size of the pre-processed pictures is typically correlated with the Fourier spectrum exhibited. More detailed information is present in an image at higher sampling frequencies. For the most accurate feature extraction in this, PSD is used in place of the intricate Fourier spectrum. The PSD truly depicts the power and frequency distribution. The Fourier transform of the image $X(t)$ is $\hat{X}(t)$, and its features can be extracted using equation (5) as follows,

$$Q = \lim_{T\to\infty} \frac{1}{2T} \int_{-T}^{T} X(t)^2 dt \tag{5}$$

Following that, the image's Fourier transform is applied in the interval $[0,T]$ can be provided in the equation (6) a follow,

$$\hat{X}_{\gamma}(f) = \frac{1}{\sqrt{T}} \int_{0}^{T} x(t) e^{-2i\pi f t} dt \tag{6}$$

Afterward, the power spectral density may be determined, and from there, the distribution of intensities the color features are obtained and specified in equation (7),

$$S_{xx}(f) = \lim_{T\to\infty} \left[\left| \hat{X}_T(f)^2 \right| \right] \tag{7}$$

Finally, by using the proposed ACE-WT approach, the shape, these qualities included colour and texture.

3.3.1. Shape Features ($Shape_{Features}$)

Extraction of shape features ($Shape_{Features}$) is essential for classifying plant diseases because it makes it possible to quantify the geometric characteristics of diseased plant sections. The extracted shape features using the proposed ACE-WT approach is represented as follows,

(A) Area (A)

The area of a region represents the overall size of the affected plant part.

(B) Perimeter (P)

The perimeter is the total length of the boundary of the region.

(C) Compactness (C)

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Compactness measures how closely the boundary of the region resembles a circle, indicating the level of compactness of the affected area. It is measured using equation (8) as follows,

$$C = \left(\frac{P^2}{4\pi A} \right) \tag{8}$$

(D) Aspect Ratio (AR ***)***

Aspect ratio measures the elongation of the region and is typically calculated for rectangular or elliptical shapes. It is computed using equation (9),

$$AR = Width / Height \tag{9}$$

(E) Eccentricity (Ecc ***)***

Eccentricity represents the elongation of an elliptical shape, indicating how stretched or elongated the region is and it is represented in equation (10) as follows,

$$Ecc = \sqrt{\left(1 - b^2\right) / a^2} \tag{10}$$

where a and b represents the fitted ellipse's principal and secondary axes. Here the shape features $Shape_{Features} = \{A + P + C + AR + Ecc\}$ are extracted more efficiently by using the proposed ACE-WT approach.

3.3.2. Color Features ($Color_{Features}$)

Color features ($Color_{Features}$) involve the analysis of the plant's color spectrum. Diseases can cause discoloration, spotting, or changes in color intensity in various plant parts. By examining color features, such as mean color values, Standard Deviation of Color, color histograms it becomes possible to identify specific color patterns associated with different diseases. And the extracted $Color_{Features}$ using ACE-WT approach is represented as follows,

(A) Mean Color

The mean color represents the average color value of a region and provides information about the overall color intensity. It is represented in equation (11) as follows,

$$Mean(M) = (1/N) * \sum Grayscale\_i \tag{11}$$

(B) Standard Deviation of Color

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The standard deviation of color measures the variation in color values within a region and indicates the color heterogeneity. It is expressed in equation (12) as follows,

$$S\tan dard\ Deviation\,(SD) = \sqrt{(1/N) * \sum\left((Grayscale\_i)^2\right)} \tag{12}$$

(C) Colour Histogram

A color histogram represents the distribution of color values in a region by counting the frequency of each color bin. It is represented in equation (13) as follows,

$$Histogram\,(H) = hist\left(Gray\,scale\,image\right) \tag{13}$$

Where, $hist\left(Gray\,scale\,image\right)$ denotes the function to compute the histogram of the respective color channel. Here, the color features, $Color_{Features} = \{M + SD + H\}$ are extracted using the ACE-WT approach. At last, the extracted $Shape_{Features}$, $Color_{Features}$ using ACE-WT approach are provided as input for Hybrid Slime Mould and Golden Eagle optimization (Hyb-SMO-GEO) for optimizing the weight parameters $Shape_{Features}$, $Color_{Features}$ from ACE-WT approach.

3.4. Hybrid Slime Mould and Golden Eagle optimization (SMO-GEO) for optimizing ACE-WT

In this section, hybrid slime mould and golden eagle optimization is proposed for optimizing the weight parameter $Shape_{Features}$ and $Color_{Features}$ of ACE-WT in order to attain higher accuracy in paddy crops disease classification. The foraging behaviour of the slime mould organism Physarum polycephalum served as the inspiration for the development of the Slime Mould Optimization Algorithm (SMOA) [36], an approach for optimization inspired by nature. Slime moulds are unicellular creatures that, in their quest for food and survival, display astoundingly adaptive behavior and optimization skills. To identify the best answers to different optimization problems, the program mimics the movement and exploring characteristics of slime molds. On the other hand, Golden Eagle Optimization (GEO) [37] is a natural optimization technique that draws inspiration from golden eagles' hunting habits. The program efficiently searches for the best answers to diverse optimization problems by emulating the hunting techniques of these strong birds. The main goal of the Golden Eagle Optimization algorithm is to mimic golden eagles' pursuit of prey during their hunting activity. The eagles employ various strategies, including soaring, diving, and climbing, to optimize their chances of locating and capturing their targets effectively. Hybrid optimization algorithms can potentially lead to improved classification accuracy compared to using individual optimization methods. By combining hybrid Slime Mould and Golden Eagle optimization, the algorithm can better explore the solution space and find optimal parameters for disease classification. The stepwise procedure of proposed SMO-GEO algorithm is provided as follows,

Step 1: Initialization

In this step, initialize the weight parameters $Shape_{Features}$ and $Color_{Features}$ from the output of ACE-WT for paddy crop disease classification.

Step 2: Random Generation

After the initialization, randomly selects the best suitable solution from the initialized input parameter.

Step 3: Fitness Function

Here, the objective function is to optimize the weight parameters $Shape_{Features}$ and $Color_{Features}$ from ACE-WT approach. And its description is represented in equation (14),

$$Fitness\ Function = Optimization\left[Shape_{Features}\ and\ Color_{Features}\right] \tag{14}$$

Step 4: Approach food of SMOA

Depending on the aroma in the air, slime mould may approach food. The following formulas are suggested to mimic the contraction mod's approaching behavior in mathematics which is represented in equation (15),

$$\overline{Y(t+1)} = \begin{cases} \overline{Y_b(t)} + \overrightarrow{ub}.\left(\vec{S}.\ \overline{Y_A(t)} - \overline{Y_B(t)}\right), & r < p \\ \overrightarrow{uc}.\overline{Y_b(t)}, & r \geq p \end{cases} \tag{15}$$

Where, $\overrightarrow{ub}$ the parameter having a range of $[-a, a]$, $\overrightarrow{uc}$ declines from one to zero, linearly, t represents the current iteration, $\overrightarrow{Y_b}$ indicates the particular place where odor concentration is highest at the moment, $\vec{Y}$ displays where the mold of slime is found, $\overrightarrow{Y_A}$ and $\overrightarrow{Y_B}$ indicates the individuals chosen at random from a slime mold. The following equation (16) is the p formula,

$$p = \tanh\left|W(i) - DF\right| \tag{16}$$

Where, $i \in 1, 2, ..., n$, $W(i)$ indicates the fitness of $\vec{Y}$, DF is the level of fitness that was achieved after all iterations. Then, $\overrightarrow{ub}$ is computed using equation (17),

$$\overrightarrow{ub} = [-a, a] \tag{17}$$

$$a = \arctan h\left(-\left(\frac{t}{\max\_t}\right)+1\right) \tag{18}$$

The expression for S is listed as in equation (19) as follows,

$$S\left(Smellindex\left(i\right)\right)=\begin{cases}1+r.\log\left(\dfrac{BF-W\left(i\right)}{BF-WF}+1\right), & If\ W\left(i\right)>half\ of\ the\ population\\ 1-r.\log\left(\dfrac{BF-W\left(i\right)}{BF-WF}+1\right), & others\end{cases} \tag{19}$$

Where, r represents the random value in the interval [0,1], represents the best fitness discovered using the current iteration process, and represents the worst fitness value discovered using the current iteration method., $Smellindex\left(i\right)$ indicates the fitness values in ascending order (as in the minimum value problem) and is computed using equation (20),

$$Smellindex\left(i\right) = Sort\left(W\right) \tag{20}$$

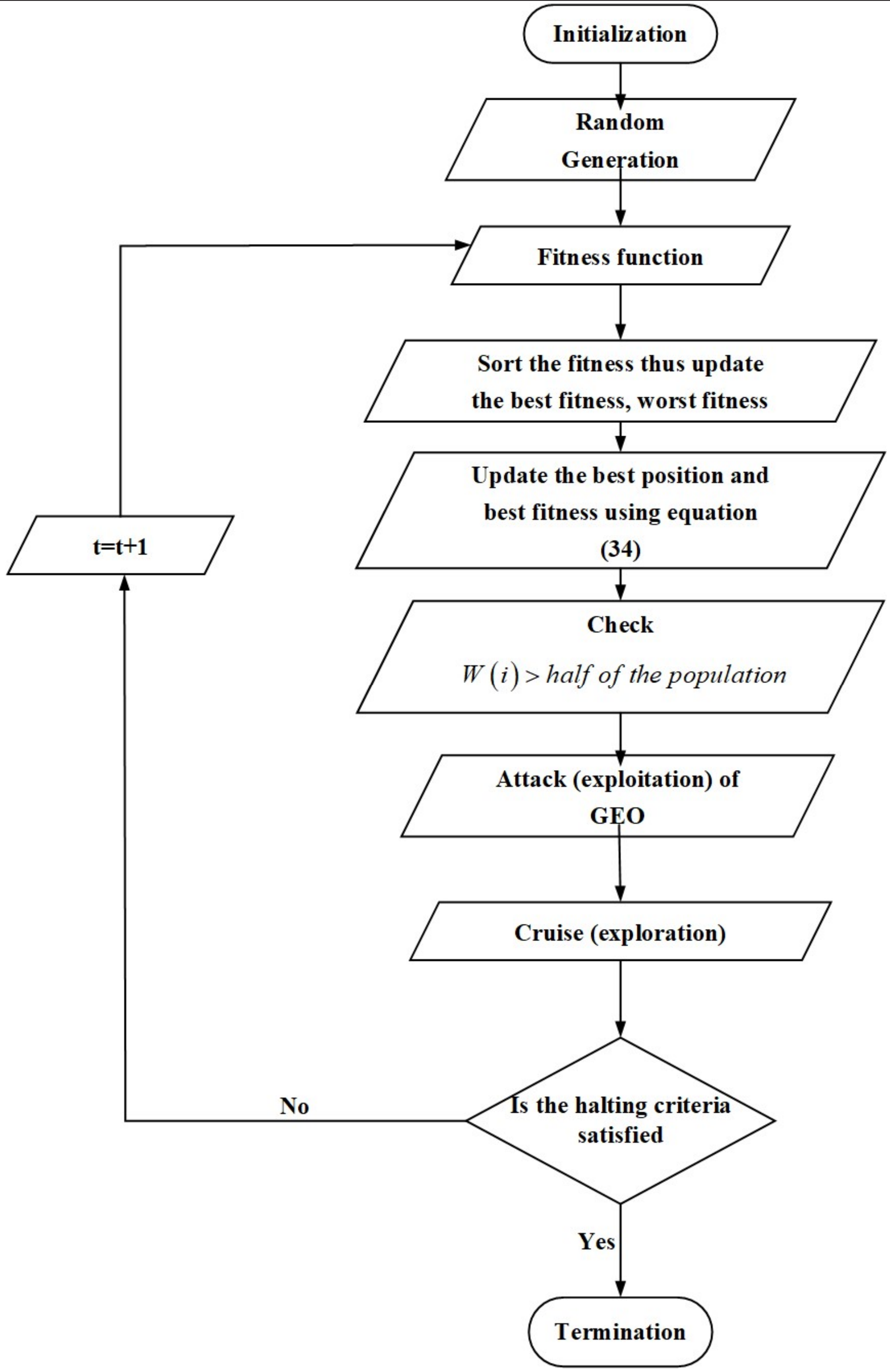

Figure 2: Flowchart of SMO-GEO Algorithm

Step 5: Attack (exploitation) of GEO

The attack can be modelled as a vector that starts at the current location of the golden eagle and ends at the location of the prey in the eagle's memory. Equation (21) is used to calculate it.

$$\vec{B_i} = \overrightarrow{X_f^*} - \vec{X_i} \tag{21}$$

Where, $\vec{B_i}$ indicates the attack vector of eagle, $\overrightarrow{X_f^*}$ represents the best location (prey) visited so far by eagle f, $\vec{X_i}$ indicates the current position of eagle i. The attack vector emphasizes the exploitation stage in GEO because it directs the population of golden eagles into the most frequently visited places.

$$p = \tanh \vec{B} \left| W(i) - DF \right| \tag{22}$$

Step 6: Cruise (exploration)

Calculating the cruise vector can be done using the attack vector. The assault vector is parallel to the circle, but the cruise vector is perpendicular to it. The golden eagle's cruise may also be thought of as its relative linear speed to its goal. Get the equation of the tangent hyperplane before computing the cruise vector because it is included within the circle's tangent hyperplane in terms of dimensions. It is possible to determine the equation of a hyperplane at any point in its dimension using the hyperplane's normal vector and its perpendicular normal.

$$l_1 x_1 + l_2 x_2 + \ldots + l_n x_n = d \Rightarrow \sum_{j=1}^{n} l_1 x_2 = d \tag{23}$$

Where, $\vec{L} = [l_1, l_2, .., l_n]$ represents the normal vector, $X = [x_1, x_2, ..x_n]$ indicates the variable vector.

Step 7: Termination

Check the stopping criteria. If the stopping criteria reach the maximum iteration stop if not, move on to step 3 of the process. At last, the proposed Hybrid Slime Mould and Golden Eagle optimization (SMO-GEO) algorithm optimize the weight parameter $Shape_{Features}$ and $Color_{Features}$ more efficiently and optimized weight parameter of ACE-WT are provided as input for the detection and classification of pests, illnesses, and nutritional shortages in rice crops. Flowchart of SMO-GEO is displayed in figure 2.

3.5. Deep Belief Networks with Bidirectional Long Short-Term Memory for Classifying Paddy Crop Disease

In this part, Deep Belief Networks with Bidirectional Long Short-Term Memory (DBN-Bi-LSTM) is proposed for classifying the pests, illnesses, and nutritional shortages in rice crops using the optimized extracted features as input. Plant disease classification involves DBNs, by themselves, may not be well-suited for disease type identification. While DBNs can be combined with Bi-

LSTM, the integration process can reduce complexity and minimize the training time. By overcoming these obstacles and enhancing the network, the DBN with Bi-LSTM: 1) The bidirectional nature of Bi-LSTM allows the DBN network to consider both past and future context when making predictions, enabling it to capture relevant temporal dependencies 2) The Bi-LSTM's bidirectional architecture, the reduced number of hidden neurons might lessen the model's instability and inefficiency; 3) dropout function is used to lessen model overfitting and increase model stability; and 4) avoid model overfitting. Combining the strength of deep learning and sequence modeling, Deep Belief Networks (DBNs) [38] with Bidirectional Long Short-Term Memory (Bi-LSTM) [39] can be utilized to classify paddy crop diseases. The input layer of the DBN-BiLSTM model receives optimized features extracted from plant samples. Then the DBN consists of multiple layers of hidden units, known as Restricted Boltzmann Machines (RBMs). Each RBM learns a set of features from the input data and acts as an unsupervised feature learning layer. On top of the feature learning layers, a BiLSTM layer is added. The BiLSTM layer processes the provided data in both forward and backward directions, capturing temporal dependencies and context in the input data. After processing the input data through the BiLSTM layer, the final output layer exhibits the classification results of crop disease. The input to the BiLSTM layer as the optimized extracted features from the Hyb-SMO-GEO from plant samples. For binary RBMs, a joint configuration's energy is represented in equation (24) as follows,

$$\begin{aligned} E(u,h;\theta) &= -\sum_{a=1}^{U}\sum_{b=1}^{H} w_{ab} v_a h_b - \sum_{a=1}^{U} i_a u_a - \sum_{b=1}^{H} j_b h_b \\ &= -j^T u - i^T h - u^T W h \end{aligned} \tag{24}$$

Where, Markov random field with "visible" units with the coordinates $u = \{0,1\}^D$, hidden" units with the coordinates $h = \{0,1\}^F$, $\theta = \{i_a, j_b, w_{ab}\}$, w_{ab} denotes the ratio of hidden units to those that are visible b, Bias terminology for visible and hidden units are i_a and j_b. In order to determine the joint distribution over the unit's equation (25) and (26) is used,

$$P(u,h;\theta) = \frac{1}{Z(\theta)} \exp\left(-E(u,h;\theta)\right) \tag{25}$$

$$Z(\theta) = \sum_{u}\sum_{h} E(u,h;\theta) \tag{26}$$

Where, $Z(\theta)$ denotes the constant that normalizes. Every input vector receives a probability from the network through the energy function. The logistic distribution function provides the hidden unit and input vector conditional distributions. This involves backpropagation and updating the network weights based on the error between predicted and actual disease labels which is computed using equation (27) and (28) respectively,

$$p\left(h_b = 1 \middle| u\right) = g\left(\sum_{a=1}^{D} W_{ab} u_a + i_b\right) \tag{27}$$

$$p\left(u_a = 1 \middle| h\right) = g\left(\sum_{b=1}^{F} W_{ab} h_b + j_b\right) \tag{28}$$

The input data can be recreated after the hidden units' states have been determined by setting each u_a to 1 with a probability of (28). The states of the concealed units are then changed to recognize the healthy and diseased plant, and equation (29) is used to learns a set of features from the input data and calculate the expected activation by a regularization penalty of this kind.

$$\lambda \sum_{b=1}^{F} \left(\rho - \frac{1}{m} \left(\sum_{k=1}^{m} E\left[h_b \middle| u^k \right] \right) \right)^2 \tag{29}$$

Where, ρ specifies the sparsity, u^k indicates the sample during training, and m denotes the number of training samples. After the performance of unsupervised feature learning layer. On top of the feature learning layers, a BiLSTM layer is added. The BiLSTM layer processes the provided data in both forward and backward directions and context in the output data from DBN.

Let the DBN network's output vector's dimension be P. Assuming that a Bi-LSTM layer contains units of Bi-LSTM neurons, the weights of each node in a Bi-LSTM unit can be expressed as follows, and the input weight function is shown in equation (30) as follows,

$$M_{xa}, M_{xf}, M_{xc}, M_{x0} \in R^{n \times P} \tag{30}$$

Then the recurrent weights are expressed in equation (31),

$$M_{hi}, M_{hf}, M_{hc}, M_{h0} \in R^{n \times n} \tag{31}$$

The output weights can be computed using equation (32) as follows,

$$\left.\begin{matrix} M_{yt-1}i, & M_{yt-1}f, & M_{yt-1}c, & M_{yt-1}o, \\ \dots & \dots & \dots & \dots \\ M_{yt-k}i, & M_{yt-k}f & M_{yt-k}c & M_{yt-k}o \end{matrix}\right\} \tag{32}$$

Then, the input gate i_t, forget gate f_t, output gate o_t, cell update state g_t, cell state c_t and the hidden state h_t for an Bi-LSTM unit can be expressed as (33)-(38),

$$f_t = \sigma\left(M_{xf} x_t + M_{hf} h_{t-1} + M_{yt-1f} y_{t-1} + \dots + M_{yt-kf} y_{t-k} + b_f\right) \tag{33}$$

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$$i_t = \sigma\left(M_{xi}x_t + M_{hi}h_{t-1} + M_{yt-1i}y_{t-1} + \ldots + M_{yt-ki}y_{t-k} + b_i\right) \quad (34)$$

$$g_t = \tanh\left(M_{xc}x_t + M_{hc}h_{t-1} + M_{yt-1c}y_{t-1} + \ldots + M_{yt-kc}y_{t-k} + b_c\right) \quad (35)$$

$$c_t = i_t \odot g_t + f_t \odot c_{t-1} \quad (36)$$

$$o_t = \sigma\left(M_{xo}x_t + M_{ho}h_t + M_{yt-1o}y_{t-1} + \ldots + M_{yt-ko}y_{t-k} + b_o\right) \quad (37)$$

$$h_t = o_t \odot \tanh\left(c_t\right) \quad (38)$$

Where, $\odot$ shows the pointwise multiplication, $\sigma(.)$ is used to represent the exponential nonlinear activation mechanism, $\tanh(.)$ represents the hyperbolic tangent function, which is a nonlinear activation function. These features are then passed to the trained Bi-LSTM for disease classification. Finally, concatenate the final hidden states from both the forward and backward LSTMs to provide a final prediction output and is represented in equation (39) as follows,

$$\tilde{h}_t = \left[\vec{h}_t \oplus \overleftarrow{h}_t\right] \quad (39)$$

Where, $\tilde{h}_t$ denotes the generated final output, $\oplus$ indicates the elementwise summation, $\vec{h}_t$ indicates the concealed state of the forward pass and $\overleftarrow{h}_t$ reflects the concealed condition of the backward pass of Bi-LSTM. Finally, the proposed DBN-Bi-LSTM approach classifies the plant disease as Brown Spot, Hispa, Leaf Blast, Neck Blast, identifies the nutrient deficit conditions as nitrogen, phosphorous and potassium and also identify the issues in paddy crops as with pest and without pest.

4. Result and Discussion

The enhanced Deep Belief Networks with Bidirectional Long Short-Term Memory (PCDC-DBN-BLSTM) simulation results for the detection and classification of pests, illnesses, and nutritional shortages in rice crops are covered in this part. The suggested technique is put into practice in MATLAB 2019a on a DELL computer with a Core i5 processor running at 1.80 GHz, 4 GB of DDRAM, 250 GB of SSD storage, and Windows 10 installed. Here, performance parameters like ROC, computing time, sensitivity, and accuracy are examined. Here, the performance of the proposed PCDC-DBN-BLSTM approach is compared with that of known methods such as Convolutional Neural Networks (CNN), Bidirectional Long Short-Term Memory (Bi-LSTM), Deep Belief Networks (DBN), and Multi-Layer Perceptron’s (MLP), respectively. Table 1shows the output result of proposed PCDC-DBN-BLSTM Methodology.

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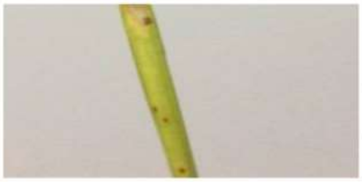
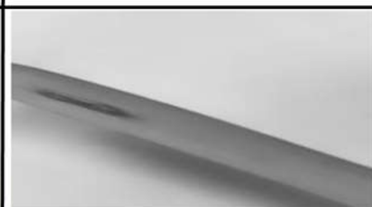
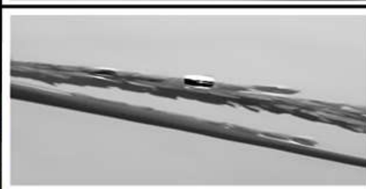
Table 1: Output result of proposed PCDC-DBN-BLSTM Methodology

Input Image	Preprocessed Image	Classification
		Brown Spot
		Hispa
		Leaf Blast
		Neck Blast

4.1. Performance Measures

Accuracy, sensitivity, specificity, precision, F-measure, and computing time are performance measures used to evaluate the performance of the proposed strategy in this case. Here, employ the metrics of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) to better understand the proposed approach.

True positives (TP): A true positive occurs when the plant disease detection system correctly identifies a diseased plant as diseased.

True negatives (TN): A true negative happens when the plant disease detection system correctly identifies a healthy plant as healthy.

False positives (FP): A false positive occurs when the plant disease detection system incorrectly identifies a healthy plant as diseased. In this case, the system produces a positive prediction (indicating the presence of disease) when it is not accurate.

False negatives (FN): A false negative occurs when the plant disease detection system incorrectly identifies a diseased plant as healthy. In this case, the system produces a negative prediction (indicating the absence of disease) when it is not accurate.

4.1.1. Accuracy

Measures the total accuracy of the model's predictions, taking into account both true positives and true negatives. It is calculated as using equation (40),

$$Accuracy = \left(\frac{TP + TN}{TP + TN + FP + FN} \right) \tag{40}$$

4.1.2. Sensitivity/Recall

The percentage of actual positive (ill plants) that the program correctly classifies as positive is what this metric measures. The calculation is performed using equation (41),

$$Sensitivity / \mathrm{Re}call = \left(\frac{TP + TN}{FN} \right) \tag{41}$$

4.2. Simulation Results of proposed approach with existing techniques

The simulation results of the suggested approach are shown in Figure 3-12 in terms of accuracy, sensitivity, specificity, precision, F-measure, computing time, and ROC. Here, the performance of the suggested technique is contrasted with that of other methods, including Bi-LSTM, DBN, CNN, and MLP

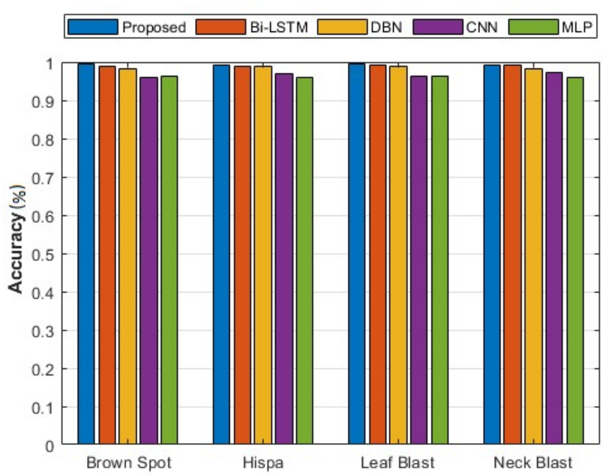


Figure 3: Performance analysis of Accuracy for Disease classification

The performance analysis of Accuracy for Disease classification is shown in Figure 3. Here the performance of proposed method provides 1.02%, 1.27%, 3.28%, 3.07% higher accuracy for Brown Spot; 0.35%, 0.31%, 2.25%, 3.25% higher accuracy for Hispa; 0.315%, 0.473%, 3.07%, 3.09% higher accuracy for Leaf Blast; 0.15%, 1.11%, 1.92%, 3.25% superior accuracy for Neck Blast as compared to existing techniques like Bi-LSTM, DBN, CNN, and MLP.

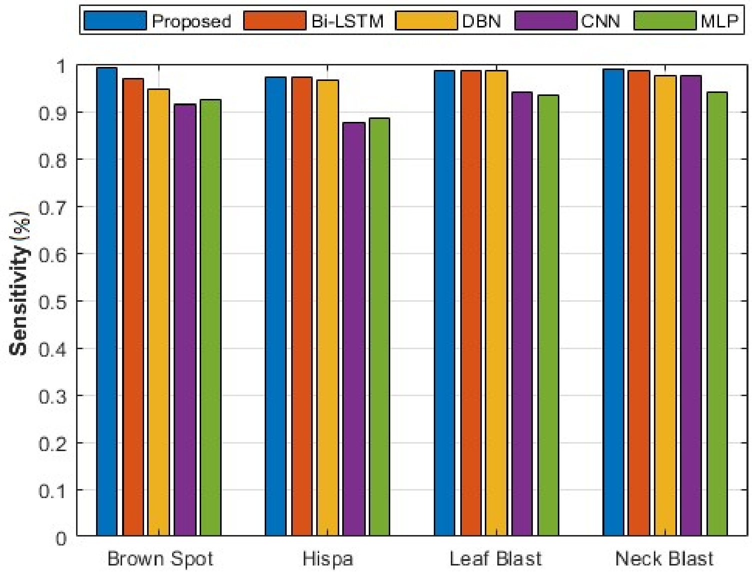


Figure 4: Performance analysis of Sensitivity for Disease classification

Figure 4 shows the performance analysis of sensitivity for Disease classification. Here the performance of proposed method provides 2.36%, 4.83%, 8.33%, 7.43% higher sensitivity for Brown Spot; 0.17%, 0.917%, 11.11%, 9.99%, higher sensitivity for Hispa; 0.13%, 0.15%, 4.89%, 5.46% higher sensitivity for Leaf Blast; 0.50%, 0.15%, 1.53%, 5.319% increased sensitivity for Neck Blast in comparison to current techniques like Bi-LSTM, DBN, CNN, and MLP, respectively.

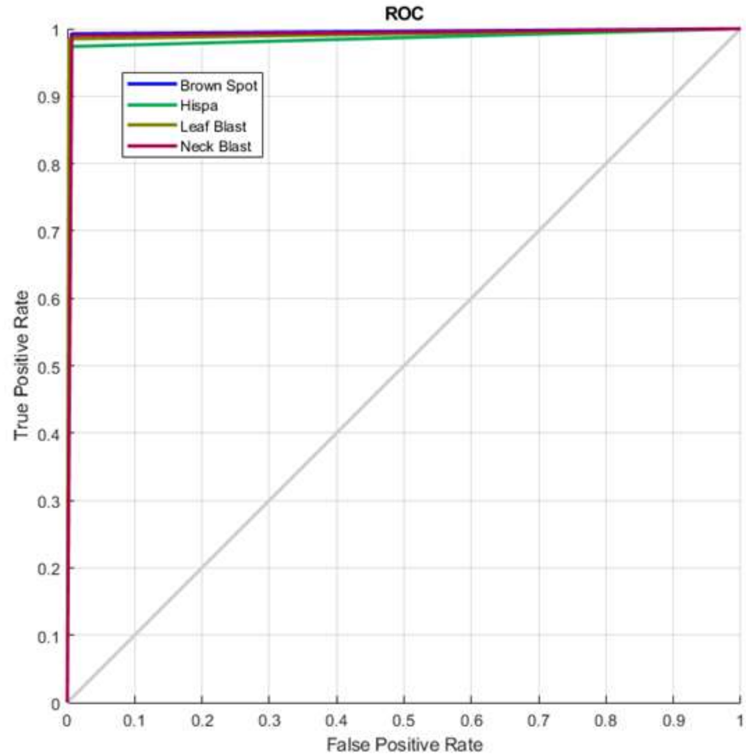


Figure 5: Performance analysis of ROC for Disease classification

Figure 5 shows the ROC for Disease categorization performance analysis. Here the performance of proposed method provides 0.99%, 0.98%, 0.99% and 0.97% higher AUC for the classification of plant disease as Brown Spot, Hispa, Leaf Blast and Neck Blast respectively.

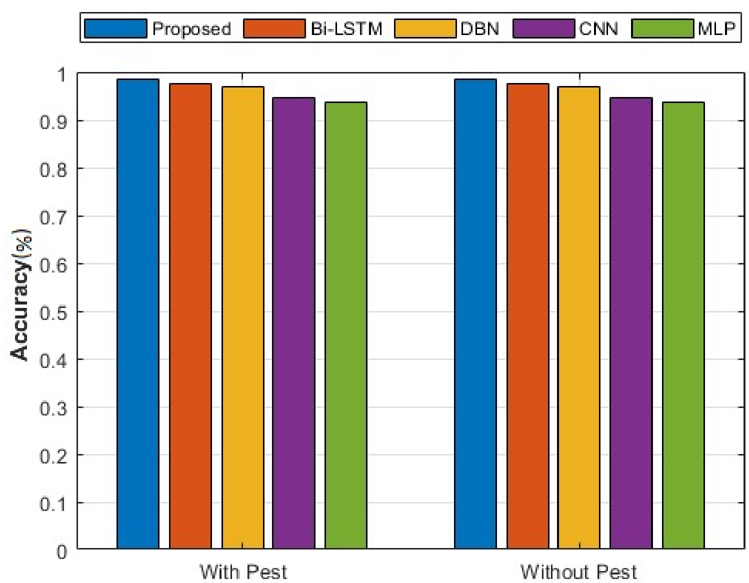


Figure 6: Performance analysis of Accuracy for pest classification

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The accuracy for pest classification performance analysis is shown in Figure 6. Here the performance of proposed method provides 0.09%, 1.58%, 4.06%, 4.07% higher accuracy for with pest; 0.07%, 1.58%, 4.06%, 4.09% greater accuracy for pest-free compared to current techniques like Bi-LSTM, DBN, CNN, and MLP, respectively.

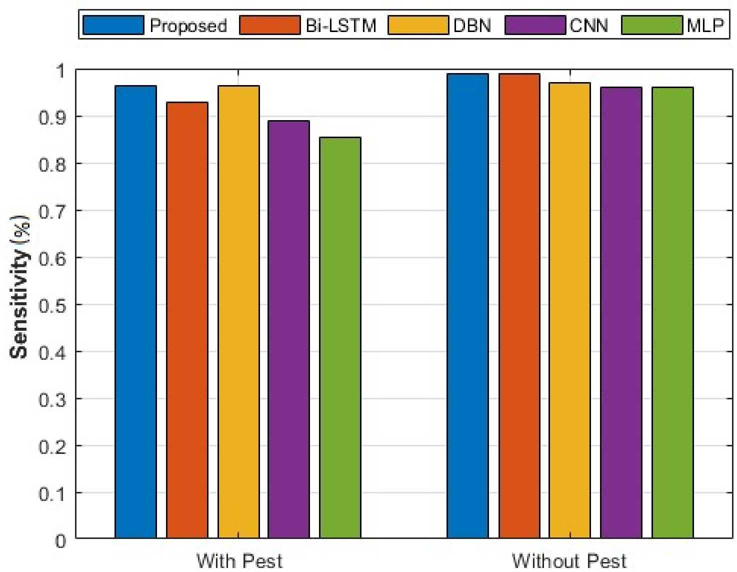

Figure 7: Performance analysis of Sensitivity for pest classification

The performance study of sensitivity for pest classification is shown in Figure 7. Here the performance of proposed method provides 0.008%, 0.019%, 3.03%, 3.033% higher sensitivity for with pest; 0.007%, 2%, 3.03%, 2.03% higher sensitivity for without pest compared with existing methods like Bi-LSTM, DBN, CNN and MLP respectively.

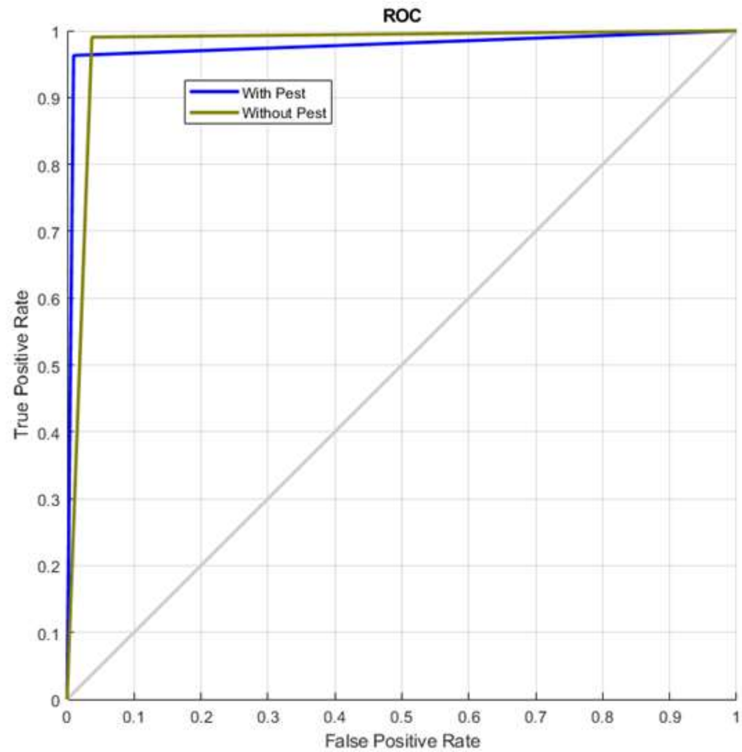

Figure 8: Performance analysis of ROC for pest classification

Figure 8 shows the performance analysis of ROC for pest classification. Here the performance of proposed method provides 0.98%,0.99% higher AUC for the classification of with and without pest.

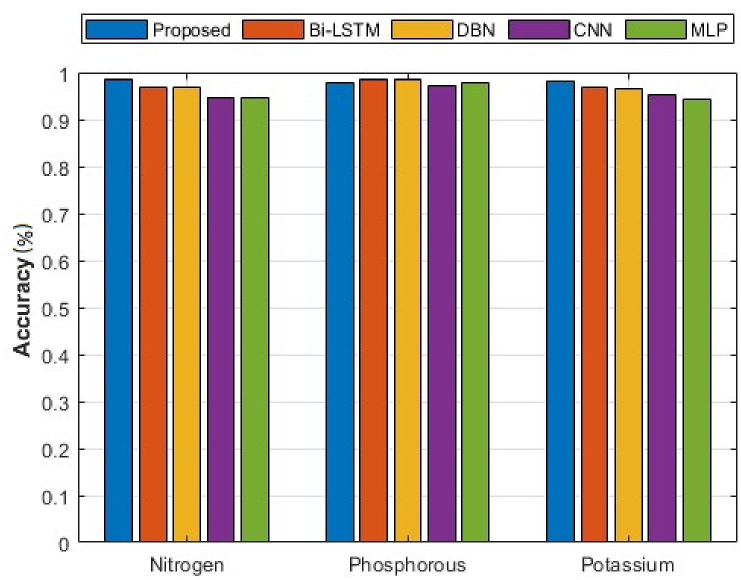

Figure 9: Performance analysis of Accuracy for Nutrient Deficiencies Classification

Figure 9 shows the performance analysis of Accuracy for nutrient deficiencies classification. Here the performance of proposed method provides 1.77%, 1.78%, 4.09%, 4.08% higher accuracy for nitrogen; 0.87%, 0.77%, 2.71%, 0.65%, higher accuracy for phosphorous; 1.33%, 1.72%, 3.16%, 4.10%, a better degree of accuracy for potassium as compared to previous techniques like Bi-LSTM, DBN, CNN, and MLP, respectively.

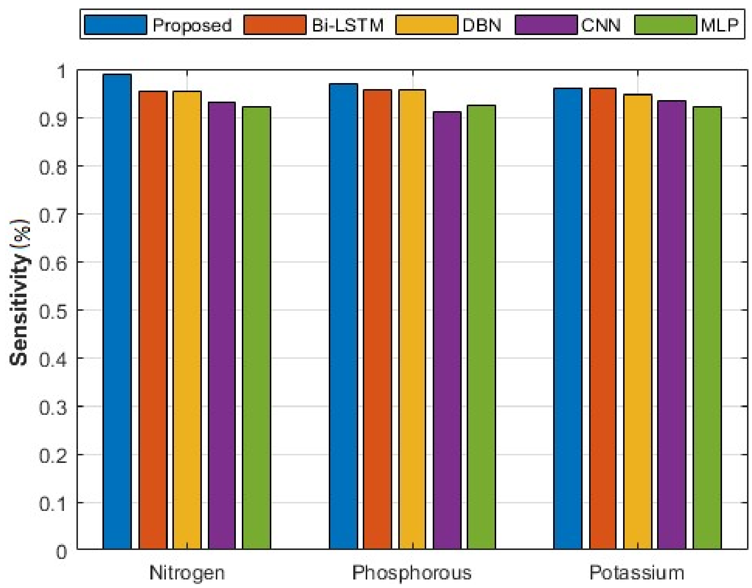

Figure 10: Performance analysis of Sensitivity for Nutrient Deficiencies classification

Figure 10 shows the performance analysis of sensitivity for Nutrient Deficiencies classification. Here the performance of proposed method provides 3.57%, 3.59%, 6.09%, 4.25% higher sensitivity for nitrogen; 1.56%, 1.43%, 4.11%, 7.40% higher sensitivity for phosphorous; 0.01%, 1.36%, 2.77%, 4.22% increased potassium sensitivity in comparison to current techniques like Bi-LSTM, DBN, CNN, and MLP, respectively.

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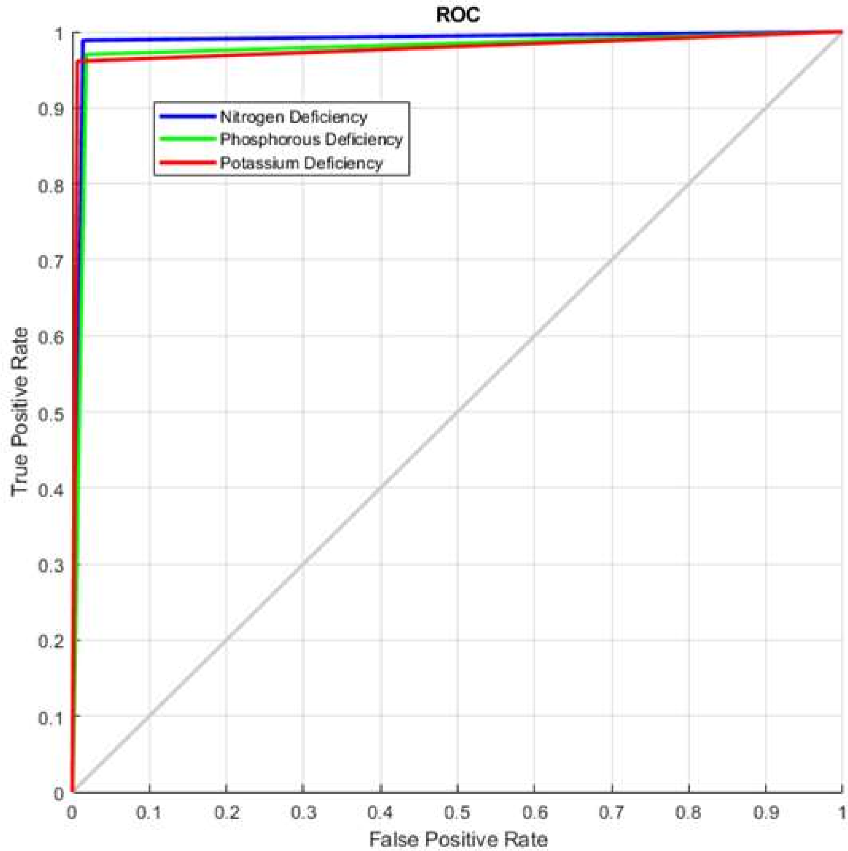

Figure 11: Performance analysis of ROC for Nutrient Deficiencies classification

The performance study of the ROC for the classification of nutrient deficiencies is shown in Figure 11. Here the performance of proposed method provides 98.09%, 99.76%, 98.88% higher AUC for Nutrient Deficiencies classification as nitrogen, phosphorous and potassium compared with existing methods like Bi-LSTM, DBN, CNN and MLP respectively.

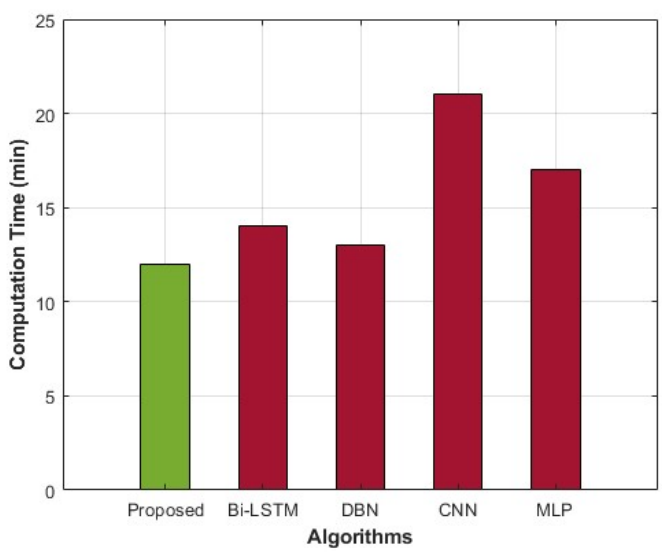

Figure 12: Performance analysis of Computational Time

The computing time performance analysis is shown in Figure 12. Here the performance of proposed method provides 14.28%, 7.69%, 42.85%, 29.41% lower computational time compared with existing methods like Bi-LSTM, DBN, CNN and MLP respectively. Table 2 shows the overall the performance analysis of proposed approach with existing techniques.

Table 2: Overall the performance analysis of proposed approach

Techniques		Types	Bi-LSTM	DBN	CNN	MLP	Proposed
Disease classification	Accuracy (%)	Brown Spot	0.989	0.981	0.960	0.964	0.993
		Hispa	0.989	0.989	0.970	0.960	0.992
		Leaf Blast	0.990	0.989	0.964	0.964	0.993
		Neck Blast	0.990	0.981	0.973	0.960	0.992
	Sensitivity (%)	Brown Spot	0.969	0.946	0.916	0.923	0.992
		Hispa	0.973	0.964	0.876	0.884	0.973
		Leaf Blast	0.974	0.964	0.938	0.933	0.984
		Neck Blast	0.985	0.975	0.975	0.941	0.996
Pest classification	Accuracy (%)	with pest	0.974	0.969	0.946	0.936	0.984
		without pest	0.952	0.969	0.946	0.946	0.989
	Sensitivity (%)	with pest	0.952	0.950	0.898	0.870	0.962
		without pest	0.980	0.970	0.961	0.951	0.990
Nutrient Deficiencies Classification	Accuracy (%)	Nitrogen	0.969	0.969	0.948	0.948	0.987
		phosphorous	0.987	0.987	0.974	0.978	0.978
		potassium	0.969	0.965	0.952	0.943	0.982
	Sensitivity (%)	Nitrogen	0.954	0.954	0.931	0.920	0.988
		phosphorous	0.955	0.940	0.910	0.925	0.970

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		potassium	0.961	0.965	0.935	0.922	0.961
Computational Time (sec)			14	13	21	17	12

5. Conclusion

In this manuscript, Improved Detection and Classification of Pests, Diseases, and Nutrient Deficiencies in Paddy Crops using optimized Deep Belief Networks with Bidirectional Long Short-Term Memory is implemented successfully. It uses MATLAB to carry out the suggested method. Performance parameters like as accuracy, sensitivity, computing time, and ROC are used to evaluate the performance of the suggested approach. Here, the performance of proposed methods achieves 23.45%, 13.42%, 5.66% and 17.89% higher sensitivity and 14.28%, 7.69%, 42.85%, 29.41% MATLAB is used to carry out the suggested method. Utilizing performance criteria like accuracy, sensitivity, computing time, and ROC, the proposed method's effectiveness is evaluated like Bi-LSTM, DBN, CNN and MLP respectively.

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Data Availability Statement: The dataset used for this study is publicly available at [31-33].
Conflicts of Interest: The authors declare that they have no conflicts of interest.

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