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Intelligent Crop Disease Detection and Classification Using Deep Convolution Neural Network with Honey Badger Algorithm on Image Data

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Abstract

Cotton is the most significant cash crop in India. Each year cotton production is decreasing because of the attack of the disease. Plant diseases are usually produced by pathogens and pest insects and reduce the yield to a large scale if not controlled in time. The hour requires an effective plant disease diagnosis system that can assist the farmers in their farming and cultivation. Nevertheless, cotton production is harmfully affected by the presence of viruses, pests, bacterial pathogens, and so on. For the past decade or so, numerous image processing or deep learning (DL)--based automated plant leaf disease recognition techniques have been established but, unluckily, they infrequently focus on the cotton leaf diseases. Therefore, this article develops an Intelligent Detection and Classification of Cotton Leaf Diseases Using Transfer Learning and the Honey Badger Algorithm (IDCCLD-TLHBA) model with Satellite Images. The proposed IDCCLD-TLHBA technique intends to determine and classify various kinds of cotton leaf diseases using satellite imagery. In the IDCCLD-TLHBA technique, the wiener filtering (WF) model is used to reduce noise and enhance image quality for subsequent analysis. For feature extraction, the IDCCLD-TLHBA technique applies the MobileNetV2 model to capture relevant features from the satellite images while maintaining computational efficiency. In addition, the stacked long short-term memory (SLSTM) method is employed for the classification and recognition of cotton leaf diseases. Eventually, the honey badger algorithm (HBA) is used to optimally select the parameters involved in the SLSTM model to ensure a better configuration of the network to enhance results. The performance validation of the IDCCLD-TLHBA method is carried out against the benchmark dataset and the stimulated results highlight the better results of the IDCCLD-TLHBA model across the existing techniques.

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Keywords: Cotton Leaf Diseases; Honey Badger Algorithm; Transfer Learning; Wiener Filtering; Satellite Images

1. Introduction

India is the second largest place for the production of crops like wheat, rice, spices, and pulses. The crop production in India profits just 30 to 60 percent owing to damages that occur throughout cultivation [1]. The farmer's economy is based on the quality and quantity of the crop. Each crop production has changed into a dream because of numerous diseases affecting the plant. It is essential to spontaneously identify disease symptoms as soon as possible they perform on plant leaves [2]. One main disease in the crop is leaf spot. It is affected because of viruses, phytoplasmas, and bacteria-fungi. The recognition of plant disease in the initial phase is very suggested for enhancing the farmer’s economy [3]. The leaf diseases minimize the quality of food. Monitoring crops from isolated places to identify diseases performs a main role in effective cultivation. Classical leaf disease detection primarily depends on human labor and needs professionals with knowledge and wide experience to judge the kind of leaf disease [4]. That flow of work not only requires effort and time but also has a higher risk of misjudgment and strong subjectivity. Laboratory testing approaches are costly and time-consuming [5]. To overwhelm these results, automated leaf disease detection depends on Computer Vision (CV) has been extremely valuable by investigators.

Remote sensing may be a proposed alternative for attaining the spatial distribution information of aphids over a wide region at relatively a lower cost [6]. The usage of remote sensing methods for such purposes depends on the assumption that stresses caused by infestation affect photosynthesis and the physical structure of plants, resulting in the modification of plant reflectance and light absorption features [7]. Plant stress may be characterized by utilizing particular responses in the visible, nearly-infrared, and short-wave infrared spectral fields, possibly to map or detect plant response to insects with remotely sensed data [8]. Recently, remote sensing technologies have made it possible to separate healthy and diseased crops, so possibility to measure automatically the spatial distribution of crop disease and pest insects. Remote sensing with Machine Learning (ML) and Deep learning (DL) are efficient models utilized for automated disease recognition [9]. DL captivates consideration as it is utilized to enhance performance on different challenges that provide data from human involvement. Various DL approaches have been presented for cotton disease recognition [10]. With the help of the DL model trained on the cotton leaf disease dataset, farmers can employ accurate agriculture methods, like particular breeding of disease-resistant cultivators and targeting pesticide application.

This article develops an Intelligent Detection and Classification of Cotton Leaf Diseases Using Transfer Learning and Honey Badger Algorithm (IDCCLD-TLHBA) model with Satellite Images. In the IDCCLD-TLHBA technique, the wiener filtering (WF) model is used to reduce noise and enhance image quality for subsequent analysis. For feature extraction, the IDCCLD-TLHBA technique applies MobileNetV2 model to capture relevant features from the satellite images while maintaining computational efficiency. In addition, the stacked long short-term memory (SLSTM) method is employed for the classification and recognition of cotton leaf diseases. Eventually, the honey badger algorithm (HBA) is used to optimally select the parameters involved in the SLSTM model to ensure a better configuration of the network to enhance results. The performance validation of the IDCCLD-TLHBA method is carried out against the benchmark dataset.

2. Literature Survey

Nagarjun et al. [11] presented a technique to enhance the recognition of cotton leaf disorder by using developed deep transfer learning (TL) methods. This paper also employs methods like Inception v2, DenseNet121, and ResNet101, and fine-tuning hyper-parameter using the Nesterov accelerated gradient. This method permits users to easily upload an image of a cotton leaf. After advanced image processing methods, a Convolutional Neural Network (CNN) is employed to identify the existence of cotton leaf disorders with higher efficiency and accuracy. In [12], an enhanced feature fusion-based method is presented, in which dual pre-trained structures named Inception-v3 and EfficientNet-b0 are applied to remove features, and every method removes the feature vector of length N × 1000. Afterwards, the removed features are serially concatenated holding a feature vector length N × 2000. The most important features are chosen with the Emperor Penguin Optimizer (EPO) technique. Rai and Pahuja [13] developed a developed approach that automated the classification and detection of diseased cotton plants and leaves through DL methods employed in the image. To deal with the task of supervised image classification, this paper applies a bagging ensemble method containing 5 TL methods: InceptionResNetV2, MobileNet, Xception, InceptionV3, and VGG16. This ensemble method was accepted essentially to enhance the performance of each mode.

Kolachi et al. [14] proposed the automated classification for curl and bacterial blight virus in cotton plants over the special application of an advanced YOLO DL structure. This disease classification is carried out on YOLOv5, and its implementation is compared to YOLOv7 and YOLOv6. The TL of the pretrained method is helped to an original image dataset. Diverse augmentation methods are applied to maximize the diversity and size of the dataset. Chaudhari et al. [15] propose an intelligent method for the recognition of cotton plant disorders utilizing CNNs focused on ResNet-152V2 structure. Utilizing DL methods, particularly ResNet-152V2, this method exhibits strong performance in identifying several disorders affecting cotton plants. This work involves the training model on a dissimilar dataset including diverse cotton leaf disorders.

In [16], SwinCNN which is a novel hybrid DL structure is proposed for reliable cotton disorder prediction. This structure integrates the strengths of Swin Transformer (ST) and CNN, the latest development in self-attention (SA) mechanisms for CV challenges. This work also utilizes a visibly accessible dataset of cotton crop images with different disorders to evaluate and train the presented structure. In [17], a DL method is recommended to classify photos of sick and healthy cotton leaves. There are 4 stages in this procedure. In the initial stage, input images are loaded from the dataset. Then, the image sizes are reduced to 200×200 in pre-processing. Next, the method of adding new data points is utilized by changing the present data, which is called data augmentation. Later, CNN is utilized to extract features. Then, the photos are classified utilizing the DL method DenseNet121 in the last stage followed by Adam Optimization method.

3. Materials and Methods

In this article, we have developed an IDCCLD-TLHBA model with Satellite Images. The proposed IDCCLD-TLHBA technique intends to determine and classify various kinds of cotton leaf diseases using satellite imagery. It comprises four various stages namely WF-based image pre-processing, feature extraction using MobileNetV2, SLSTM-based leaf disease classification, and HBA-based parameter tuning are demonstrated in Fig. 1.

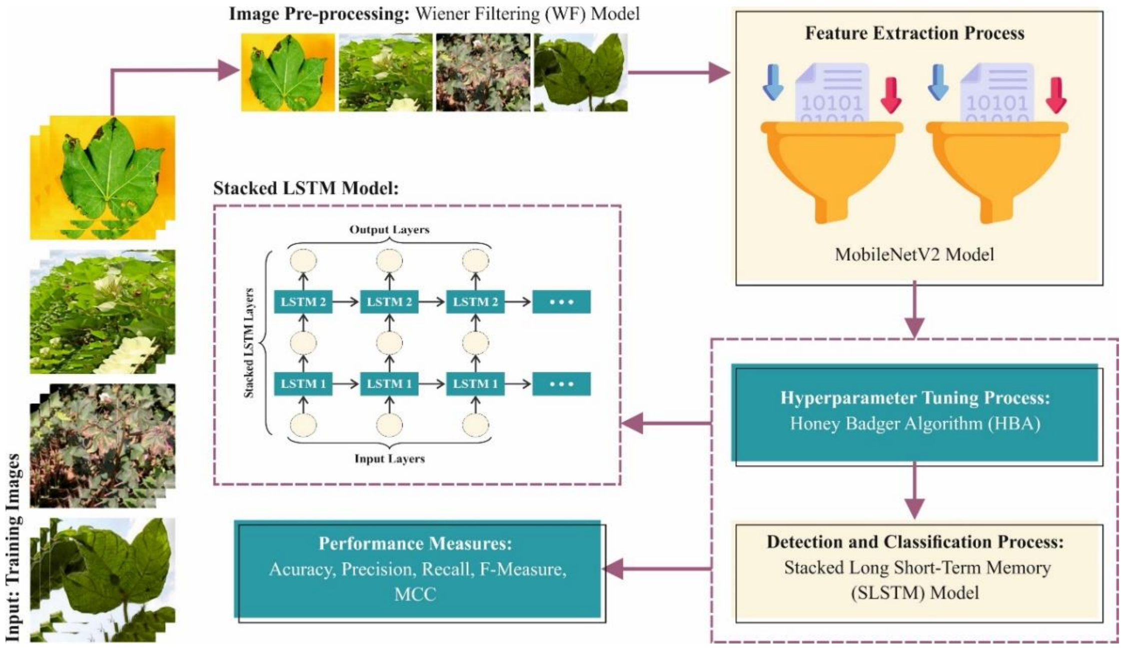

Figure 1. Workflow of IDCCLD-TLHBA model

A. WF-based Image Preprocessing

Initially, the IDCCLD-TLHBA technique takes place WF model and is used to reduce noise and enhance image quality for subsequent analysis. WF is a great image pre-processing model utilized to improve the qualities of cotton plant leaf images by decreasing noise [18]. It works by fine-tuning the pixel values depending on the local image difference, efficiently smoothening unnecessary noise while preserving significant features. In terms of cotton plant leaf disease detection, WF assistances enhance the precision of succeeding image studies by making disease symptoms more different. This model is mainly beneficial after addressing noisy, lower-quality images, guaranteeing superior classification and feature extraction outcomes.

B. Feature Extraction using MobileNetV2

For feature extraction, the IDCCLD-TLHBA technique applies MobileNetV2 model to capture relevant features from the satellite images while maintaining computational efficiency. The MobileNet-V2 application depends upon the precise, quick, and scalable image-based diagnostics, which is must [19]. The analysis typically contains huge higher-dimensional datasets, which are very costly, particularly in data processing, analysis, and modeling. MobileNet-V2 is a general DL structure, which executes both lightweight and DL tactics without compromising the outcomes. The restricted sources that need fast and effectual computerization like edge devices and mobile. To verify that the model executes on factors that it enhanced for, few exact steps are executed. Upholding consistency relates to regularizing pixel values and helps in model learning across the databases. Transfer learning (TL) permits the technique to employ the data, which is already seized in rich features of a general method that is trained on ImageNet with the MobileNet-V2. Furthermore, average pooling is generally employed for dimension reduction. It is desired in constructing a study to collapse spatial data without overfitting the imageries. The dropout layer application and an amount of regularization models decrease the risk of overfitting and therefore it applies to novel data. In essence, the intention is to use innovative DL technologies while resolving the tasks of restricted computing sources to generate a trustworthy and effective method. The first algorithm is a CNN utilizing MobileNetV2: initially begins with data pre-processing, resizing to an input of 224x224 pixels, and regularizing among the 0 to 1 range. The convolutional layers are employed for extracting features from the imageries. Then, the feature maps were downsized over a decrease of dimension to improve these features, an extra higher-level layer recognized as fully connected (FC) or dense layer was combined. To overpower overfitting, a layer of dropout has been employed. The cross-validation has been completed on a dissimilar cross-validation sub-set. Eventually, the last performance is measured on the test database to verify its precision and other related performance metrics. Fig. 2 depicts the architecture of MobileNetV2.

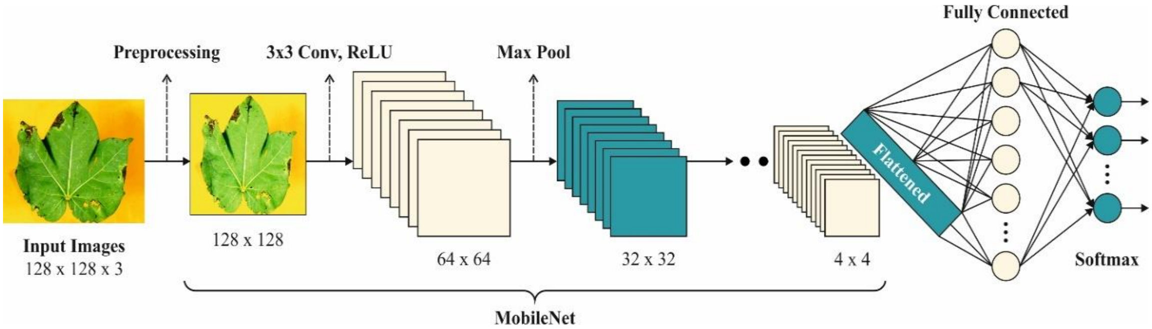

Figure 2. Architecture of MobileNetV2

C. Cotton Leaf Disease using SLSTM Classifier

In addition, the SLSTM method is employed for classification and recognition of cotton leaf diseases. Even though the RNN can efficiently extract temporal data from temporal information, RNN meets problems of exploding and vanishing gradients throughout training on long sequences [20]. To overwhelm the RNN limitations, the authors developed the architecture of LSTM. LSTM inserts four gates such as input, forget, output, and update to RNN. The forget gate defines the percentage of long-term memory that is ignored, the input gate defines what ratio of the current moment is delivered to the quantity of cell state at the present moment, the update gate is employed to upgrade the cell state and the output gate yields an output at the present moment. These 4 major modules of the LSTM will function and relate with each other in a special method. The forget gate defines the ratio by which the preceding time-step cell state, helps long-term memory, which wants to be neglected. The forget gate has hidden layer (HL) of the preceding moment and the input of the present moment, which is lastly attained by the activation function. The method of computing the forget gate f_t is expressed in Eq. (1):

$$f_t = \sigma\left(W_{if}x_t + W_{hf}h_{t-1} + b_f\right), \quad (1)$$

Here, x_t denotes an input of the present moment, W_{if} refers to a weight of present input, h_{t-1} means the HL functioning as short-term memory from the preceding time-step, W_{hf} denotes the

weight of HL in the preceding moment, and b_f means a bias of forgetting gate. o signifies an activation function within the range of [0,1], while 0 indicates whole forgetting and 1 specifies whole retention.

The input gate defines the proportion of short-term data at the present moment, which is upgraded into long-term memory, and the procedure of computing the input gate. i_t is formulated in Eq. (2):

$$i_t = \sigma(W_{ii}x_t + W_{hi}h_{t-1} + b_i), \quad (2)$$

Here, W_{ii}, W_{hi} and b_i denotes weight matrix of the present input, the weight matrix of the HL, and the bias of the input gate, correspondingly.

The update gate is employed to control the upgrade of candidate cell state. g_t, which is attained by tanh, within the range of $[-1,1]$. Its mathematical equation is given in Eq. (3):

$$g_t = \tanh\left(W_{ig}x_t + W_{hg}h_{t-1} + b_g\right), \quad (3)$$

While, W_{ig}, W_{hg} and b_g represent the weight matrix of the present input, HL at the preceding moment, and the bias, respectively. The cell state at the present moment is jointly defined by the forget gate and the input gate. Its mathematical formulation is denoted below:

$$c_t = f_t^* c_{t-1} + i_t^* g_t, \quad (4)$$

The output gate is employed to control an output of a cell state and move that state to the subsequent cell. The procedure of computing an output gate 0_t value is exposed in Eq. (5):

$$o_t = \sigma(W_{io}x_t + W_{ho}h_{t-1} + b_o), \quad (5)$$

Here, W_{io} epitomizes the weight matrix, W_{ho} refers to weight of HL in the preceding moment and b_o is the bias.

Depending upon computing the input, output, update, forget gates, and candidate cell state, LSTM will compute an output and upgrade the HL with the below-mentioned formulation:

$$y_t = o_t^* \tanh(c_t), \tag{6}$$

$$h_t = y_t. \tag{7}$$

Deep network structures have established robust abilities in dealing with intricate non-linear feature representations. Research states that a one LSTM unit can resolve the problems of gradient vanishing and explosion in RNN technique. Its prediction accuracy is still restricted by the simple structure of network. Hence, by enlarging the stacking depth of LSTM, the input sequence feature can be well learned, thus enhancing the performance of network.

The SLSTM structure comprises manifold LSTM layers, where an input of 1st LSTM layer is the original data and the last LSTM layer output is the prediction outcome. The inputs of other intermediate LSTM layers originate from the output of their preceding LSTM layer, and the outputs are employed as an input to the final LSTM layer. As with the novel LSTM, the HLs and cell states in the SLSTM are also distributed to the following moment. The main difference is that the size is enlarged in this stacked structure. While stacking manifold LSTM layers, which improves the system's ability to acquire from long series, extreme layer stacking must be avoided. An upsurge in the number of layers can lead to slower model upgrade iterations, decreased convergence efficiency, and exponential development in time-based and memory costs throughout training. This can make the model vulnerable to problems like gradient vanishing. So, the SLSTM module is selected, which contains three LSTM layers.

D. Hyper parameter Tuning using HBA

Eventually, the HBA is employed to optimally select the parameters intricate in the SLSTM technique to ensure the better configuration of the network to improve results. The HBA is a meta-heuristic technique [21]. This algorithm is stimulated by the hunting behaviour of honey badgers naturally. This technique contains dual parts such as exploration and exploitation stages. The exploration stage represents the digging and sniffing behaviour of honey badger while discovering targets by widely hunting the space of solution for finding novel areas, which might cover superior solutions. The exploitation stage is demonstrated after the foraging behaviour to find a hive, and this phase enhances the recognized optimum solution for finding a good solution. HBA evades dropping into local optimum solutions and attempts its best to discover global optimum solutions to balance the phases of exploitation and exploration. The technique can efficiently deal with intricate non-linear issues, and experimentation outcomes on numerous normal benchmark function and design issues have established its sturdy global search ability and quick convergence speed. The procedure of this technique primarily depends upon the below-mentioned steps:

(1) Initialization. In this stage, the parameters comprise iteration count $iter_{\max}$ and the dimension of population n. The candidate solution is signified by an $n \times D$ dimensional matrix P:

$$P = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1D} \\ x_{21} & x_{22} & \cdots & x_{2D} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nD} \end{bmatrix} \tag{8}$$

While every row parallels to an individual and the columns signify the values of coordinate; D represents the dimension.

The mathematical formulation for computing the position of every individual has been given below:

$$x_i = lb_i + r_1 \times (ub_i - lb_i), \tag{9}$$

While, r_1 denotes a randomly generated value among 0 and 1, ub_i and lb_i signify the upper and lower bounds, correspondingly.

(2) Assess early individual fitness. In every honey badger, the fitness f_i is assessed depending on the function of the objective. The individual through the finest fitness P was originated. The position of this honey badger is denoted by x_{prey}, and the fitness is represented as f_{prey} for upgrading the population to the next level.

(3) Describe density factor α and intensity I_i . I_i is linked to the intensity of honey badgers in the searching space and the distance among prey and honey badgers. If I_i is higher, then the honey badger would travel superior. Its mathematical formulation is given below:

$$I_i = r_2 \frac{S}{4\pi d_i^2}, \tag{10}$$

Here, $S = (x_i - x_{i+1})^2$ signifies the concentration of honey badgers, $d_i = x_{prey} - x_i$ represents the distance between ith honey badger and prey, and r_2 refers to a randomly generated value among $(0,1)$. A small value of S specifies that the ith honey badger is near to another honey badger, which leads the technique to decrease I_i for minimizing redundant drive and averting conflicts with other honey badgers. On the other hand, a small d_i specifies that the honey badger can observe the target position, by demanding an upsurge in I_i to hasten its method.

Eq. (11) is applied for upgrading the factor of density α that reduces using the iteration counts, thus certifying a smooth evolution.

$$\alpha = C_1 \times \exp\left(-\frac{iter}{iter_{\max}}\right), \tag{12}$$

where C_1 denotes a constant, which is bigger than 1, and $iter_{\max}$ refers to a maximum iteration count.

(4) Jump out of local optima. For avoiding the technique from dropping into a local optimal, a searching direction fag F has been definite, which can be established by a randomly generated value over Eq. (13). F is expressed below:

$$F = \begin{cases} 1 \; if \; r_3 \leq 0.5 \\ -1 \; else \end{cases}, \tag{13}$$

Here, r_3 means a randomly produced value among 0 and 1.

(5) Honey badger location upgrade. This technique contains dual parts such as exploration and exploitation stages. In the exploration stage, the upgraded honey badger location is computed below:

$$x_{new} = x_{prey} + FC_2 I x_{prey} + Fr_4 \alpha d_i |\cos(2\pi r_5)[1 - \cos(2\pi r_6)]|, \tag{14}$$

In the exploitation stage, the upgraded honey badger location was expressed below.

$$x_{new} = x_{prey} + Fr_7 \alpha d_i, \tag{15}$$

While, r_7 refers to a randomly generated value between 0 and 1.

In the HBA, the purpose of whether to use the exploitation or exploration stage to upgrade the position of a honey badger is defined by a randomly generated numbers. Particularly, if randomly produced number r_3 is lesser than or equivalent to 0.5, then the technique picks the position upgrade formulation for the exploration stage. If random number r_3 is better than 0.5, the method picks the position upgrade calculation for the exploitation stage.

(6) Assess fitness of upgraded individual. The novel individual was assessed over the assumed function of the objective, and the values of fitness of new and older individuals were equated. If the novel individual attains improved fitness, then the older individual is substituted by the novel one; or else, the old honey badger and fitness are preserved. If every location is upgraded, then finest fitness value is obtained and equated with x_{prey}. The outcomes are employed to define whether upgrading. x_{prey} and f_{prey}.

The fitness choice is an important feature manipulating the performance in the HBA. The hyper parameter choice process holds the solution encoder model to estimate the competence of the candidate solutions. In this work, the HBA considers precision as the key condition for intention of the fitness function, which is stated as shown.

$$Fitness \; = \; \max(P) \tag{16}$$

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

Here, TP symbolizes the true positive and FP indicates the false positive value.

4. Performance Validation

The stimulated validation of the IDCCLD-TLHBA method is established below the cotton leaf disease dataset [22]. The dataset contains 4 classes with a total of 1600 images gathered in real-world conditions and from internet, as denoted in Table 1. Fig. 3 depicts the sample images.

Figure 3. Sample images of (a) Bacterial Blight, (b) Curl Virus, (c) Fussarium Wilt, and (d) Healthy

Table 1: Details of Dataset

Classes	No. of Images
Bacterial Blight	400
Curl Virus	400
Fussarium Wilt	400
Healthy	400
Total Images	1600

The classifier results of the IDCCLD-TLHBA algorithm are presented in Fig. 4. Figs. 4a-4b shows the confusion matrix with precise classification and recognition of each class under 70%TRPH and 30%TSPH. Fig. 4c displays the PR analysis, indicating enhanced performance across all classes. Lastly, Fig. 4d depicts the ROC study, signifying proficient results with high ROC outcomes for distinct class labels.

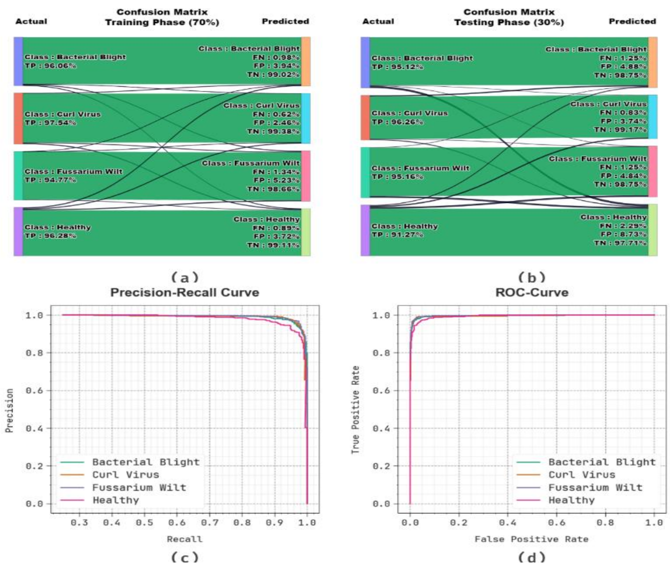

Figure 4. Classifier result of (a-b) 70% TRPH and 30% TSPH confusion matrix, (c) curve of PR, and (d) curve of ROC

Table 2 denotes the cotton leaf disease detection results of IDCCLD-TLHBA approach under 70%TRPH and 30%TSPH.

Fig. 5 exemplifies the average performance of IDCCLD-TLHBA model under 70%TRPH. The solutions imply that the IDCCLD-TLHBA system properly identified the samples. With 70%TRPH, the IDCCLD-TLHBA algorithm offers average $accu_y, prec_n,\ reca_l,\ \ F_{measure}$ and MCC of 98.08%, 96.16%, 96.17%, 96.15%, and 94.89%, respectively.

Fig. 6 illustrates the average result of IDCCLD-TLHBA system under 30%TSPH. The outcomes imply that the IDCCLD-TLHBA approach properly identified the samples. With 30%TSPH, the IDCCLD-TLHBA method offers average $accu_y, prec_n,\ reca_l,\ \ F_{measure}$ and MCC of 97.19%, 94.45%, 94.38%, 94.41%, and 92.54%, correspondingly.

Table 2: Cotton leaf disease detection of ISLCERS-HDLTL model under 70%TRPH and 30%TSPH

Class Labels	$Accu_y$	$Prec_n$	$Reca_l$	$F_{measure}$	MCC
TRPH (70%)					
Bacterial Blight	98.30	96.06	97.10	96.58	95.45
Curl Virus	98.21	97.54	95.53	96.53	95.34
Fussarium Wilt	98.21	94.77	98.19	96.45	95.29
Healthy	97.59	96.28	93.84	95.05	93.47
Average	98.08	96.16	96.17	96.15	94.89
TSPH (30%)					
Bacterial Blight	97.29	95.12	94.35	94.74	92.91
Curl Virus	97.92	96.26	94.50	95.37	94.03
Fussarium Wilt	97.71	95.16	95.93	95.55	94.01
Healthy	95.83	91.27	92.74	92.00	89.19
Average	97.19	94.45	94.38	94.41	92.54

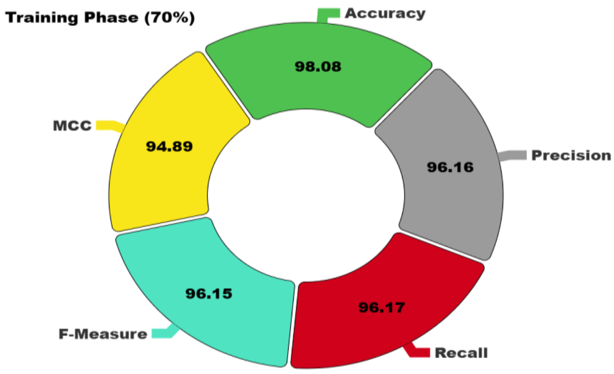

Figure 5. Average of IDCCLD-TLHBA model under 70%TRPH

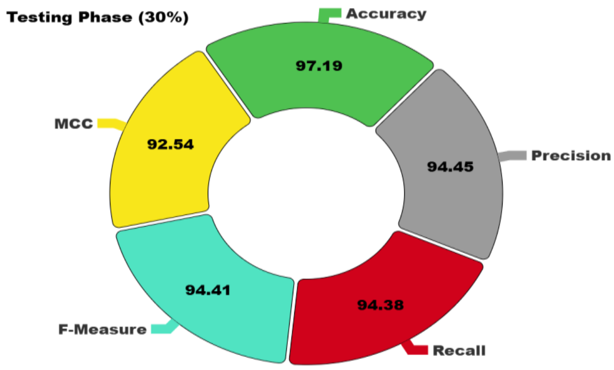

Figure 6. Average of IDCCLD-TLHBA model under 30%TSPH

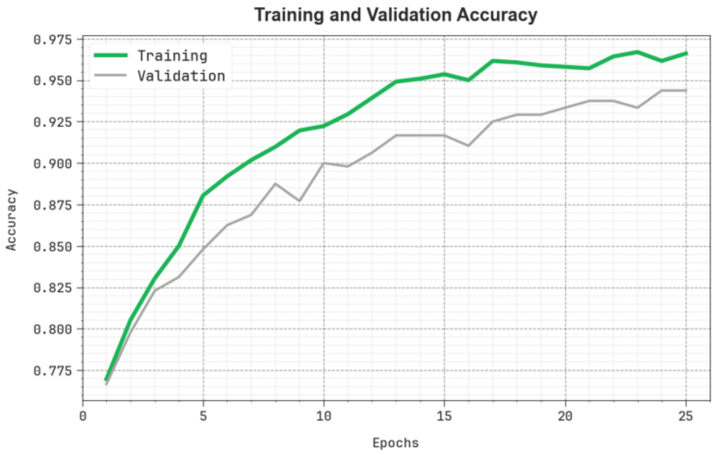

Figure 7. $Accu_y$ Curve of IDCCLD-TLHBA model

In Fig. 7, the training (TRA) $accu_y$ and validation (VAL) $accu_y$ performances of the IDCCLD-TLHBA technique are showcased. The $accu_y$ values are computed during a timeframe of 0-25 epoch counts. The figure highlighted that the TRA and VAL $accu_y$ values show growing tendencies, notifying the IDCCLD-TLHBA algorithm's proficiency with superior performance through several iterations. Moreover, the TRA and VAL $accu_y$remains nearer above the epoch counts, representing diminished overfitting and revealing better performance of the IDCCLD-TLHBA system, ensuring continual prediction on undetected instances.

In Fig. 8, the TRA loss (TRALOS) and VAL loss (VALLOS) graph of the IDCCLD-TLHBA system is exhibited. The loss values are computed for 0-25 epoch counts. It is exemplified that the TRALS and VALLS values depict subsiding tendencies, conveying the potential of the IDCCLD-TLHBA system in harmonizing a trade-off between generality and data fitting. The continual reduction in loss values as well promises the maximum performance of the IDCCLD-TLHBA technique and tuning of the prediction results as time progresses.

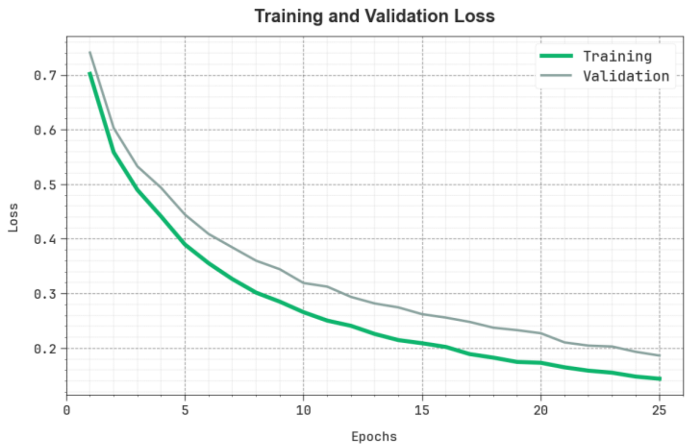

Figure 8. Loss curve of IDCCLD-TLHBA model

The comparative inspection of IDCCLD-TLHBA methodology with recent models is illustrated in Table 3 and Fig. 9 [23, 24]. The simulation result stated that the IDCCLD-TLHBA method outperformed well performances. Based on $accu_y$, the IDCCLD-TLHBA technique has enhanced $accu_y$ of 98.08% while the Custom CNN, LBP and GLCM, Mask-RCNN, Alex-Network, Deep Features, VGG16, SENet, CBAM, and ResNet50 models have diminished $accu_y$ of 97.67%, 92.20%, 94.00%, 97.69%, 96.40%, 88.93%, 95.54%, 96.07%, and 94.82%, correspondingly.

Table 3: Comparative study of IDCCLD-TLHBA model with existing techniques

Approach	Accuracy	Precision	Recall	F-Measure
IDCCLD-TLHBA	98.08	96.16	96.17	96.15
Custom CNN	97.67	90.07	90.99	93.48
LBP and GLCM	92.20	91.65	92.03	90.97

Mask-RCNN	94.00	94.21	90.07	91.93
Alex-Network	97.69	92.50	91.40	91.20
Deep Features	96.40	93.11	90.56	95.65
VGG16 Algorithm	88.93	88.50	88.20	90.10
SENet Methodology	95.54	94.00	94.30	90.17
CBAM Method	96.07	92.70	93.00	91.64
ResNet50 Classifier	94.82	93.30	93.10	94.34

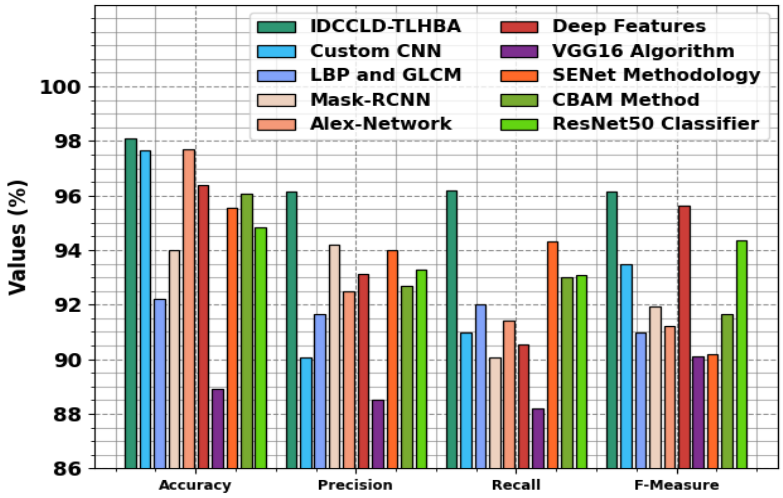

Figure 9. Comparative analysis of IDCCLD-TLHBA model with existing models

Similarly, based on $prec_n$, the IDCCLD-TLHBA algorithm has maximal $prec_n$ of 96.16% while the Custom CNN, LBP and GLCM, Mask-RCNN, Alex-Network, Deep Features, VGG16, SENet, CBAM, and ResNet50 techniques have minimal $prec_n$ of 90.07%, 91.65%, 94.21%, 92.50%, 93.11%, 88.50%, 94.00%, 92.70%, and 93.30%, respectively. Eventually, based on $F_{measure}$, the IDCCLD-TLHBA system has superior $F_{measure}$ of 96.15% while the Custom CNN, LBP and GLCM, Mask-RCNN, Alex-Network, Deep Features, VGG16, SENet, CBAM, and ResNet50 algorithms have lower $F_{measure}$ of 93.48%, 90.97%, 91.93%, 91.20%, 95.65%, 90.10%, 90.17%, 91.64%, and 94.34%, respectively.

5. Conclusion

In this article, we have developed an IDCCLD-TLHBA model with Satellite Images. The proposed IDCCLD-TLHBA technique intends to determine and classify various kinds of cotton leaf diseases using satellite imagery. In the IDCCLD-TLHBA technique, the WF model is used to reduce noise and enhance image quality for subsequent analysis. For feature extraction, the IDCCLD-TLHBA technique applies MobileNetV2 model to capture relevant features from the satellite images while maintaining computational efficiency. In addition, the SLSTM method is employed for classification and recognition of cotton leaf diseases. Eventually, the honey badger algorithm (HBA) is used to optimally select the parameters involved in the SLSTM model to ensure a better configuration of the network to enhance results. The performance validation of the IDCCLD-TLHBA method is carried out against the benchmark dataset and the stimulated results highlight the better results of the IDCCLD-TLHBA model across the existing techniques.

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References

[1] Adeel, et al., Entropy-controlled deep features selection framework for grape leaf diseases recognition, Expert. Syst. (2020).

[2] Fan, X.; Luo, P.; Mu, Y.; Zhou, R.; Tjahjadi, T.; Ren, Y. Leaf image based plant disease identification using transfer learning and feature fusion. Comput. Electron. Agric. 2022, 196, 106892.

[3] Jiang, F.; Lu, Y.; Chen, Y.; Cai, D.; Li, G. Image recognition of four rice leaf diseases based on deep learning and support vector machine. Comput. Electron. Agric. 2020, 179, 105824.
[4] Zhang, J.H.; Kong, F.T.; Wu, J.Z.; Han, S.Q.; Zhai, Z.F. Automatic image segmentation method for cotton leaves with disease under natural environment. J. Integr. Agric. 2018, 17, 1800–1814.
[5] M.A. khan, T. Akram, M. Sharif, T. Saba, Fruits diseases classification: exploiting a hierarchical framework for deep features fusion and selection, Multimed. Tools Appl. 79 (35–36) (2020).
[6] Sun, S.; Li, C.; Paterson, A.H.; Chee, P.W.; Robertson, J.S. Image processing algorithms for infield single cotton boll counting and yield prediction. Comput. Electron. Agric. 2019, 166, 104976.
[7] Udawant, P.; Srinath, P. Cotton leaf disease detection using instance segmentation. J. Cases Inf. Technol. (JCIT) 2022, 24, 1–10.
[8] B.M. Patil, V. Burkpalli, A perspective view of cotton leaf image classification using machine learning algorithms using WEKA, Adv. Hum.-Comput. Interact. 2021
[9] Zhang, S.; Zhang, C.; Wu, Z.; Xie, L. Preliminary report on the whole process control Technology of cotton disease. China Cotton 2020, 47, 20–22, 46.
[10] SELVAM, R.P., 2022. Earthworm optimization with deep transfer learning enabled aerial image classification model in IoT enabled UAV networks. Full Length Article, 7(1), pp.41-1.
[11] Nagarjun, A., Manju, N., Darem, A.A., Siddesha, S., Yahya, A.E. and Alhashmi, A.A., 2024. An Advanced Deep Learning Approach for Precision Diagnosis of Cotton Leaf Diseases: A Multifaceted Agricultural Technology Solution. Engineering, Technology & Applied Science Research, 14(4), pp.15813-15820.
[12] Zafar, M., Amin, J., Sharif, M., Anjum, M.A., Kadry, S. and Kim, J., 2023. CNN Based Features Extraction and Selection Using EPO Optimizer for Cotton Leaf Diseases Classification. Computers, Materials and Continua, 76(3), pp.2779-2793.
[13] Rai, C.K. and Pahuja, R., 2024. An ensemble transfer learning-based deep convolution neural network for the detection and classification of diseased cotton leaves and plants. Multimedia Tools and Applications, pp.1-34.
[14] Kolachi, A.R., Soomro, S.R., Baloch, S.K., Patoli, A.A. and Anwar, S., 2023. Cotton leaf disease classification using YOLO deep learning framework and indigenous dataset. International Journal of Systematic Innovation, 7(7), pp.80-88.
[15] Chaudhari, P., Patil, R.V. and Mahalle, P.N., 2024. An Intelligent Approach for Cotton Plant Disease Detection using Convolutional Neural Networks: A Deep Learning Perspective. Journal of Electrical Systems, 20(1s), pp.891-899.
[16] Muthurajkumar, S. and Kumar, G.K., 2023, August. Swincnn: A hybrid deep learning architecture for accurate cotton disease prediction. In 2023 12th International Conference on Advanced Computing (ICoAC) (pp. 1-7). IEEE.
[17] Jyothi, T., Soujanya, A. and Radhika, T., 2024, June. Classification of Cotton Leaf Images Using DenseNet. In 2024 OPJU International Technology Conference (OTCON) on Smart Computing for Innovation and Advancement in Industry 4.0 (pp. 1-5). IEEE.
[18] Göreke, V., 2023. A novel method based on Wiener filter for denoising Poisson noise from medical X-Ray images. Biomedical Signal Processing and Control, 79, p.104031.
[19] Sankar, M., Baiju, B.V., Preethi, D., Kumar, A., Mathivanan, S.K. and Shah, M.A., 2024. Efficient brain tumor grade classification using ensemble deep learning models. BMC Medical Imaging, 24, p.297.
[20] Tian, C., Lin, L., Yan, Y., Wang, R., Wang, F. and Chi, Q., 2024. Photovoltaic power prediction based on dilated causal convolutional network and stacked LSTM. MBE, 21, pp.1167-1185.
[21] Zhu, X., Hu, Y., Yu, Y., Zeng, D., Yang, J. and Carbone, G., 2024. Research on online optimization scheme and deployment of PMSM control parameters based on honey badger algorithm. Scientific Reports, 14(1), p.26670.
[22] https://www.kaggle.com/datasets/seroshkarim/cotton-leaf-disease-dataset
[23] Amin, J., Anjum, M.A., Sharif, M., Kadry, S. and Kim, J., 2022. Explainable Neural Network for Classification of Cotton Leaf Diseases. Agriculture, 12(12), p.2029.
[24] Shao, M., He, P., Zhang, Y., Zhou, S., Zhang, N. and Zhang, J., 2022. Identification method of cotton leaf diseases based on bilinear coordinate attention enhancement module. Agronomy, 13(1), p.88.