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Automated Cotton Leaf Identification Using Feature Selection Techniques

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Abstract: Agriculture is the backbone of any prosperous nation. Pest infestations and bacterial or viral illnesses cause significant economic losses in the cotton farming commercial, costing Indian farmers an average of 10-20% of their annual income. Cash crops include cotton and other valuable agricultural products. Cotton is highly susceptible to the vast majority of crop-damaging diseases. Several diseases affect crop production by attacking the leaves. The early diagnosis of diseases helps prevent additional damage to crops. Many diseases can afflict cotton, including leaf spot, nutrient insufficiency, powdery mildew, leaf curl, and many others. Correctly diagnosing a condition is crucial for taking appropriate action. Accurately diagnosing plant diseases requires. The suggested model based on the Biattention process makes accurate diagnosis of cotton leaf diseases possible. Also, useless features lower categorization precision. These issues are tackled by the IGWO (Improved Grey Wolf Optimization) method. We photographed cotton leaves in the field for our analysis. There are 2385 images in the dataset, including both leaves. The dataset was expanded with the use of data increase techniques. A meta-learning strategy has been devised and applied to deliver high precision and generalization. The projected model has a higher accuracy on the Cotton Dataset, at 97.45%.

Keywords: Cotton Disease; Improved Grey Wolf Optimization; Agriculture; Indian Economy; Farmers; Bacterial blight.

1. Introduction

Rice, wheat, pulses, and spices are among India's crops in the second-largest amount. Due to losses sustained during cultivation, crop production in India only yields between 30 and 60 percent [1]. The quantity and quality of the crop affect farmers' economies. Due to numerous plant diseases, every crop production has become a nightmare [2] [3]. As soon as possible after they appear on plant leaves, disease symptoms must be automatically detected [4]. Due to diseases that severely harm the cotton crop, it is problematic to detect them with the naked eye [5]. The plant's Leaf is the part most severely affected by the disease. The leaves of the plant are where 80–90% of the disease is located. Some illustrations of both diseased and healthy cotton leaves are shown in Fig. 1. Therefore, rather than studying the entire cotton crop, our study is focused on its leaves [6]. The types of crop diseases include:

- Red Spot Disease
- Crumple Leaf Disease
- White Spot Disease

(a) Usual Leaf (b) Red Advertisement (c) White Spot (d) Leaf Crumple.

Fig. 1 Cotton Leaves (a) Usual and (b)(c)(d) Unhealthy.

Early plant disease detection is highly advised to boost a farmer's financial situation. Food quality is decreased by leaf diseases [7-9]. Successful farming depends on monitoring crops from far-off locations for disease detection. A large team of experts must perform naked-eye observation for disease detection using the current method, which is very expensive [10–11]. Therefore, an automatic, more precise, affordable disease detection method is necessary [12]. One method for automatic disease detection uses machine learning and image processing. The agronomist is helped by the computational technique for identifying and identifying plant diseases [13]. Disease diagnosis may still be performed subjectively using antiquated procedures.

Nonetheless, contemporary technology has provided reliable plant disease identification [14]. One example of an automated method that may reliably and accurately identify

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agricultural diseases while also saving time and money is Deep Learning. Due to the nature of the disease is an important topic in computer vision. The busy background, unusual perspective, and minute symptoms in the leaf image all add to the difficulty [15]. The visual signs help doctors determine what's wrong.

As a result, accurate disease diagnosis is crucial. Alternatively, farmers can seek the assistance of agricultural technical experts who will make wise recommendations regarding improving crop productivity and identifying diseases. The chief objective of this education is to suggest and create a generalized model for precisely classifying leaf disease. This study aims to develop a Deep Learning model that can make generalizations. Bacterial disfigurement, target spot, and verticillium wilt are a few of the diseases we concentrate on. The standard grey wolf optimization (GWO) algorithm's convergence rate changes, creating a better GWO algorithm for choosing the crucial features. The break of the document is organized as shadows: The relevant works for diagnosing cotton leaf disease are presented in Section 2. Section 3 mentions a brief explanation of the projected perfect. Section 4 provides the experimental analysis of the suggested model using various techniques. Section 5 presents the conclusion to the paper.

2. Related Works

Cotton plant disease is identified and predicted using deep learning by Rai and Pahuja [16] using photos of leaves and plants composed in an unrestrained setting. This research creates a model based on Deep Convolution Neural Networks to solve the disease detection and classification issue in cotton plants. Three experimental setups were examined to compare the influences of varying the data split ratio, the pooling layer selection, and the epoch size. We used a file including 2293 pictures of cotton plants and leaves to prepare the deployment models. The data includes combinations of plant diseases across all four leaf classes and the related categories for each. Our model accurately classified cotton plant leaf characteristics and plant illnesses at a rate of 97.98%. The proposed method outperformed the most up-to-date methods discussed in the literature above all relevant parameters. The method's goal is to reduce the amount of time needed to detect cotton leaf disease in key production locations and the amount of time needed to assess the disease's severity.

Using a transform learning approach, Naeem et al. [17] trained (CNN) to detect three distinct forms of cotton leaf disease. Diseases (viral leaf curl, fungal wilt, bacterial blight) that affect cotton. The primary aim of this investigation was to mature a unified scheme for the detection, identification, and diagnosis of cotton leaf illness. The Adam and RMSProp optimizers were also tested to see if optimizing with larger weight parameters would improve their efficiency when applied to datasets including healthy and allergic cotton leaves. The Inception- extractor outperformed the other DL meta-architectures in terms of accuracy. The proposed technique was found to be novel since it discriminated unhealthy. If cotton leaf disease could be correctly detected using the DL method, it would be easier to prevent the detrimental effects of issues with dietary control. The model has been taught to recognize and classify the four categories in cotton leaf photos. Curl virus on cotton leaves, bacterial blight, fusarium wilt, and a clean bill of health. CNN had an overall precision of 98%.

Zhou et al. [18] examined the spectral index's capacity to approximation ANC across a range of VZAs, and they utilized the Relief-F procedure to optimize the band for ANC that is robust to VZA. Using the formula (R530 R704)/(R1412 + R704), the viewpoint insensitive nitrogen index (AINI) was determined for a selection of VZAs. The results show that the chosen ANC has a stronger link with the spectral index than with off-nadir observations and that the strongest correlations among the PRI, AINI, and ANC occur at VZA = 20° and 50°) model, which was created by combining the ANC estimate model of the ideal indices AINI techniques. This research shows that the AINI index may be used to predict cotton ANC over a range of VZAs. It is also demonstrated that the backscattered direction is more useful for estimating ANC in cotton. In addition to improving the efficacy of ground-based and cable sensors, the findings lend credence to using multi-angle explanations for crop nutrient assessment.

For precise and time-saving dynamic surveillance of cotton verticillium wilt, an intelligent vision-based system was proposed by Huang et al. [19]. A 3-coordinate motion platform with a range of 6,100 mm, 950 mm 500 mm was originally built to accomplish precise motion and automatic imaging. The VarifocalNet (VFNet) model has the highest mean average precision (mAP) of the six deep learning models used to build verticillium wilt recognition (0.932). Using flexible maximal suppression optimization, the mAP of the VFNet perfect was boosted by 1.8%. The superior to VFNet in all cases, with a more pronounced effect on the ill leaf case than the fine leaf case. Regression testing presented that the VFNet-Improved-based system measurement was highly congruent with human measurements. The findings of the dynamic observations demonstrated that the VFNet-Improved-based user software accurately probed cotton verticillium wilt and measured the occurrence rate of dissimilar resilient cultivars. This study successfully established a novel intelligent method for real-time monitoring of cotton verticillium wilt on the seedbed, providing a practical and valuable resource for studies of cotton breeding and disease confrontation.

Amin et al. [20] state that this strategy has two primary phases: feature extraction and categorization. As a first stage in the projected procedure, data increase normalizes the raw data. The likelihood of the lesion region is calculated using an anomaly map score, which is generated by sending the features of 16 models through 11 fully convolutional layers, where the bulk of the features are frozen and initialized at random. The suggested model is trained using the optimal ones that yield the best classification results. The effectiveness of the projected model is evaluated using two openly Disease datasets from Kaggle. The proposed method's 99.99% accuracy is competitive with existing approaches.

Zhang et al. [21] and [22] developed a real-time detection model built on improved YOLOX. The enhanced YOLOX's discovery speed, accuracy, and capacity to extract visual features, thereby solving the problem of sample imbalance. A total of 5760 manually labeled photos of cotton diseases and pests were utilized to refine and evaluate the model. These images included damage, cotton spider mite damage, verticillium wilt, and five varieties of red leaf blight. Cotton disease and pest detection have an F1-score of 0.90, precision of 94.04%, mean Average Precision (mAP) of 94.60%, and FPS of 74.21. Five standard object detection techniques were also used to compare the results. This includes (Faster R-CNN,). The detection speed of the enhanced model met the requirements of real-time applications, and its mAP was higher than that of the other five algorithms by percentages ranging from 11.50% to 21.17%. A cotton diseases and pest detection app was created and deployed on smartphones using the enhanced model for real-time monitoring of cotton diseases and pests in the field. The updated model provides useful technical aid and theoretical support for managing cotton illnesses and pests by pinpointing affected patches of cotton leaves in the arena.

3. Proposed System

3.1. Dataset

Our dataset includes 2384 pictures of cotton leaves divided into seven categories. (Leaf curl). The photos were taken in Matiari, a city in Sindh Province, Pakistan [23], [24], [25]. The images were taken in the morning, noon, and evening. With a mobile camera, 3120X4160 pixels were used to create a dataset after adding contextual noise. We used a vivo V21 smartphone to take pictures of the leaves. The images were 3120 x 4160 at their original size. The field had many leaves and some weeds making noise in the background. The Leaf was manually removed from the image by cropping it. The images were flipped horizontally and vertically and rotated at a 30° angle. The next step after gathering the images was to eliminate any extraneous noise. This process was completed manually to complete the dataset.

Image pre-processing methods, such as rescaling, image enhancement, and contrast enhancement, were used to create a final dataset. A team of agriculture experts annotated the dataset, labeling each image with the disease it depicts. The dataset was then split into training and test sets for the model. For the test set, we only used 20% of the data. Health, Leafspot, Nutrient Deficiency, Powdery Mildew, Target Spot, Verticillium Wilt, and Leaf Curl are among the various disease classes. A total of 2385 datasets and 475 for testing. Seven disease classes were included in the dataset. Table 1 presents the total training and testing images used in this research work.

Table 1. Entire Training and Test Leaf Images.

Disease Class	Test	Training
Powdery mildew	46	182
Target spot	57	225
healthy	50	204
leaf curl	84	334
leafspot	116	479
Nutrient Deficiency	64	257
Veticillium Wilt	58	229

3.2. Image Pre-processing

Researchers who focus on profound learning typically spend time pre-processing data before moving on to model development. Data pre-processing includes tasks including an external search, handling missing values, and removing irrelevant or noisy information. In deep learning, the phrase for processing images before they are used represents the most primitive level of abstraction. If information content is measured in terms of entropy, these processes have the opposite effect and reduce the amount of information contained. These processes have the opposite effect and reduce the information in the image. In contrast, pre-processing aims to modify image data to either reduce background noise or improve certain features that will be used in subsequent processing steps.

3.3. Feature Selection using Improved Grey Wolf Optimization Algorithm

This research aids the IGWO algorithm in selecting optimal features for leaf classification.

3.3.1. Improved Grey Wolf Optimization

Group B's IGWO, who identifies the optimal solution, rises to the top of the social leadership ladder as a result of GWO's group hunting behaviour [26], [27], [28] to the advantage of the rest of the group and the prey's location, as shown in equation. (1). Then, we utilize the IGWO to determine which traits are most helpful in spotting cotton infections.

$$M_r^{k(t)} = \left(\left(W_\beta \times M_\beta^k(t)\right)\right) + \left(W_\gamma \times M_\beta^k(t)\right) + \left(W_\delta \times M_\delta^k(t)\right) + \mu(t) \tag{1}$$

The solution to each d-dimensional issue can be expressed as k = 1,2..d, and the location of the prey can be computed for the kth element at the t repetition using the notation F M r(k(t)). Equations (2) and (3) demonstrate that the strict social leadership of a pack and its relative weights can be characterized by the disparity and equity criteria offered therein. as $W = (W_\beta, W_\gamma, W_\delta)$, where each their aggregate equals 1.

$$1 \geq W_\beta > W_\gamma > W_\delta \geq 0 \tag{2}$$

$$W_\beta + W_\gamma + W_\delta = 1 \tag{3}$$

The mean and standard deviation of a Gaussian delivery are denoted as (t) and (t), and the stochastic error can be computed as (t) X(0,(t)). We define the attribute of dynamic deviation as provided by equation to update the position of the kth wolf in the population (4). (5). In the end, we take a look at the tth and jth solutions in dimension k. as $M_r^{k(t)}$.

$$\sigma(t) > \sigma(t+1) \tag{4}$$

$$M_r^k(t+1) = M_r^k(t) - R \times \left|M_r^k(t) - M_{j(t)}^k\right| \tag{5}$$

The new local optimal is traveled for |R| > 1, and the prey search and assault are implied for |R| > 0 and |R| 1, correspondingly, while employing the random (R) in the intermission [2, 2]. When the restrictions are estimated with random steps, the corresponding equation shows how a new position can be derived using GWO beyond the restriction. (6).

$$M_r^k(t+1) = \begin{cases} M_r^k(t) + v \times \left(U^k - M_j^k(t)\right), & if\ M_j^k(t+1) > U^k \\ M_r^k(t) + v \times \left(L^k - M_j^k(t)\right), & if M_j^k(t+1) > L^k \end{cases} \tag{6}$$

V is a real number between zero and one, and Uk and Lk are upper and lower bounds on the restrictions. The prey-finding process heavily influences the wolf's seemingly random actions.

Since the GWO converges slowly, with a smaller stage, we integrated Equations (7) and (8) to update the convergence rates at those stages.

$$h = 0.9 \times \left(2 - t \times \frac{2}{Max\_iter}\right) \tag{7}$$

$$h = 1.2 \times \left(2 - t \times \frac{2}{Max\_iter}\right) \tag{8}$$

Max iter is the maximum sum of iterations, t represents the iteration index, and h represents the convergence rate. Similar to how we employ the sine-cosine functions in equation (9) to reduce the local optimal fall, the enhanced GWO method is then applied to select the most informative characteristics for cotton leaves disease diagnosis [29].

$$M_j^k(t+1) = \sin(t)\, M_1 + \sin(t)\cos(t)\, M_2 + \cos(t) M_3 \tag{9}$$

3.4. Classification using a Bi-attention mechanism

Given the preceding, an attention mechanism that focuses on only one dimension of the input matrix may misjudge its components' relative importance. To properly evaluate the significance of each element in the matrix, we suggest a bi-attention device made up of two (SA) that work in tandem to get a new weighted input with unpredictable relevance.

The core idea of BA is to generate a new weighted input matrix by combining attention matrices along all dimensions of the input matrix. In this research, we employed a cotton leaf prediction input matrix with two dimensions, time and feature, and its original form may be represented as Eq (10).

$$X_{org} = \begin{bmatrix} x_{t-T}^1 & x_{t-T}^2 & \cdots & x_{t-T}^F \\ x_{t-T+1}^1 & x_{t-T+1}^2 & \cdots & x_{t-T+1}^F \\ \vdots & \vdots & \ddots & \vdots \\ x_{t-T}^1 & x_{t-1}^2 & \cdots & x_{t-1}^F \end{bmatrix}_{(T\times F)} \tag{10}$$

where $x_w = [x_w^1, x_w^2, \dots, x_w^F]$, $(w = t-T, t-T+1, \dots, t-1)$ is the feature vector at period w in the matrix, $x^k = [x_{t-T}^k, x_{t-T+1}^k, \dots, x_{t-1}^k], (k = 1,2,..,F)$ is the time course of length T consistent with the k-th feature in the study, the sum of topographies is 4 (i.e., F=4), which are selected by IGWO, respectively. Temporarily, T is set to be 6.

The (TA)) is applied to the two input matrices. X_{org} to produce the feature attention matrix $X_{\text{feature\_att\_matrix}}$ and the time attention matrix, respectively. Among them, FA and TA are done simultaneously. X_{org} is used as input to introduce the FA operation mechanism:

$$\begin{cases} U_{(T\times F)} = X_{org}W_f + b_f \\ A_{(T\times F)} = \frac{\exp(U_{ij})}{\sum_{j=1}^{F}\exp(U_{ij})}, i \in [t-T, t-1] \\ a\frac{\sum_{q=1}^{T} A_{qr}}{T} = [a_1, a_2, \dots, a_F], r \in [1, F] \end{cases} \tag{11}$$

Where W f is the weight network, bf is a bias vector, and U is the unnormalized feature probability weight matrix computed by applying the neural network operation on the input matrix X org. U is normalized by the softmax activation function so that the probability weights in each row equals 1 before being stored in the network. The matrix A represents the standardized feature probability weights. The focus vector for a feature of length F is denoted by an (i.e., the output of FA). Shortened form of "attention to features matrix."$X_{\text{feature\_att\_matrix}}$ is then created by multiplying each row in the matrix X_{org} by a dot.

$$X_{\text{feature\_att\_matrix}} = X_{org} \odot a$$

$$X_{org} = \begin{bmatrix} a_1 x_{t-T}^1 & a_2 x_{t-T}^2 & \cdots & a_F x_{t-T}^F \\ a_1 x_{t-T+1}^1 & a_2 x_{t-T+1}^2 & \cdots & a_F x_{t-T+1}^F \\ \vdots & \vdots & \ddots & \vdots \\ a_1 x_{t-T}^1 & a_2 x_{t-1}^2 & \cdots & a_F x_{t-1}^F \end{bmatrix}_{(T\times F)} \tag{12}$$

Similarly, the process mechanism of TA is presented with the move of X_{org} as input:

$$\begin{cases} \vartheta_{(F\times T)} = (x_{org})^T W_t + \perp_t \\ \beta_{(F\times T)} = \frac{\exp(V_{ij})}{\sum_{j=t-T}^{T}\exp(\vartheta_{ij})}, i \in [1, F] \\ \beta = \frac{\sum_{m=1}^{F}\beta_{mn}}{F} = [\beta_{t-T}, \beta_{t-T+1}, \dots., \beta_{t-1}], n \in [t-T, t-1] \end{cases} \tag{13}$$

Where W t is the weight medium of the neural system, b t is the bias vector, and V is the unnormalized time probability weight matrix derived from the neural network operation with the transpose of the input matrix X org. V is normalized so that each row's total probability weight equals 1 using the softmax activation function. The time probability weight matrix, B, has been normalized. Time focus vector b is of length T. Something which results from TA. Each column of X org is then dot multiplied by the move of b to produce the time attention matrix X. The final attention output matrix can be obtained by fusing the feature care matrix (X (feature att matrix)) with the time attention matrix. What happens during fusion is as follows:

$$X_{\text{feature\_att\_matrix}} = \begin{bmatrix} \beta_{t-T}x_{t-T}^1 & \beta_{t-T}x_{t-T}^2 & \cdots & \beta_{t-T}x_{t-T}^F \\ \beta_{t-T+1}x_{t-T+1}^1 & \beta_{t-T+1}x_{t-T+1}^2 & \cdots & \beta_{t-T+1}x_{t-T+1}^F \\ \vdots & \vdots & \ddots & \vdots \\ \beta_{t-1}x_{t-1}^1 & \beta_{t-1}x_{t-1}^2 & \cdots & \beta_{t-1}x_{t-1}^F \end{bmatrix}_{(T\times F)} \tag{14}$$

$$\begin{cases} X_{att\_out} = \mu.X_{feature\_att\_matrix} + \lambda.X_{time\_att\_matrix} \\ \mu + \lambda = 1 \end{cases} \tag{15}$$

Matrix fusion factor coefficients m and l sum to 1 such that the attention output matrix Xatt out has a TxF output shape. Then, we scale Xatt out to TFC to retrieve the RGRU model's input X. C equals one in this investigation. Due to its nature as a neural network-based dynamic evaluation process, the proposed BA requires training alongside the prediction model.

4. Results and Discussion

4.1. Performance Matrix

The performance of each model was assessed using several criteria, including accuracy. The equation is used to compute the model's accuracy. (16).

$$Accuracy = \frac{TP+TN}{(TP+FN)+(FP+TN)} \tag{16}$$

$$Sensitivity = \frac{(TP)}{(TP+FN)} \tag{17}$$

$$Specificity = \frac{(TN)}{(TN+FP)} \tag{18}$$

$$Precision = \frac{(TP)}{(TP+FP)} \tag{19}$$

$$F1Score = \frac{(2*TP)}{(2*TP+FN+FP)} \tag{20}$$

The number of properly identified images of healthy leaves (TP) equals the sum of correctly identified images of unhealthy leaves. (TN). False Positives (FP) and False Negatives (FN) describe the incorrectly labeled healthy and unhealthy leaf images. The percentage of accurate predictions among all predictions is used to calculate the confidence interval for classification accuracy. We also use the f1 score, precision, and recall as additional parameters to evaluate the presentation of the model. The proposed model achieved 93.85%, 94.08% of precision, 93.85% of sensitivity, F1-score, and specificity for healthy leaves. For leaf curl and verticillium wilt, the proposed model scored between 97% and 98% on all metrics, including accuracy, precision, F1 score, specificity, and sensitivity. Additionally, the projected model's accuracy, precision, f1-score, sensitivity, and specificity ranged from 95% to 96%. The graphical analysis of the suggested model for various diseases is presented in Figures 2 and 3.

Table 2: Analysis of Proposed Model for various diseases on cotton crops

Various Cotton Diseases	Accuracy	Specificity	Sensitivity	Precision	F1-score
healthy	93.85	93.91	93.85	94.08	93.84
leaf curl	97.96	97.93	97.96	98	97.96
verticillium wilt	97.07	97.36	97.07	97.34	97.14
powdery mildew	96.84	97.42	96.48	97.14	96.96
Nutrient deficiency	95.72	95.92	95.73	95.92	95.73
leafspot	96.47	96.51	96.47	96.62	96.47
target spot	95.07	95.1	95.07	95.27	95.07

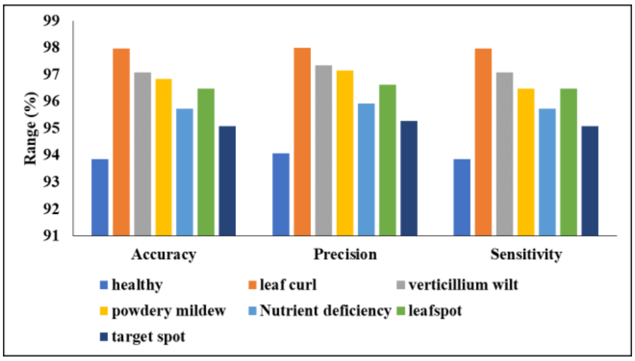

Figure 2: Analysis of Proposed Model

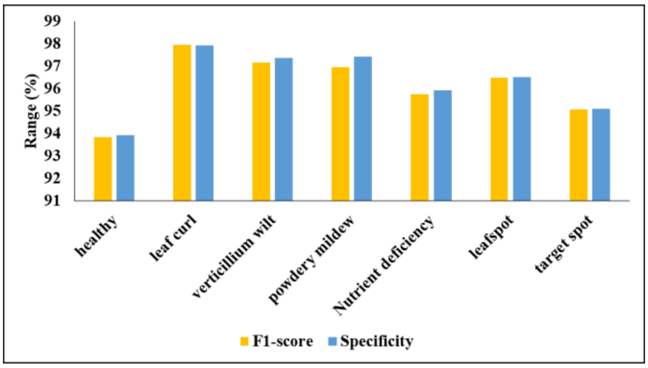

Figure 3: Performance analysis of the proposed model

Table 3: Analysis of Various Models

Model	Accuracy
AE	90.37
DBN	92.42
RNN	94.19
CNN	95.02
LSTM	96.55
Bi-attention	**97.45**

The generic models currently in use are considered because the research uses its own dataset for diagnosis. The outcomes are therefore averaged in Table 3. When the models were tested for accuracy, the AE model scored 90.37%, the DBN model scored 92.42%, the RNN model scored 94.19%, the CNN model scored 95.02%, the LSTM model scored 96.55%, and the proposed model scored 97.45%. The comparative analysis of various models is shown in Figure 4.

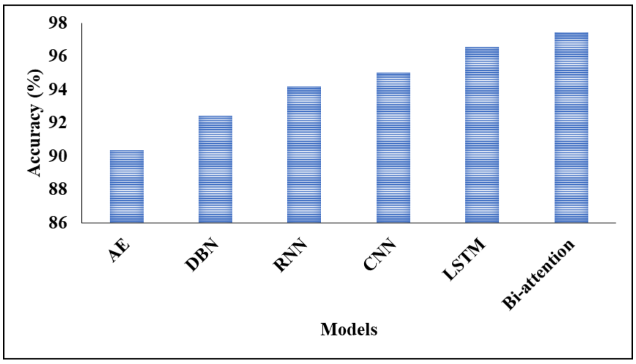

Figure 4: Validation Analysis of the proposed model with existing techniques

5. Conclusion

Across the world, plant diseases are a major problem for farmers. Accurate diagnosis of leaf diseases is crucial for preventing further crop loss. This study proposes a new approach to boost the effectiveness of Deep Learning models. For the cotton harvest, we relied on our own in-house data set. The detection of leaf diseases is a difficult task. A Bi-attention mechanism based on Deep Learning is used in the suggested model. Because the IGWO model prioritizes the most critical details, the method can detect diseases in various crops. It is best to take a broad approach to arrive at a correct diagnosis. Future improvements to the model may include making it more compact and capable of effectively handling low-resolution images. The suggested perfect will deliver a method for detecting illnesses in all major crops using a broad-based approach.

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