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Optimal Trained Deep LSTM Model for Detecting Plant Leave Diseases

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***Abstract*— Automated plant leaf disease detection has the advantage of removing a lot of monitoring work from increased crop farms and spotting disease symptoms when they first appear on plant leaves, which is when they are most treatable. The proposed plant leaf disease detection has 3 steps: preprocessing, feature extraction and detection. In preprocessing phase, histogram equalization will takes place. A technique for adjusting contrast in image processing is called histogram equalization. In feature extraction, 3 features were extracted like statistical features, LGP and color features. In detection phase, we use an optimized LSTM to identify plant leaf diseases and classify them. SI-BMO algorithm is proposed to optimize the weight in the LSTM classifier. Finally, the model's performance was evaluated and the result was analyzed successfully.**

***Keywords*—**plant leave disease detection system; feature extraction; Preprocessing; LSTM; SI-BMO

NOMENCLATURE

Abbreviation	Description
SVM	support vector machine
DL	deep learning
SI-BMO	Self Improved Blue Monkey Optimization
BM	blue monkey
ML	machine learning
OMNCNN	optimal mobile network-based convolutional neural network
BF	bilateral filtering
DCNN	deep convolutional neural networks
2D AADF	2D Adaptive Anisotropic Diffusion Filter
LGP	Local Gradient Pattern
AMA	Adaptive Mean Adjustment
ILSM	Intelligent Leaf Scanning Mechanism
LSTM	Long term short memory

I. INTRODUCTION

The benefit of automatic plant disease detection [9] [10] is that it eliminates a significant amount of monitoring work in large crop farms and identifies disease symptoms at an extremely early stage, when they first emerge on plant leaves. As a result, one of the key components of a plants pathologist's education is diagnosis. Illness control procedures can be a sunk cost and can result in additional plant losses if the disease and its cause are not correctly identified.

Therefore, accurate illness diagnosis is essential. Pathogenic fungi, on the other hand, are the culprits behind plant ailments like aphid, leaf blight, rust, wilt, blight, coiled, scab, gout, blight, cooling, root rot, mildew, and overgrowth. Major contributors to yield, commercial crop, and crop quality losses include systemic foliar infections. A plant disease symptom [12] [13] is a disease's outward manifestation in the plant. [8] A noticeable alteration in the plant's color, shape, or functionality as a result of the disease is one of the symptoms. Reduced economic and aesthetically detrimental effects of plant diseases are the main objective of plant protection [14]. This has historically been referred regarded as plant disease control [15], however modern social and environmental principles view "control" as being excessively rigid and uncompromising.

The farmland mass is used for more than just growing food in the modern world. The Indian economy is heavily reliant on agricultural output. [6] As a result, it is crucial to identify plant diseases in the sector of agriculture. Automatic plant disease diagnosis from raw photos is now achievable because to developments in artificial intelligence research [7]. Today, picture segmentation is most frequently performed using soft computing, which has the capacity to deal with uncertainty. To identify the Semi-automatic leaf disease, SVM [11] classifier were developed. This research work's main contribution is:

- New plant leave disease detection is introduced which has 3 stages: Preprocessing, feature extraction and Detection.
- Optimized LSTM classifier is used to detect the plant leave disease.
- Optimal training of LSTM classifier is done by a new SI-BMO algorithm.

This report is categorized as follows:

Section I gives a description of the Introduction. The subject of the literature review is discussed in Section II. Architectural description of suggested plant leave disease detection is discussed in Section III. Section IV discusses preprocessing, feature extraction, and detection. Section V: Optimized LSTM classifier. In Section VI, SI-BMO algorithm is studied. The conclusion is the topic of Section VII.

I. LITERATURE REVIEW

A. Literature Review

In 2021, R. Sujatha et al. [1] established approaches for identifying plant diseases, including DL and (ML). In terms of detecting citrus plant diseases, the effectiveness of ML (SVM, Random Forest, Stochastic Gradient Descent, and VGG-16) and DL (Inception-v3, VGG-16, and VGG-19) was compared.

In 2021, S. Ashwinkumar et al. [2] suggested a convolutional neural network based on an ideal mobile network for detecting and categorizing plant leaf diseases. The suggested OMNCNN system uses preprocessing, segmentation, feature extraction, and classification as its primary operational steps. Preprocessing based on BF was included.

In 2021, M. Yogeshwari and G. Thailambal [3] developed a new method using DCNN for the identification of plant leaf diseases. The plant leaf images in the suggested scheme are first preprocessed utilizing filtering and enhancement methods. The 2D AADF is used in this work's image filtering to remove noise. AMA approach was used to enhance these denoised photos.

In 2020, Navneet Kaur and V. Devendran [4] suggested the optimization-oriented segmentation and law mask framework as a solution to the classification of leaf disease with various sample classes and sizes. In the end, the leaves were classified mostly in learnt metric space using the SVM as a classifier.

In 2021, U. Maheswaran et al. [5] unveiled a novel, portable smart device called SmartBox, which utilizes an ILSM to function. This ILSM technique was related to the SmartBox, which is built with a variety of intelligent parts like a camera and WiFi.

Table 1 depicts the features and challenges of conventional approaches.

TABLE I. FEATURES AND CHALLENGES OF CONVENTIONAL METHODS

Author [citation]	**Methods**	**Features**	**Challenges**
R. Sujatha *et al.* [1]	SVM	Performs similarly effectively when there has been a discernible margin of class separation	Plant diseases that harm the leaf can significantly reduce crop production and market value.
S. Ashwinkumar *et al.* [2]	OMNCNN method	Automated prevention and detection methods are useful for easing the burdensome work of keeping track on large agricultural farms.	A large amount of trained data is needed.
M. Yogeshwari and G. Thailambal [3]	DCNN	Identify plant leaf ailments	Lack of appropriate detection could seriously harm the amount and quality of the agricultural harvest.
Navneet Kaur and V. Devendran [4]	law mask framework	Classify the issue of leaf disease using various sample sizes and types.	Need to spend a bit more time
U. Maheswaran *et al.* [5]	ILSM	Sort the leaf photos into regions that are affected and those that are not.	Maintaining an agricultural field is difficult.

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II. PROPOSED PLANT LEAVE DISEASE DETECTION: ARCHITECTURAL DESCRIPTION

Automated plant leaf disease detection has the advantage of removing a lot of monitoring work from increased crop farms and spotting disease symptoms when they first appear on plant leaves, which is when they are most treatable. The proposed plant leaf disease detection has 3 steps: preprocessing, feature extraction and detection. Fig. 1 depicts the suggested plant leave disease detection architecture.

- Preprocessing: In this phase, histogram equalization will takes place. A technique for adjusting contrast in image processing is called histogram equalization.
- Feature extraction: In this phase, 3 features were extracted like statistical features, LGP and color features.
- Detection: In this phase, we use an optimized LSTM to identify plant leaf diseases and classify them.

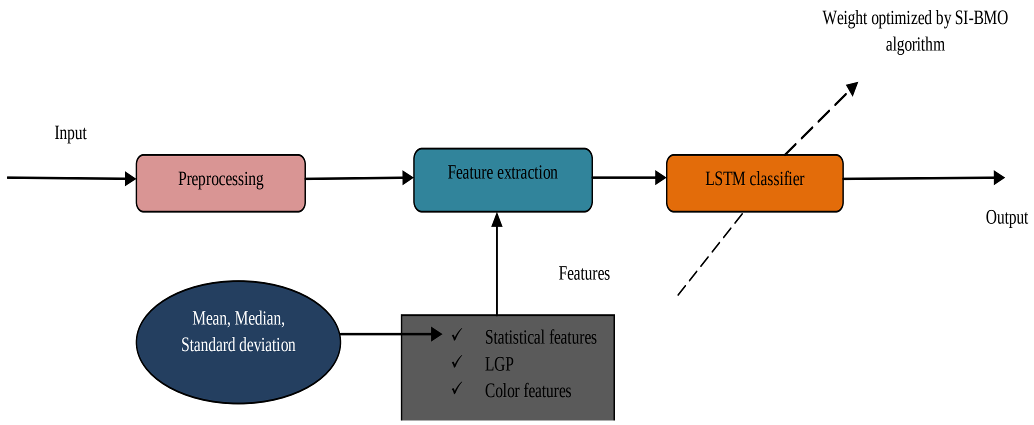

Fig. 1. Proposed plat leave disease detection system

III. DESCRIPTION ON PREPROCESSING AND FEATURE EXTRACTION

A. Preprocessing

Histogram equalization [16] will happen during this phase for image enhancement. When the image's useable data is considered to be adequate values, this strategy typically raises the overall contrast of numerous images. The intensities on the histogram can be more evenly spread by making this adjustment. This makes it possible for regions with less local contrast to acquire more contrast. This is accomplished by histogram equalization by evenly distributing the most prevalent intensity values.

The technique works well in images where the foreground and background are both dark and both bright. When applied to photos with poor color depth, histogram equalization can also have undesired effects (such a visible image gradient). The preprocessed image is depicted as P .

B. Feature extraction

From the preprocessed image P , 3 features like statistical features, LGP and color features were extracted.

- ❖ Statistical features: Mean $(Mean)$, Median (Mid) , Standard deviation (STD) were the statistical features extracted here.
- ❖ LGP [17]: LGP is widely utilized in numerous applications for image classification. In order to generate the fluctuation of local intensity for a given pixel A_b , LGP first determines the gradient values, e_i , of adjacent pixel A_i as $e_i = |A_i - A_b|$. Later, the threshold is determined using the average of the gradient values for N neighboring pixels, or e_{am} , which is computed using AM as $e_{am} = \frac{1}{N}\sum_{i=0}^{N-1} e_i$. The LGP then compares each surrounding pixel's gradient value to the threshold, e_{am} , and sets a binary value of "1" if the gradient value is greater than or equal to e_{am} and a binary number of "0" otherwise. Finally, the center pixel was given the binary number sequence in any direction that was encoded

- as the equal decimal value. The concluding equations of LGP are Equations 1 and 2.

$$LGP_{N,r}(x_b, y_b) = \sum_{i=0}^{N-1} c(e_i - e_{am}).2^i \quad (1)$$

$$c(b) = \begin{cases} 1, if b \succ 0 \\ 0, otherwise \end{cases} \quad (2)$$

Where,
r = radius
x_b, y_b =coordinate of centre pixel
b = threshold difference
e_{am} =threshold

- Color features [18]: The LDF filters and arranges images from a database using global criteria. After that, they look for regional traits in both the target image and all other images. They must also evaluate the image's color distribution data. They use a histogram that contains site color occurrence of picture colors and local color occurrence within particular regions for each bin block to generate an area-wise directional statistical histogram. Color feature is depicted as $ColorF$.

  The final feature set $Final - F$ is depicted as $Final - F = \{Mean, Mid, STD, LGP, ColorF\}$.

IV. OPTIMIZED LSTM CLASSIFIER

To find the plant leaf disease, the chosen feature set $Final - F$ will be put to the test. In this study, we identify and categorize plant leaf diseases using an optimized LSTM [19]. Furthermore, a recently introduced SI-BMO algorithm performs the training by tuning the optimal weights, which improves the results of the designed LSTM classifier.

The test pattern must be acquired and retained by the

W_1	W_2	……..	W_N

Fig. 2. Solution encoding

particular gated units in order for LSTM to sustain relatively long series data dependence and achieve high precision forecasting. The forget gate, input gate, and output gate are the three gating components that make up the majority of the LSTM neural network. The specialized gate units learn and retain the sequence analysis in order to preserve lengthy period series information reliance and make significant predictions. The forget gate regulates how efficiently a cell can retain knowledge from the past. The neuron's output is represented by the output gate. Consider that the input data $(r^1, r^2, ..., r^t)$ is the time t . The processing method for each

LSTM is as follows in eq. (3), eq. 94), eq. (5), eq. (6), and eq. (7):

$$g_t = p(l_l \times [u_{t-1}, h_t] + w_l) \quad (3)$$

$$d_t = p(l_m \times [u_{t-1}, h_t] + w_m) \quad (4)$$

$$q_t = p(l_n \times [s_t, u_{t-1}, h_t] + w_n) \quad (5)$$

$$s_t = d_t \times s_{t-1} + g_t \times \tan u(l_b \times [u_{t-1}, h_t]) \quad (6)$$

$$u_t = q_t \times \tan u(s_t) \quad (7)$$

Where,
h_t = input LSTM
u_{t-1} = hidden layer output
g_t, d_t, q_t = input gate input
l_l, l_d, l_q = weight matrix
w_l, w_d, w_q = offset vector
l_b = the cell unit's weight in relation to the input
u_t = hidden layer output
J = sigmoid function

The SI-BMO (Self Improved Blue Monkey Optimization) algorithm, which is thoroughly described in section VI, is used to optimize the weight W in the LSTM classifier.

A. *Objective function and solution encoding*

In this proposed work, weight is optimized by defining the objective function $Obj - F$ given by eq. (8).

$$Obj - F = \min(error) \quad (8)$$

Solution encoding of proposed SI-BMO algorithm is depicted in fig. 2.

V. SELF IMPROVED BLUE MONKEY OPTIMIZATION (SI-BMO) ALGORITHM

A novel metaheuristic program optimization called BM is based on how blue monkey swarms function in nature. The number of men in a group is determined by the BMO algorithm [20]. The blue monkeys differ from other species of monkeys. They typically reside in social systems where women predominate, meaning that females remain in their birth groupings. The males depart from their groupings as soon as they reach the mature stage. There are typically many females and young in each blue monkey group, but still only one male. Inbreeding is made challenging by this issue. The BM algorithmic rule imitates Blue Monkey behavior. Every group of monkeys had to go across the search area in order to simulate

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these interactions. Little to no interaction exists between the ale Cercopithecus mitis and the young. Young males should

venture outside as soon as they can because of the cercopithecus mitis's territorial character in order to succeed. Typically, blue monkey groups consist of one male and a large number of females and young.

- Improved Position Update: In conventional position update, better blue monkey position in each group determines the updating position for every blue monkey in that group. The following equations 9 and 10 characterize this behavior:

$$Rating_{i+1} = (0.7 * Rating_i) + (W_{lead} - W_i) * rando * (M_{best} - M_i) \quad (9)$$

$$M_{i+1} = M_i + Rating_{i+1} * rando \quad (10)$$

Where,

W_{lead}=leader weight

W_i =monkey weight

M_{best}=leader position

M_i =position of monkey

$rando$=random number

$Rating$ = power rate of monkey

As per the SI-BMO algorithm, the improved position update is depicted in eq. (11).

$$M_{i+1} = M_i + Rating_{i+1} * rando + Levy(\chi) \quad (11)$$

$Levy(\chi)$ [21] is calculated in eq. (12)

$$Levy(\chi) = \left(2 - \frac{t}{t_{\max}}\right) * \frac{r1 * \sigma}{|r2|^{1/\chi}} \quad (12)$$

Where,

t = current iteration

$t_{\max}$ =maximum iteration

χ = constant

$r1, r2$ =random number

- **Children update:** The model equation (13) and (14) were utilized for children update of BM.

$$Rating_{i+1}^{child} = (0.7 * Rating_i^{child}) + (W_{leader}^{child} - W_i^{ch}) * rando * (M_{best}^{child} - M_i^{child}) \quad (13)$$

$$M_{i+1}^{child} = M_i^{child} + Rating_{i+1}^{child} * rando \quad (14)$$

Where,

$Rating^{child}$ = child power rate

W_{lead}^{child} =weight of leader child

W_i^{child} = child weight

X_i^{child} = child position

As per the SI-BMO algorithm, $rand$ value of children update can be calculated using logistic map function. A logistic map [22] produces chaotic patterns in (0, 1). The following equation (15) provides the formal definition of this map:

$$x_{k+1} = Qx_k(1 - x_k) \quad (15)$$

Where,

Q = adjustable parameter

The pseudo-code of proposed SI-BMO algorithm is shown below:

Algorithm 1: Self Improved Blue Monkey Optimization
Initialize the population of BM and child
Initialize the weight W and the power rate $Rating$.
Put the blue monkeys into teams (T) at random, with the entire child in one team.
Determine the fitness levels of each group's BM and youngsters.
Choose the worst and greatest fitness values for each group, and then save them in Current Best. Children choose the fittest option.
$t = 1$
while $t \le \max iterations$
Swapping the least fit members of each group for the fit members of the child's group.
Improved position update is done in eq. (11) and eq. (12)
Improved children update is done in eq. (15)
Fitness update of every BM and child.
Current best update
Current Best Equals New Best if New Best is superior to Current Best.
$t = t + 1$
end while
return optimal BM

VI. RESULTS AND DISCUSSION

A. Simulation set up

This work was done in "python". The performance of LSTM + SI-BMO for detecting plant leave disease was

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computed using data from [23]. The adopted LSTM + SI-BMO was distinguished with LSTM + SSO, LSTM + CMBO, LSTM + PRO, LSTM + BMO, and CNN, SVM, DBN and GRU.

"Dataset description: Human society needs to increase food production by an estimated 70% by 2050 to feed an expected population size that is predicted to be over 9 billion people.

Currently, infectious diseases reduce the potential yield by an average of 40% with many farmers in the developing world experiencing yield losses as high as 100%. The widespread distribution of smart phones among crop growers around the world with an expected 5 billion smart phones by 2020 offers the potential of turning the smart phone into a valuable tool for diverse communities growing food. One potential application is the development of mobile disease diagnostics through machine learning and crowd sourcing. Here we announce the release of over 50,000 expertly curated images on healthy and infected leaves of crops plants through the existing online platform Plant Village. We describe both the data and the platform. These data are the beginning of an on-going, crowd sourcing effort to enable computer vision approaches to help solve the problem of yield losses in crop plants due to infectious diseases". The sample image showing the affected and healthy leaves after HE is shown in Fig. 3.

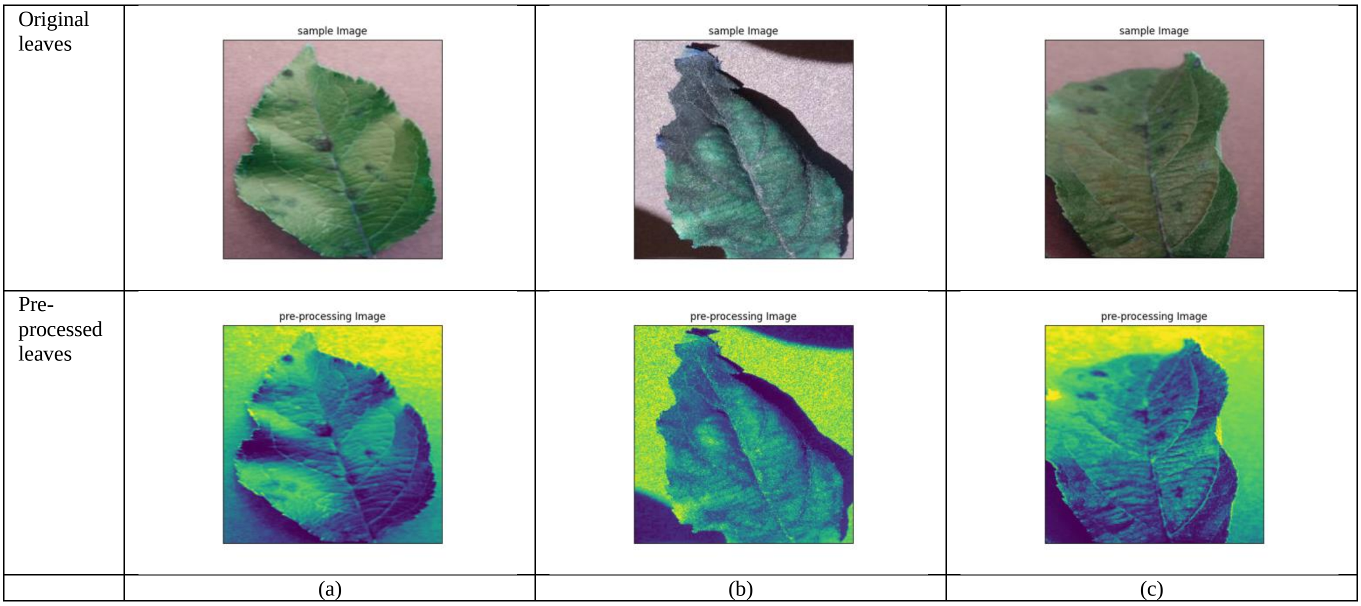

Fig. 3. Sample image revealing (a) image 1 (b) image 2 (c) image 3

B. Convergence Analysis

The cost analysis of SI-BMO scheme for diverse iterations is exposed in Fig. 4. Here, analysis was done on SI-BMO over LSTM + SSO, LSTM + CMBO, LSTM + PRO, LSTM + BMO.

On examining Fig. 4, SI-BMO has got lesser cost from iteration 17 to 25. On the other hand, a high cost of 1.061 is achieved by CMBO from iteration 0 to 8. Next to that, BMO has achieved a high cost of 1.060. Thus, when compared over others, SI-BMO has accomplished lesser cost.

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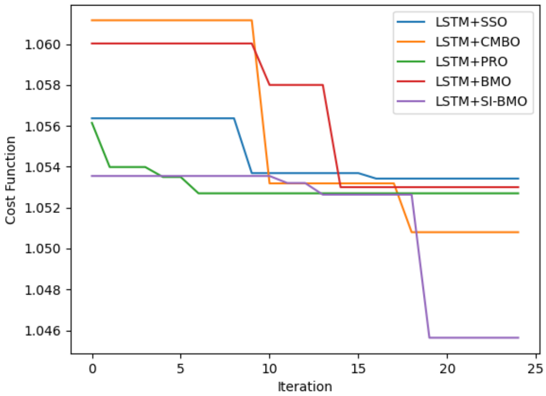
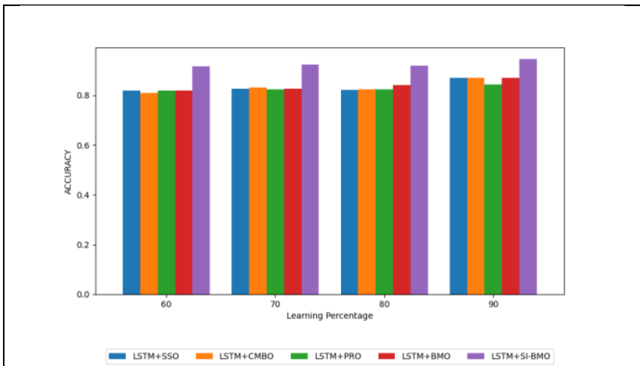


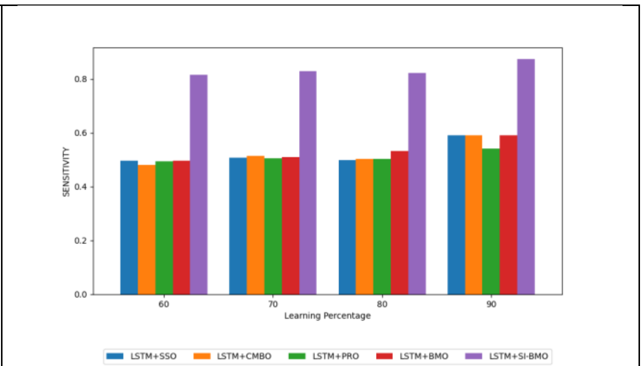
Fig. 4. Convergence analysis of SI-BMO model over others

C. Performance Analysis

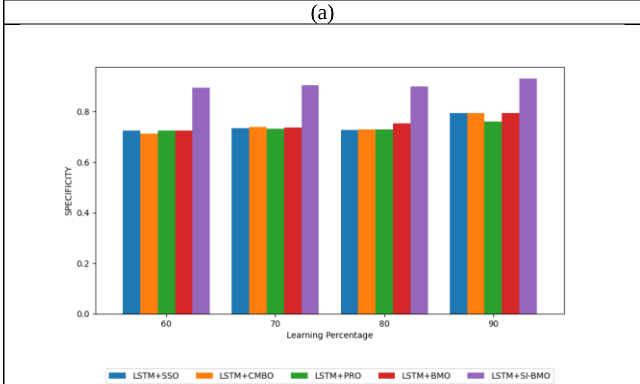
The SI-BMO is validated regarding "accuracy, sensitivity, specificity, and precision, FPR, FNR and so on". The analysis using SI-BMO for varied LPs is shown in Fig. 5 – 7. On investigating Fig. 5, a high accuracy of 0.95 is achieved by SI-BMO at 90th LP, while at 60th, 70th and 80th LPs; the accuracy achieved by SI-BMO is comparatively less, at 60th, 70th and 80th LPs, the accuracy achieved by SI-BMO is 0.9, 0.91 and 0.92 respectively. Likewise, the FNR achieved by SI-BMO at 90th LP is much less than LSTM + SSO, LSTM + CMBO, LSTM + PRO, LSTM + BMO. Table II shows the examination of SI-BMO on varied classifiers like CNN, SVM, DBN and GRU. In Table II, for every variant of LP, SI-BMO model has depicted better values over 90%.



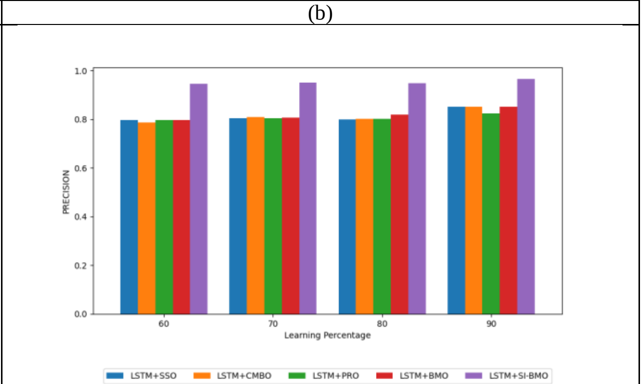
(a)



(b)



(c)



(d)

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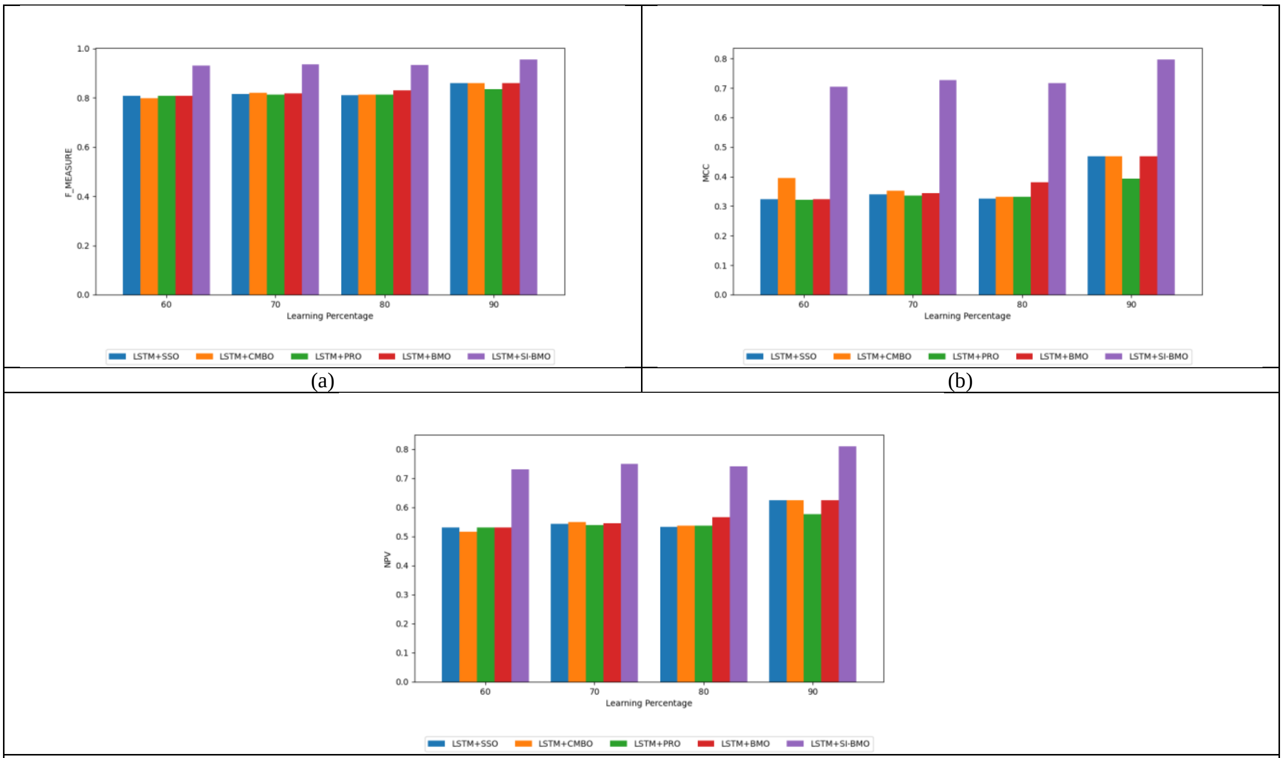
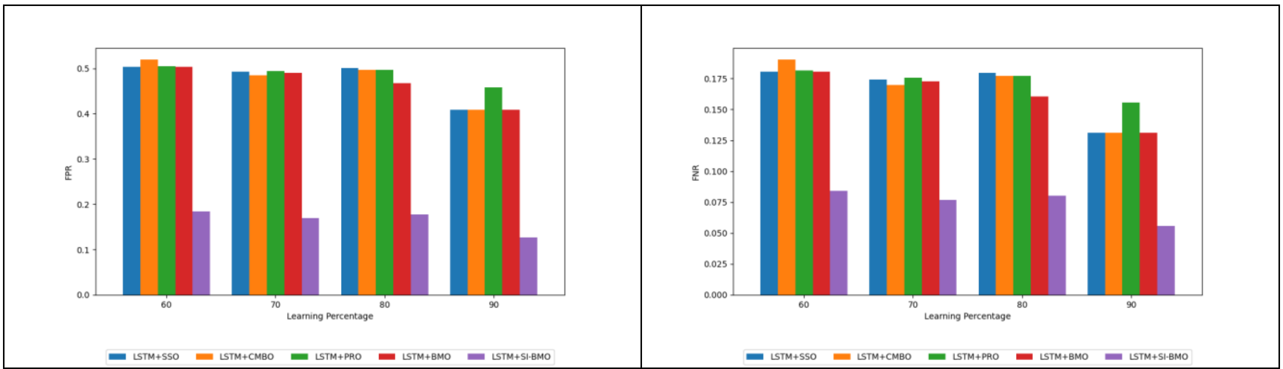
Fig. 5. Analysis on (a) accuracy (b) sensitivity (c) specificity and (d) precision



(a) (b) (c)

Fig. 6. Analysis on (a) F-measure (b) MCC and (c) NPV



(a) (b)

Fig. 7. Analysis on (a) FPR (b) FNR

TABLE II. ANALYSIS OF SI-BMO ON VARIED CLASSIFIERS

Metrics	CNN	SVM	DBN	GRU	SI-BMO
NPV	0.602566	0.536042	0.502564	0.546174	0.808989
Specificity	0.816199	0.771897	0.747419	0.779002	0.929117
F-measure	0.87662	0.8441	0.82562	0.849395	0.954488
Accuracy	0.858448	0.822111	0.801636	0.828	0.944262
MCC	0.518841	0.422443	0.371336	0.437549	0.795348

Precision	0.895579	0.867299	0.851083	0.871926	0.964938
FPR	0.318052	0.37966	0.411727	0.370098	0.126899
Sensitivity	0.681948	0.62034	0.588273	0.629902	0.873101
FNR	0.141552	0.177889	0.198364	0.172	0.055738

D. Ablation Study

Table III examines the presented LSTM + SI-BMO model over other extensive features. This section explains the impact of developed model on optimization. Since, we have deployed enhancements in conventional BMO optimization, better outcomes are achieved. In Table III, it could be noted that the

accuracy for LSTM with no optimization (0.739268) is less than LSTM with optimization (0.944262). Thus, enhancements done in conventional BMO had outcome in better outputs.

TABLE III. ANALYSIS OF PROPOSED MODEL OVER PROPOSED WITHOUT OPTIMIZATION

Metrics	Proposed with no optimization	LSTM + SI-BMO
MCC	0.322225	0.795348
Specificity	0.681059	0.929117
FNR	0.260732	0.055738
Precision	0.811235	0.964938
F-measure	0.773581	0.954488
Sensitivity	0.517932	0.873101
NPV	0.414807	0.808989
Accuracy	0.739268	0.944262
FPR	0.482068	0.126899

VII. CONCLUSION

Proposed plant leaf disease detection has 3 steps: preprocessing, feature extraction and detection. In preprocessing phase, histogram equalization will takes place. A technique for adjusting contrast in image processing is called histogram equalization. In feature extraction, 3 features were extracted like statistical features, LGP and color features. In detection phase, we use an optimized LSTM to identify plant leaf diseases and classify them. SI-BMO algorithm is proposed to optimize the weight in the LSTM classifier. Finally, SI-BMO algorithm performance was evaluated and the result was analyzed successfully.

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