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RESEARCH ARTICLE

Multiclass Paddy Disease Detection Using Filter-Based Feature Transformation Technique

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ABSTRACT Pests and diseases are the big issues in paddy production and they make the farmers to lose around 20% of rice yield world-wide. Identification of rice leaves diseases at early stage through thermal image cameras will be helpful for avoiding such losses. The objective of this work is to implement a Modified Lemurs Optimization Algorithm as a filter-based feature transformation technique for enhancing the accuracy of detecting various paddy diseases through machine learning techniques by processing the thermal images of paddy leaves. The original Lemurs Optimization is altered through the inspiration of Sine Cosine Optimization for developing the proposed Modified Lemurs Optimization Algorithm. Five paddy diseases namely rice blast, brown leaf spot, leaf folder, hispa, and bacterial leaf blight are considered in this work. A total of six hundred and thirty-six thermal images including healthy paddy and diseased paddy leaves are analysed. Seven statistical features and seven Box-Cox transformed statistical features are extracted from each thermal image and four machine learning techniques namely K-Nearest Neighbor classifier, Random Forest classifier, Linear Discriminant Analysis Classifier, and Histogram Gradient Boosting Classifier are tested. All these classifiers provide balanced accuracy less than 65% and their performance is improved by the usage of feature transform based on Modified Lemurs Optimization. Especially, the balanced accuracy of 90% is achieved by using the proposed feature transform for K-Nearest Neighbor classifier.

INDEX TERMS Paddy disease, machine learning, swarm optimization, modified lemurs optimization, thermal image processing.

I. INTRODUCTION

More than 40% of the people in World consumes Rice as their important food. According to a statistic, six hundred tons of rice was produced world-wide in the year 2000 and this production rate may increase by 1.5 times in the year 2030 [1]. The major challenges in producing the rice includes pests, rice diseases, pathogens, and climate change, etc. With the increasing population world-wide, it is very important to meet the required rice production in the upcoming years. Different kinds of pathogens including fungi, virus, and bacteria poses threat to the rice production through the diseases like blast, bakane disease, brown leaf spot, leaf folder, sheath blight, hispa, sheath rot, bacterial leaf blight etc., [2], [3]. On an average around 20% of loss happens in paddy production because of these diseases and it is also affecting the farmers heavily. In addition to reduced quantity issues, quality of the rice produced is also affected due to these diseases [4], [5].

Sometimes more than 50% of loss also can happen in a paddy field if early diagnosis and corrective measures are not taken. For example, the degree of infection and varietal susceptibility decides the loss happening due to blast infections. If the corrective measures like fungicide application is done at early stage, huge losses can be avoided [6], [7]. Hence early

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detection of these diseases becomes crucial to overcome this issue. Visual inspection of paddy crops at regular intervals is the conventional method to identify these diseases since many of these disease shows symptoms which are visible to naked eye. But this method is subjective and more susceptible to errors because of human negligence and so an automated system which can identify the paddy disease at early stage and alert the farmer is very much required.

Since there are varieties of rice diseases, image sensor will be very helpful when compared to all other sensors. Capturing the images of rice through image sensors and analysing them for identification of rice diseases is a fine approach. But instead of using regular image sensors, usage of thermal image sensors will be more appropriate since thermal cameras possess more advantages than normal cameras. The advantages include high contrast images, insensitivity to amount of surrounding light, longer viewing range, and better performance in all weather conditions. Thermal image sensors are very much suitable for this application since they employ infrared thermography sensor to identify the differences in temperature on the leaf surface and plant canopy [8]. To identify the rice leaf diseases, the thermal images should be analyzed through a computerized technique. The conventional image processing algorithms like thresholding fails to identify the rice leaf diseases properly and so there is a need for Machine Learning (ML) algorithms for enabling early diagnosis of rice leaf diseases.

Machine learning algorithms are currently employed in variety of fields including agriculture, smart cities, military, medical, etc. Machine learning algorithms are broadly categorized as supervised, unsupervised and reinforcement learning. Supervised ML algorithms are very common for variety of applications and they are based on the concept of training and testing [9]. Some of the popular supervised ML algorithms are K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Random Forest Classifier (RFC), Decision Trees (DT) [10], [11], [12]. Even though there are hundreds of ML algorithms, none of them can be stated as the best for all type of applications since these ML algorithms are data-dependent [13]. Accuracy is a very popular metric for assessing ML algorithms and it is equal to the number of correct predictions divided by the total number of predictions. The accuracy of ML algorithms can be improved in number of ways. One of the approaches is to provide the transformed data that is more suitable for classification instead of giving the direct data. Various transforms like log transformation, box-cox transformation, O'Brien transformation are popular to transform the data. But usage of Swarm Intelligence (SI) algorithms for transforming the data is less reported.

SI algorithms belongs to a category of optimization algorithms and they are used to solve the real-world optimization problems by mimicking the characteristics exhibited by a group of animals. Some of the popular SI algorithms are Particle Swarm Optimization (PSO), Ant Colony Optimization, Artificial Bee Colony, Grey Wolf Optimization [14]. Generally, SI algorithms are iterative optimization algorithms which tries to improve their solution in each iteration. For example, PSO tries to mimic the characteristics exhibited by fish school or bird flock. Considering bird flock in PSO, the position of 'n' number of birds is initialized randomly and then their position will be updated in each iteration based on the objective function. Objective functions depend on the problem which needs to be solved and play a vital role in solving the problem [15], [16].

Some of the important works related to rice plant disease detection can be stated as follows: Manoj Mukherjee et al. [17] proposed a framework to process the images of rice plant leaves through histogram technique for disease classification. Gayathri and Neelamegam [18] presented a technique to detect leaf diseases through the usage of Discrete Wavelet Transform and Grey Level Co-occurrence matrix for producing the feature set which is categorized using classifier techniques like KNN, SVM, Naive Bayes, etc. Khaing and Chit Su [19] suggested application of Principal Component Analysis (PCA) and Color-grid based moment on the statistical features extracted from images of rice plant leaves; finally they applied SVM as classifier to predict the label. Shampa Sengupta and Asit K. Das [20] PSO centered incremental classifier with reduced computational time to identify the various rice plant diseases. Maohua Xiao et al. [21] suggested PCA and Neural Network architecture for detecting the Rice Blast disease. Toran Verma and Sipi Dubey [22] implemented Radial -Basis Function Network for identifying different rice plant diseases. Many recent works propose the usage of deep learning models like Convolutional Neural Network for rice plant leaves detection and their accuracies are pretty good when compared conventional supervised classifiers like KNN, SVM, etc. [23], [24], [25], [26], [27]. But architecture of deep learning techniques is comparatively complex and it requires complicated hardware circuits to implement it for a real-time application. Hence it is a better idea to improve the accuracy of conventional supervised classifiers through some feature processing techniques. To improve the performance of supervised classifiers, Modified Lemurs Optimization Algorithm (MLOA) based transform is proposed in this research work.

The sections of remaining paper are outlined as follows: Second section represents the Lemurs Optimization algorithm and methodology used is illustrated in the third section. Proposed methodology is presented in the fourth section. Results are discussed and concluded in the fifth and sixth sections respectively.

II. RELATED WORK

Lemurs Optimization Algorithm (LOA) is proposed by Ammar Kamal Abasi et al. in the year 2022 for solving global optimization problems and it is developed based on the inspiration from social behavior of Lemurs [28]. Lemurs are coming under the category of prosimian primates and except monkeys & apes, all the primates are considered as Lemurs. Usually they live in groups which are called as troops [29].

LOA mainly uses two types of locomotive behavior exhibited by Lemurs namely leap up and dance-hup. The former is the inspiration for exploitation phase i.e., local search and the latter is the inspiration for exploration phase i.e., global search [30]. The position of lemurs is considered as candidate solutions and they will be updated in each iteration based on the objective function or fitness function. The population of Lemurs is generally defined as shown in equation (1).

$$T = \begin{bmatrix} L_1^1 & \cdots & L_1^d \\ \vdots & \ddots & \vdots \\ L_s^1 & \cdots & L_s^d \end{bmatrix} \tag{1}$$

The size of the population matrix is $s*d$ where s denotes the number of candidate solutions which is equal to number of Lemurs and d denotes the number of decision variables. Generally, the position of Lemurs is initialized randomly as shown in equation (2).

$$L_i^j = \text{rand}() \times (ub_j - lb_j) + \text{lb}) \\ \forall i \in (1, 2, \ldots, n) \wedge \forall j \in (1, 2, \ldots, d) \tag{2}$$

Here *rand* is a random number between 0 and 1; Upper and lower bound limits are denoted as ub_j and lb_j respectively. In each iteration, the global best lemur and best nearest lemur are identified based on the fitness function and the position of Lemurs are updated according to the following equation (3):

$$L_{i+1}^j = \begin{cases} L_i^j + abs\left(L_i^j - gbest^j\right) * (rand - 0.5) * 2 \\ \quad if\ rand \geq FRR \\ L_i^j + abs\left(L_i^j - nbest^j\right) * (rand - 0.5) * 2 \\ \quad if\ rand < FRR \end{cases} \tag{3}$$

Here i and j indicates the iteration number and decision variable respectively, *gbest* denotes the global best Lemur position and *nbest* represents the best nearest Lemur position; L is the position of Lemur, *rand* is a random number between 0 and 1; Free Risk Rate (FRR) indicates the risk level of all the Lemurs in the troop and this coefficient can be computed by the equation (4).

$$\text{FRR} = \text{FRR(HRR)} - \text{Crnt\_Iter} \\ \times ((\text{HRR} - \text{LRR})/\text{Max\_Iter}) \tag{4}$$

In equation 4, *HRR* stands for the High-Risk Rate and *LRR* stands for the Low-Risk Rate and they are constant predefined values. *Crnt_Iter* denotes the current iteration and *Max_Iter* denotes the maximum number of iterations.

III. METHODOLOGY

Thermal Images of totally 636 rice plant leaves are considered in this research work and it was originally contributed by Aarthy S L and Sujatha R [31].

Table 1 presents the number of thermal images considered in each class. These images are captured using high resolution thermal camera FLIR E8 and size of each image is 320∗240 pixels. Sample images of each class can be witnessed in Fig.1 and flowchart depicting the proposed methodology is shown in Fig.2.

TABLE 1. Number of thermal images considered in each class.

Class	No. of Thermal Images
Healthy	93
Bacterial leaf blight	220
Blast	67
Leaf spot	80
Leaf folder	34
Hispa	142

Seven Statistical features namely Mean, Variance, Entropy, Skewness, Kurtosis, Variation and Standard Error of Mean (SEM) are extracted from each thermal image and they are transformed individually using Box-Cox transform [32], [33]. This transform is used to convert the non-normal feature into feature that follows normal distribution. For example, variance feature before and after Box-Cox transform is shown in Fig.3. Totally fourteen statistical features are considered for analysis including seven original statistical features and seven Box-Cox transformed statistical features. Then the extracted features are passed to the Robust scaler. It is implemented for converting features to a common scale. Robust scaler is mainly preferred because of its ability to treat outliers [34]. Scaling technique will learn its coefficient from training set and it will be used to transform both training and testing sets. Then the scaled features are passed to the proposed filter-based Modified LOA transform which will convert the input data into the output data that is more suitable for classification. The output data will closely resemble the linearly separable features.

The transformed features are given as input for supervised classifiers to predict the class. Four supervised classifiers namely KNN [35], RFC [36], Linear Discriminant Analysis (LDA) Classifier [37], and Histogram Gradient Boosting Classifier (HGBC) [38] are tested. Finally, the predicted labels are used to compute the performance metrics by comparing it with original labels. Performance metrics like Balanced Accuracy Score, Matthews Correlation Coefficient (MCC), F1 score, Jaccard Score (JAC), Recall, and precision are computed [39]. 80% of the data is considered for training and remaining 20% is considered for testing. To split the data into training and testing sets, Stratified Shuffle Split is implemented which will randomly split the data while maintaining the same class ratio in both training and testing sets. Stratified shuffle split is preferred over other splitting techniques since this dataset is highly imbalanced. K-fold cross-validation is used during training to avoid overfitting problem and K value is considered as ten [40].

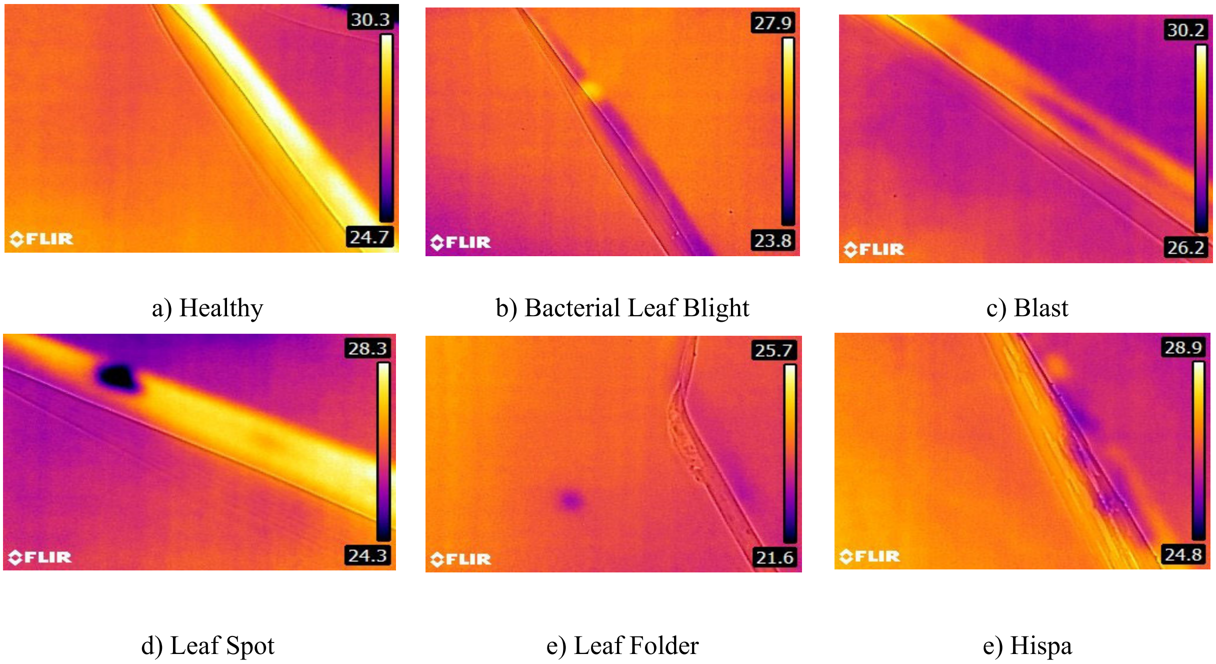


FIGURE 1. Thermal images of various classes.

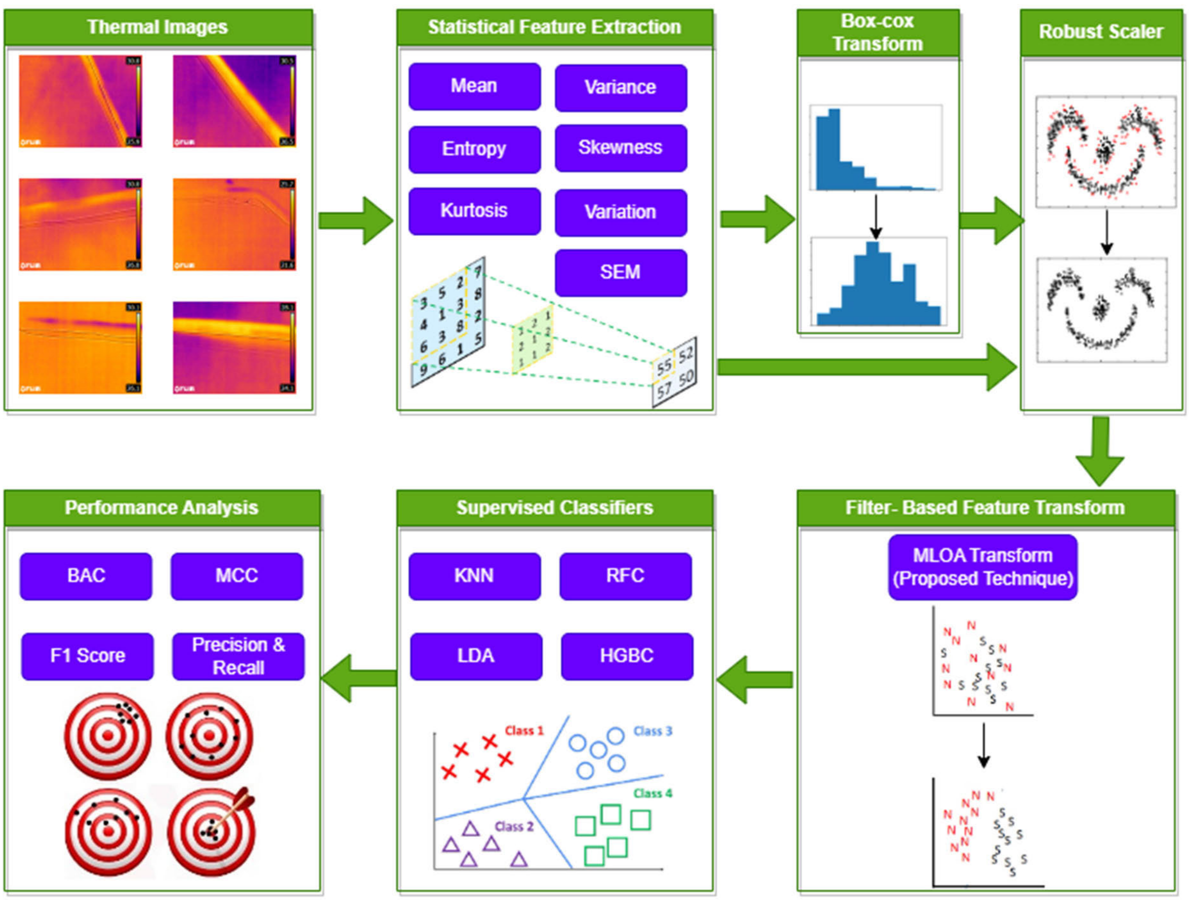


FIGURE 2. Proposed methodology.

IV. MODIFIED LOA AS FILTER-BASED FEATURE TRANSFORM

A. MODIFIED LEMURS OPTIMIZATION ALGORITHM

Two important modifications are proposed in the existing LOA for the development of Modified Lemurs Optimization Algorithm (MLOA). Firstly, the equation used to update Lemur's position mentioned in equation (3) is modified as follows (5):

$$L_{i+1}^{j} = \begin{cases} L_i^j + r1 * \sin(abs\left(L_i^j - gbest^j\right)) \\ * (rand - 0.5) * 2 if\ FRR \geq 0.5 \\ L_i^j + r1 * \cos\left(abs\left(L_i^j - nbest^j\right)\right) \\ * (rand - 0.5) * 2 if\ FRR < 0.5 \end{cases} \tag{5}$$

The equation (5) is inspired from the Sine Cosine Algorithm (SCA) and the usage of Sine & Cosine functions in an optimization algorithm increases the exploration and exploitation capability of the Swarm [41], [42]. The value of r1 will be computed as (6).

$$\mathrm{r1} = \mathrm{a} - \mathrm{Crnt\_Iter} \times \left(\frac{\mathrm{a}}{\mathrm{Max_{Iter}}}\right) \tag{6}$$

In equation (6), *Crnt_Iter* denotes the current iteration and *Max_Iter* denotes the maximum number of iterations; a is a constant and it is considered as three as suggested in [41]. In equation (5), the FRR is used to select exploration phase or exploitation phase in each iteration by comparing it with a constant instead of a random value used in original LOA. Introduction of this constant is responsible for better convergence and through empirical tests, the ideal value of that constant is found as 0.5. If the FRR is greater than 0.5, then Lemurs will be exploration phase making Global search while FRR less than 0.5 will make the Lemurs to enter exploitation phase i.e., local search.

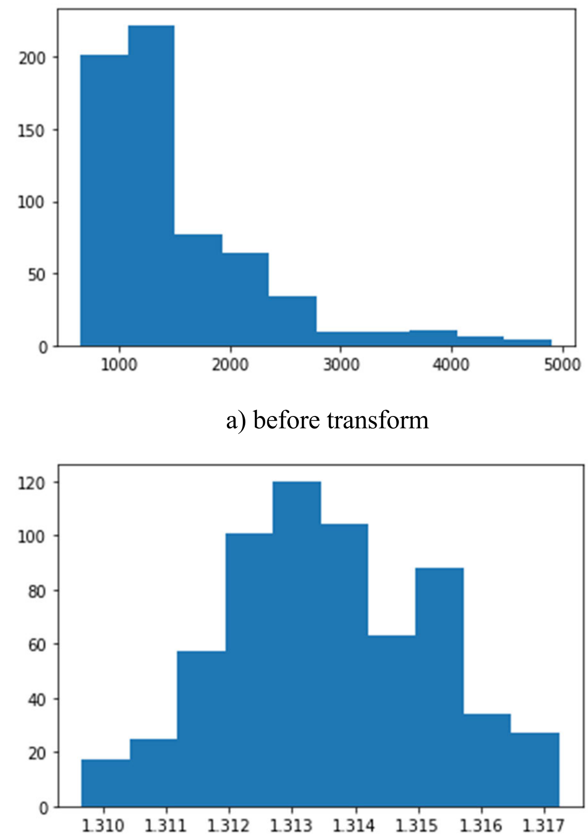
The second modification proposed in MLOA when compared to original LOA is the introduction of updation equation for updating the value of Worst Lemur in each iteration. The Lemur with least fitness value is identified and that Worst Lemur's position is updated using equation (7).

$$L_{worst,i} = L_{min} + (L_{max} - L_{min}) * rand \tag{7}$$

Here, L_{max} and L_{min} are the maximum and minimum position of Lemurs respectively and they are computed based upon the initial population of Lemurs; *rand* is the random number between 0 and 1.

B. INITIALIZATION AND FITNESS FUNCTION OF MLOA

To solve general optimization problems, the positions of Lemurs are initially generated randomly but to use MLOA as Feature Transform, the position of Lemurs are initially assigned with the statistical features extracted from each thermal image. Features of each thermal images will be transformed individually and the transformation of one image features is independent of another image features. For fourteen statistical features of a thermal image, fourteen Lemurs will be considered in the troop and their position will be updated in each iteration using the equations (5)-(7).



a) before transform

b) after transform

FIGURE 3. Histogram of variance feature before and after Box-Cox transform.

The objective function or fitness function plays a vital role in implementation of any Swarm Intelligence algorithms for solving real-world problems. The fitness of each Lemur will be calculated in each iteration to decide the global best (*gbest*) and local best (*nbest*). The Lemur with highest fitness value in the entire troop will be considered as *gbest* while the Lemur with highest fitness value among the three adjacent Lemurs including the current Lemur is considered as *nbest* of that Lemur. In this research work, fitness function of Lemurs are computed using the following equation:

$$\mathrm{F(L_i)} = \mathrm{Var(L_{i-1}, L_i}, L_{i+1}) \tag{8}$$

$\mathrm{F(L_i)}$ is the fitness function of current Lemur; variance of three adjacent Lemurs including the current Lemur is used for computing the Fitness function.

C. UPDATION OF THE WEIGHT PARAMETER – FRR

The selection of value for the FRR parameter present in equation (5) is very crucial and this FRR value decides the overall performance of the MLOA. To determine this FRR in each iteration, two approaches can be used. These two approaches are similar to two approaches used in feature selection. First one is the Wrapper-based approach in which the value of a parameter can be computed based upon the Error Rate (or) Accuracy with the help of a Machine Learning algorithm. Second one is the Filter-based approach in which no machine learning algorithms are used to update the parameter in each iteration and the updation takes placed based on the intrinsic characteristics of features. Comparatively, the second approach is faster and less complex since it avoids the usage of a prediction algorithm. So, Filter-based approach that uses variance and Stochastic Gradient Descent (SGD) for updating the weight parameter FRR is proposed in this research work. Usually, the weights are updated in SGD using the equation (9).

$$w_{t+1} = w_t - Lrate * \frac{\partial L}{\partial w_t} \quad (9)$$

Here, $w_t \& w_{t+1}$ denotes the old and new weights respectively while $Lrate$ denotes the learning rate; $\frac{\partial L}{\partial w_t}$ denotes the gradient of L i.e., the loss function to minimize with respect to weight w. In this work, inverse of variance is considered as loss function and it needs to be minimized for computing the optimal value for the weight parameter FRR (Here FRR is considered as weight w). The loss function considered is,

$$\frac{\partial L}{\partial FRR_t} = \begin{cases} \frac{Ivar_t}{FRR_{initial}} & if\ t = 1 \\ \frac{Ivar_t - Ivar_{t-1}}{FRR_t - FRR_{t-1}} & if\ t > 1 \end{cases} \quad (10)$$

In equation (10), t represents the current iteration number; $Ivar$ represents the inverse of variance of the entire Lemur population and it is equal to $[1/(variance\left(L^1, L^2, \ldots, L^{14}\right)]$. Using trial and error method, the ideal values for MLOA parameters are found as $Max\_Iter = 12, FRR_{initial} = 0.5,$ and $Lrate = 0.5$.

V. RESULTS AND DISCUSSIONS

To prove the efficiency of the proposed MLOA based feature transform, the performance of classifiers with and without this proposed transform are compared in this section. Four supervised classifiers namely KNN, RFC, LDA, and HGBC are tested in this research work. These classifiers are picked randomly from the bunch of supervised classifiers since our objective is to demonstrate the performance improvement in classification through the usage of MLOA based feature transform. Various performance metrics are available in literature to assess the performance of classifier and in this work five performance metrics namely Balanced Accuracy (BAC), Mathews Correlation Coefficient (MCC), Weighted Average F1-score, Weighted Average Precision, and Weighted Average Recall. These performance metrics will consider the number of subjects in each class as weights and so very much suitable for imbalanced multi-class dataset. BAC and MCC presents the overall summary about the classification and the improvement of these performance metrics through the usage of proposed MLOA transform can be clearly witnessed in Table 2. To justify the performance of proposed MLOA as filter-based feature transform, results produced by original

Algorithm 1 Algorithm to Implement the Proposed MLOA as Filter-Based Feature Transform for Each Thermal Image

1. Extract the 14 statistical features mentioned in Section III from the thermal image
2. Initialize the position of Lemurs with the extracted statistical features as L
3. Initialize the parameters of MLOA: $L_{max} = \max(L^1, L^2, \ldots, L^{14})$, $L_{min} = \min(L^1, L^2, \ldots, L^{14})$, $Max\_Iter = 12, FRR_{initial} = 0.5, Lrate = 0.5$
4. Compute the fitness value of each Lemur using equation (8)
5. Based on the fitness value, find the *gbest* and *nbest*
6. Update the position of all the Lemurs using equations (5) & (6)
7. Identify the Lemur with lowest fitness value as Worst Lemur and update its position using equation (7)
8. Compute the Loss function and update the weight parameter FRR using equations (9) & (10)
9. Repeat steps 4 to 8 until maximum number of iterations is reached. If the maximum number of iterations are completed, then go to step 9.
10. Consider the final position of Lemurs as the output of Feature Transform and give them as input to the classifiers.

TABLE 2. Performance summary of various supervised classifiers and feature transforms.

	BAC (%)	MCC (%)	Weighted Average F1-score (%)	Weighted Average Recall (%)	Weighted Average Precision (%)
RFC	59	51	66	67	66
KNN	64	58	67	67	68
LDA	58	47	59	59	61
HGBC	64	59	68	68	68
PSO-RFC	67	62	70	70	70
PSO-KNN	72	66	74	74	74
PSO-LDA	61	50	62	62	63
PSO-HGBC	63	57	67	66	68
LOA-RFC	80	77	82	82	82
LOA-KNN	80	77	83	83	83
LOA-LDA	66	57	67	66	68
LOA-HGBC	68	64	72	72	72
MLOA-RFC	84	82	86	86	86
MLOA-KNN	90	87	91	91	91
MLOA-LDA	72	64	72	72	74
MLOA-HGBC	74	71	77	77	78

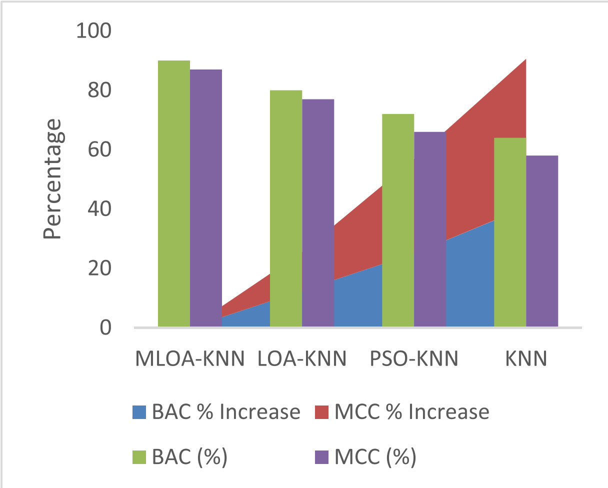


FIGURE 4. BAC & MCC of KNN classifier without and with various transforms.

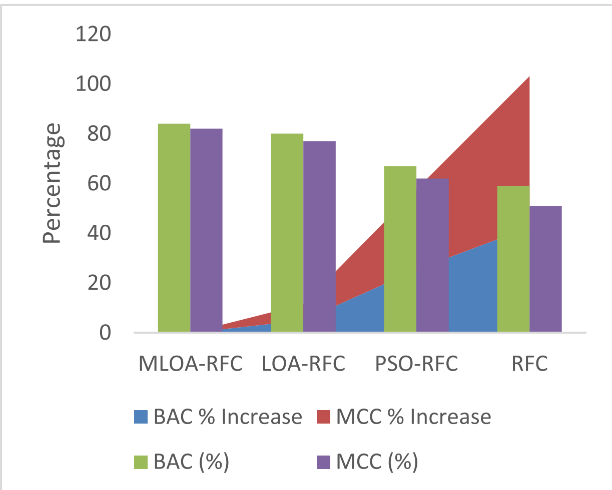


FIGURE 5. BAC & MCC of RFC classifier without & with various transforms.

LOA as filter-based feature transform is presented. To support the selection of LOA/MLOA on this work, PSO is also implemented as filter-based feature transform and the results are compared. PSO is used for comparison since it is one of the most popular and frequently used SI techniques.

Out of the four classifiers without any transform, KNN and HGBC provides the comparatively higher balanced accuracy of 64%. All the four classifiers tested are producing BAC in the range of 58% - 64% and this BAC is very much less and needs lot of improvement. Highly non-linearly separable data which is fed to these classifiers may be the underlying reason for such poor performance. If the proposed MLOA feature transform is used, then the BAC increases significantly for all the four classifiers. Notably, 90% of BAC is attained by KNN classifier if it is fed with the features transformed by the MLOA. BAC & MCC attained by each classifier with and without feature transforms are shown in Fig.4 to Fig.7. In addition, the percentage increase when compared

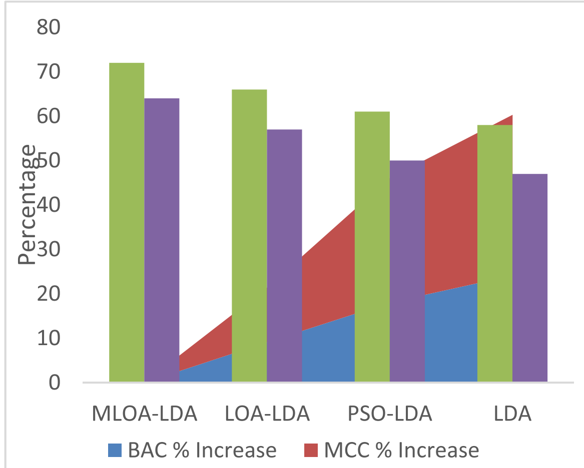


FIGURE 6. BAC & MCC of LDA classifier without and with various transforms.

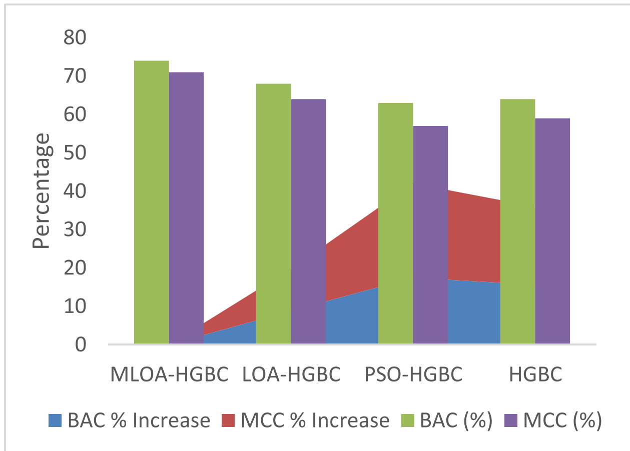


FIGURE 7. BAC & MCC of HGBC classifier without and with various transforms.

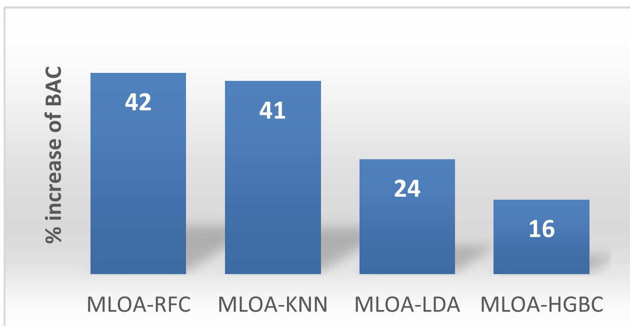


FIGURE 8. Percentage increase of BAC of various classifiers with MLOA based transform over classifiers without transform.

to MLOA transform is also presented in Fig.4 to Fig.7. PSO feature transform worked well for two classifiers namely KNN and RFC while it fails to provide considerable amount BAC increase for the remaining two classifiers. In fact, PSO feature transform slightly reduces the BAC of HGBC. LOA

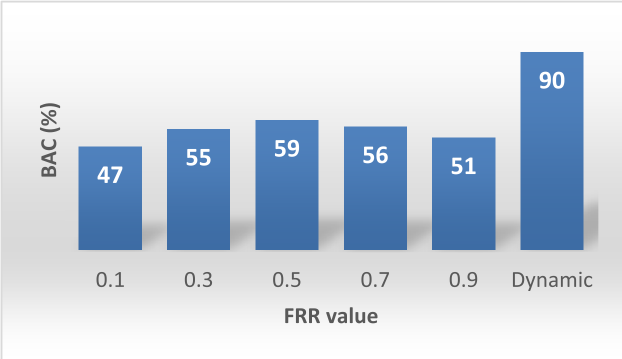


FIGURE 9. BAC attained in MLOA transform with fixed weights and dynamic weights for FRR parameter.

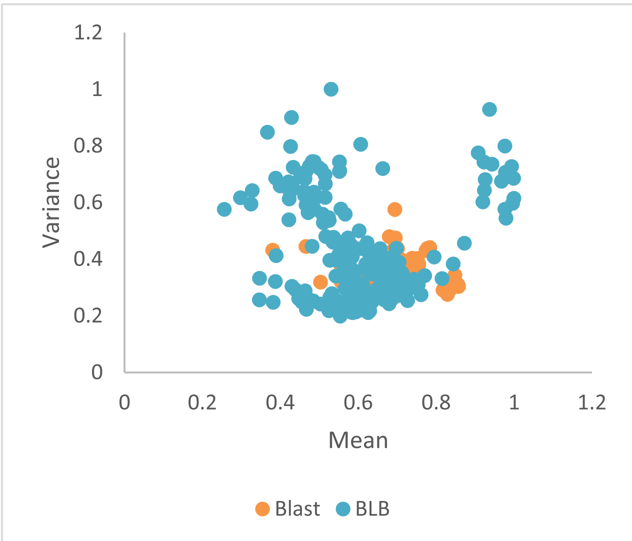


FIGURE 10. Initial data points of BLB & Blast class considering Mean & variance features before MLOA transform.

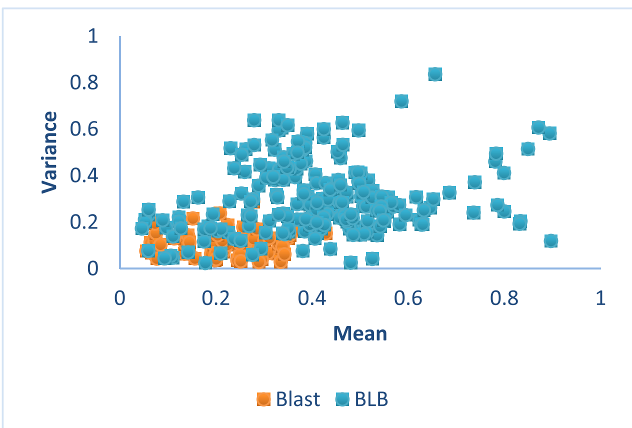


FIGURE 11. Final data points of BLB & Blast class considering Mean & variance features after MLOA transform.

feature transform outperforms PSO feature transform in all the four classifiers and it produces 80% BAC for both RFC & KNN classifiers. As stated by Ammar Kamal Abasi et.al., the structure of LOA has the capability to outperform many existing SI algorithms through its better exploration and exploitation capabilities for achieving the global optima [28].

Due to the changes mentioned in section IV, MLOA feature transform performs better than the LOA & PSO feature transform. The two main reasons for this notable performance of MLOA feature transform can be stated as follows: Firstly, the usage of SCA concepts in LOA combines the advantages of both optimization algorithms and results in the powerful MLOA algorithm. Secondly, updation of the worst Lemur position updation through equation (7), avoids the local optima problem by assigning the worst position with a random value. The increase in BAC percentage due to the usage of proposed MLOA transform over the classification techniques without transform can be seen in Fig.8. More than 40% BAC increase is witnessed in RFC & KNN classifiers with MLOA feature transform when they are compared with the RFC & KNN classifiers without feature transforms.

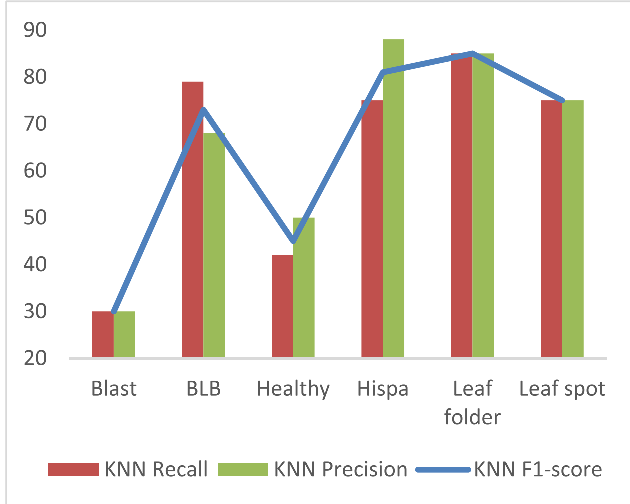


FIGURE 12. Precision, Recall, and F1 score of KNN classifier for individual classes without any transform.

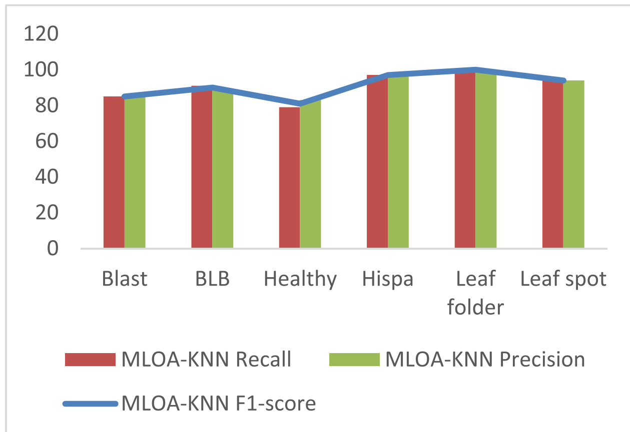


FIGURE 13. Precision, Recall, and F1 score of KNN classifier for individual classes with MLOA transform.

TABLE 3. Class-wise Comparison of Precision, Recall & F1-score of classifiers with PSO as feature transform and without any transform.

		Blast	BLB	Healthy	Hispa	Leaf folder	Leaf spot
RFC	F1-score	16	75	51	77	85	72
	Recall	15	75	52	79	85	75
	Precision	18	76	50	76	85	70
KNN	F1-score	30	73	45	81	85	75
	Recall	30	79	42	75	85	75
	Precision	30	68	50	88	85	75
LDA	F1-score	32	68	39	66	82	55
	Recall	30	75	42	55	100	50
	Precision	33	63	36	84	70	61
HGBC	F1-score	15	76	50	85	85	70
	Recall	15	75	52	82	85	75
	Precision	15	78	47	88	85	66
PSO-RFC	F1-score	32	77	55	81	86	75
	Recall	31	75	58	83	86	75
	Precision	33	79	52	80	86	75
PSO-KNN	F1-score	46	77	63	83	85	78
	Recall	46	79	63	79	85	81
	Precision	46	76	63	88	85	76
PSO-LDA	F1-score	32	70	43	69	88	60
	Recall	31	75	47	59	100	56
	Precision	33	66	39	85	78	64
PSO-HGBC	F1-score	15	75	48	84	86	71
	Recall	15	73	53	79	86	75
	Precision	15	78	43	88	86	67

TABLE 4. Class-wise Comparison of Precision, Recall & F1-score of various classifiers with LOA & MLOA as feature transform.

		Blast	BLB	Healthy	Hispa	Leaf folder	Leaf spot
LOA-RFC	F1-score	61	84	75	92	86	82
	Recall	54	82	79	93	86	88
	Precision	70	86	71	90	86	78
LOA-KNN	F1-score	62	85	74	91	92	85
	Recall	62	86	74	90	86	88
	Precision	62	84	74	93	100	82
LOA-LDA	F1-score	46	73	51	75	88	62
	Recall	46	75	58	66	100	56
	Precision	46	70	46	86	78	69
LOA-HGBC	F1-score	30	78	58	88	86	73
	Recall	31	77	58	86	86	75
	Precision	29	79	58	89	86	71
MLOA-RFC	F1-score	72	87	79	93	86	88
	Recall	69	84	79	97	86	94
	Precision	75	90	79	90	86	83
MLOA-KNN	F1-score	85	90	81	97	100	94
	Recall	85	91	79	97	100	94
	Precision	85	89	83	97	100	94
MLOA-LDA	F1-score	52	77	62	79	88	69
	Recall	54	75	74	72	100	63
	Precision	50	79	54	88	78	77
MLOA-HGBC	F1-score	40	83	63	95	86	74
	Recall	38	80	68	93	86	81
	Precision	42	88	59	96	86	68

Increase in 24% and 16% BAC is witnessed when the remaining two classifiers namely LDA & HGBC are fed with the MLOA transformed features respectively.

Apart from the efficiency of MLOA algorithm, the implementation strategy followed for feature transform will be another prime reason for this better performance. The implementation strategy of feature transform includes the proper initialization of population and parameters, selection of appropriate fitness function, updation of weight parameter FRR using equations (9 & 10). Especially the filter-based approach for updating the weight parameter FRR dynamically pays very good performance enhancement over the usage of fixed weight parameter FRR. This was proved through an experiment result provided in Fig.9 which was conducted on MLOA-KNN with fixed and dynamic weights for FRR parameter. From that figure, the usage of SGD for updating FRR dynamically by considering variance as filter technique is proved as good idea since dynamic FRR attains 90% of BAC while fixed weights for FRR produces BAC in the range of 47% - 59% only.

Due to the above-mentioned reasons, MLOA feature transform works well by transforming the features that is more suitable form for classification. The significance of this transformation can be understood from the Fig.10 & Fig.11 which shows the scatter plot before and after implementing the MLOA transform on two normalized features namely mean and variance that belongs to two classes namely Blast & BLB. Only two features are considered since two-dimensional scatter plot is easier for analysis. The usefulness of proposed MLOA feature transform is clearly visible on comparison of Fig.11 with Fig.10. Separation between the features of Blast & BLB class can be seen in Fig.11 after implementation of MLOA transform while this separation between the features of Blast & BLB is very less as shown in Fig.10 before implementation of the proposed transform.

Apart from BAC & MCC metrics mentioned in Table 2, remaining metrics namely weighted F1 score, Weighted precision and Weighted recall are almost equal for each classifier. F1 score is harmonic mean of precision and recall. Accidentally weighted precision and weighted recall are almost equal for each classifier model used in this work as shown in Table 2. But there is wide gap between precision and recall if individual classes are considered as shown in Table 3 & Table 4. These two tables are useful if there is a requirement to target on a particular class i.e., a particular rice leaf disease. The usefulness of MLOA based feature transform can be again witnessed in the improvisation of precision and recall scores by comparing the Fig.12 and Fig.13. In Fig.12, the imbalance in precision and recall scores can be seen in three classes namely BLB, Healthy, and Hispa. But in Fig.13, this imbalance is mitigated through the usage of MLOA transform. In addition, the F1 score of each class is improved by MLOA transform and this can be witnessed by comparing Fig.12 and Fig.13.

VI. CONCLUSION

Through the results presented in the previous section, the efficiency of MLOA as feature transform for improving the classification accuracy of various ML techniques is proved in detection of rice leaf diseases. In addition, the proposed MLOA transform performs better than the PSO and LOA based transforms. In MLOA transform, proper initialization of population and parameters, selection of appropriate fitness function and updation of weight parameter FRR dynamically using filter-based technique based on SGD has resulted in the improved classification performance when compared to other techniques. Importantly, 90% BAC is achieved with the MLOA-KNN classifier and this BAC increase is significant since the KNN offers BAC of only 64%. Not only KNN, other three tested classifiers also provided substantial improved classification performance with the help of MLOA feature transform in the detection of rice leaf diseases. The efficiency of MLOA feature transform for other applications and other types of features needs to be investigated in future. Additionally, the proposed transform needs to be tested for different classifiers set for this rice leaf disease detection problem for getting BAC around 95% or more.

DATA AVAILABILITY STATEMENT

Data availability is mentioned in this manuscript.

CONFLICTS OF INTEREST

There is no conflict of interest among the authors.

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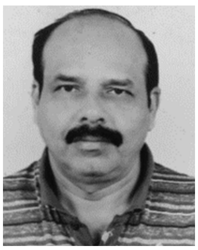

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