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Classification of Maize (*Zea May L*) Leaf Diseases Variants Based on Sobel Edge Detection and Machine Learning Technique

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ARTICLE INFO	ABSTRACT
Published Online: **29 March 2025** **Corresponding Author:** **Olusola Bamidele Ayoade**	*Zeae-maydis*, also known as maize gray leaf spot, and *porcinia sorghi*, known as maize common rust, are the two most prevalent and dangerous diseases that harm maize crops in Nigeria. Plant diseases are difficult for Nigerian farmers to recognize correctly, and it is impossible to assess their severity with the unaided eye. However, hiring a pathologist is more costly and time-consuming for large farms. Moreover, many support vector machine (SVM) classification models for maize leaf disease classification have been developed by different researchers. However, these existing models are impacted by imbalanced datasets, irrelevant feature selection, and difficulty in fine-tuning the hyperparameters of the SVM. Consequently, to resolve these problems, two optimized multiclass support vector machine classification models (BPSO-SVM and RSA-SVM) were trained to categorize maize leaves disease into *Zeae-maydis* and *porcinia sorghi* using 1,648 photos of maize leaves across all maize datasets, which included 574 photos of gray leaf spot disease, 574 photos of common rust disease, and 500 photos of healthy leaves obtained from the Kaggle village datasets. The images were scaled down, converted to grayscale, and enhanced using morphological filtering, bi-histogram equalisation techniques, and adaptive median filtering before the affected area was segmented through the Sobel edge detection method. The Gray Level Spatial Dependence and colour moment were then used to extract texture, shape, and colour features, which were then fused using the linear combination method. The 10-fold approach was used to train and test each classification model. The comparative experiments demonstrate that the BPSO-SVM model outperforms the RSA-SVM model at a threshold value of 0.80. The RSA-SVM model has a performance accuracy of 95.62% and 95.25% on the datasets for gray leaf spot and common rust disease, respectively, while the BPSO-SVM has a performance accuracy of 96.37% and 96.93% on the same datasets. The two models can be used to classify *Zeae-maydis* and *porcinia sorghi* in maize, according to a comparison with the current models. However, this study only identified two of the numerous diseases that affect maize, and it offered no suggestions for how to prevent any of these illnesses.

KEYWORDS: BPSO-SVM**,** Machine Learning Technique, *porcinia sorghi*, RSA-SVM, *Zeae-maydis*

I. INTRODUCTION

One of the most significant cereal crops is maize (Zea mays L.), which is produced in the largest quantities worldwide and can be cultivated in various climates. It is also highly prized for its extensive use as a staple diet for humans, premium feed for animals, and the main raw material for various industrial goods [46]. Although maize has a high potential for grain yields, its susceptibility to different diseases poses a major obstacle to raising yields and results in an annual production loss of 6–10% [39]. Thus, early detection and monitoring are crucial to halting the spread of diseases that affect maize during the growing season. Good observational abilities, familiarity with particular disease symptoms, and the availability of subject matter experts and plant pathologists are all necessary for accurate disease identification [46].

However, the manual identification process is tedious, time-consuming, and inaccurate because some diseases have similar symptoms that can make it challenging to identify the specific disease affecting maize. Furthermore, using manual methods on large farms will take much time and resources to monitor the plants. Therefore, it's important to have quick and accurate methods for identifying maize diseases to monitor the crop and treat any infections immediately. Plant disease identification is currently seeing an increase in the use of computer vision (CV) technology and machine learning (ML)--based techniques due to their expert-level performance under challenging conditions [45]. Therefore, an automatic disease diagnosis strategy based on digital images is a feasible and workable replacement for the manual inspection process in the maize crop.

Moreover, to recognize and classify crop illnesses, scientists have developed several classification models, notably “Support Vector Machines (SVM)” ([7], [15], [40], [32], [36]), “Decision Trees (DT)” ([1], [4], [5], [18], [19]), “Random Forests (RF)” ([29], [26], [11], [24]), “K-Nearest Neighbours (KNN)” ([30], [27], [21], [20], [3]), “Logistic Regression (LR)” ([33], [25]), “Naïve Bayes (NB)” ([34], [13], [35]), and “Artificial Neural Network (ANN)” ([2], [23], [17], [8], [9], [10]). However, most of these studies used imbalanced datasets, which typically results in bias in performance accuracy. Care must be taken when deciding which features to extract to avoid overfitting and increase the computational complexity of the classification model. Binary Particle Swarm Optimization-Support Vector Machine, or BPSO-SVM, and Reptile Search Algorithm-Support Vector Machine, or RSA-SVM, are the two multiclass support vector machine classification models that this study proposed. These models aim to improve the detection of diseases specific to maize and to choose support vector machine discriminating parameters that minimize algorithmic computational complexity by preventing the overfitting of the classification models. To avoid the imbalanced dataset, an equal number of datasets were assigned to each of the two diseased datasets. This ensured that the accuracy of the classification models would not be biased towards any specific disease.

The main contributions of this study can be summarized as follows:

• To select relevant features and avoid overfitting of the classification models, the recently developed multiclass classification models of BPSO-SVM and RSA-SVM were used.

• A refined Multiclass Support Vector Machine classification model (i.e. BPSO-SVM and RSA-SVM) that adjusts the SVM classifier's parameters (penalty cost, C, and kernel function, γ) lowers the false positive rate and increases the system's classification accuracy for a specific set of diseases affecting the maize were developed.

• This work advances the understanding of computer vision, particularly pattern recognition, by adding fresh findings to maize leaf disease categorization models.

• The experimental results obtained show that these models have low computational complexity and minimum computational load; therefore, they can be used in real-time applications that require high classification accuracy.

II. RELATED STUDIES

Table 1 provides a pertinent research summary of the studies conducted by the different authors on maize disease detection systems and classification models. It includes information about the author(s) and the year, the kind of crop disease, the number of datasets overall, where the datasets came from, the classification model that was created, and the classification model's outcomes.

Table 1: Summary of the Research Papers Reviewed in Maize Disease Detection and Classification Models

Authors	Types of Crop Disease	Total Number of Dataset	Data Source	Classification Model	Results of the Model(s)
[15]	“Northern Leaf Blight, Gray Leaf Spot, Common Rust”	3445	Kaggle	Fish Swarm Optimizer (FSO)+Support Vector Machine (FSO+SVM)	Gray Leaf Spot Accuracy=98.60, Common Rust Accuracy=98.50
[40]	“Northern Leaf Blight, Brown Spot, Gray Leaf Spot, Curvularia Lunata, Round Spot, Common Rust”	Not Specify	Self-Created	“Genetic Algorithm (GA) +Support Vector Machine (SVM) (GA+SVM), SVM”	GA-SVM Accuracy Gray Leaf Spot=89.45%, Common Rust=88.55% SVM Gray Leaf Spot=85.59%, Common Rust=81.48%

[12]	“Gray Leaf Spot, Northern Leaf Blight, Northern Leaf Spot”	2112	Corn Disease and Severity (CD&S)	Faster-RCNN (Recurrent Convolutional Neural Network)	Gray Leaf Spot Precision=98.80%, Recall=97.90%, Accuracy=98.20%,
[14]	“Common Rust, Northern Leaf Blight, Gray Leaf Spot”	4800	Bangladesh’s Corn Field	ResNet GAP (Global Average Pooling), DenseNet 121, VGG 19, SqueezeNet, AlexNet, VGG 16, ResNet 101, XCeption	VGG 16 Gray Leaf Spot “Precision=100.00%, Recall=82.00%”, Common Rust “Precision=100.00%, Recall=100.00”, XCeption Gray Leaf Spot Precision=54.00%, Recall=82.00%, Common Rust Precision=78.00%, Recall=95.00
[16]	“Gray leaf Spot, Northern Leaf, Blight, Common Rust”	3820	Kaggle	EKNN (Enhanced K-Nearest Neighbour)	Gray Leaf Spot Precision=99.87%, Recall=99.10%, Common Rust Precision=99.77%, Recall=99.88%
[23]	“Northern Leaf Blight, Gray Leaf Spot, Powdery Mildew, Common Rust, Smut”	750	Plant Pathology Repository	SVM, ANN (Artificial Neural Network)	SVM Accuracy=88.83%, Precision=89.17%, Recall=78.50%, ANN Accuracy=77.75%, Computation Time=404.156seconds, Gray Leaf Spot Precision=85.00%, Recall=74.00%, Common Rust Precision=90.00%, Recall=80.00%
[22]	“Common Rust, Northern Leaf Blight, Cercospora Leaf Spot or Gray Leaf Spot”	7332	Kaggle	ResNet-9	Accuracy Gray Leaf Spot=97.81%, Common Rust=99.94%
[39]	“Common Rust, Gray Leaf Spot, Northern Leaf Blight”	5970	Kaggle	OSCRNet	Accuracy Common Rust=95.67%, Gray Leaf Spot=93.86%, OSCRNet=93.53, Computation Time=413.69secods
[31]	“Gray Leaf Spot, Northern Leaf Blight, Common Rust”	3852	Mendeley	“Improved Convolutional Neural Network (CNN)”	Gray Leaf Spot “Precision=100.00%, Recall=90.00%,Common Rust Precision=100.00%, Recall=100.00%”
[28]	“Common Rust, Gray Leaf Spot, Northern Leaf Blight”	Not Specified	Self-Created	“Convolutional Neural Network (CNN)”	Accuracy Gray Leaf Spot=91.00%, Common Rust=87.00%, Model Accuracy=92.85%
[6]	“Gray Leaf Spot, Northern Leaf Blight, Common Rust”	8640	Kaggle, Open DataLab, PaddlePaddle	YOLOv5s-C3CBAM	Gray Leaf Spot Accuracy=81.80%, Precision=81.20%, Recall=60.70% Common Rust Accuracy=90.70%, Precision=88.30%, Recall=71.70%

III METHODOLOGY

This section includes a flowchart that illustrates the trained and tested maize dataset using BPSO-SVM or RSA-SVM classification models, as well as detailed information on the acquired dataset, preprocessing operations, segmentation, and feature extraction.

A. Dataset, Preprocessing, Segmentation and Feature Extraction

The dataset on maize diseases was obtained using the Kaggle village plant dataset, which comprises 1,648 samples with two types of maize leaf diseases (i.e., 574 photos of common rust, and 574 photos of gray leaf spot, also known as Cercospora leaf spot) and 500 photos of healthy maize leaves. The samples of the dataset used in the study are shown in Figure 1. RGB images were converted to grayscale and then resized to 256 X 256 pixels resolution to improve the final images. By applying morphological filtering to sharpen the image and utilizing the Sobel edge detection method to distinguish between the lesion and healthy parts of the leaf, the image quality was further improved. Then, using the Gray Level Spatial Dependence Matrix for the extraction of the texture and shape features and four colour moments for the extraction of the colour features.

B. Block Diagram for the Structure of the BPSO-SVM or RSA-SVM and Flowchart Showing Trained and Tested Maize Dataset with BPSO-SVM or RSA-SVM Classification Model

Figure 2 depicts the block diagram for the structure of the BPSO-SVM and RSA-SVM and Figure 3 depicts the flowchart for the trained and tested maize dataset using the BPSO-SVM or RSA-SVM classification model.

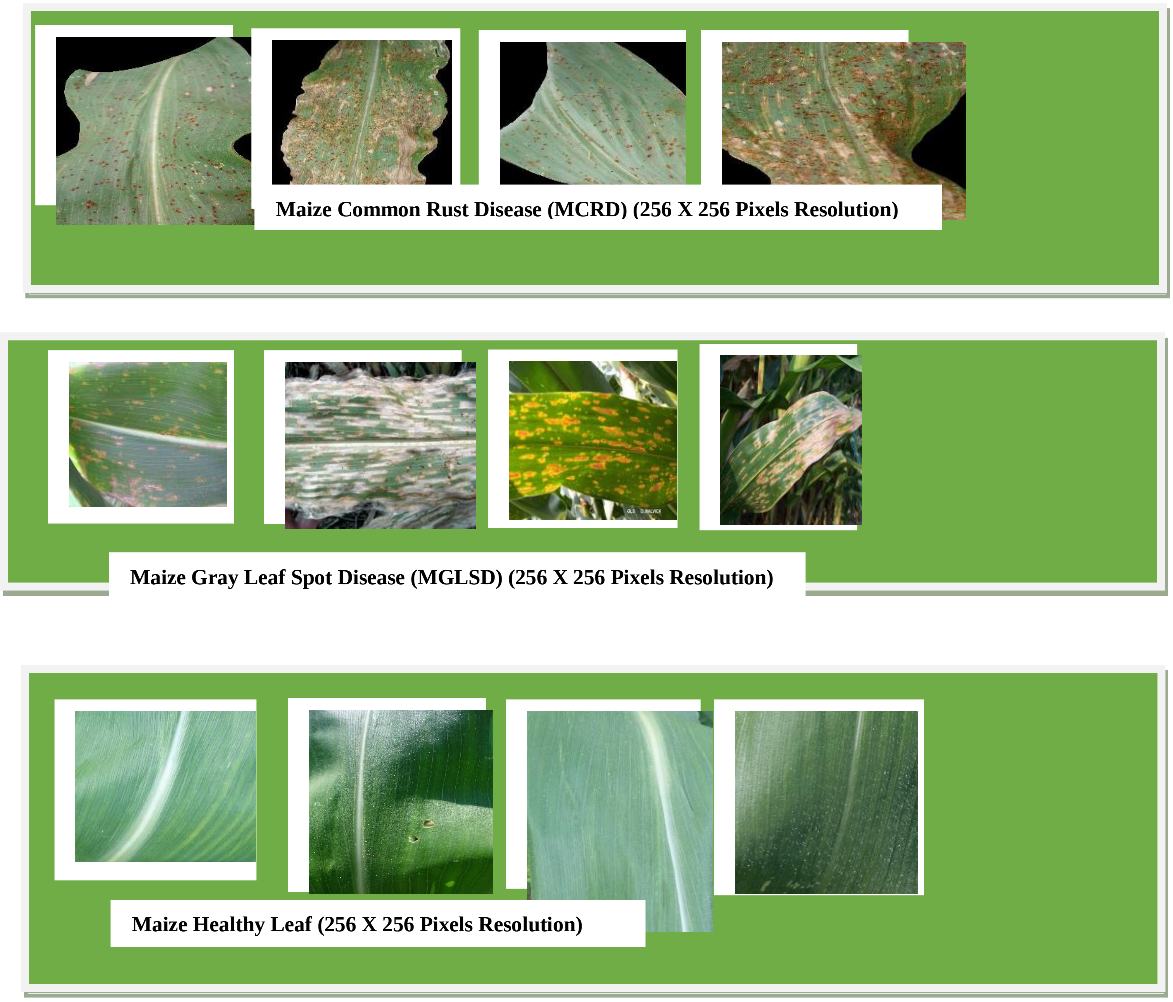

Fig. 1: Samples of the Maize Dataset used for the study

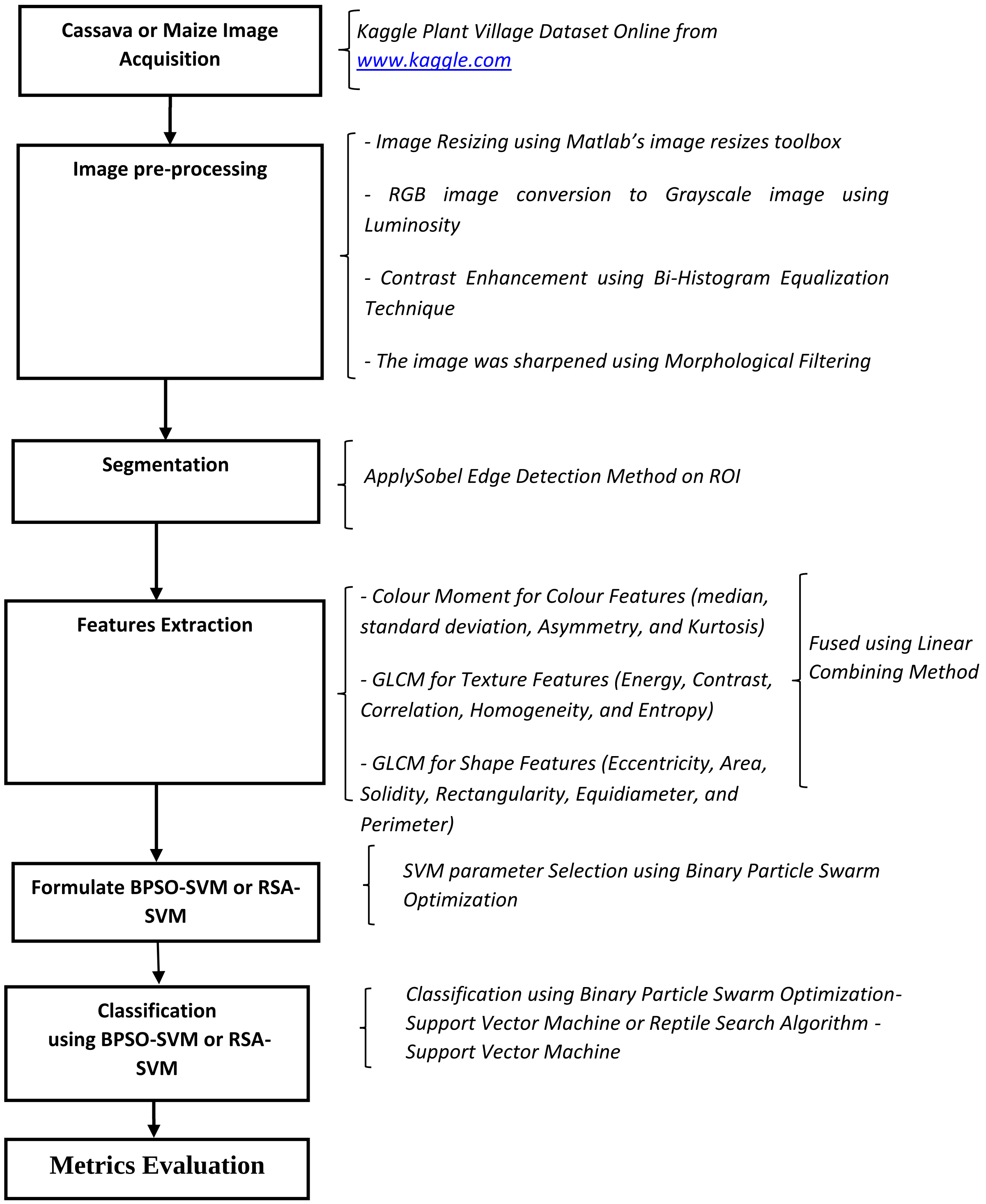

Fig. 2: Block Diagram for the Structure of the BPSO-SVM or RSA-SVM Classification Model

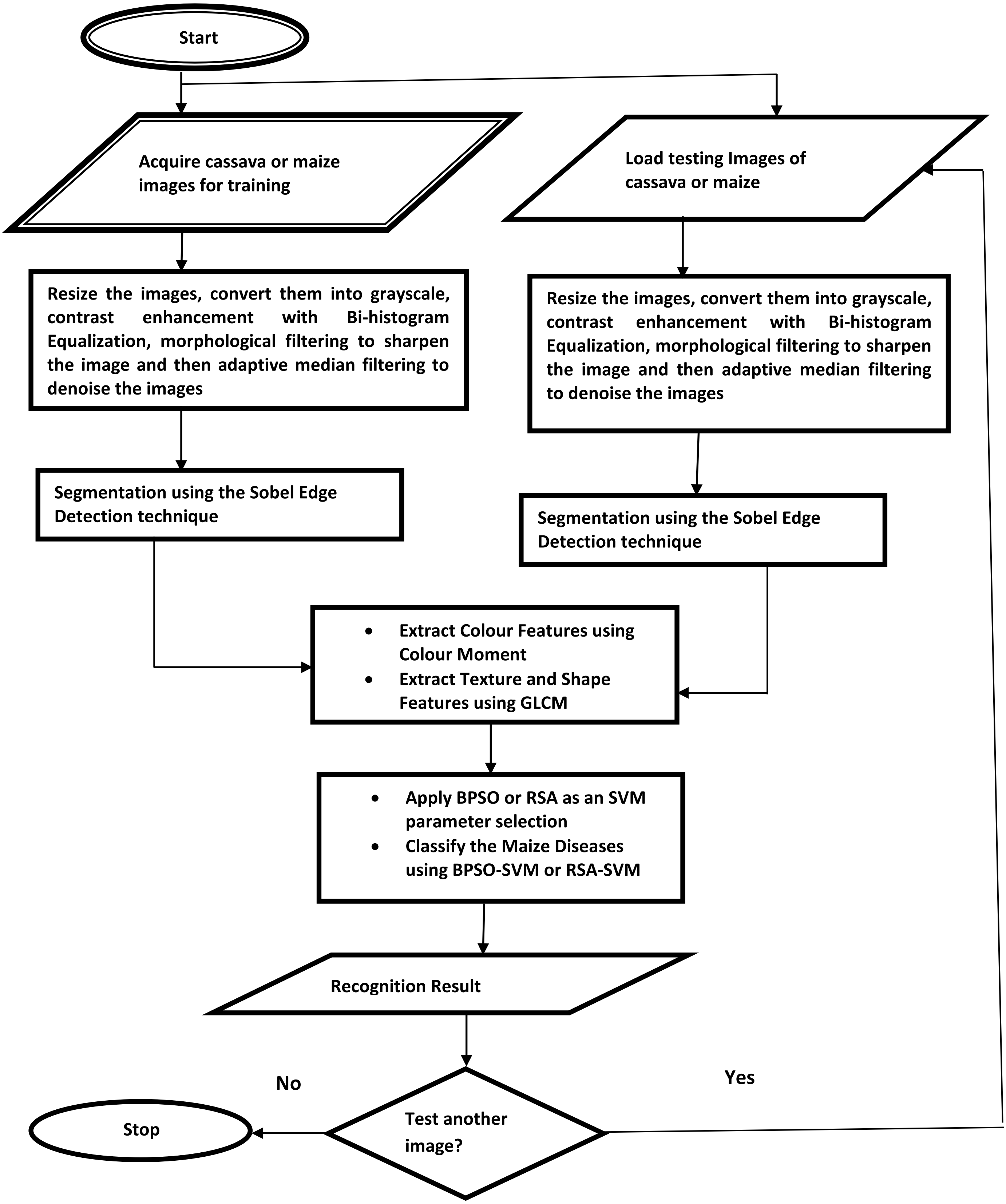

Fig. 3: Flowchart showing trained and tested maize with BPSO-SVM or RSA-SVM Classification Model

IV.RESULTS AND DISCUSSION

A. Performance Comparison of BPSO-SVM and RSA-SVM Classification Models

The dataset created to confirm the efficacy of the multiclass support vector machine classification models was used to train and assess the two models. The false positive rate (FPR), specificity, sensitivity, precision, accuracy, and computation time of the RSA-SVM and BPSO-SVM models are contrasted in Table 2. The findings demonstrate that the BPSO-SVM model outperforms the RSA-SVM model in every performance evaluation metric, except computation time for All maize datasets. Table 2 also shows that misclassification for “maize gray leaf spot disease (MGLSD) or maize Cercospora leaf spot disease (MCLSD)” is much higher than for “maize common rust disease (MCRD)”. These findings demonstrate the degree of accuracy with which the two models classify common rust disease (MCRD) and maize gray leaf spot disease (MGLSD), also referred to as maize Cercospora leaf spot disease (MCLSD).

Table 2: Performance Comparison of BPSO-SVM and RSA-SVM Classification Models on the Maize Datasets

	Maize Common Rust Disease (MCRD)	**Maize Gray Leaf Spot Disease (MGLSD) or Maize Cercospora Leaf Spot Disease (MCLSD)**	**All Maize Dataset**
False Positive Rate (FPR) (%)			
BPSO-SVM	3.00	3.60	5.00
RSA-SVM	4.40	4.80	6.20
Specificity (%)			
BPSO-SVM	97.00	96.40	95.00
RSA-SVM	95.60	95.20	93.80
Sensitivity (%)			
BPSO-SVM	96.86	96.34	97.56
RSA-SVM	95.64	95.30	97.04
Precision (%)			
BPSO-SVM	97.37	96.85	97.82
RSA-SVM	96.15	95.80	97.29
Accuracy (%)			
BPSO-SVM	96.93	96.37	96.78
RSA-SVM	95.62	95.25	96.06
Computation Time (sec)			
BPSO-SVM	59.84	59.43	165.67
RSA-SVM	60.64	61.22	163.28

B. Performance Comparison of the Evaluation Metrics of BPSO-SVM, RSA-SVM Models and Existing Classification Models on Maize Datasets

The comparison results between other currently used classification models and the developed multiclass models (BPSO-SVM and RSA-SVM) are shown in Table 3. The methodology employed in this study is comparable to studies by [40] and [15], in which the authors similarly optimized support vector machines using meta-heuristic algorithms as classifiers for their classification models. The accuracy, precision, sensitivity, and specificity performances of the RSA-SVM and BPSO-SVM models are better than the models developed by [40], [23], [28], [14], [39], and [6].

In comparison, the accuracy, sensitivity, and precision performances of the Faster-RCNN, ResNet-9, and EKNN models created by [12], [22], and [16], respectively are better than the BPSO-SVM and RSA-SVM. Except for gray leaf spot sensitivity, the VGG16 and FSO+SVM models created by [14] and [15] respectively perform better than the BPSO-SVM and RSA-SVM models. The improved CNN model by [31] outperformed BPSO-SVM and RSA-SVM on the common rust dataset.

Table 3: Performance Comparison of the Evaluation Metrics of BPSO-SVM, RSA-SVM Models and Existing Classification Models on Maize Datasets

Model and Evaluation Metrics	Maize Common Rust Disease (MCRD)	Maize Gray Leaf Spot Disease (MGLSD) or Maize Cercospora Leaf Spot Disease (MCLSD)
False Positive Rate (FPR) (%)		
BPSO-SVM	**3.00**	**3.60**
RSA-SVM	**4.40**	**4.80**
Specificity (%)		
BPSO-SVM	**97.00**	**96.40**
RSA-SVM	**95.60**	**95.20**
Sensitivity (%)		
[15] Fish Swarm Optimizer (FSO)+SVM	98.30	94.20
[16] Enhanced K-Nearest Neighbour (EKNN)	99.88	99.10
[23] Artificial Neural Network (ANN)	80.00	74.00
[14] Visual Geometry Group 16 (VGG16)	100.00	82.00
[14] Extreme Inception (Xception)	95.00	82.00
[31] Improved Convolutional Neural Network (CNN)	100.00	90.00
[6] YOLOv5s-C3CBAM	71.70	60.70
[12] Faster-Recurrent Convolutional Neural Network (RCNN)	-	97.90
BPSO-SVM	**96.86**	**96.34**
RSA-SVM	**95.64**	**95.30**
Precision (%)		
[15] FSO+SVM	99.10	97.40
[[16] EKNN	99.77	99.87
[23] ANN	90.00	85.00
[14] VGG16	100.00	100.00
[14] Xception	78.00	54.00
[31] Improved CNN	100.00	100.00
[6] YOLOv5s-C3CBAM	88.70	81.20
[12] Faster-RCNN	-	98.80
BPSO-SVM	**97.37**	**96.85**
RSA-SVM	**96.15**	**95.80**
Accuracy (%)		
[[40] Genetic Algorithm (GA)+SVM	88.55	89.45
[40] SVM	81.48	85.59
[15] FSO+SVM	98.50	98.60
[28] CNN	87.00	91.00
[22] ResNet-9	99.94	97.81
[39] OSCRNet	95.67	93.86
[6] YOLOv5s-C3CBAM	90.70	81.80
[12] Faster-RCNN	-	98.20
BPSO-SVM	**96.93**	**96.37**
RSA-SVM	**95.62**	**95.25**
Computation Time (sec)		
BPSO-SVM	**59.84**	**59.43**
RSA-SVM	**60.64**	**61.22**

C. Discussion of the Findings

The results in Table 2 showed that, across all performance evaluation metrics employed in the study on maize gray leaf spot disease (MGLSD) and maize common rust disease (MCRD), the BPSO-SVM model performs better than the RSA-SVM model. However, the RSA is a powerful optimization technique, but its performance is limited by some problems, including population diversity, premature convergence, getting stuck in a local optimum, computational complexity, and the algorithm's challenging behaviour in striking a balance between exploration and exploitation. Additionally, several researchers have extensively utilized BPSO to boost the performance of the classifier in classification problems; however, the performance of the BPSO is also impacted by some problems, including population diversity, premature convergence, getting stuck in the local optimum, and the difficulty of maintaining a balance between the algorithm's exploitation and exploration capabilities. In addition, several researchers have used various approaches to address this problem.

To raise the performance of BPSO, for example, [42] used two methods to solve the problems associated with BPSO (i.e., local minima trapping and premature convergence). First, to quicken the convergence rate and counteract the inclination to abruptly reach the local optimum, the BPSO includes a self-adaptive inertia weight factor. Secondly, the acceleration coefficient was adjusted using a chaotic sequence to maintain a balance between the exploration and exploitation capability of the BPSO. [41] improved the performance of BPSO by utilizing chaotic search and dynamic adaptive adjustment techniques, which addressed the problems "of low search precision, poor local search ability, and local minimum trapping". It is possible to achieve better global search capabilities, higher convergence accuracy, and the ability to stop the BPSO algorithm from converging too soon by combining the chaotic search method with the dynamic adaptive adjustment.

In addition, [43] "used three improvement techniques to boost RSA's efficiency. Adding a local escaping operator to RSA first improves its ability to escape the local optimum. The restart method is then modified to enhance global space exploration". Ultimately, new candidate positions are generated and an effective balance between the algorithms' exploitation and exploration behaviours is preserved by employing ghost opposition-based learning that combines different positions. However, nothing was done to address the problems affecting the RSA algorithm, the BPSO's performance in this study was, however, enhanced by carefully chosen parameters like maximum velocity ($V_{\max}$), acceleration limitations that represent cognitive (c_1) and social variables (c_2), and inertia weight (w) based on literature. These findings suggest that to enhance the efficiency of the optimization technique during the optimization of the classifier, you should identify and address any problems that are influencing the effectiveness of this type of optimization technique.

Furthermore, the results in Table 3 showed that the RSA-SVM and BPSO-SVM models outperform the SVM and SVM & ANN models developed by [40] and [23] on datasets related to gray leaf spot disease and common rust disease, respectively. These findings suggest that using an optimization algorithm to refine the SVM may be necessary to improve its performance in the classification task. Nonetheless, the effectiveness of the optimization algorithm employed could impact the performance of the classification model. As demonstrated in Table 3, the performance accuracy of RSA-SVM and BPSO-SVM is higher than that of the GA-SVM model created by [40], and the FSO-SVM model created by [15] is higher than both of them.

Finally, Table 3 shows that the RSA-SVM and BPSO-SVM models both outperform the deep learning models OSCRNet, CNN, and YOLOv5s-C3BAM models, which were developed by [39], [28], and [6], respectively, in terms of performance accuracy. However, "In numerous fields, such as cybersecurity, natural language processing, bioinformatics, robotics and control, and medical information processing, among many others, the Deep Learning model has been shown to outperform popular machine learning techniques."[44]. The performance accuracy results of the deep learning models Faster-RCNN and ResNet-9 developed by [12] and [22] are higher than those of the BPSO-SVM and RSA-SVM models, as shown in Table III, to support this claim. Moreover, as demonstrated in Table III, the FSO-SVM model created by [15] outperforms BPSO-SVM and RSA-SVM in terms of performance accuracy, though both models are machine learning models. These results imply that the best classification models may not always come from optimizing the classifier alone. Various factors influence performance, such as the size of the dataset collected, the methods used for preprocessing and segmentation, the methods for feature extraction and selection, and the strength of the classifier and optimizer.

Moreover, the application of the recently created classification models (BPSO-SVM and RSA-SVM) in the field of crop pathology will make early crop disease detection simpler and less expensive. This will help a lot of farmers because it will stop the disease from moving from sick to healthy crops. The suggested models will also prevent crop losses, such as a reduction in yield quantity and quality or a loss in agricultural fields, and increase the efficacy of disease control strategies.

V. CONCLUSION AND FUTURE WORKS

It is thought to be imperative to detect diseases of crop leaves as soon as possible since a delayed detection of the disease can reduce the quantity and quality of crop products. The research produced an improved support vector machine (SVM) that can accurately identify common rust and gray leaf spot maize diseases. The binary particle swarm optimization (BPSO) and reptile search algorithm (RSA) meta-heuristic algorithm were used to fine-tune the hyperparameters in the SVM and select the discriminating parameter of the classifier and features of the lesions to avoid overfitting of the classification models and improve performance accuracy. The proposed models, RSA-SVM and BPSO-SVM, are evaluated and contrasted with the current models of classification within the framework of different conventional and contemporary mechanisms.

Furthermore, in every performance metric that was used to compare the two models, the BPSO-SVM model outperforms the RSA-SVM model. Additional comparisons of accuracy, sensitivity, and precision between the suggested models and the existing models indicate that the suggested model can rival some of the existing models. Future research could look into the best approach to use the models for disease detection and real-time maize monitoring. Moreover, additional research can leverage the hybridization of the two models' strengths to create a potent optimizer for fine-tuning the SVM's hyperparameters and choosing features that set it apart from the diseased leaf lesion to improve performance accuracy.

CONFLICTS OF INTEREST STATEMENT

On behalf of authors whose names appeared above, I certify that we have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

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