Published by
NIGERIAN SOCIETY OF PHYSICAL SCIENCES
Available online @ https://asr.nsps.org.ng/index.php/asr

African Scientific Reports 4 (2025) 320

African Scientific Reports

Hyperparameter optimisation for support vector machine-based disease detection in maize leaf variants

O. B. Ayoade*, M. O. Raji, A. A. Akindele, K. J. Yusuf-Mashopa, M. F. Abdulrauff, I. A. Raji, F. B. Musah

Department of Data Science, Informatics and Computer Science, Emmanuel Alayande University of Education, Oyo, Nigeria

Abstract

One of the main staple crops farmed and extensively consumed in Africa is maize. However, despite being widely used as a human diet and a raw material for animal feed, several diseases on leaves endanger their productivity and result in a sizable yield loss. However, Nigerian farmers typically employ antiquated techniques to detect plant diseases, which are labour-intensive and prone to mistakes, making the constant need for more effective solutions necessary. Although numerous researchers have developed classification models using Support Vector Machine (SVM) to identify and classify diseases in crop leaves. However, optimising a Support Vector Machine (SVM) is critical because it allows for fine-tuning of its parameters to achieve the best possible performance on a given dataset. Therefore, to optimise Support Vector Machines, this study created a hybrid model that combines Binary Particle Swarm Optimisation (BPSO) with a Reptile Search Algorithm (RSA). The Kaggle village datasets provided images of the leaves of maize. After being converted to grayscale, the pictures were improved with bi-histogram equalisation methods. After segmenting the leaf's affected area using the Sobel edge detection method, texture, shape, and colour features were extracted using Gray Level Spatial Dependence and colour moment. Every classification model was trained and tested using the 10-fold approach. The performance of the suggested method was compared with a few other machine learning and deep learning models that are currently in use. Regarding identifying maize diseases, the results showed that the BPSO-RSA-SVM model performed better than all other optimised support vector machine models and some deep learning state-of-the-art models. The model demonstrates its efficiency in advancing agricultural disease detection with an average accuracy of 97.01% and a false positive rate of 3.85% compared with BPSO-SVM and RSA-SVM which achieved 96.65% & 95.44% and 3.30% & 4.60% for accuracy and false positive rate, respectively.

DOI:10.46481/asr.2025.4.3.320

Keywords: Farmers, Livestock, Machine learning, RSA, SVM

Article History :
Received: 16 May 2025
Received in revised form: 05 October 2025
Accepted for publication: 06 October 2025
Published: 28 October 2025

1. Introduction

Maize, scientifically known as *Zea mays*, is a vital staple food crop that plays a crucial role in global food security and is extensively cultivated throughout Sub-Saharan Africa [1, 2]. After South Africa, Nigeria is arguably Africa's second-largest producer of maize. Ethiopia was ranked third among the African countries that produce the most maize. In 2019, the combined output of maize

*Corresponding author Tel. No: +234-805-414-1040.
Email address: ayoadeob@eauedoyo.edu.ng (O. B. Ayoade)

in South Africa, Nigeria, and Ethiopia accounted for approximately 39% of the total output of the continent. Approximately two-thirds (64%) of the maize produced in Nigeria is produced in the top ten states (Borno, Niger, Plateau, Katsina, Gombe, Bauchi, Kogi, Kaduna, Oyo, and Taraba [3]. It is by far the largest cereal crop in terms of area and production volume and is the most consumed staple food in Nigeria [4].

In Nigeria, maize is widely used for human consumption, in animal feed, pharmaceutical industries, food manufacturers, breweries, flour mills and other industries. Nearly 80 per cent of the maize grain is used for human consumption and animal feed, with the remaining 20 per cent utilised for industrial processing of diverse products [4]. With a per capita consumption of about 35 kg per person per year, maize accounts for an estimated 10% of the daily calorie intake in the country. The crop is also an important source of cash income for farmers and contributes significantly to agro-industrial development, particularly in the livestock feed industry [5]. Maize production is significantly hampered by maize leaf diseases brought on by fungi and viruses. Notably, maize gray leaf spot (MGLS) disease and maize common rust (MCR) disease are two of the most destructive diseases limiting maize production in Nigeria [6].

Many researchers use the visual analysis of symptomatic leaves as the primary method for identifying crop diseases in the most common parts of the crop [7]. Early crop disease detection is crucial for enabling farmers to take the necessary control actions, such as selecting the appropriate pesticides to boost crop yield and improve overall quality [8, 9]. Besides, farmers in Nigeria frequently use visual analysis of disease symptoms on leaves to determine the type and severity of crop diseases. However, this technique is subjective, prone to errors, time-consuming, and costly [10]. Moreover, incorrect disease diagnosis can result in inappropriate pesticide application, decreased maize yield, pollution of the environment from pesticide waste, and possible harm to humans and non-target organisms [11].

Computer vision-based automatic systems have also demonstrated the ability to decrease losses and boost productivity, making them one of the most promising methods to get around the aforementioned constraints [12]. Digital images have been utilised to identify plant diseases through the use of machine learning and deep learning techniques [13]. For example, Khade and Patil [14] created a hybrid deep learning method for maize crop disease severity level prediction that combines CNN with transfer learning features with ResNet 101 and Inception-V3 models. 4,308 datasets were created by augmenting a total of 1077 of the five disease levels. Inception-V3 and ResNet 101 were both utilised to extract features from the input datasets. The classifier's hyperparameters have been adjusted appropriately, and the training and testing datasets were chosen using a 5-fold analysis. With an accuracy of 0.956, a high specificity of 0.985, a sensitivity of 0,956, and an F1-Score of 0.956, the results show the best performance.

Moreover, Li *et al.* [15] created the Sim-ConvNext convolutional neural network model, which included a parameter-free Sim AM attention module for the maize classification system. The researchers made use of a publicly accessible maize dataset that included 3,534 photos and eight distinct types of maize disease: "dwarf leaf", "healthy", "grey", "severe grey", "rust", "severe rust", "leaf spot", and "severe leaf spot". Five data augmentation techniques (resizing, hue, cropping, rotation, and edge padding) were applied to the dataset to improve it and produce 17,670 images. After preprocessing the data and adjusting the image size to 224 × 224, the dataset was divided into training, validation, and testing sets with a 6:2:2 ratio. The enhanced model was then compared to other models in a comparative analysis, and the methodology showed a 95.2% accuracy rate.

Furthermore, Song *et al.* [16] created a deep-learning model for maize disease detection based on an Attention Generative Adversarial Network. Part of the data used in this study was gathered in the field at Clung Agricultural University's West District Science Park. The 1,040 dataset consists of five diseased dataset classes (i.e., "healthy leaves", "rust", "large spot disease", "small spot disease", and "maize smut"). Through data augmentation techniques like cut out, cut in, cut mix, and mix up, the dataset's diversity was increased to 2,286. A high-accuracy detection method based on few-shot learning and Attention Generative Adversarial Network (Attention-GAN) was developed to address the problem of maize disease detection. According to experimental results, this model achieves 97%, 92%, and 95% accuracy, recall, and mean average precision, respectively, which are higher than other baseline models.

In addition, an automated system for identifying maize leaf disease using the PRF-SVM model was proposed by Bachhal *et al.* [1]. Three potent parts were combined to create the PRF-SVM model: PSPNet, ResNet50, and Fuzzy Support Vector Machine (FUSSYSVM). The dataset was taken from the Plant Village dataset by the authors. The dataset contained "574 photos of maydis leaf blight", "456 images of turcicum leaf blight", "1,532 images of common rust", "1,430 images of southern rust", and "1,139 images of grey leaf spot". There are "1,587 pictures of maize in a healthy state". The pictures were enlarged to 224 x 224 x 3. For noise reduction, the Gaussian blurring technique is employed. Data augmentation techniques like rotation, flipping, zooming, and cropping were carried out. With the suggested approach, an average accuracy of roughly 96.67% and a maximum average precision of 81.0% are attained. Zeb *et al.* [17] used the AlexNet model to create a deep learning framework for the detection and categorisation of diseases affecting maize leaves. Four categories of maize disease are present in the dataset used: "common rust", "northern leaf blight", "Cercospora leaf spot", "grey", and "normal". This model's accuracy rate was 96%.

A deep transfer learning model for fine-grained maize leaf disease classification was developed by Khan *et al.* [18]. The dataset was gathered by the authors from the Plant Village dataset, which is openly available. Nine maize diseases and one healthy maize leaf make up the dataset. "Maize Common Rust (MCR)", "Maize Curvularia Leaf Spot (MCLS)", "Maize Maydis Leaf Blight (MMLB)", "Maize Post Flowering Stocks Rots (MPFSR)", "Maize Rajasthan Downy Mildew (MRDM)", "Maize Bacterial Leaf and Sheath Blight (MBLSB)", and "Maize Turcicum Leaf Blight (MTLB)" are the maize diseases. To improve model training and convergence, the images were resized to 224 × 224 pixels and three different deep-learning optimisers were used. Adaptive Moment Estimation (ADAM), Root Mean Square Propagation (RMSPROP), and Stochastic Gradient Descent (SGD) are the three optimisers. Four deep learning frameworks were created by the authors: Inception V3, ResNet50, VGGNET, and InceptionResNetV2. The highest validation accuracy of 87.57%, precision of 90.33%, and recall of 99.80% are attained by the ResNet50.

Elmasry *et al.* [19] created a brand-new hybrid method for maize disease detection based on CNN. The researchers gathered 4,126 photos of 1,306 common rust, 512 gray leaf spots, 1,146 blight, and 1,162 healthy leaves in four classes from a dataset of maize leaf diseases. To expedite the convergence speed, the dataset was preprocessed by first resizing the images to 224 × 224 pixels and normalising the dataset. The DNN layer, in conjunction with DenseNet 121, forms the basis of the suggested model. Four popular pre-trained models are compared with this proposed model: ResNet50, MobileNet, EfficientNetB0, and Xception. With an accuracy of 96.1%, precision of 95.2%, and recall of 95.8%, the DenseNetDNN model outperforms all other models in the identification of maize disease, according to the results.

The Support Vector Machine (SVM) can effectively find the best separating hyperplane between classes, maximising the margin between them, but fine-tuning the SVM hyperparameters can be difficult Pannakkong *et al.* [20]. However, Individual algorithms, or those improved by any of the aforementioned strategies, can increase the diversity of initial solutions and potentially improve exploration in algorithms such as RSA, but they do not provide the same level of exploitation as RSA and BPSO combined. Hybridisation of two or more optimisation techniques allows for a more comprehensive search of the parameter space, resulting in a balance of exploitation and exploration search behaviours, as well as a potentially more robust solution for scaling SVM input features, resolving SVM challenges of hyperparameter tuning, datasets with noise, outliers, and overlapping classes than using a single algorithm with or without these strategies. As a result, this study used a hybrid optimisation approach (BPSO-RSA) to fine-tune the support vector machine's hyperparameters. The BPSO and RSA algorithms were run concurrently to overcome the high computational complexity posed by either algorithm, resulting in a shorter computational time for the experiment, which was reported equally.

2. Methodology

This section contains comprehensive details on the obtained dataset, preprocessing procedures, segmentation, and feature extraction, in addition to a suggested methodology block diagram. The block diagram that illustrates the suggested classification model's methodology is shown in Figure 1.

2.1. Dataset

One thousand, six hundred and forty images of maize leaf disease were gathered to serve as input images. The Kaggle village plant dataset is the source of the image dataset. Images of maize leaf diseases, such as maize common rust disease (MCRD), maize gray leaf spot disease (MGLSD), and healthy maize leaves, are included in the dataset. Samples of healthy and diseased maize leaves used in the investigation are shown in Figure 2. The distribution of the dataset that was obtained for the study from the Kaggle Village Dataset (https://www.kaggle.com/datasets/smaranjitghose/corn-or-maize-leaf-disease-dataset) is shown in Table 1.

2.2. Image preprocessing

During the image preprocessing stage, images were first resized to streamline the classification model and remove unnecessary pixel information. Later, the RGB images were converted to grayscale, and the bi-histogram equalisation technique was used to improve the image contrast. The image quality was further enhanced by using morphological filtering to sharpen the image. Finally, the adaptive median filtering method was used to denoise the images before segmentation processing. There were several challenges with preprocessing procedures, such as the loss of discriminative colour information when converting RGB images to greyscale and distortion and detail loss during resizing. Additionally, using adaptive median filtering during the denoising process, which is computationally demanding, increased the experiment's computational complexity.

2.3. Image Segmentation and feature extraction

The Sobel edge detection method was used to differentiate between the lesioned and healthy portions of the leaf. Then, a Gray Level Cooccurrence Matrix was used to extract the following texture features from a haralic statistical feature: Energy, Contrast, Correlation, Homogeneity, and Entropy. The following shape features were also extracted using it: eccentricity, area, solidity, rectangle, equidimeter, and perimeter. Four colour moment methods were used to extract the following colour features: Median, Standard Deviation, Asymmetry, and Kurtosis. The linear combining method, as outlined in Anantharatnasamy *et al.* [21], is used to combine the three retrieved features (colour, texture, and shape).

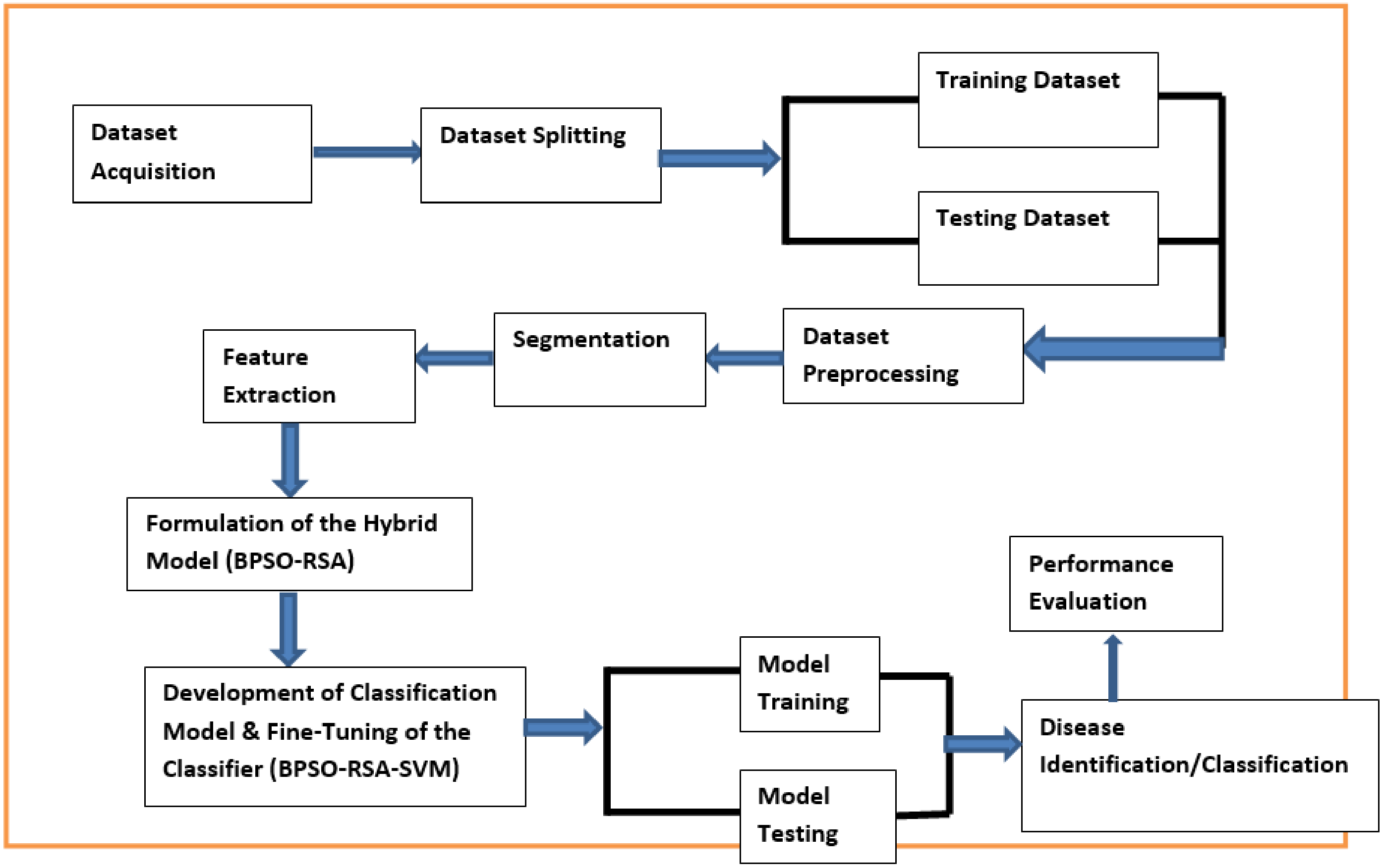

Figure 1. Proposed methodology block diagram.

Table 1. Distribution of the dataset acquired from the Kaggle village dataset.

Type of dataset	Quantity of the dataset		
	Actual images	Training images	Testing images
Maize Common Rust Disease (MCRD)	570	513	57
Maize Gray leaf Spot Disease (MGLSD)	570	513	57
Healthy	500	450	50
Total	1,640	1,476	164
Percentage		90%	10%

2.4. *Classification techniques*

The performance of Support Vector Machines (SVMs) is largely dependent on the careful selection of feature subsets and parameters (such as kernel type, penalty parameter, and gamma). Conventional optimisation techniques frequently have slow convergence, poor search space exploration, or local optima. These issues can be resolved more successfully by combining Binary Particle Swarm Optimisation (BPSO) with the Reptile Search Algorithm (RSA). Because the hybrid BPSO-RSA-SVM model combines the global exploration capability of RSA with the effective discrete search of BPSO, the result is a more balanced optimisation process that improves SVM generalisation, lowers feature dimensionality, and increases classification accuracy. The hybrid BPSO-RSA-SVM combines the robust exploration and local optima avoidance of RSA with the quick convergence and binary optimisation capabilities of BPSO to produce a more dependable and effective optimisation framework for SVM classification tasks.

3. Results and discussion of the findings

The proposed work was implemented in the MATLAB R2020a environment to build a graphics processing Unit (GPU) for the development of machine learning models, which is powered by Intel Xeon CPU @1.20 GHz, 13 GB RAM, and 12 GB DDR5 VRAM.

Figure 2. Samples of the maize dataset used for the study.

3.1. Performance evaluation metrics BPSO-RSA-SVM classification model

The model was trained and evaluated using the dataset generated to verify the effectiveness of the multiclass support vector machine classification model. Table 2 shows the performance evaluation results of the developed model. The findings indicate that, with an average accuracy of 97.02%, precision of 97.46%, sensitivity of 96.95%, specificity of 97.10%, false positive rate of 2.90%, and computational time of 46.95s, the BPSO-RSA-SVM model demonstrated a good performance in classifying maize diseases. Additionally, Table 2 demonstrates that misclassification for ”maize common rust disease (MCRD) is much lower than for ”maize gray leaf spot disease (MGLSD)”. These results show how accurately the BPSO-RSA-SVM model classifies the diseases maize gray leaf spot disease (MGLSD) and common rust disease (MCRD).

3.2. Performance comparison of the evaluation metrics of BPSO-RSA-SVM and existing classification models on maize datasets

The developed hybridised model (BPSO-RSA-SVM) and other currently in use classification models are compared in Table 3. The methodology employed in this study is similar to studies carried out by Nivethithaa and Vijayalakshmi [22], in which the authors similarly optimised support vector machines using a meta-heuristic algorithm as a classifier for their classification model. In terms of sensitivity, accuracy, and precision, the BPSO-RSA-SVM model performs better than the models developed by Li *et al.* [15], Song *et al.* [16], Bachhal *et al.* [1], Zeb *et al.* [17], Elmasry *et al.* [19], Solihin *et al.* [23], and Restil *et al.* [24]. Besides, in terms of accuracy, specificity, and sensitivity, the Enhanced KNN, SVM & Back Propagation Neural Network (BPNN), Multi-Kernel Support

Table 2. Performance evaluation metrics of BPSO-RSA-SVM on the maize datasets.

Type of Dataset	Performance Evaluation Metrics Results					
	False Positive Rate (FPR) (%)	Specificity (%)	Sensitivity (%)	Precision (%)	Accuracy (%)	Computation Time (sec)
Maize Common Rust Disease (MCRD)	2.80	97.20	97.04	97.55	97.11	46.63
Maize Gray Leaf Spot Disease (MGLSD)	3.00	97.00	96.86	97.37	96.93	47.27
Average	2.90	97.10	96.95	97.46	97.02	46.95

Table 3. Performance comparison of the evaluation metrics of BPSO-RSA-SVM and existing classification models on maize datasets.

Author(s) and Models	False Positive Rate (%)	Specificity (%)	Sensitivity (%)	Precision (%)	Accuracy (%)	Computation Time (Sec)
Khade and Patil [14] "ResNet101+Inception V3"	-	98.5	-	-	95.60	-
Li *et al.* [15] "SIM-ConVNeXt"	-	-	93.30	93.90	95.20	-
Song *et al.* [16] "Attention-GAN"	-	-	92.00	95.00	97.00	-
Bachhal *et al.* [1] "PRF-SVM"	-	-	78.70	84.10	95.40	-
Zeb *et al.* [17] "AlexNet"	-	-	96.00	-	95.00	-
Khan *et al.* [18] "ResNet50"	-	-	99.80	90.33	87.51	-
Elmasry *et al.* [19] "DenseNetDNN"	-	-	95.80	95.20	96.10	-
Nivethithaa and Vijayalakshmi [22] "Fish Swarm Optimiser (FSO)-SVM"	-	-	97.58	98.10	98.30	-
Solihin *et al.* [23] "SVM"	-	-	56.44	58.89	56.44	-
"K-Nearest Neighbour (KNN)"	-	-	65.86	65.47	65.86	-
"Stochastic Gradient Descent (SGD)"	-	-	71.44	70.08	71.44	-
Restil *et al.* [24] "Multinomial Naïve Bayes (MNB)"	-	-	79.24	79.88	92.72	-
"KNN"	-	-	94.38	88.57	99.54	-
Noola and Bassavaraju [25] "Enhanced KNN"	-	99.71	99.60	-	-	-
Ibrahim *et al.* [26] "SVM"	-	98.48	99.18	-	98.74	99.71
"Random Forest (RF)"	-	95.27	97.46	-	96.49	156.79
"Back Propagation Neural Network (BPNN)"	-	97.16	98.47	-	97.82	133.35
Jayanthi and Shashikumar [27] "Multi-Kernel Support Vector Machine (MKSVM)"	-	99.02	97.34	-	97.34	-
"KNN"	-	96.00	89.00	-	87.30	-
"SVM"	-	97.00	91.04	-	90.00	-
Ayoade *et al.* [28] "BPSO-SVM"	3.30	96.70	96.60	97.11	96.65	59.64
"RSA-SVM"	4.60	95.40	95.47	95.98	95.44	60.93
Developed Model BPSO-RSA-SVM	2.90	97.10	96.95	97.46	97.02	46.95

Table 4. One-Sample Statistics (BPSO-RSA-SVM Model).

	N		Std. Deviation	Std. Error Mean				95% Confidence Interval of the Difference	
Performance Metrics	12	Mean Difference	2.11546	.61068	T	Df	Sig. (2-tailed)	Lower	Upper
Accuracy	12	4.86667	2.11546	.61068	7.969	11	.000	3.5226	6.2108
False Positive Rate	12	95.13333	.38848	.11214	155.783	11	.000	93.7892	96.4774
Specificity	12	97.40128	.60329	.17415	868.544	11	.000	97.1545	97.6481
Sensitivity	12	97.23934	.21019	.06068	558.352	11	.000	96.8560	97.6226
Precision	12	96.78367	39.23991	11.32759	1595.098	11	.000	96.6501	96.9172
Computational Time	12	73.76681	2.11546		6.512	11	.000	48.8350	98.6987

Vector Machine (MKSVM) models created by Noola and Bassavaraju [25], Ibrahim *et al.* [26], and Jayanthi and Shashikumar [27] all outperform the BPSO-RSA-SVM model.

Furthermore, results in Table 4 show that the BPSO-RSA-SVM classification model is statistically significant since the p-values for all the performance evaluation metrics used to evaluate the classification model are less than 0.05.

3.3. Discussion of the findings

Table 2's results 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-RSA-SVM model performs better than both the BPSO-SVM and RSA-SVM models developed by Ayoade *et al.* [28], shown in Table 3. The BPSO-RSA-SVM model outperforms current systems by combining hybrid feature selection for the best dimensionality reduction with robust preprocessing for clean input data. In feature selection, RSA preserves diversity and avoids local minima, whereas BPSO accelerates convergence. Comparing them to models that rely on traditional preprocessing or individual optimisation algorithms, they provide a small, noise-resistant, and discriminative feature set for SVM, which greatly improves classification performance.

Another explanation is that the BPSO-RSA adaptive threshold of the hybrid model may have a significant impact on the BPSO-RSA-SVM hybridised classification model, ultimately allowing it to surpass both the RSA-SVM and BPSO-SVM classification models. But when the advantages of RSA and BPSO were combined, a strong hybrid optimiser that could choose the best SVM parameter values was created. The results of Bousmaha [29] and Liu and Fu [30], who found that hybrid optimisers outperformed non-hybrid optimisers in improving classifier performance, can be used to support this claim. Liu and Fu [30] created an optimised support vector machine classification model by hybridising the Cuckoo Search Algorithm (CS) with Particle Swarm Optimisation (PSO), while Bousmaha [29] created an optimised model by hybridising the Aquila Optimiser (AO) with the Whale Optimisation

Algorithm (WOA). Liu and Fu [30]'s study found that the CS-PSO-SVM classification model performed better than both the CS-SVM and PSO-SVM classification models, and Bousmaha [29] found that the AOWOA-SVM classification models performed better than WOA-SVM and AO-SVM.

Moreover, the results presented in Table 3 demonstrate that the BPSO-RSA-SVM classification models perform better than the MNB and KNN models developed by Restil *et al.* [24], as well as the SVM, KNN, and SGD models developed by Solihin *et al.* [23]. According to these results, the classification task's performance might be enhanced by optimising supervised machine learning methods like SVM, KNN, SGD, and MNB. The classification model's performance, however, may be impacted by how well the optimisation algorithm used is working. The FSO-SVM classification model, created by Nivethithaa and Vijayalaskshmi [22], achieves higher performance accuracy than the BPSO-RSA-SVM classification model, as shown in Table 2.

Furthermore, Table 3's findings demonstrate that, in terms of sensitivity, accuracy, and precision, the BPSO-RSA-SVM model performs better than the deep learning models SIM-ConVNext, Attention-GAN, PRF-SVM, AlexNet, and DenseNetDNN. But "the Deep Learning model has been shown to outperform popular machine learning techniques in numerous fields, such as cybersecurity, natural language processing, bioinformatics, robotics and control, and medical information processing, among many others" [31]. This assertion is supported by the fact that, as Table 3 demonstrates, the deep learning models created by Khade and Patil [14] and Khan *et al.* [18] have higher specificity and sensitivity performances, respectively, than the BPSO-RSA-SVM model.

Furthermore, Table 3 shows that, although the proposed model and all of these models were machine learning models, the FSO-SVM, EKNN, SVM & BPNN, and MKSVM models developed by Nivethithaa and Vijayalaskshmi [22], Noola and Bassavaruju [25], Ibrahim *et al.* [26], and Jayanthi and Shashikumar [27], respectively, outperform BPSO-RSA-SVM in terms of specificity, sensitivity, precision, and accuracy. These results suggest that just optimising the classifier does not guarantee that the classification model will perform at its best; rather, many other factors, in addition to the optimiser, improve the model's performance. These factors include the size of the dataset collected, the preprocessing and segmentation techniques used, the feature extraction and selection techniques, and the classifier and optimiser's combined strength.

Ultimately, in the field of crop pathology, the recently developed classification model (BPSO-RSA-SVM) will simplify and lower the cost of early crop disease detection. Many farmers will benefit from this, as it will prevent the disease from spreading from diseased to healthy crops. Additionally, the proposed models will boost the effectiveness of disease control tactics and avoid crop losses, such as a decline in yield quantity and quality or a loss in agricultural fields.

3.4. Implications for practice

The development of the BPSO-RSA-SVM model presents noteworthy implications for practical agricultural applications, particularly in maize disease management. The model underscores the potential to enhance precision agriculture by facilitating the early and accurate detection of maize leaf diseases. Timely diagnosis is crucial for minimising crop losses, enhancing sustainable food security, and reducing the financial burden on farmers by preventing the escalation of disease outbreaks. The model's capacity to optimise classification performance enables it to function effectively across diverse environmental conditions, thereby supporting its suitability for real-world field deployment.

Additionally, the model is applicable on devices with limited resources due to the computational efficiency attained through the hybridisation of RSA and BPSO. This enables smooth integration into low-cost sensors, mobile-based applications, or imaging systems mounted on drones for continuous field surveillance. Through this integration, rural communities and smallholder farmers can take advantage of cutting-edge digital farming tools without requiring expensive computer infrastructure.

Lastly, since the model framework can be retrained for use in other staple crops like rice, cassava, or wheat, the implications go beyond the production of maize. This scalability demonstrates the suggested approach's adaptability and potential to support digital transformation in agriculture across various crop systems and geographic locations.

3.5. Steps for real-world implementation

1. Development of datasets: Create a sizable collection of maize leaf photos taken in various lighting, disease, and location scenarios.
2. Training and validation of the model: For disease classification, use BPSO-RSA-SVM and verify against actual field settings.
3. Deployment of the Platform:
    (a) A mobile application for farmers.
    (b) A cloud platform for extensive surveillance.
    (c) Integration with drones or IoT sensors
4. Capacity building: Training farmers and extension agents on how to utilise the mobile application or devices.
5. Government & NGO Support: Collaborate with agricultural agencies to promote broader adoption and policy integration.

4. Conclusion

This study has introduced BPSO-RSA-SVM, a hybrid optimisation framework that improves Support Vector Machine performance by combining Binary Particle Swarm Optimisation with the Reptile Search Algorithm. When combined with hybrid feature selection, robust preprocessing techniques allowed the model to achieve higher generalisation, lower dimensionality, and better accuracy than previous methods. It has been demonstrated that RSA and BPSO's complementary strengths balance exploration and exploitation, overcoming common drawbacks like local optima and premature convergence. The results show promise for agricultural image classification tasks, but more work is needed to evaluate the model's performance on various crop datasets, improve feature extraction techniques, and look into scalable deployment methods for large-scale applications.

Despite its high performance, the BPSO-RSA-SVM model may not be scalable on large datasets due to memory and computational constraints. To mitigate these challenges, parallelised optimisation to speed up training, dimensionality reduction, and approximate SVM solvers can all be used. Additionally, future studies should look into cloud–edge integration and incremental retraining to ensure the model remains useful and effective in real-world agricultural applications.

Data availability

Data is available at Kaggle Village Dataset (https://www.kaggle.com/datasets/smaranjitghose/corn-or-maize-leaf-disease-dataset).

Acknowledgment

We appreciate the reviewers and the editorial team for all their efforts put into making this paper a reality.

References

[1] P. Bachhal, V. Kukreja, S. Ahuja, U.K. Lilhore, S. Simaiya, A. Bijalwan, R. Alroobaea & S. Algarni, "Maize leaf disease recognition using PRF-SVM integration: A breakthrough technique", Scientific Reports **14** (2024) 3. https://doi.org/10.1038/s41598-024-60506-8.
[2] U. Grote, A. Fasse, T.T. Nguyen & O. Erenstein, "Food security and the dynamics of wheat and maize value chains in Africa and Asia", Frontiers in Sustainable Food Systems **4** (2021) 2. https://www.frontiersin.org/journals/sustainable-food-systems/articles/10.3389/fsufs.2020.617009/pdf.
[3] PwC, "Positioning Nigeria as Africa's leader in maize production for AfCFTA: Insights on global maize production and how Nigeria can position itself as Africa's leader in maize production" (2021). https://www.pwc.com/ng/en/assets/pdf/positioning-nigeria-as-africa-leader-in-maize-production-for-afcfta.pdf.
[4] T. Wossen, A. Menkir, A. Alene, T. Abdoulaye, S. Ajala, B. Badu-Apraku, M. Gedil, W. Mengesha & S. Meseka, "Drivers of transformation of the maize sector in Nigeria", Elsevier **38** (2023) 100713. https://doi.org/10.1016/j.gfs.2023.100713.
[5] T. Wossen, T. Abdoulaye, A. Alene, S. Feleke, A. Menkir & V. Manyong, "Measuring the impacts of adaptation strategies to drought stress: the case of drought tolerant maize varieties", Journal of Environmental Management **203** (2017) 108. https://doi.org/10.1016/j.jenvman.2017.06.058.
[6] M. Alhassan, "Most important pest and diseases of maize (Zea mays)" (2022). https://www.agriculturenigeria.com/main-pests-and-diseases-of-maize-zea-mays/.
[7] B. Natesan, A. Singaravelan, J.-L. Hsu, Y.-H. Lin, B. Lei & C.M. Liu, "Channel–spatial segmentation network for classifying leaf diseases", Agriculture **12** (2022) 5. https://doi.org/10.3390/agriculture12111886.
[8] A. Dubois, F. Teytaud & S. Verel, "Short term soil moisture forecasts for potato crop farming: a machine learning approach", Computers and Electronics in Agriculture **18** (2021) 10. https://www.sciencedirect.com/science/article/pii/S0168169920331070.
[9] E.L. Da Rocha, L. Rodrigues & J.F. Mari, "Maize leaf disease classification using convolutional neural networks and hyperparameter optimization", in Anais do XVI Workshop de Visão Computacional (WVC 2020), Brasil: Sociedade Brasileira de Computação - SBC, Oct. 2020, pp. 104–110. https://doi.org/10.5753/wvc.2020.13489.
[10] A. Waheed, M. Goyal, D. Gupta, A. Khanna, A. E. Hassanien & H. M. Pandey, "An optimized dense convolutional neural network model for disease recognition and classification in corn leaf", Computers and Electronics in Agriculture **175** (2020) 4. https://doi.org/10.1016/j.compag.2020.105456.
[11] T. Gunstone, T. Cornelisse, K. Klein, A. Dubey & N. Donley, "Pesticides and soil invertebrates: a hazard assessment", Frontiers in Environmental Science **9** (2021) 12. https://doi.org/10.3389/fenvs.2021.643847.
[12] A. Owino, "Challenges of computer vision adoption in the Kenyan agricultural sector and how to solve them: a general perspective", Advances in Agriculture **2** (2023) 6. https://doi.org/10.1155/2023/1530629.
[13] R. Kumar, A. Chug, A. P. Singh & D. Singh, "A systematic analysis of machine learning and deep learning based approaches for plant leaf disease classification: a review", Journal of Sensors **4** (2022) 5. https://doi.org/10.1155/2022/3287561.
[14] V. C. Khade & S. B. Patil, "A hybrid deep learning approach for crop disease severity level prediction", International Journal of Intelligent Systems and Applications in Engineering **12** (2023) 217. https://ijisae.org/index.php/IJISAE/article/view/4267.
[15] H. Li, M. Qi, B. Du, Q. Li, H. Gao, J. Yu, C. Bi, H. Yu, M. Liang, G. Ye & Y. Tang, "Maize disease classification system design based on improved ConvNeXt", Sustainability **15** (2023) 7. https://doi.org/10.3390/su152014858.
[16] Y. Song, H. Zhang, J. Li, R. Ye, X. Zhou, B. Dong, D. Fan & L. Li, "High-accuracy maize disease detection based on attention generative adversarial network and few-shot learning", Plants **12** (2023) 4. https://doi.org/10.3390/plants12173105.
[17] P. Zeb, A. M. Qasim, M. Qadir & S. U. Islam, "Maize leaves disease detection and classification using AlexNet model", The Science Tech **5** (2024) 124. https://www.researchgate.net/publication/380911196_Maize_Leaves_Disease_Detection_and_Classification_using_AlexNet_Model/link/6655bbba479366623a1b0f4d/download?_tp=eyJjb250ZXh0Ijp7InBhZ2UiOiJwdWJsaWNhdGlvbiIsInByZXZpb3VzUGFnZSI6bnVsbH19.
[18] I. I. Khan, S. S. Sohail, D. O. Madsen & B. K. Khare, "Deep transfer learning for fine-grained maize leaf disease classification", Journal of Agriculture and Food Research **16** (2024) 6. https://doi.org/10.1016/j.biosystemseng.2025.104162.
[19] A. Elmasry, W. Abdullah, B. Kang & Y. Nam, "A novel hybrid approach based on CNN for corn diseases detection", Optimization Agriculture **1** (2024) 98. https://doi.org/10.61356/j.oia.2024.1273.
[20] W. Pannakkong, K. Thiwa-Anont, K. Singthong, P. Parthanadee & J. Buddhakulsomsiri, "Hyperparameter tuning of machine learning algorithms using response surface methodology: a case study of ANN, SVM, and DBN", Mathematical Problems in Engineering **2022** (2022) 8. https://doi.org/10.1155/2022/8513719.

[21] P. Anantharatnasamy, K. Sriskandaraja, V. Nandakumar & S. Deegalla, "Fusion of colour, shape and texture features for content based image retrieval", Proceedings of the 8th International Conference on Computer Science and Education (ICCSE), 2013, p. 424. https://www.researchgate.net/profile/Kaavya-Sriskandaraja/publication/261424092_Fusion_of_colour_shape_and_texture_features_for_content_based_image_retrieval/links/5b21f4eeaca272277fa9741b/Fusion-of-colour-shape-and-texture-features-for-content-based-image-retrieval.pdf.

[22] K. K. Nivethithaa & S. Vijayalakshmi, "Optimized SVM model for maize and rice leaf disease detection", Data Acquisition and Processing **38** (2023) 3149. https://sjcjycl.cn/article/view-2023/pdf/02_3146.pdf.

[23] F. Solihin, M. Syarief, E. M. Rochman & A. Rachmad, "Comparison of support vector machine (SVM), k-nearest neighbour (KNN), and stochastic gradient descent (SGD) for classifying corn leaf disease based on histogram of oriented gradients (HOG) feature extraction", Electronics, Informatics, and Vocational Education (ELINVO) **8** (2023) 123. https://doi.org/10.21831/elinvo.v8i1.55759.

[24] Y. Restil, C. Irsan, M. T. Putril, I. Yani, B. Anshori & B. Suprihatin, "Identification of corn plant diseases and pests based on digital images using multinomial naive Bayes and k-nearest neighbour", Science and Technology Indonesia **7** (2022) 32. https://sciencetechindonesia.com/index.php/jsti/article/view/415.

[25] D. A. Noola & D. R. Bassavaraju, "Corn leaf image classification based on machine learning technique for accurate leaf disease detection", International Journal of Electrical and Computer Engineering (IJECE) **12** (2022) 2512. https://ijece.iaescore.com/index.php/IJECE/article/view/25952.

[26] M. A. Ibrahim, O. O. Ayotunde, A. A. Abeke, B. O. Samushudeen & O. O. Obiyemi, "Development of hybrid learning technique for detection and classification of plant diseases", Adeleke University Journal of Engineering and Technology **5** (2022) 89. http://aujet.adelekeuniversity.edu.ng/index.php/aujet/article/view/227/155.

[27] M. G. Jayanthi & D. R. Shashikumar, "Automatic tomato plant leaf disease classification using multi-kernel support vector machine", International Journal of Engineering and Advanced Technology (IJEAT) **9** (2020) 562. https://www.ijeat.org/wp-content/uploads/papers/v9i5/E9689069520.pdf.

[28] O. B. Ayoade, M. O. Oyediran, F. W. Ipeayeda, M. O. Raji, K. J. Yusuf-Mashopa & A. A. Akindele, "Classification of maize (Zea mays L.) leaf diseases variants based on Sobel edge detection and machine learning technique", International Journal of Mathematics and Computer Research **13** (2025) 5017. https://journals.indexcopernicus.com/api/file/viewByFileId/2314539.

[29] R. Bousmaha, "A novel hybrid Aquila optimizer with Whale optimization algorithm for global optimization, feature selection and optimizing SVM parameters", Proceedings of the 4th International Conference on Pattern Analysis and Intelligent Systems (PAIS), Oum El Bouaghi, Algeria, 2022, pp. 1–8. https://doi.org/10.1109/PAIS56586.2022.9946891.

[30] X. Liu & H. Fu, "PSO-based support vector machine with cuckoo search technique for clinical disease diagnoses", The Scientific World Journal (2014) 3. https://doi.org/10.1155/2014/548483.

[31] L. Alzubaidi, J. Zhang, A. J. Humaidi, A. Al-Dujaili, Y. Duan, O. Al-Shamma, J. Santamaria & M. A. Fadhel, "Review of deep learning: Concepts, CNN architectures, challenges, applications, future directions", Journal of Big Data **8** (2021) 1. https://doi.org/10.1186/s40537-021-00444-8.