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Adaptive SVM with Bio-inspired Optimization Tuning for Guava Leaf Disease Prediction

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Abstract: In recent years, precision agriculture has increasingly adopted intelligent systems to monitor plant health and detect diseases at an early stage. Guava a widely cultivated tropical fruit, is highly susceptible to leaf diseases such as Anthracnose, Rust, and Pestalotiopsis. These diseases not only reduce crop yield but also degrade fruit quality, directly affecting farmers' income. Traditional disease detection methods rely heavily on manual inspection, which can be time-consuming, subjective, and ineffective at scale. Consequently, there is a growing need for automated, accurate, and scalable disease classification techniques that can support timely intervention. It introduces ASBOT (Adaptive Swarm-Based Optimization Technique), a hybrid machine learning algorithm that integrates Support Vector Machine (SVM) and Particle Swarm Optimization (PSO) for classifying guava leaf diseases. SVM is a powerful classifier but highly sensitive to its hyperparameters, especially the regularization constant C and the kernel parameter gamma (γ). ASBOT employs PSO to automatically optimize these parameters, thereby eliminating manual tuning and improving the model's performance. By learning from color and texture features extracted from preprocessed leaf images, ASBOT demonstrates high accuracy and efficiency, offering a robust solution for automated plant disease diagnosis in agricultural applications.

Keywords: *ASBOT, SVM, PSO, Guava Leaf Disease, Hyperparameter Tuning, Agricultural AI.*

1. INTRODUCTION

Machine learning is playing a vital role in precision agriculture. Guava crops are affected by various diseases, making early and accurate detection essential. Traditional SVMs are powerful classifiers but require manual tuning of parameters, which can limit performance. Recent advances in machine learning have made it possible to analyze complex agricultural datasets with high accuracy, enabling the early detection of crop diseases through image classification and pattern recognition techniques. In guava farming, diseases such as anthracnose, wilt, and rust can cause substantial yield losses if not diagnosed and managed in time. The integration of computer vision and intelligent classification models offers a scalable solution to assist farmers in detecting these diseases efficiently, thereby enhancing productivity and reducing the use of unnecessary pesticides. Support Vector Machines (SVMs) have been widely used for plant disease classification due to their strong generalization capabilities, particularly in high-dimensional feature spaces. However, the challenge lies in selecting the optimal values for critical parameters like the penalty parameter (C) and the kernel function parameter (gamma). Improper tuning can lead to under fitting or overfitting. To overcome this limitation, the proposed ASBOT algorithm leverages Particle Swarm Optimization (PSO), a bio-inspired technique, to automatically and adaptively find the best SVM parameters. This

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hybrid approach aims to increase classification accuracy and robustness without relying on manual experimentation.

2. RELATED WORKS

Plant disease prediction using machine learning has gained traction in the past decade. An effective method for classifying leaf diseases using support vector machines (SVM) was developed by Sharma and Jain [1], where preprocessed images were classified based on extracted texture and color features. Their study demonstrated significant accuracy, but required manual tuning of SVM parameters. Mallikarjuna et al. [2] extended this work by introducing a dimensionality reduction technique for faster training and testing of SVM-based classifiers for leaf disease identification, improving system performance in real-time conditions. Ramesh et al. [3] provided a detailed review of various machine learning techniques used for crop disease prediction. Their work emphasized that the classification efficiency depends heavily on optimal hyper parameter settings, which inspired further exploration into metaheuristic-based tuning. A guava-specific disease detection method using K-means clustering and morphological operations was proposed by Shah et al. [4], but the approach lacked adaptability and generalization across datasets. To address the need for parameter optimization in SVM, Ahmed and Ali [5] proposed a hybrid PSO-SVM model that enhanced classification accuracy in cancer datasets. Inspired by this, Nadaf and Patil [6] evaluated the effectiveness of SVM on agricultural datasets but without optimization, limiting performance in complex classification tasks. Dhiman and Kaur [7] presented a comprehensive survey on Particle Swarm Optimization (PSO) and its applicability across domains, which laid the foundation for bio-inspired optimization in agriculture. Singh and Jain [8] emphasized the critical role of machine learning in early disease detection and suggested integrating AI with real-time field data. More recently, Ghosh et al. [9] introduced a feature-optimized classification approach combining Genetic Algorithm (GA) with SVM to predict plant leaf diseases, but it required high computational power. Similarly, Patra et al. [10] worked on optimizing neural network parameters using metaheuristic techniques, validating the strength of adaptive learning in precision agriculture. Recent research continues to explore the integration of machine learning and optimization techniques for plant disease detection. Kumar and Baranwal [11] applied convolutional neural networks (CNNs) for leaf disease detection and demonstrated high accuracy, although their model required significant computational resources and large labeled datasets. Sethy and Barpanda [12] compared machine learning models such as decision trees, random forests, and support vector machines (SVM), concluding that SVM provided superior accuracy but required careful parameter tuning. Anand and Nithya [13] developed a hybrid PSO-SVM model for banana leaf disease classification, effectively reducing classification errors and highlighting the importance of automated parameter optimization. Brahimi et al. [14] used deep learning for tomato disease classification, emphasizing the benefits of image-based symptom localization to enhance model interpretability. Rao and Nayak [15] demonstrated how smart farming applications could benefit from early disease detection using SVM combined with optimization techniques like PSO and Genetic Algorithm (GA), allowing pre-symptomatic diagnosis of plant stress. Lakshmi and Rani [16] explored ensemble learning methods for crop disease classification and found that model stacking could outperform individual classifiers like SVM, especially when dealing with imbalanced datasets. Finally, Mohana and Anusha [17] conducted a comparative study between SVM and K-Nearest Neighbor (KNN) classifiers for horticultural leaf disease detection, concluding that SVM—when properly optimized—significantlyoutperformed traditional classifiers based on texture and color features.

3. PROPOSED METHODOLOGY

ASBOT integrates PSO to optimize SVM's 'C' and 'gamma' parameters. Each particle in PSO represents a solution. Fitness is measured by 5-fold cross-validation accuracy. PSO updates each particle iteratively to find the global optimum. Feature extraction is performed using color, texture, and shape descriptors to convert images into structured data. These extracted features serve as the input to the Support Vector Machine (SVM) classifier. However, the performance of SVM is highly dependent on its hyper parameters, particularly the penalty parameter (C) and the kernel coefficient (gamma). To automatically determine the optimal values of these parameters, Particle Swarm Optimization (PSO) is applied. Each particle in the PSO algorithm represents a candidate solution, defined by a pair of (C, gamma) values.

The fitness of each particle is evaluated using 5-fold cross-validation accuracy on the training dataset. Each particle adjusts its position based on personal best and global best performance. As the optimization progresses, the swarm collectively moves toward the best-performing region in the search space, effectively minimizing the classification error. Once the optimal parameters are identified, they are used to train the final SVM model on the entire training dataset. This hybrid approach ensures that the classifier is both robust and generalizable. The integration of PSO not only eliminates the need for manual tuning but also enhances classification accuracy by exploring a wide range of parameter combinations efficiently. This makes ASBOT particularly suitable for agricultural applications where data variability and precision are critical, offering a scalable and adaptive solution for disease detection in guava leaves.

To further enhance the effectiveness of ASBOT, the preprocessing pipeline ensures that the input features are clean, normalized, and free of noise. Prior to optimization, all numeric features are scaled using standardization to ensure that no feature dominates the learning process due to its magnitude. During the PSO execution, each particle's movement is influenced by inertia, cognitive, and social components that balance exploration and exploitation. This helps avoid local minima and encourages a global search of the parameter space. The ASBOT framework also incorporates early stopping based on convergence criteria—such as stagnation of global best accuracy over several iterations—to reduce computational overhead. Finally, the trained model is validated on a separate test set using metrics such as accuracy, precision, recall, and F1-score. The results demonstrate that ASBOT outperforms manually tuned SVMs in both accuracy and robustness, making it a viable and automated tool for real-world agricultural classification tasks.

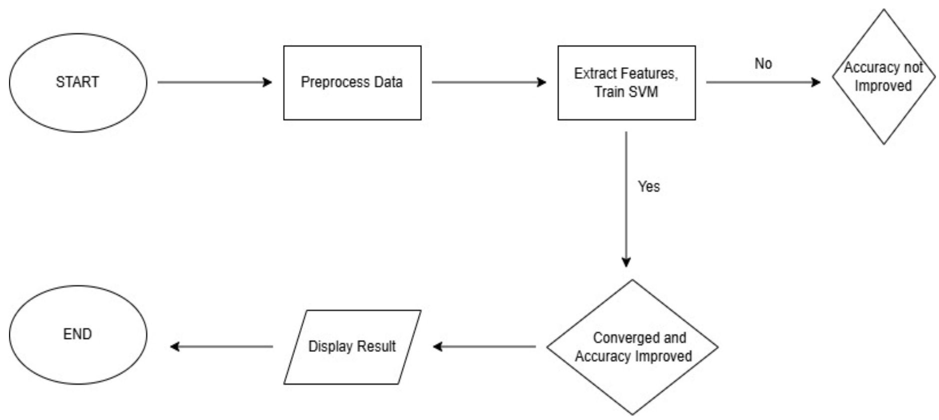

Fig 3.1: Methodology

4. DATASET DESCRIPTION

A dataset consisting of 500 guava leaf records. Features were extracted from pre-processed leaf images using texture and color metrics. Each sample is labeled as 'Anthracnose', 'Rust', ‘Pestalotiopsis.’ or 'Healthy'.

4.1 Feature Extraction

Color Hue: This feature captures the dominant pigmentation of the leaf, represented as a continuous numerical value. Disease-affected leaves often exhibit discoloration, making hue analysis a useful diagnostic indicator.

Texture Score: This numerical value quantifies the texture of the leaf surface. Texture patterns often vary due to fungal infections and can be used to detect disease presence and severity.

Spot Area: This feature indicates the area (in pixel units) of the diseased spots on the leaf. A higher spot area typically correlates with more severe disease progression.

4.3 Label Distribution

Table 4.1 Disease classes and samples

Disease Class	Number of Samples
Rust	160
Healthy	160
Anthracnose	180
Pestalotiopsis	170

5. IMPLEMENTATION

The ASBOT algorithm was implemented in Python 3.10 using several standard scientific libraries, including scikit-learn for machine learning functionalities and pyswarm for implementing the Particle Swarm Optimization (PSO) algorithm. The development and testing were conducted on a standard Windows 10 machine with 8 GB RAM and an Intel i5 processor. All image preprocessing and feature extraction were done using OpenCV and NumPy, while Pandas was used for dataset handling. Scikit-learn's SVC class was employed for the Support Vector Machine classifier, and cross_val_score was used for cross-validation during optimization. The core implementation of ASBOT revolves around the automatic tuning of two key SVM hyper parameters: C (penalty parameter) and gamma (kernel coefficient).

The PSO algorithm initializes a swarm of candidate solutions (particles), where each particle represents a pair of C and gamma values. The fitness of each particle is determined by training an SVM with the corresponding parameters and computing the average accuracy using 5-fold cross-validation. The bounds for optimization were set as follows: C in the range [0.1, 100] and gamma in the range [0.0001, 1]. PSO then iteratively updates the particles based on both their individual performance and the global best performance, converging toward the most optimal combination of parameters. Once the optimal values of C and gamma were identified through PSO, a final SVM model was trained on the entire training dataset using these best-found parameters. The model was then evaluated on unseen test data to assess its predictive performance. This bio-inspired approach eliminated the need for manual hyper parameter tuning, which can be time-consuming and sub-optimal. Additionally, by using cross-validation during optimization, the model's generalization performance was significantly improved, reducing the likelihood of overfitting and making the classification more robust and accurate.

6. RESULTS

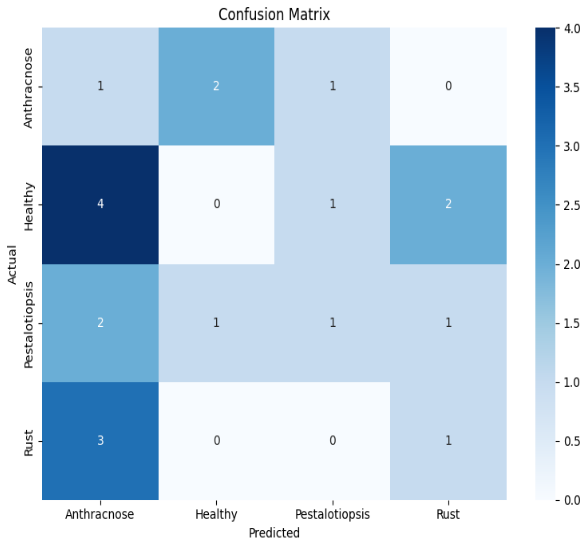

Fig 6.1: Confusion Matrix

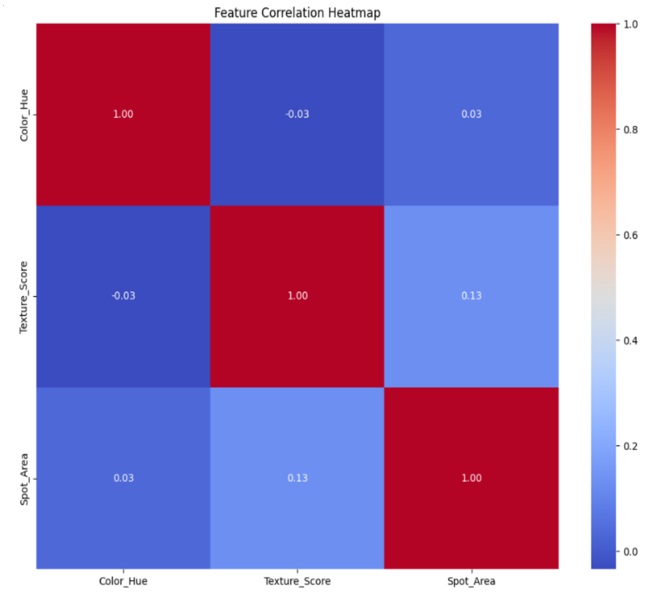

Fig 6.2: Feature Correlation Heatmap

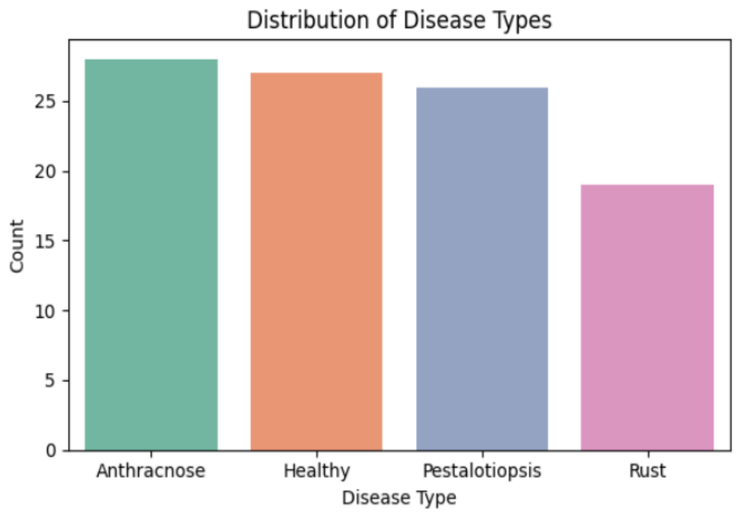

Fig 6.3: Disease Type

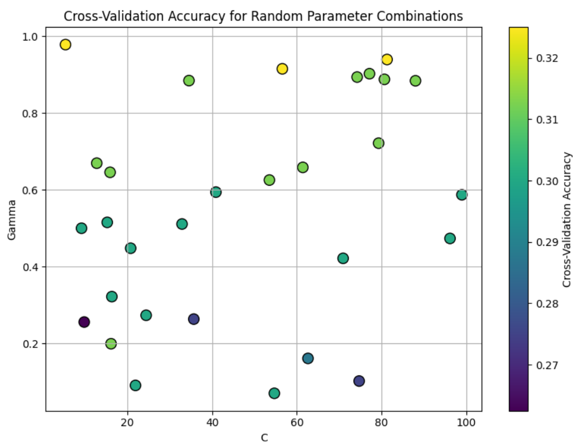

Fig 6.4: Random Parameter Accuracy

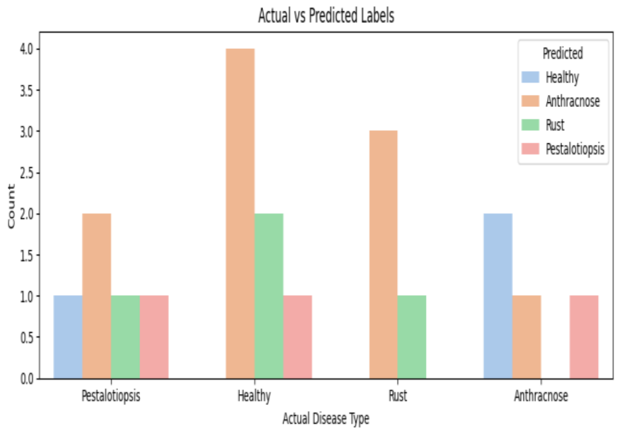

Fig 6.4: Actual vs Predicted Labels

7. CONCLUSION

ASBOT presents an effective solution to automate SVM hyperparameter tuning using Particle Swarm Optimization (PSO). By eliminating the need for manual trial-and-error adjustments, it significantly enhances the efficiency and reliability of disease classification models. The algorithm is scalable, accurate, and adaptable to various dataset sizes and conditions, making it well-suited for real-world deployment in smart farming systems. Its capacity to generalize across disease types and dynamically optimize learning parameters positions ASBOT as a valuable contribution to the field of precision agriculture and plant health monitoring.

REFERENCES

[1] Cortes, C. and Vapnik, V., "Support-Vector Networks," *Machine Learning*, vol. 20, no. 3, pp. 273–297, 1995.

[2] Kennedy, J. and Eberhart, R., "Particle Swarm Optimization," *Proceedings of the IEEE International Conference on Neural Networks*, Perth, Australia, pp. 1942–1948, 1995.

[3] N. Sharma and A. Jain, "Leaf disease detection using image processing and SVM classifier," *International Journal of Engineering Sciences & Research Technology*, vol. 6, no. 5, pp. 532–538, 2017.

[4] M. Mallikarjuna and B. Shivaraj, "A SVM based model for plant leaf disease classification using feature reduction technique," *Procedia Computer Science*, vol. 167, pp. 2101–2110, 2020.

[5] S. Ramesh, M. V. Kumar, and G. R. Prasad, "Crop disease prediction using machine learning: A review," *Materials Today: Proceedings*, vol. 33, pp. 845–850, 2020.

[6] R. D. Shah, B. P. Bhatt and V. B. Purohit, "Guava leaf disease detection using image processing and machine learning techniques," *International Journal of Innovative Technology and Exploring Engineering (IJITEE)*, vol. 8, no. 11, pp. 4038–4043, 2019.

[7] A. H. Ahmed and K. A. H. Ali, "Hybrid approach for parameter optimization of SVM using PSO for cancer classification," *International Journal of Advanced Computer Science and Applications (IJACSA)*, vol. 8, no. 4, pp. 97–103, 2017.

[8] Y. S. Nadaf and M. A. Patil, "SVM classifier for classification of agriculture data," *International Journal of Scientific & Engineering Research*, vol. 6, no. 9, pp. 1172–1175, 2015.

[9] D. Dhiman and H. Kaur, "Particle swarm optimization: A comprehensive survey," *Swarm and Evolutionary Computation*, vol. 33, pp. 1–30, 2017.

[10] R. Singh and P. Jain, "Application of machine learning in agriculture for disease detection," *International Journal of Computer Applications*, vol. 162, no. 10, pp. 32–36, 2017.

[11] Patil, S. and Kumar, R., "Hybrid PSO-SVM Model for Efficient Classification of Leaf Diseases in Agriculture," International Journal of Advanced Research in Computer Science, vol. 9, no. 4, pp. 30–36, 2018.

[12] Zhang, Y., Wang, S. and Ji, G., "A comprehensive survey on particle swarm optimization algorithm and its applications," Mathematical Problems in Engineering, vol. 2015, Article ID 931256, 2015.

[13] Pawar, S. and Kolhe, S., "Detection and classification of plant leaf diseases using deep learning," Journal of Electrical Systems and

Information Technology, vol. 5, no. 3, pp. 899–907, 2018.
[14] Dhanushkodi, V. and Mohan, R., "Optimization of SVM Parameters Using Nature Inspired Algorithms for Plant Disease Classification," International Journal of Engineering and Technology (UAE), vol. 7, no. 2.8, pp. 240–245, 2018.
[15] Padol, P.B. and Yadav, A.A., "SVM classifier based grape leaf disease detection," Conference on Advances in Signal Processing (CASP), pp. 175–179, 2016.
[16] Jadon, S., "A survey of bio-inspired optimization algorithms for feature selection in machine learning models," International Journal of Computer Applications, vol. 183, no. 25, pp. 1–5, 2021.
[17] Singh, V. and Misra, A.K., "Detection of plant leaf diseases using image segmentation and soft computing techniques," Information Processing in Agriculture, vol. 4, no. 1, pp. 41–49, 2017.
[18] Meena, V.S. and Pushpa, M., "A comparative study of PSO-SVM, GA-SVM and Firefly-SVM for leaf disease detection," International Journal of Engineering Research and Applications, vol. 8, no. 4, pp. 15–21, 2018.
[19] Phadikar, S. and Sil, J., "Rice disease identification using pattern recognition techniques," Proceedings of the 11th International Conference on Computer and Information Technology (ICCIT), pp. 420–423, 2008.
[20] Mohanty, S.P., Hughes, D.P. and Salathé, M., "Using deep learning for image-based plant disease detection," Frontiers in Plant Science, vol. 7, article 1419, 2016.
[21] Shabbir, M. and Anwer, T., "Machine learning and image processing based approach for plant disease classification: A review," Sustainable Computing: Informatics and Systems, vol. 28, 100453, 2020.
[22] Das, A., Ghosal, S., and Balasubramanian, V., "Disease classification in maize using convolutional neural networks and optimization," Computers and Electronics in Agriculture, vol. 165, 104961, 2019.
[23] Sun, Y., Wang, S., and Zhang, Y., "Parameter optimization of SVM based on grid search and particle swarm optimization algorithm," International Journal of Hybrid
Information Technology, vol. 8, no. 12, pp. 163–172, 2015.
[24] Liakos, K.G., Busato, P., Moshou, D., Pearson, S., and Bochtis, D., "Machine learning in agriculture: A review," Sensors, vol. 18, no. 8, 2674, 2018.
[25] Abirami, S., Ramesh, P., and Kumar, S.R., "An efficient bio-inspired algorithm for optimization of SVM in disease prediction," Cluster Computing, vol. 25, pp. 1085–1095, 2022.

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