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# Comparison of Support Vector Machine Optimization Methods for Chili Pepper Nutrient Deficiency Identification

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## ABSTRACT

Deficiencies of macronutrients such as nitrogen, phosphorus, and potassium in chili pepper plants can cause visible changes in leaf characteristics, which can be utilized as information for identifying plant conditions through digital images. The performance of the Support Vector Machine in classifying leaf conditions is highly influenced by its hyperparameter configuration; therefore, an appropriate optimization strategy is required. This study aims to compare the performance of four Support Vector Machine optimization methods, namely Grid Search, Particle Swarm Optimization, Principal Component Analysis, and Adaptive Boosting, combined with RGB color features and Gray Level Co-occurrence Matrix texture features to classify four conditions of chili pepper leaves: healthy, nitrogen-deficient, phosphorus-deficient, and potassium-deficient leaves. The classification was performed using two image resolutions, namely 120 × 120 and 244 × 244 pixels. This study employed a quantitative approach using 1,040 chili pepper leaf images obtained from primary data and secondary datasets from Kaggle and Roboflow. The research process consisted of data augmentation, feature extraction, Support Vector Machine modeling, and evaluation using accuracy, precision, recall, and F1-score. The experimental results showed that the Particle Swarm Optimization configuration achieved the highest accuracy, reaching 86.06% for 244 × 244 pixel images and increasing to 91.83% for 120 × 120 pixel images. It was followed by Grid Search, which achieved 84.13% and 90.38%, respectively, while Principal Component Analysis and Adaptive Boosting achieved lower accuracy at both image resolutions. This study concludes that the combination of RGB and Gray Level Co-occurrence Matrix features with Particle Swarm Optimization provides the best classification performance for identifying nutrient conditions in chili pepper plants based on leaf images. The findings also indicate that image resolution affects classification accuracy differently across optimization methods.

## INTRODUCTION

Chili pepper (*Capsicum annuum L.*) is one of the horticultural commodities with high economic value in Indonesia. However, its productivity can be adversely affected by deficiencies of macronutrients such as nitrogen (N), phosphorus (P), and potassium (K). Nutrient deficiencies can cause visible changes in leaf characteristics, which can be utilized as information for identifying plant conditions (Rahadiyan et al., 2023). In chili pepper plants, the identification of nutrient deficiencies based on leaf images has been conducted using the *Support Vector Machine* (SVM) method by utilizing color and texture characteristics (Qur'ania et al., 2023). Image-based identification can support a more objective assessment of plant conditions compared with manual visual observation.

The development of digital image processing and *machine learning* technologies provides opportunities to develop automated, rapid, and consistent systems for identifying leaf conditions. Color features can be used to represent color characteristics in images, while the *Gray Level Co-occurrence Matrix* (GLCM) can be used to extract texture information from leaf images (Qur'ania et al., 2023). The use of GLCM as a texture feature has also been applied to leaf classification using SVM (Purnawansyah et al., 2023). The application of GLCM and SVM to leaf images has demonstrated that texture characteristics can be utilized in the classification of leaf conditions or quality (Sriani & Rizky, 2024). Therefore, a combination of RGB and GLCM features can be used to represent the color and texture characteristics of chili pepper leaf images.

The performance of SVM in classification can be influenced by the model configuration and the *hyperparameter* values used. Parameter optimization using *Grid Search* can be performed through a systematic search of parameter combinations to obtain an appropriate SVM configuration (Irianandа et al., 2024). The use of *Grid Search* can also be compared with other parameter-search methods to determine which optimization strategy provides better classification

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performance (Dendi Rachmatsyah et al., 2025). In addition to *Grid Search*, *Particle Swarm Optimization* (PSO) can be used to optimize SVM *hyperparameters* in digital image classification (Wijayanti et al., 2021). Another approach is *Principal Component Analysis* (PCA), which can be used to reduce feature dimensionality before the classification process (Herteno et al., 2024). Meanwhile, *Adaptive Boosting* (AdaBoost) can be employed as an *ensemble* approach to improve classification performance (Siddik Hasibuan & Harahap, 2024a).

Based on previous studies, the use of leaf images, color and texture features, and SVM has demonstrated potential for identifying nutrient conditions and classifying leaves. However, comparisons of several SVM optimization methods for identifying nutrient conditions in chili pepper plants, particularly with consideration of different image resolutions, remain limited. Therefore, this study aims to compare the performance of four SVM optimization methods, namely SVM+RGB+GLCM+Grid Search, SVM+RGB+GLCM+PSO, SVM+RGB+GLCM+PCA, and SVM Linear+RGB+GLCM+AdaBoost, in classifying four chili pepper leaf conditions: healthy, nitrogen-deficient, phosphorus-deficient, and potassium-deficient leaves. The comparison was conducted using two image resolutions, namely 120 × 120 pixels and 244 × 244 pixels, to examine the consistency of each method's performance under different input data resolutions. The evaluation was performed using *accuracy*, *precision*, *recall*, and *F1-score* to determine the SVM optimization method that provides the best performance for identifying nutrient conditions in chili pepper plants based on leaf images.

## LITERATURE REVIEW

Research on image-based identification of leaf conditions using digital image processing and machine learning has been widely conducted across various agricultural commodities. SVM and Artificial Neural Networks have been employed to classify primary nutrient deficiencies in soybean leaves based on texture features (Munir & Eddy Purnama, 2015). SVM has also been applied to identify four classes of nutrient deficiencies in chili pepper plants using RGB color and texture features, with results indicating that the combination of color and GLCM texture features can improve classification accuracy compared with the use of a single feature type (Qur'ania et al., 2023). The identification of diseases in chili pepper leaves has also been investigated using a combination of color and texture features (Agrerio Firera et al., 2026). In addition, GLCM-Wavelet feature extraction has been employed for disease identification in chili pepper leaves (Apriani & Supatman, 2025). These studies indicate that combining color and texture features can consistently provide better classification performance than relying on a single type of feature.

In terms of texture feature extraction, the Gray Level Co-occurrence Matrix (GLCM) has been widely used to characterize leaf surface properties. GLCM has been applied to the classification of pests and diseases in Capsicum frutescens (Nazila et al., 2023). The combination of GLCM and SVM has also been employed for herbal leaf classification (Purnawansyah et al., 2023). GLCM has further been applied to herbal leaf classification to characterize the texture properties of leaf images (Samir et al., 2023). These studies demonstrate that GLCM is effective in capturing variations in leaf surface texture that cannot be adequately represented by color features alone. Therefore, the combination of RGB and GLCM features has become a commonly used approach in plant leaf image classification.

Regarding SVM hyperparameter optimization, Grid Search is a commonly used method because it provides a systematic parameter-search process. SVM with Grid Search has been compared with SVM optimized using a Genetic Algorithm in the classification of hypertension to investigate the effects of different optimization strategies on classification performance (Awalullaili et al., 2023). Grid Search has also been employed to optimize SVM for sentiment classification and demonstrated improved performance compared with SVM without optimization (Iriananda et al., 2024). Similarly, Grid Search has been applied to SVM optimization in sentiment classification to obtain more optimal parameter combinations (Dendi Rachmatsyah et al., 2025). In addition to Grid Search, Particle Swarm Optimization (PSO) can be used as a metaheuristic-based optimization alternative. PSO has been applied to hand-image segmentation to determine optimal parameter configurations (Sanora & Wulanningrum, 2022). PSO has also been employed in imbalanced digital image classification and demonstrated its ability to identify more optimal combinations of the C and gamma parameters than grid-based searches in several cases (Lubis et al., 2024).

Machine learning approaches based on GLCM features have also been proposed for the identification of nutrient deficiencies in plant leaves. A combination of PCA and SVM optimization has been applied to sugarcane leaf classification, with the results indicating that PCA-SVM can maintain high classification accuracy despite a reduction in the number of features through PCA. PCA and SVM have also been employed for the identification of diseases in maize leaves and stems, where PCA was used to reduce the dimensionality of features extracted using VGG16 before classification with SVM (Putri et al., 2026). In addition to PCA, ensemble learning approaches such as Adaptive Boosting (AdaBoost) can also be applied to plant image classification. The combination of SVM and AdaBoost has been employed for sugarcane leaf image classification and demonstrated the potential of ensemble learning to improve the classification process (Chiatra & Lestari, 2026). AdaBoost has also been combined with Haar-like features for pest classification in coffee plants (Siddik Hasibuan & Harahap, 2024b).

Based on the reviewed literature, a research gap can be identified in the limited number of studies that directly and systematically compare four SVM optimization strategies, namely Grid Search, PSO, PCA, and AdaBoost, for the identification of nutrient conditions in chili pepper plants while considering the effect of input image resolution. This

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study addresses this gap by comparing the classification performance of the four optimization methods using two different image resolutions.

## METHOD

This study employed a quantitative approach to classify the nutrient conditions of chili pepper plants based on leaf images using the *Support Vector Machine* (SVM) algorithm. The research stages consisted of problem identification, literature review, data collection, data augmentation, image preprocessing, feature extraction, SVM modeling using several optimization methods, and model evaluation. The chili pepper leaf image dataset was obtained from primary data collected through direct image acquisition and secondary data obtained from Kaggle and Roboflow. The study used two image resolutions, namely 120 × 120 pixels and 244 × 244 pixels, to investigate the effect of image resolution on classification performance. The overall research workflow is presented in Figure 1.

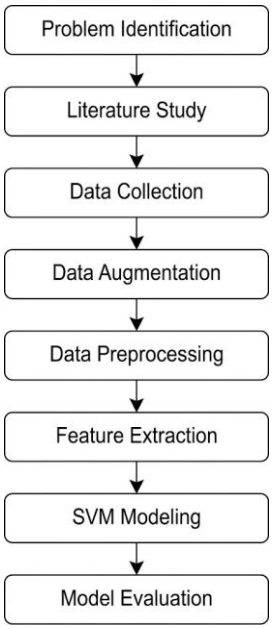



Figure 1. Research Stages

### Problem Identification

Problem identification was conducted to define the research problem, namely the classification of nutrient conditions in chili pepper plants based on the characteristics of leaf images. The SVM algorithm was employed as the classification method to distinguish leaf conditions based on features extracted from the images.

### Literature Review

A literature review was conducted by examining journals, books, and other scientific sources related to leaf image classification, plant nutrient conditions, RGB and GLCM feature extraction, the SVM algorithm, and the optimization methods employed in this study. The findings from the literature review were used as the basis for determining the research methods and parameters.

### Data Collection

The dataset consisted of primary and secondary data. Primary data were obtained by capturing images of chili pepper leaves using a mobile phone camera, while secondary data were obtained from the Kaggle and Roboflow platforms. All images were subsequently grouped according to the leaf-condition classes defined in this study.

### Data Augmentation

Data augmentation was performed to increase image variability and reduce the risk of overfitting. The augmentation techniques included rotation, flipping, scaling, brightness adjustment, and noise addition. Augmentation was applied only to the training data to prevent data leakage between the training and testing sets.

### Data Preprocessing

The preprocessing stage was performed by standardizing the image dimensions to 120 × 120 pixels and 244 × 244 pixels. In general, the image resizing process can be expressed as:

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$$I'(x', y') = I(x, y) \quad (1)$$

where $I(x, y)$ represents the pixel values of the original image, and $I'(x', y')$ represents the pixel values after the resizing process. The two image resolutions were used to compare the effect of image resolution on feature extraction and classification performance.

**Feature Extraction**

Feature extraction was performed to obtain color and texture information from the leaf images. Color features were extracted using RGB histograms with 32 bins for each channel, resulting in a total of 96 color features. In general, the color histogram can be expressed as::

$$H_k = \sum_{i=1}^{M} \sum_{j=1}^{N} \delta\left(I(i, j) - k\right) \quad (2)$$

where $H_k$ represents the number of pixels at intensity level $k$, $M$ and $N$ represent the image dimensions, and $\delta$ takes a value of 1 when the pixel value corresponds to bin $k$ and 0 otherwise.

Texture features were extracted using the *Gray Level Co-occurrence Matrix* (GLCM), with *Contrast, Energy, Homogeneity,* and *Entropy* used as the texture descriptors. In general, the GLCM can be expressed as:

$$P(i, j) = \frac{N(i, j)}{\sum_i \sum_j N(i, j)} \quad (3)$$

where $N(i, j)$ represents the number of occurrences of the pixel intensity pair $i$ and $j$, while $P(i, j)$ denotes the probability of occurrence of the corresponding pixel intensity pair.

**SVM Modeling**

SVM modeling was performed to classify leaf conditions based on the extracted features. The general decision function of the SVM can be expressed as follows:

$$f(x) = w^T x + b \quad (4)$$

where $w$ represents the weight vector, $x$ represents the feature vector, and $b$ represents the *bias*. Four configurations were compared in this study, namely SVM + AdaBoost, SVM + Grid Search, SVM + PCA, and SVM + PSO.

**Model Evaluation**

Model evaluation was conducted to assess the performance of each configuration using *Accuracy, Precision, Recall,* and *F1-Score*, along with the *Confusion Matrix*. In general, *Accuracy* is calculated as follows:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (5)$$

*Precision*:

$$Precision = \frac{TP}{TP+FP} \quad (6)$$

*Recall*:

$$Recall = \frac{TP}{TP+FN} \quad (7)$$

dan *F1-Score*:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (8)$$

## RESULT

**Data Analysis**

A total of 1,040 chili pepper leaf images were used in this study, comprising four classes: healthy leaves, phosphorus-deficient leaves, potassium-deficient leaves, and nitrogen-deficient leaves. The dataset was divided into 832 images for training and 208 images for testing, with 52 testing images allocated to each class. The experiments were conducted using two image resolutions, namely 244 × 244 pixels and 120 × 120 pixels. Four SVM configurations were

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compared to analyze the effects of the optimization methods and image resolution on classification performance.

**Experimental Results**

A total of 208 testing images were used for each image-resolution scenario. Model performance was evaluated based on Accuracy, Precision, Recall, and F1-score. A comparison of the results obtained from the four SVM configurations using 244 × 244-pixel and 120 × 120 pixel images is presented in Table 1.

Table 1. Comparison of Test Results for Two Image Sizes

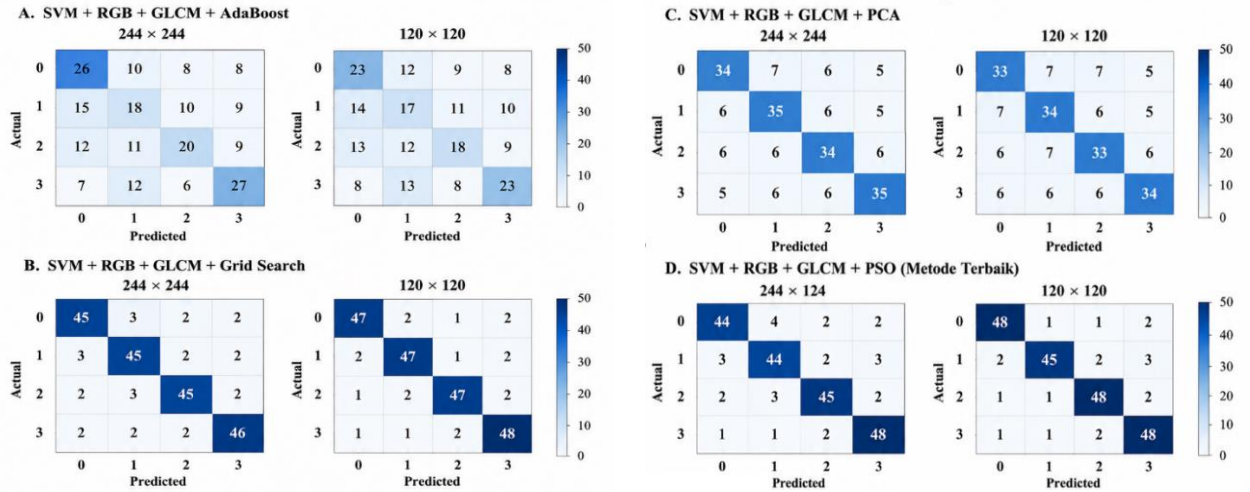
| Metode | Acc. 244 | Prec. 244 | Rec. 244 | F1 244 | Acc. 120 | Prec. 120 | Rec. 120 | F1 120 |
|---|---|---|---|---|---|---|---|---|
| SVM + RGB + GLCM + AdaBoost | 56,25% | 57,35% | 56,25% | 56,65 % | 54,33% | 55,31% | 54,33% | 53,55 % |
| SVM + RGB + GLCM + Grid Search | 84,13% | 84,84% | 84,13% | 84,29 % | 90,38% | 90,00% | 90,38% | 90,00 % |
| SVM + RGB + GLCM + PCA | 66,35% | 66,70% | 66,35% | 66,34 % | 64,90% | 67,00% | 64,90% | 65,00 % |
| SVM + RGB + GLCM + PSO | 86,06% | 86,50% | 86,06% | 86,17 % | 91,83% | 92,00% | 91,83% | 92,00 % |

Based on Table 1, differences in performance were observed among the four SVM configurations evaluated. For the 244 × 244-pixel images, the SVM + RGB + GLCM + PSO configuration achieved the highest accuracy of 86.06%, followed by SVM + RGB + GLCM + Grid Search at 84.13%, SVM + RGB + GLCM + PCA at 66.35%, and SVM + RGB + GLCM + AdaBoost at 56.25%. The precision, recall, and F1-score results showed a similar pattern, with PSO achieving the highest values among the evaluated methods.

For the 120 × 120 pixel images, SVM + RGB + GLCM + PSO again achieved the highest accuracy at 91.83%, followed by Grid Search at 90.38%, PCA at 64.90%, and AdaBoost at 54.33%. The PSO configuration also achieved a precision of 92.00%, a recall of 91.83%, and an F1-score of 92.00%.

**Confusion Matrix**

A confusion matrix analysis was performed to examine the distribution of correct predictions and classification errors across the respective classes. The confusion matrix presents the number of images correctly classified according to their actual classes, as well as the images that were incorrectly classified. The confusion matrices obtained from the four SVM configurations using 244 × 244-pixel and 120 × 120-pixel images are presented in Figure 2.




Class description: (0) Healthy leaf; (1) Phosphorus deficiency; (2) Potassium deficiency; (3) Nitrogen deficiency

Figure 2. Confusion Matrices of the Four SVM Configurations at Two Image Resolutions

Based on Figure 2, each SVM configuration produced a different distribution of predictions across the four leaf classes. Predictions that correspond to the actual classes are represented along the diagonal of the confusion matrix, whereas predictions outside the diagonal indicate classification errors.

**Effect of Image Resolution on Identification Results**

To examine the effect of image resolution, a comparison of the accuracy values between the 244 × 244-pixel and 120 × 120 pixel images is presented in Table 2.

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Table 2. Changes in Accuracy Based on Image Size

| Methods | Accuracy 244px | Accuracy 120px | Changes | Performance |
|---|---|---|---|---|
| SVM + RGB + GLCM + AdaBoost | 56,25% | 54,33% | -1,92% | Decrease |
| SVM + RGB + GLCM + Grid Search | 84,13% | 90,38% | +6,25% | Increase |
| SVM + RGB + GLCM + PCA | 66,35% | 64,90% | -1,45% | Decrease |
| SVM + RGB + GLCM + PSO | 86,06% | 91,83% | +5,77% | Increase |

Based on Table 2, image resolution had different effects on the identification performance of each SVM optimization method. Using 120 × 120-pixel images increased the accuracy of Grid Search by 6.25% and PSO by 5.77%. In contrast, the accuracy of AdaBoost decreased by 1.92%, while that of PCA decreased by 1.45%. Thus, the 120 × 120-pixel resolution resulted in higher accuracy for the Grid Search and PSO methods, whereas the 244 × 244-pixel resolution produced higher accuracy for AdaBoost and PCA.

## DISCUSSION

### Performance Comparison of SVM Configurations

The differences in performance among the four SVM configurations indicate that the optimization strategy employed affects the classification results. PSO achieved an accuracy of 86.06% for the 244 × 244-pixel images, which increased to 91.83% for the 120 × 120-pixel images. Grid Search also showed an improvement, from 84.13% to 90.38%. Meanwhile, PCA and AdaBoost achieved lower accuracy values at both image resolutions. The higher performance of PSO can be attributed to the optimization of SVM hyperparameters using Particle Swarm Optimization (PSO), which searches for an optimal combination of model parameters. The use of PSO for SVM hyperparameter optimization in image classification has also been reported in previous studies.

The combination of RGB and GLCM features provides color and texture information as inputs to the SVM model. RGB features represent the color characteristics of the leaves, whereas GLCM features represent texture characteristics through Contrast, Energy, Homogeneity, and Entropy. The combination of color and texture features with SVM has also been applied to the identification of nutrient deficiencies in chili pepper plants. The results of this study demonstrate that this feature combination can be integrated with optimization strategies to distinguish the four leaf conditions evaluated.

### Effect of Image Size

The change in image resolution from 244 × 244 pixels to 120 × 120 pixels resulted in different responses across the SVM configurations. For PSO, accuracy increased by 5.77 percentage points, from 86.06% to 91.83%, while Grid Search showed an increase of 6.25 percentage points, from 84.13% to 90.38%. In contrast, PCA experienced a decrease of 1.45 percentage points, from 66.35% to 64.90%, and AdaBoost decreased by 1.92 percentage points, from 56.25% to 54.33%. These results indicate that using lower-resolution images does not necessarily lead to lower classification performance.

The differences in results between the 244 × 244-pixel and 120 × 120-pixel images are related to the characteristics of the information used during feature extraction. The 244 × 244-pixel images contain a larger number of pixels, whereas the 120 × 120-pixel images contain fewer pixels. Nevertheless, the features used in this study consisted of RGB histograms with 96 color features and GLCM-based texture features. Therefore, classification performance is not determined solely by the number of pixels, but also by the color and texture information extracted from the images. In this study, the 120 × 120-pixel resolution resulted in improved performance for PSO and Grid Search, whereas the 244 × 244-pixel resolution produced higher performance for PCA and AdaBoost.

### Classification Results of the Best Method

Based on the evaluation results for the two image resolutions, the SVM + RGB + GLCM + PSO configuration achieved the highest *accuracy* compared with the other configurations. The classification results obtained using this configuration were subsequently analyzed for each individual class. The *precision, recall, F1-score,* and *support* values for the 244 × 244-pixel and 120 × 120-pixel image resolutions are presented in Table 3.

Table 3. Classification Results of SVM + RGB + GLCM + PSO

| Size | Class | Precision | Recall | F1-score | Support |
|---|---|---|---|---|---|
| 244 × 244 | Healthy Leaf | 0,94 | 0,85 | 0,89 | 52 |
| 244 × 244 | Phosphorus Deficiency | 0,79 | 0,85 | 0,81 | 52 |
| 244 × 244 | Potassium Deficiency | 0,82 | 0,87 | 0,84 | 52 |
| 244 × 244 | Nitrogen Deficiency | 0,92 | 0,88 | 0,90 | 52 |
| 120 × 120 | Healthy Leaf | 0,88 | 1,00 | 0,94 | 52 |
| 120 × 120 | Phosphorus Deficiency | 0,90 | 0,83 | 0,86 | 52 |
| 120 × 120 | Potassium Deficiency | 0,92 | 0,92 | 0,92 | 52 |
| 120 × 120 | Nitrogen Deficiency | 0,98 | 0,92 | 0,95 | 52 |

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For the 244 × 244-pixel resolution, the healthy leaf class achieved the highest precision of 0.94, while the nitrogen-deficient class achieved the highest F1-score of 0.90. For the 120 × 120-pixel resolution, the healthy leaf class achieved a recall of 1.00, while the nitrogen-deficient class achieved the highest precision and F1-score, at 0.98 and 0.95, respectively.

Overall, the SVM + RGB + GLCM + PSO configuration using 120 × 120-pixel images achieved the highest performance, with an accuracy of 91.83%, precision of 92.00%, recall of 91.83%, and F1-score of 92.00%. These results indicate that the PSO-based configuration provided better classification performance than the AdaBoost, Grid Search, and PCA configurations on the dataset used in this study.

## CONCLUSION

This study compared four SVM configurations, namely SVM + RGB + GLCM + AdaBoost, Grid Search, PCA, and PSO, using two image resolutions for the classification of chili pepper leaf conditions. The experimental results showed that the SVM + RGB + GLCM + PSO configuration achieved the highest accuracy at both image resolutions. For the 244 × 244-pixel resolution, an accuracy of 86.06% was obtained, while the accuracy increased to 91.83% for the 120 × 120-pixel resolution, with a precision of 92.00%, recall of 91.83%, and F1-score of 92.00%.

Changes in image resolution produced different effects across the evaluated configurations. The 120 × 120-pixel resolution improved accuracy for PSO and Grid Search, whereas the 244 × 244-pixel resolution produced higher accuracy values for PCA and AdaBoost. These findings indicate that the combination of RGB and GLCM features with PSO optimization can be used to classify four conditions of chili pepper leaves.

Future research may increase the size and diversity of the dataset, evaluate additional image resolutions, and perform validation using external datasets. These developments are necessary to assess the consistency and generalizability of the model under more diverse image conditions and datasets.

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## REFERENCES

Agrerio Firera, R., Nugraha, W., & Sa'adah, R. (2026). Identifikasi Penyakit Tanaman Cabai Berdasarkan Ekstrasi Fitur Warna Tekstur Menggunakan SVM dan Random Forest. *Jurnal Komputer Teknologi Informasi Sistem Komputer (JUKTISI)*, *5*(2), 1654–1663. https://doi.org/10.62712/juktisi.v5i2.1415

Apriani, N., & Supatman. (2025). Analisis Ekstraksi Citra GLCM Dan Wavelet Untuk Klasifikasi Penyakit Cabai Dengan Metode SVM. *Jurnal Informatika Teknologi Dan Sains (JINTEKS)*, *7*, 895–903. https://doi.org/https://doi.org/10.51401/jinteks.v7i2.5860

Awalullaili, F. O., Ispriyanti, D., & Widiharih, T. (2023). Klasifikasi Penyakit Hipertensi Menggunakan Metode SVM Grid Search Dan SVM Genetic Algorithm (GA). *Jurnal Gaussian*, *11*(4), 488–498. https://doi.org/10.14710/j.gauss.11.4.488-498

Chiatra, S., & Lestari, S. (2026). Optimization of Machine Learning Model for Sugarcane Leaf Detection Using Ensemble Methods. *MALCOM: Indonesian Journal of Machine Learning and Computer Science*, *6*(1), 332–340. https://doi.org/10.57152/malcom.v6i1.2577

Dendi Rachmatsyah, A., Sugihartono, T., & Irfan, K. (2025). Perbandingan Teknik Optimasi Grid Search dan Randomized Search dalam Meningkatkan Akurasi Metode Klasifikasi SVM Pada Sentimen Ulasan Pengguna Aplikasi JKN Mobile. *SKANIKA: Sistem Komputer Dan Teknik Informatika*, *8*(1), 13–22.

Herteno, R., Kartini, D., Budiman, I., Komputer, I., & Matematika dan Ilmu Pengetahuan Alam, F. (2024). *Implementasi Metode Principal Component Analysis (PCA) Dan Modified K-Nearest Neighbor Pada Klasifikasi Citra Daun Tanaman Herbal* (Vol. 7, Number 1).

Iriananda, S. W., Budiawan, R. W., Rahman, A. Y., & Istiadi, I. (2024). Optimasi Klasifikasi Sentimen Komentar Pengguna Game Bergerak Menggunakan Svm, Grid Search Dan Kombinasi N-Gram. *Jurnal Teknologi Informasi Dan Ilmu Komputer*, *11*(4), 743–752. https://doi.org/10.25126/jtiik.1148244

Lubis, S. W., Adikara, P. P., & Darma, B. (2024). *Optimasi Hyperparameter Support Vector Machine Dengan Particle Swarm Optimization Terhadap Klasifikasi Citra Digital Imbalanced*. https://j-ptiik.ub.ac.id/index.php/j-ptiik/article/download/13508/6003/95540

Munir, M. S., & Eddy Purnama, I. K. (2015). IDENTIFIKASI KEKURANGAN UNSUR HARA PRIMER PADA PERTUMBUHAN TANAMAN KEDELAI BERDASARKAN TEKSTUR DAUN MENGGUNAKAN SUPPORT VEKTOR MACHINE. *Scan : Jurnal Teknologi Informasi Dan Komunikasi*, *10*(2). https://doi.org/10.33005/scan.v10i2.607

Nazila, S. F., Arman, Y., Wahyuni, D., Nurhasanah, N., & Putra, Y. S. (2023). Deteksi Dini Serangan Hama Penyakit

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https://doi.org/10.47709/brilliance.v6i4.9730

pada Cabai Rawit Menggunakan Metode Image Recognition. *Jurnal Teknik Informatika Dan Sistem Informasi*, *9*(2). https://doi.org/10.28932/jutisi.v9i2.6342

Purnawansyah, P., Wibawa, A. P., Widyaningtyas, T., Haviluddin, H., Hasihi, C. E., Teng, M. F., & Darwis, H. (2023). Comparative Study of Herbal Leaves Classification using Hybrid of GLCM-SVM and GLCM-CNN. *ILKOM Jurnal Ilmiah*, *15*(2), 382–389. https://doi.org/10.33096/ilkom.v15i2.1759.382-389

Putri, S. W., Sari, A. P., & Aditiawan, F. P. (2026). Identifikasi Penyakit Daun Dan Batang Tanaman Jagung Menggunakan VGG16-SVM. *JIPI (Jurnal Ilmiah Penelitian Dan Pembelajaran Informatika)*, *11*(2), 794–802. https://doi.org/10.29100/jipi.v11i2.8020

Qur'ania, A., Karlitasari, L., Maryana, S., Sudrajat, C., & Zolla, Z. (2023). Identifikasi Defisiensi Unsur Hara Pada Tanaman Cabai Menggunakan Support Vector Machine. *Jurnal Komputer Dan Informatika*, *11*(1), 62–67. https://doi.org/10.35508/jicon.v11i1.9803

Rahadiyan, D., Hartati, S., Wahyono, & Nugroho, A. P. (2023). Feature aggregation for nutrient deficiency identification in chili based on machine learning. *Artificial Intelligence in Agriculture*, *8*, 77–90. https://doi.org/10.1016/j.aiia.2023.04.001

Samir, M., Purnawansyah, Darwis, H., & Umar, F. (2023). Fourier Descriptor Pada Klasifikasi Daun Herbal Menggunakan Support Vector Machine Dan Naive Bayes. *Jurnal Teknologi Informasi Dan Ilmu Komputer*, *10*(6), 1205–1212. https://doi.org/10.25126/jtiik.2023107309

Sanora, S., & Wulanningrum, R. (2022). *Segmentasi Metode Particle Swarm Optimization Pada Pendeteksi Citra Tangan*. https://doi.org/10.30736/informatika.v7i2.847

Siddik Hasibuan, M., & Harahap, H. (2024a). Penerapan Metode Haar-Like Feature Dan Algoritma Adaboost Dalam Penentuan Klasifikasi Hama Tanaman Kopi. In *Journal of Science and Social Research* (Number 1). http://jurnal.goretanpena.com/index.php/JSSR

Siddik Hasibuan, M., & Harahap, H. (2024b). Penerapan Metode Haar-Like Feature Dan Algoritma AdaBoost Dalam Penentuan Klasifikasi Hama Tanaman Kopi. In *Journal of Science and Social Research* (Number 1). https://doi.org/10.54314/jssr.v7i1.1718

Sriani, S., & Rizky, Y. (2024). Klasifikasi Kualitas Daun Tembakau Menggunakan Glcm (Gray Level Co-Occurrence Matrix) Dan Svm (Support Vector Machine). *Jurnal Informatika Dan Teknik Elektro Terapan*, *12*(3). https://doi.org/10.23960/jitet.v12i3.4599

Wijayanti, E. A., Rahmadanti, T. F., & Enri, U. (2021). Perbandingan Algoritma SVM dan SVM Berbasis Particle Swarm Optimization Pada Klasifikasi Beras Mekongga. In *Generation Journal* (Vol. 5, Number 2).

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