Volume 4, No. 8 August 2026
p-ISSN 3032-3037 | e-ISSN 3031-5786

Classification of Sweet Corn Maturity Using a Support Vector Machine with Grid Search Hyperparameter Optimization

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Keywords:
sweet corn; maturity classification; SVM; gridsearch; HSV.

Abstract
Manual determination of sweet corn maturity levels still relies on visual observation, which may lead to subjectivity and inconsistency. This research aims to develop a classification model for sweet corn maturity levels based on digital images using the Support Vector Machine (SVM) algorithm with Grid Search hyperparameter optimization. The dataset consists of 600 sweet corn images divided into three classes: immature, optimally mature, and fully mature. The research stages include preprocessing, feature extraction, dataset splitting, SVM implementation, hyperparameter tuning, and model evaluation. Feature extraction results show that all images were successfully processed with a 100% success rate. Testing the SVM model under several dataset splitting scenarios revealed that the 90:10 ratio achieved the highest accuracy of 88.33%. Hyperparameter optimization using Grid Search produced the best parameter combination, namely C = 100, gamma = 1, and Radial Basis Function (RBF) kernel, with a validation accuracy of 89.44%. The optimized model achieved an accuracy of 90.00%, with the best performance in the fully mature class, reaching 95% precision, 100% recall, and a 98% F1-score. The results indicate that the combination of HSV and GLCM features along with hyperparameter optimization can enhance the performance of SVM in classifying sweet corn maturity levels.

INTRODUCTION

Sweet corn (Zea mays L. saccharata Sturt.) is a botanical variety derived from common or field corn (Firmansyah et al., 2025). It is widely cultivated in Indonesia due to its sweet taste and high nutritional value, leading to steadily increasing market demand (Kantikowati et al., 2022). Sweet corn consumption in Indonesia has risen over the past three years, increasing from 0.32 kg/capita in 2021 to 0.34 kg/capita in 2022, and further to 0.36 kg/capita in 2023 (Naimatul et al., 2024). With this rising demand, determining the maturity level has become increasingly important to ensure the optimal harvest time and maintain produce quality.

Manual determination of maturity levels still relies on visual observation, resulting in assessments that are subjective and inconsistent (Ismail et al., 2023). Approaches based on experience make it difficult to standardize assessment results (Alfaruq et al., 2023). These conditions highlight the need for a more objective and consistent method for determining sweet corn maturity; one such approach involves the use of digital image processing.

Feature extraction is a crucial stage in digital image processing for obtaining a representation of object characteristics to be used in the classification process (Ayu et al., 2023). Utilizing Hue, Saturation, and Value (HSV) color features allows for a color representation that is more stable against changes in light intensity compared to the RGB color space (ZAMAZANI et al., 2025). Furthermore, texture features derived from the Gray Level Co-occurrence Matrix (GLCM) have been shown to enhance a model's ability to recognize the characteristics of image objects (Hutagaol et al., 2025). Combining color and texture features provides a more comprehensive image representation, thereby potentially improving the accuracy of sweet corn maturity classification. Digital image processing currently makes extensive use of artificial intelligence to assist in the analysis and classification of objects within images (Tambunana et al., 2025). Machine learning is one widely used branch of artificial intelligence. Image processing combined with machine learning has been widely applied to automatically identify and classify various objects (Melani et al., 2026). Machine learning enables computers to learn patterns from data, allowing for the automatic identification and classification of objects (Ningrum & Ismawardi, 2025). Support Vector Machine (SVM) is a machine learning classification algorithm frequently applied in digital image processing (Wajidi & Arifin, 2025). The SVM algorithm demonstrates strong performance across various classification tasks, such as image classification and tasks involving limited datasets (Pratiwi et al., 2025; Rahayu et al., 2025). SVM is also capable of performing classification relatively quickly (Prima et al., 2023). These characteristics make SVM suitable for classifying sweet corn maturity levels. However, SVM has limitations when classifying data points located very close to the hyperplane, which can potentially lead to misclassification (Sucipto & Khotimah, 2025). Therefore, hyperparameter optimization is necessary to identify the optimal parameter combination and improve the SVM model's performance and accuracy. Grid Search is a hyperparameter tuning method that systematically searches for the best parameter combination (Azzaria et al., 2025). The use of Grid Search has been shown to improve SVM model performance and accuracy, resulting in more optimal classification outcomes (Sahona et al., 2026). Various previous studies have applied the SVM algorithm to image classification. The application of the SVM algorithm has proven capable of classifying various commodities, such as melons (RA Saputra et al., 2022), oil palm fruit (Oktaviana & Suriati, 2025), mangosteens (Yustianisa et al., 2025), and Kersen fruit (Arinala & Patricia, 2024). Furthermore, studies comparing SVM with other machine learning algorithms indicate that SVM delivers competitive performance in image classification, making it a widely used algorithm for classifying fruit ripeness (Muchtar & Muchtar, 2024).

Previous research has also optimized SVM algorithm performance through hyperparameter optimization using the Grid Search method. Research by Kamila and Budiyanto (2025) demonstrated that the Grid Search method could improve Support Vector model performance by optimizing hyperparameter combinations. Similar conclusions were reached by Pratiwi et al. (2025), showing that the use of Grid Search successfully improved SVM model accuracy compared to initial parameters. Furthermore, Abdillah and Prihandono (2026) stated that hyperparameter optimization using Grid Search yields an SVM model with superior classification performance and higher accuracy.

Based on these studies, the SVM algorithm and hyperparameter optimization using Grid Search have demonstrated strong performance across various image classification tasks. However, the application of the SVM algorithm combined with Grid Search hyperparameter optimization for sweet corn maturity classification remains limited. Therefore, this study aims to develop a sweet corn maturity classification model using the SVM algorithm with Grid Search hyperparameter optimization to achieve optimal classification performance. This research provides theoretical and practical benefits. Theoretically, it contributes to digital image processing and machine learning by applying HSV and GLCM feature extraction with SVM optimization using Grid Search, while offering empirical evidence on hyperparameter tuning effectiveness and serving as a reference for future studies. Practically, it offers an objective digital solution for determining sweet corn maturity, helping farmers optimize harvest timing to improve quality and economic value, and supporting the advancement of precision agriculture in Indonesia.

METHOD

This research was conducted through systematic stages to develop a digital image-based sweet corn maturity classification model using the SVM algorithm with *Grid Search hyperparameter optimization*. The research stages include data acquisition, *preprocessing*, feature extraction, dataset division, SVM application, *hyperparameter tuning*, and evaluation of optimization results. The following is a flowchart that illustrates the overall research stages.

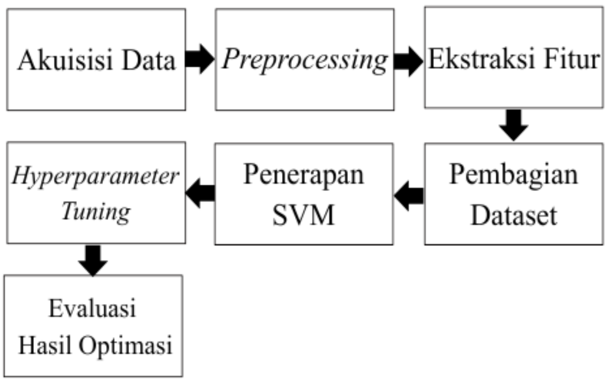

Figure 1 Research Flowchart
Source: Author's documentation, 2026

Data Acquisition

Data acquisition is the process of collecting, gathering, and preparing data (Bulaka et al., 2025) This stage begins with determining the maturity category of sweet corn into three classes: immature, optimally ripe, and fully ripe. The following is an example of an image from the three classes of the dataset.

(a) Not yet ripe (b)optimally ripe (c) ripe full

Figure 2 Dataset Image
Source: Author's documentation, 2026

The immature category has bright green husks, white to light brown silk, and kernels that are not yet fully filled. The optimally mature category has green husks, brown silk, and bright yellow kernels that are fully filled. Meanwhile, the fully mature category has green-brown husks, dark brown silk, and dark yellow kernels that are starting to wrinkle. Each category consists of 200 images, resulting in a total of 600 images obtained using a Samsung *mobile phone camera* in Central Java with varying lighting, shooting angles, and open and closed husk conditions.

Preprocessing

Preprocessing is the initial stage of image processing that aims to improve image quality before feature extraction and classification using the SVM algorithm (Amalia et al., 2025) *Preprocessing* begins with an image quality check to identify damaged, blurry, too dark, or too bright images. Images that do not meet the quality criteria are eliminated so as not to affect the classification process. Next, *cropping is performed* to focus on the sweet corn object, *resizing* to 128 × 128 pixels to standardize the image size, and color adjustments to make the image quality more uniform.

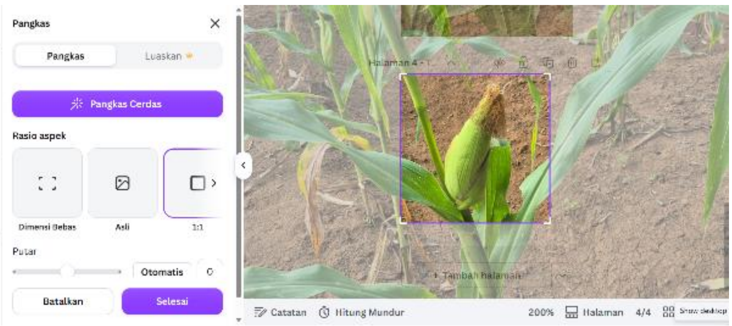

Figure 3 Image *Cropping*
Source: Author's documentation, 2026

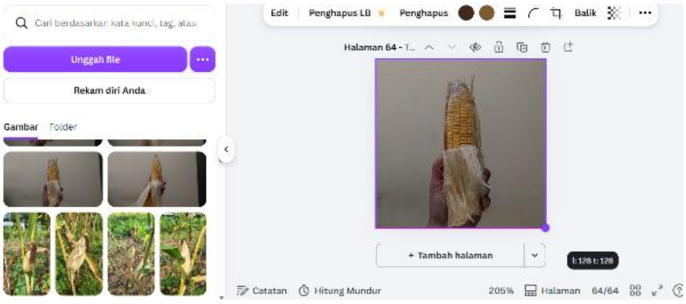

Figure 4 Image *Resizing*
Source: Author's documentation, 2026

Stage *preprocessing* also includes data augmentation for add variation image without need do new data acquisition in amount large ((Vedanty et al., 2025). Implementation technique This aim For reduce data imbalance and improve ability SVM algorithm in learn data (Putra & Nugroho, 2026)Augmentation process carried out throughout image use technique *horizontal flip* and *vertical flip* until every class has 200 images. The following is an example of applying *the horizontal flip* and *vertical flip* techniques to sweet corn images.

(a) before (b) after

Figure 5*Horizontal Flip* Technique
Source: Author's documentation, 2026

(a) before (b) after

Figure 6. *Vertical Flip Technique*
Source: Author's documentation, 2026

Feature Extraction

Feature extraction is an important stage in image processing that aims to transform visual information into meaningful numerical representations (Muflich, 2026) Feature extraction is performed using *the Hue*, *Saturation*, *Value (HSV) color features and the Gray Level Co-occurrence Matrix (GLCM)* texture features as input to the classification model. The following are the HSV and GLCM formulas.

RGB to HSV conversion:

$V = \max(R, G, B)$(1)

$S = \begin{cases} 0, & jika\ V = 0 \\ \frac{V - min(R,G,B)}{V}, & jika\ V > 0 \end{cases}$(2)

$$H = \begin{cases} 60° \left(\frac{G - B}{V - min(R,G,B)} \right), & V = R \\ 60° \left(2 + \frac{B - R}{V - min(R,G,B)} \right), & V = G \\ 60° \left(4 + \frac{R - G}{V - min(R,G,B)} \right), & V = B \end{cases} (3)$$

Calculate the average value of each HSV component:

$\overline{H} = \frac{1}{N} \sum_{i=1}^{N} H_i,\ \overline{S} = \frac{1}{N} \sum_{i=1}^{N} S_i,\ \overline{V} = \frac{1}{N} \sum_{i=1}^{N} V_i$(4)

Where:
N is the number of pixels in the image
Calculate the GLCM formed using pixel d = 1 and angle 0 º :
Contrast = $\sum i \sum j\ (i - j)^2 P(i,j)$(5)
$Correlation = \sum i \sum j \frac{(i - \mu_i)(j - \mu_j)P(i,j)}{\sigma_i \sigma_j}$(6)
$Energy = \sum i \sum j\ P(i,j)^2$(7)
$Homogeneity\ = \sum i \sum j \frac{P(i,j)}{1+|i - j|}$(8)
Where:
P(i,j): probability of occurrence of gray level pair i and j in the GLCM matrix
$\mu_i \mu_j$: average gray level
$\sigma_i \sigma_j$: standard deviation of gray level

Dataset Sharing

Dataset division aims to ensure that the model training and testing processes are carried out using different data, so that the evaluation results are more objective (Suryanooradja et al., 2025). Dataset division is carried out randomly so that the data distribution in each class remains representative. This study uses dataset divisions of 90:10, 80:20, 70:30, and 60:40 to evaluate model performance, then the data division ratio with the best accuracy is selected as the basis for optimization using *Grid Search.*

Implementation of SVM

The SVM implementation was performed using *input from* HSV and GLCM feature extraction results. The SVM model was trained to learn the patterns of each sweet corn maturity level. Next, the model was tested on each dataset sharing scenario to determine the data sharing ratio with the best accuracy before *hyperparameter optimization* using *Grid Search*. The SVM algorithm implementation flow in this study is summarized in *pseudocode*, shown in Figure 7 as a representation of the classification process stages.

Input: Dataset hasil ekstraksi fitur (Hue, Saturation, Value, Contrast, Correlation, Energy, Homogeneity) dan kelas kematangan jagung manis.
Output: Nilai akurasi model SVM.
Mulai
1. Masukkan dataset hasil ekstraksi fitur.
2. Tentukan fitur sebagai variabel input dan kelas kematangan sebagai variabel target.
3. Bagi dataset menjadi data latih dan data uji sesuai rasio pembagian data.
4. Bentuk model SVM menggunakan kernel RBF.
5. Latih model SVM menggunakan data latih.
6. Prediksi kelas kematangan jagung manis pada data uji.
7. Hitung nilai akurasi berdasarkan perbandingan kelas aktual dan kelas prediksi.
8. Tampilkan nilai akurasi model SVM.

Selesai

Figure 7. SVM *pseudocode*
Source: Google Colab, Processed 2026

Figure 7 shows the pseudocode for the sweet corn ripeness classification process using the SVM algorithm. The process begins by inputting the dataset from HSV and GLCM feature extraction, then defining the features as *input variables* and the ripeness class as the target variable. The dataset is then divided into training and test data according to the data split ratio used. An SVM model is then built using the RBF kernel and trained using the training data. After the training process is complete, the model is used to predict the sweet corn ripeness class on the test data. The final stage is carried out by calculating the accuracy value based on the comparison between the actual class and the predicted class, then displaying the accuracy results of the SVM model.

Hyperparameter Tuning

Hyperparameter tuning is a hyperparameter optimization process with the aim of obtaining an optimal parameter combination to improve model performance (Rusman et al., 2023) *Hyperparameter tuning is* performed using *the Grid Search method*. This process is carried out by testing the C, gamma, and kernel parameters. The C parameter functions to control classification errors, gamma regulates the influence of data in forming decision boundaries, while the kernel is used to map data to a higher-dimensional feature space (Misriati & Aryanti, 2024).

Table 1. *Grid Search* Parameters

Parameter	Tested values
C	0.1; 1; 10; 100
Gamma	1; 0.1; 0.01; 0.001
Kernel	RBF

The range of C and gamma parameter values is defined as the search space in *the Grid Search process* to evaluate various combinations. This range of values is commonly used in SVM algorithm optimization (Saputra et al., 2025) Meanwhile, the RBF kernel was chosen because it is effective in handling nonlinear data and is capable of producing high classification performance (Mehta et al., 2023)

Evaluation of Classification Results

Classification results were evaluated using *a confusion matrix with accuracy*, *precision*, *recall*, and *F1-score* indicators. *Accuracy* measures the overall classification accuracy, *precision* measures the accuracy of predictions for each class, *recall* measures the model's ability to identify all data in each class, and F1 *-score* measures the balance between *precision* and *recall* (Apriani et al., 2022). is formula *accuracy, precision*, *recall*, and *F1-score.*

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (9)$$

$$Precision = \frac{TP}{TP+FP} \quad (10)$$

$$Recall = \frac{TP}{TP+FN} \quad (11)$$

$$F1 - score = 2x \frac{PrecisionxRecall}{Precision+Recall} \quad (12)$$

Where:

TP (*True Positive)*: the number of data that is correctly predicted as a particular class.

TN (*True Negative)*: the number of data that is correctly predicted not to be that class.

FP (*False Positive)*: the number of data that is predicted as a certain class, but is not actually that class

FN (*False Negative)*: the number of data that actually belongs to a certain class, but is predicted as another class

RESULTS AND DISCUSSION

HSV and GLCM Feature Extraction Results

The feature extraction stage was performed to obtain a numerical representation of the color and texture characteristics of sweet corn images. The following are the results of feature extraction from 600 datasets.

Table 2 Extraction Results Based on Class

Class	Number of Images	Succeed	Fail	Success (%)
Immature	200	200	0	100
Optimal Ripeness	200	200	0	100
Ripe Full	200	200	0	100
Total	600	600	0	100

Source: Google Colab, Processed 2026

Table 3(HSV)

No	***Hue***	***Saturation***	***Value***	***Class***
1	41,7264	0.7001	0.6118	Immature
2	54,2804	0.4846	0.5455	Immature
3	42,5368	0.6681	0.4916	Immature
4	51,1418	0.6886	0.4766	Immature
5	45,5069	0.5681	0.4948	Immature
⋮	⋮	⋮	⋮	⋮
600	...	...	...	Ripe Full

Source: Google Colab, Processed 2026

Table 4 Texture Feature Extraction Results (GLCM)

No	***Contrast***	***Correlation***	***Energy***	***Homogeneity***
1	231,8766	0.9732	0.0128	0.1495
2	94,1964	0.9801	0.018	0.229
3	83,2228	0.9767	0.0173	0.1959
4	283,7779	0.9648	0.0136	0.1529
5	150,8709	0.958	0.0211	0.1943
⋮	⋮	⋮	⋮	⋮
600	...	...	...	...

Source: Google Colab, Processed 2026

Based on Table 2, the feature extraction process was successfully performed on the entire dataset. A total of 600 images, consisting of 200 immature images, 200 optimally mature images, and 200 fully mature images, were successfully extracted without any failures. Therefore, the success rate reached 100% for each class. These results indicate that all images were of adequate quality for processing in the feature extraction stage and that no obstacles were encountered during the image processing.

Tables 2 and 3 show some of the results of the color and texture feature extraction. consists of on *Hue*, *Saturation*, *Value*, *Contrast*, *Correlation*, *Energy*, and *Homogeneity*. Each row represents one sweet corn image that has been converted into seven numerical values and their classes. The difference in values in each feature indicates that the color and texture characteristics of each image differ according to its ripeness level. Thus, the feature extraction results can be used as input data for the SVM algorithm to learn patterns and classify the ripeness level of sweet corn.

SVM Implementation Results

The SVM was implemented using the feature extraction results *as input*. Model testing was conducted on four dataset split scenarios: 90:10, 80:20, 70:30, and 60:40. These scenarios were applied to determine the data split ratio with the best accuracy.

Table 4. Results of SVM Application

Dataset Sharing	Data Practice	Data Test	Accuracy (%)
90:10	540	60	88.33

Dataset Sharing	Data Practice	Data Test	Accuracy (%)
80:20	480	120	84.17
70:30	420	180	83.89
60:40	360	240	81.25

Source: Google Colab, Processed 2026

Based on Table 4, the 90:10 dataset split yielded the highest accuracy of 88.33%, while the 80:20, 70:30, and 60:40 dataset splits yielded accuracies of 84.17%, 83.89%, and 81.25%, respectively. Therefore, the 90:10 dataset split was chosen as the best ratio to be used in the *hyperparameter optimization stage* using *Grid Search.*

Grid Search Hyperparameter Optimization Results

hyperparameter optimization was performed using *the Grid Search method*. The optimization results are presented in Table 4.

Table 5. *Grid Search Hyperparameter* Optimization Results

Parameter	Best Value
C	100
Gamma	1
Kernel	RBF
accuracy validation (%)	89.44

Source: Google Colab, Processed 2026

Based on Table 5, *the Grid Search process* produced the best *hyperparameter combination* : C of 100, gamma of 1, and an RBF kernel. This combination yielded a validation accuracy of 89.44%, and was therefore used as a parameter in the SVM model training process. The model with the best parameters was then used to classify the data.

SVM Evaluation Results with *Grid Search*

An SVM evaluation using *Grid Search* was conducted using test data to determine the performance of sweet corn maturity classification. The following are the results of the SVM evaluation using *Grid Search*.

Table 6. Results of SVM Evaluation with *Grid Search*

Class	***Precision*** **(%)**	***Recall*** **(%)**	***F1 - Score*** **(%)**
Immature	85	85	85
Optimal Ripeness	89	85	87
Ripe Full	95	100	98
Accuracy			90

Source: Google Colab, Processed 2026

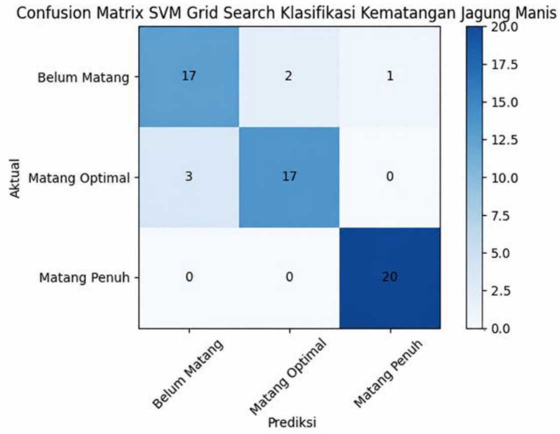

Figure 8. *Confusion Matrix* SVM with *Grid Search*
Source: Google Colab, Processed 2026

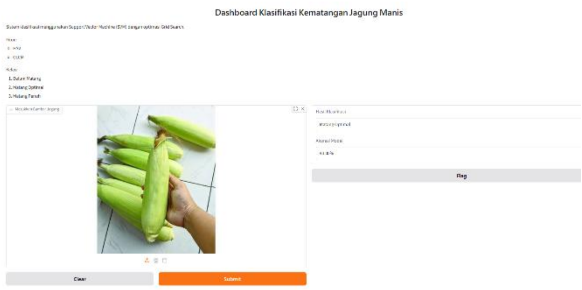

Figure 9. Sweet Corn Maturity Classification *Dashboard*
Source: Google Colab, Processed 2026

Based on Table 6, the SVM evaluation results with *Grid Search optimization* achieved an accuracy of 90.00%. The fully mature class demonstrated the best performance with *a precision* of 95.00%, *a recall* of 100.00%, and an *F1 - score of 98.00%*, indicating that all test data in that class was correctly classified. that, class Not yet ripe get *precision*, *recall*, and *F1 - score* were each 85.00%, while class optimal maturity to obtain *precision* 89.00%, *recall* 85.00%, and *F1 - score* 87.00%.

Figure 8 shows that in class ripe full all test data passed predicted with right. Meanwhile that, class Not yet mature and optimally mature each have 17 predictions true. Class Not yet ripe has 2 misclassified data as optimal maturity and 1 data as ripe full, while class optimal maturity has 3 misclassified data as Not yet ripe.

The success of feature extraction demonstrates that the combination of HSV and GLCM effectively represents the color and texture characteristics of sweet corn at various maturity levels, making it suitable as input for the SVM algorithm. HSV features offer color representation that is more stable against changes in light intensity, while GLCM is effective at capturing image texture variations (Zamzani et al., 2025; Hutagaol et al., 2025). Testing results indicate that a 90:10 dataset split yields the highest accuracy, suggesting that a larger proportion of training data enables the model to better learn the patterns associated with each class. Research by Azmira et al. (2025) similarly reports that the 90:10 ratio produces the highest SVM accuracy. Testing of dataset splits focuses on the initial SVM setup, as this stage aims to determine the optimal training-to-test data ratio for model construction; subsequent Grid Search optimization was applied to this best-performing split to ensure tuning occurred on the data configuration that had already demonstrated superior initial performance.

Model accuracy improved from 88.33% to 90.00% following Grid Search optimization. This improvement indicates that the optimal hyperparameter combination identified C=100, gamma=1, and an RBF kernel aligns better with the characteristics of the HSV and GLCM features, allowing the model to establish a more optimal decision boundary for distinguishing sweet corn maturity levels. This helps reduce classification errors, particularly between the "immature" and "optimally mature" classes, which share similar visual characteristics. Conversely, the "fully mature" class achieved the best classification results due to its distinct color and texture. These findings align with previous research indicating that hyperparameter optimization via Grid Search can improve SVM model performance and accuracy (Pratiwi et al., 2025; Abdillah & Prihandono, 2026). Overall, the combination of SVM and Grid Search effectively supports the classification of sweet corn maturity levels.

CONCLUSION

This study successfully developed a sweet corn maturity classification model using a combination of HSV and GLCM features, a Support Vector Machine (SVM) algorithm, and Grid Search hyperparameter optimization. Feature extraction results demonstrated that all 600 images were successfully converted into numerical representations specifically color and texture feature suitable for use as input for the classification model. Testing across various dataset split scenarios revealed that a 90:10 ratio yielded the highest accuracy (88.33%) prior to optimization. Following Grid Search hyperparameter optimization, the SVM model configured with optimal parameters of C=100, gamma=1, and an RBF kernel achieved an improved accuracy of 90.00%. These results indicate that the combination of HSV and GLCM features and Grid Search hyperparameter optimization is effective for classifying sweet corn maturity levels. For future research, it is recommended to expand the dataset with more variations in lighting, angles, and corn varieties, explore other feature extraction methods or deep learning approaches such as CNN for comparison, and develop the model into a real-time mobile-based application to facilitate practical use by farmers and agricultural industries.

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