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Research Article

Classification of Noni Fruit Ripeness Using Support Vector Machine (SVM) Method

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Abstract:
The classification of Noni fruit (Morinda citrifolia) ripeness is crucial for enhancing its medicinal benefits and ensuring product quality. This research aimed to classify Noni fruit ripeness using the Support Vector Machine (SVM) method, comparing three kernel functions: linear, Radial Basis Function (RBF), and polynomial. A dataset of ripe and unripe Noni fruit images was used, with preprocessing steps involving color and texture feature extraction. Performance evaluation showed that the RBF kernel achieved the highest accuracy at 86.18%, followed by the polynomial kernel, and the linear kernel. The RBF kernel demonstrated superior capability in capturing the non-linear patterns within the dataset, resulting in the highest precision of 88.71%, recall of 84.62%, and F1-score of 86.61%. These findings underscore the effectiveness of the RBF kernel for this classification task and highlight the importance of color and texture features in achieving accurate predictions. The results contribute to advancements in agricultural technology by providing insights into SVM kernel performance for fruit ripeness classification and establishing a foundation for further improvements in automated fruit sorting systems. Future research should focus on expanding the dataset and exploring ensemble methods to enhance classification performance and generalizability under varying environmental conditions.

Keywords: Feature Extraction, Kernel Comparison, Machine Learning, Noni Ripeness, SVM
Dataset: https://www.kaggle.com/datasets/sitigayatri/noni-dataset-plant

1. Introduction

Noni fruit (*Morinda citrifolia*), widely recognized for its medicinal benefits, is commonly used for its antioxidant and antimicrobial properties in traditional medicine. The ripeness of the fruit plays a crucial role in determining its quality and therapeutic potential. Traditionally, ripeness classification has been performed manually, a method prone to subjectivity and inconsistencies, which often results in uneven quality control. This challenge calls for a more reliable and automated approach to ripeness classification. Machine learning techniques, particularly Support Vector Machine (SVM), have shown promise in agricultural applications for handling complex data patterns and providing consistent results [1], [2], [3]. SVM's adaptability with different kernel functions, such as linear, Radial Basis Function (RBF), and polynomial, allows it to handle diverse data distributions effectively, making it suitable for fruit classification tasks that involve non-linear relationships.

Research in agricultural machine learning indicates that SVM can outperform traditional classification methods, particularly when used with polynomial kernels that excel in modelling complex, non-linear relationships. This performance advantage has been observed in various agricultural datasets where non-linear characteristics are prominent [4], [5]. However, kernel selection remains a critical factor that can significantly impact the accuracy of the classification model. For Noni fruit ripeness, evaluating the suitability of different kernels could provide insights into optimizing the SVM approach for automated quality assessment [6], [7].

This study addresses the problem of inconsistency in manual Noni fruit ripeness assessment by developing an automated classification model using SVM. The main objective is to compare the effectiveness of linear, RBF, and polynomial kernels in distinguishing between ripe and unripe fruit. The hypothesis guiding this research is that the polynomial kernel will demonstrate superior accuracy due to its capacity for capturing complex patterns in the data, which linear and RBF kernels may struggle [8]. In the broader context of agricultural technology, this investigation aims to enhance the consistency and reliability of automated ripeness classification, providing an alternative to labour-intensive manual methods.

The scope of the study focuses on binary classification, targeting the differentiation between ripe and unripe Noni fruit based on image data. Image features, such as color and texture, are extracted to train the SVM models. While this approach establishes a baseline for automated classification, it does not extend to multi-class classification or account for factors like varying environmental conditions during image acquisition. Additionally, the research limits its exploration to SVM models and does not compare other machine learning algorithms, which could offer different advantages [9], [10].

The study's contributions are significant in advancing the application of machine learning in agriculture by evaluating how different SVM kernels perform in fruit classification tasks. Insights gained from comparing these kernels can inform the development of more effective automated quality control processes, potentially leading to broader adoption of machine learning technologies in agricultural practices [11], [12], [13].

2. Method

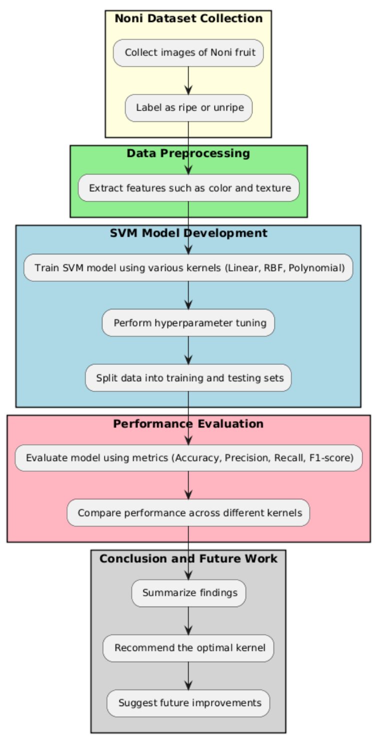

Figure 1. General Research Design

This research, as shown in **Figure 1**, focuses on classifying Noni fruit ripeness using (SVM). It begins with Noni Dataset Collection, where images are gathered and labelled as ripe or unripe to establish a dataset for analysis. The next step is Data Preprocessing, which include feature extraction using color and texture. In the SVM Model Development stage, the model is trained using different kernel functions (Linear, RBF, and Polynomial), with hyperparameter tuning and data splitting into training and testing sets for optimal performance. During Performance Evaluation, the model's effectiveness is assessed using metrics such as accuracy, precision, recall, and F1-score, while comparing results across different kernels to identify the best-performing approach. Finally, Conclusion and Future Work summarize the findings, recommend the optimal kernel, and suggest future research improvements. Previous studies have shown that SVM is highly effective for fruit classification tasks; for example, [14], [15] reported high accuracy in strawberry ripeness classification using color and texture features. Similarly, [16], [17], [18] found that polynomial kernels performed better for complex data in fruit classification.

Dataset Collections

The dataset used for this research consists of labelled images of Noni fruit, which are essential for building a classification model to distinguish between ripe and unripe fruits. In **Table 1**, the dataset is presented with details of the image paths and their corresponding labels, indicating whether each fruit is categorized as "ripe" or "not ripe." This structured labelling provides a foundation for supervised learning, enabling the model to learn from the provided examples.

The distribution of the dataset is further illustrated in **Figure 2**, which shows a pie chart depicting the proportion of ripe and unripe Noni fruit images. The chart indicates that 52.0% of the images (319 samples) are classified as "not ripe," while the remaining 48.0% (295 samples) are labelled as "ripe." This relatively balanced distribution ensures that the model can be trained without significant bias toward either class, thus improving the classification accuracy for both categories.

Table 1. Noni Images Dataset Labelled

No	Path	Label
1	/kaggle/input/noni-dataset-plant/noni/ripe/208.jpg	ripe
2	/kaggle/input/noni-dataset-plant/noni/ripe/45.jpg	ripe
3	/kaggle/input/noni-dataset-plant/noni/ripe/56.jpg	ripe
4	/kaggle/input/noni-dataset-plant/noni/ripe/89.jpg	ripe
5	/kaggle/input/noni-dataset-plant/noni/ripe/20.jpg	ripe
	...	
610	/kaggle/input/noni-dataset-plant/noni/unripe566.jpg	not_ripe
611	/kaggle/input/noni-dataset-plant/noni/unripe345.jpg	not_ripe
612	/kaggle/input/noni-dataset-plant/noni/unripe223.jpg	not_ripe
613	/kaggle/input/noni-dataset-plant/noni/unripe445.jpg	not_ripe
614	/kaggle/input/noni-dataset-plant/noni/unripe343.jpg	not_ripe

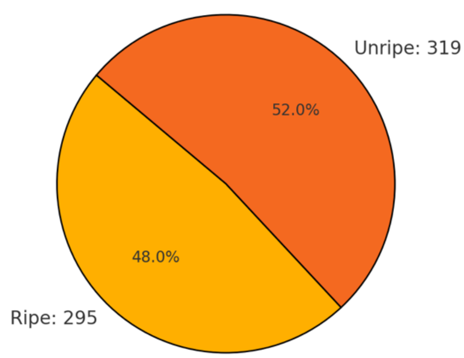

Figure 2. Distribution of Noni Fruits (Ripe vs Unripe)

Data Preprocessing

Before resizing, images are scaled to a fixed size to ensure consistency across the dataset and improve model performance. The bilinear interpolation method is used, which calculates pixel values in the resized image based on the weighted average of the four nearest pixels from the original image. The formula 1 for bilinear interpolation is:

$$I(x, y) = (1 - a)(1 - b)I_{\{11\}} + a(1 - b)I_{\{21\}} + (1 - a)b\, I_{\{12\}} + ab\, I_{\{22\}} \quad (1)$$

where $I_{\{11\}}$, $I_{\{21\}}$, $I_{\{12\}}$, $I_{\{22\}}$ are the nearest pixel values, and a and b are the fractional parts of the coordinates. This technique helps maintain important details in the image, supporting accurate feature extraction for classification [19], [20].

Before preprocessing, images are resized to a fixed dimension using bilinear interpolation, which calculates pixel values from the nearest four pixels to maintain important details. This step ensures a consistent input size for the dataset. Data preprocessing then prepares the Noni fruit images for classification, as shown in **Figure 3**, with examples of ripe and unripe fruits before and after resizing. The first row shows ripe fruits, while the second row displays unripe ones, highlighting ripeness differences.

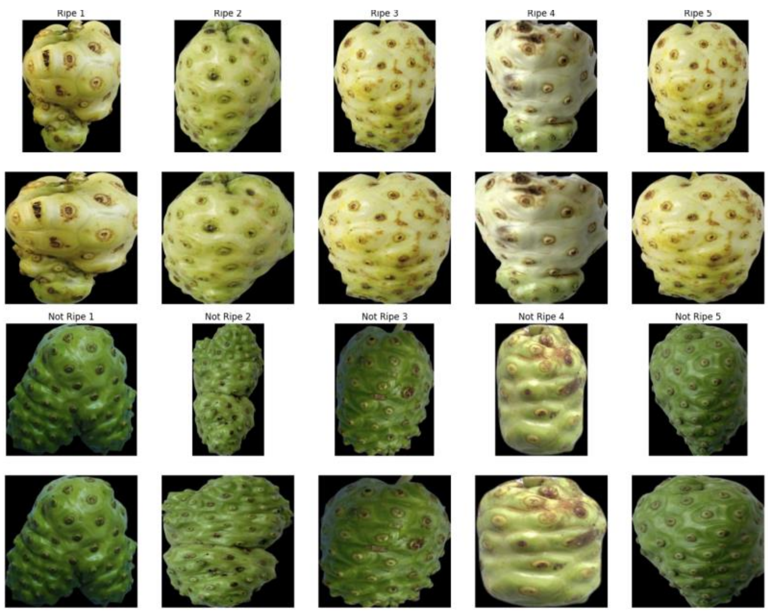

Figure 3. Before and After Resize

Segmentation is an important step in data preprocessing to enhance the features used for classification. **Figure 4** shows the segmentation process applied to Noni fruit images based on color, specifically using the hue. The segmentation is performed by converting the images to the HSV (Hue, Saturation, Value) color space and isolating the hue component, which captures the dominant color . The segmentation formula 2 used to create a binary mask is:

$$\text{Mask}(x, y) = \begin{cases} 1, & \text{if } H_{min} \leq \text{Hue}\,(x, y) \leq H_{max} \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

where (H_{min}) and (H_{max}) define the range of hue values used to segment the fruit regions. The first column displays the original images of the Noni fruit, while the second column presents the segmented images, where regions with similar color are highlighted. This approach helps identify areas that indicate ripeness based on color changes in the fruit.

The third column illustrates the masked images, where the background has been removed to retain only the essential parts of the fruit. This step helps reduce irrelevant details and allows the model to focus on key features, such as color patterns, which are important for determining ripeness. By using hue-based segmentation, the preprocessing aims to improve classification accuracy by emphasizing the color features that are critical indicators of the fruit's maturity.

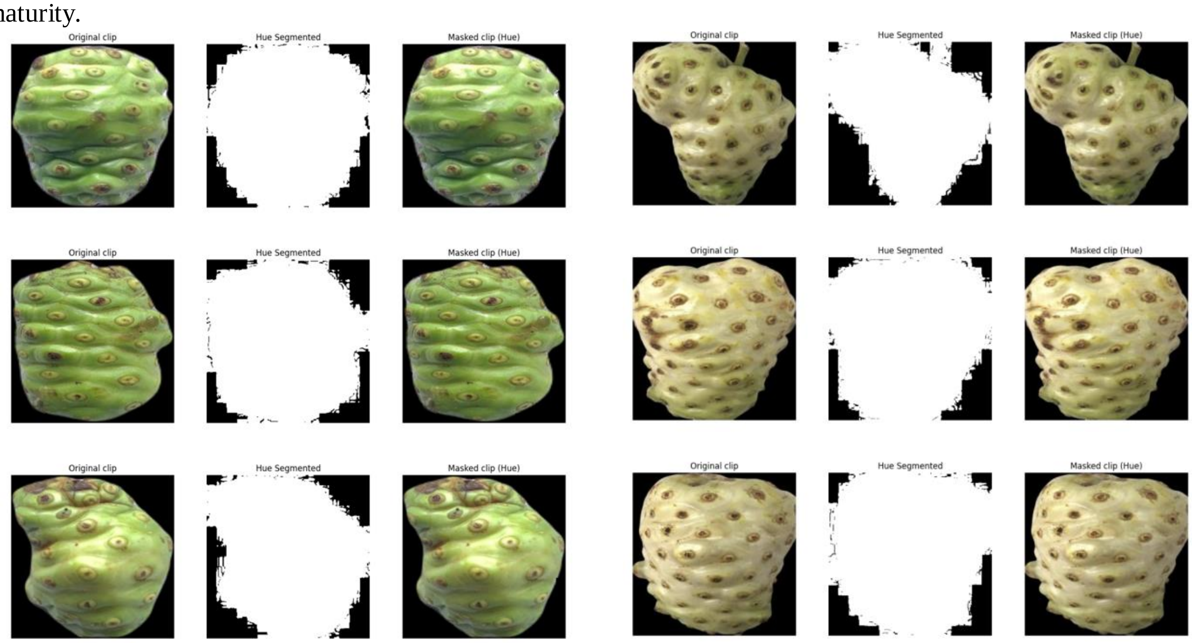

Figure 4. Segmentation with Feature Color

Table 2. Feature Extracted based Color and Texture

No	Path	mean_lbp	variance_lbp	entropy_lbp	hue	saturation	intensity	label
1	/kaggle/input/noni-dataset-plant/noni/ripe/208.jpg	19.232269	62.2172	2.16288	0.830669	0.491707	0.376751	ripe
2	/kaggle/input/noni-dataset-plant/noni/ripe/45.jpg	19.538788	60.368735	2.208332	0.821312	0.423549	0.404864	ripe
3	/kaggle/input/noni-dataset-plant/noni/ripe/56.jpg	19.442474	63.203997	2.209886	0.832136	0.433573	0.466132	ripe
4	/kaggle/input/noni-dataset-plant/noni/ripe/89.jpg	18.961823	63.629432	2.19475	0.829933	0.255129	0.430399	ripe
5	/kaggle/input/noni-dataset-plant/noni/ripe/20.jpg	19.569992	62.491225	2.203514	0.832989	0.422747	0.453988	ripe

The extracted features used for classification in the research are presented in Table 2, which combines color and texture attributes. The table lists the file paths of Noni fruit images along with the extracted features, including texture features such as mean LBP, variance LBP, and entropy LBP, which are derived from the Local Binary Patterns (LBP) method. These texture features help capture the surface patterns of the fruit, which can vary between ripe and unripe states.

Local Binary Patterns (LBP) is a method used to describe the texture of an image by comparing each pixel with its neighbors. For a pixel (g_c), The LBP value is calculated using the formula 3 below

$$\mathrm{LBP}(x,y) = \sum_{p=0}^{P-1} s\left(g_p - g_c\right) \cdot 2^p \tag{3}$$

Where g_c is the intensity of the central pixel, and g_p represents the intensity of the neighboring pixels. The threshold function $s(x)$ assigns a value of 1 if $g_p \geq g_c$ (neighbor is brighter or equal) and 0 if $g_p < g_c$ (neighbor is darker), converting local texture information into a binary pattern.

$$s(x) = \begin{cases} 1, & \text{if } x \geq 0 \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

The color features include hue, saturation, and intensity (HSI), which provide important information about the color characteristics of the fruit. The formulas 5-8 for these features are given as:

$$H = \begin{cases} \theta, & \text{if } B \leq G \\ 360^\circ - \theta, & \text{if } B > G \end{cases} \tag{5}$$

$$\theta = \cos^{-1}\left(\frac{1/2[(R-G)+(R-B)]}{\sqrt{(R-G)^2+(R-B)(G-B)}}\right) \tag{6}$$

$$S = 1 - \frac{3}{R+G+B}\min(R, G, B) \tag{7}$$

$$I = \frac{R+G+B}{3} \tag{8}$$

These color features help indicate ripeness based on changes in color properties. The label column specifies whether each image represents a "ripe" or "not ripe" fruit, serving as the target for classification. Combining these color and texture features provides a comprehensive representation of the fruit's characteristics, which is essential for accurately distinguishing between different ripeness levels using machine learning models.

SVM Model Development

Support Vector Machine (SVM) is used in this research to classify Noni fruit ripeness based on extracted color and texture features. The SVM algorithm works by finding the optimal hyperplane that separates the data into different classes (ripe and unripe). It does this by maximizing the margin between the data points of different classes, which helps to generalize the model for better classification accuracy. The formula 9 for SVM is given by

$$f(x) = w \cdot x + b \tag{9}$$

where w is the weight vector that defines the orientation of the hyperplane, b is the bias term that shifts the hyperplane from the origin, and x represents the input feature vector. The goal of SVM is to find the values of w and b that maximize the margin, defined as the distance between the hyperplane and the nearest data points from either class (support vectors). The optimization problem for SVM is formulated using Formula 10 and is subject to the conditions specified in Formula 11:

$$\text{Minimize} = \frac{1}{2}|w|^2 \tag{10}$$

$$y_i(w \cdot x_i + b) \geq 1 \quad \text{for all } i \tag{11}$$

where y_i denotes the class label, with $y_i \in \{-1,1\}$, and x_i represents the feature vector of the i-th training sample. This condition ensures that each data point is correctly classified with the maximum margin.

For cases where the data is not linearly separable, SVM uses kernel functions to transform the input space into a higher-dimensional feature space, allowing a linear hyperplane to separate the classes more effectively. In this research, different kernel functions such as Linear, Radial Basis Function (RBF), and Polynomial are explored to find the optimal configuration for classifying Noni fruit ripeness. Hyperparameter tuning is performed to adjust the kernel parameters and improve the model's performance, ensuring accurate classification.

Performance Evaluation

Performance evaluation is essential for determining the effectiveness of the SVM model in classifying Noni fruit ripeness. Several metrics are used, including accuracy, precision, recall, and F1-score, which help assess the model's ability to distinguish between ripe and unripe classes.

Where accuracy measures the proportion of correctly classified instances out of the total number of instances, and is given by the formula 12

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{12}$$

where TP (True Positive) represents correctly classified ripe fruits, TN (True Negative) indicates correctly classified unripe fruits, FP (False Positive) denotes unripe fruits misclassified as ripe, and FN (False Negative) is the number of ripe fruits misclassified as unripe. Precision, calculated as Precision $= \frac{TP}{TP+FP}$, shows how many of the fruits predicted as ripe are actually ripe, reflecting the model's ability to avoid false positives. Recall, given by Recall $= \frac{TP}{TP+FN}$, measures the proportion of actual ripe fruits correctly identified by the model, indicating the model's sensitivity to true positives. The F1-score, calculated as the harmonic mean of precision and recall using the formula 13

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{13}$$

provides a balance between precision and recall, making it particularly valuable when dealing with imbalanced datasets. These metrics collectively give a comprehensive evaluation of the model's performance, highlighting its strengths and areas for improvement in classifying ripe and unripe Noni fruits.

3. Result and Discussion:

Result

The SVM model's performance for different kernel functions, as shown in **Table 3**, is evaluated based on several metrics, including accuracy, precision, recall, and F1-score. The results indicate how well each kernel (Linear, RBF, and Polynomial) performs in classifying Noni fruit ripeness. The Linear kernel achieved an accuracy of 81.30%, with a precision of 85.00% and a recall of 78.46%, indicating a relatively lower performance in correctly identifying ripe fruits compared to the other kernels. The Polynomial kernel performed better, with an accuracy of 84.55%, precision of 88.33%, and recall of 81.54%, showing an improvement in balancing the detection of both classes.

The RBF kernel outperformed the other kernels, achieving the highest accuracy of 86.18%, precision of 88.71%, recall of 84.62%, and an F1-score of 86.61%. This suggests that the RBF kernel is more effective in capturing the non-linear relationships in the data, making it the best choice for this classification task. The results in **Table 3** highlight the importance of kernel selection in SVM modelling, as it significantly impacts the model's ability to generalize and accurately classify different ripeness levels of Noni fruit.

Table 3. SVM model performance of each kernel

Kernel	C	Gamma	Degree	Coef0	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
linear	100	0.0001	2	0	81.30	85.00	78.46	81.60
rbf	100	1	2	0	86.18	88.71	84.62	86.61
poly	10	1	3	0	84.55	88.33	81.54	84.80

Figure 5 presents the confusion matrices for the SVM model using different kernels: Linear, Polynomial, and RBF. Each confusion matrix shows the number of correct and incorrect classifications for the "ripe" and "not ripe" categories. The matrix for the Linear kernel indicates that 49 "not ripe" fruits were correctly classified, while 9 were misclassified as "ripe." Additionally, 51 "ripe" fruits were correctly identified, with 14 being incorrectly classified as "not ripe." This shows some limitations in distinguishing the classes, particularly in predicting "ripe" fruits.

The Polynomial kernel shows slight improvement, with 51 correctly classified "not ripe" fruits and only 7 misclassified as "ripe." It also correctly identified 53 "ripe" fruits, with 12 misclassified as "not ripe." The RBF kernel demonstrates the best performance, with 51 correctly identified "not ripe" fruits and only 7 misclassified, while 55 "ripe" fruits were accurately classified, and 10 were incorrectly predicted as "not ripe." These results highlight that the RBF kernel is more effective at distinguishing between "ripe" and "not ripe" Noni fruits, offering better classification performance compared to the Linear and Polynomial kernels.

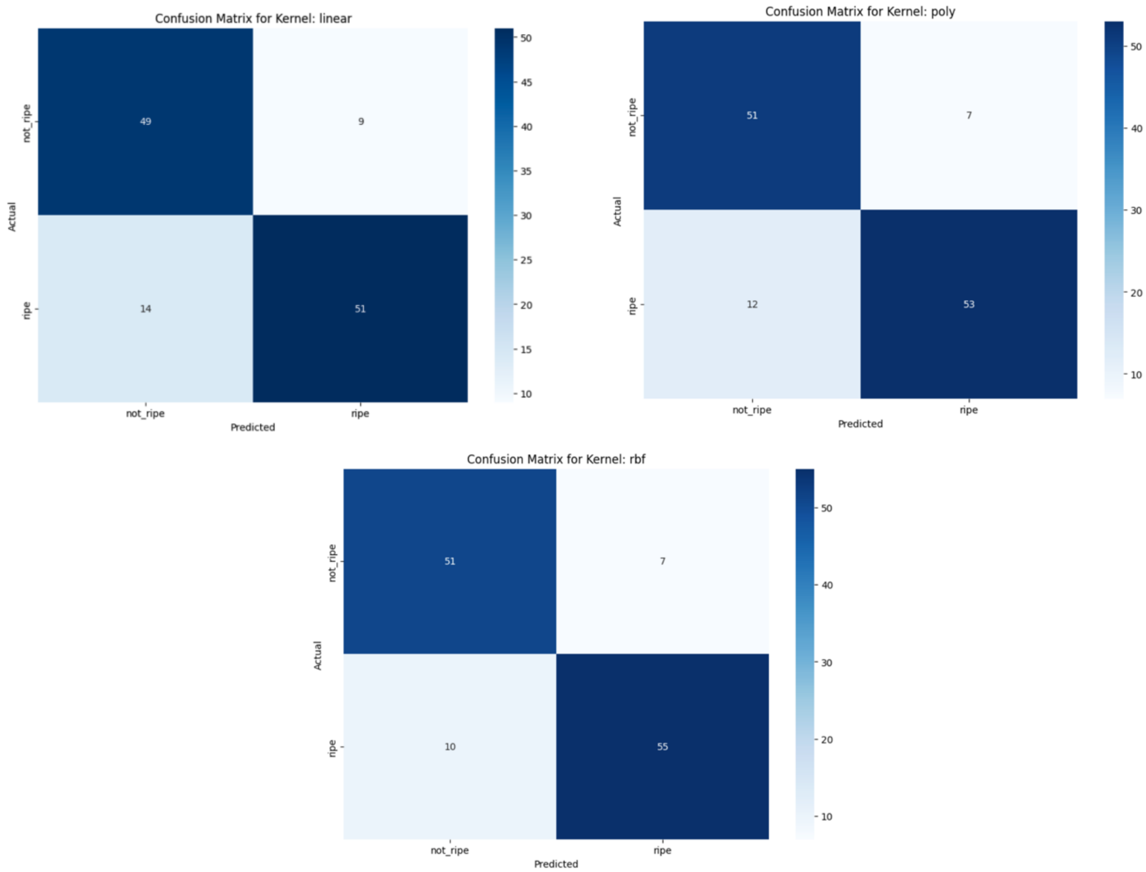

Figure 5. Confusion Matrix for Each Kernel

Discussion

The results, as shown in the confusion matrices in Figure 5, indicate that the SVM model demonstrates potential in classifying Noni fruit ripeness accurately, particularly when using the RBF kernel. The RBF kernel achieved the highest accuracy, precision, and F1-score, outperforming the Linear and Polynomial kernels. However, there is still room for improvement in consistency, as some misclassifications occurred across all kernels, particularly with predicting "ripe" fruits. This variation in performance aligns with findings from other studies employing SVM for classification tasks in agriculture, where different kernel functions yielded varying levels of success.

The practical implications of these results are relevant to agricultural practices, as the ability to reliably classify fruit ripeness can improve the efficiency of harvesting, reduce waste, and ensure better quality control. Accurate ripeness detection can lead to more precise harvesting decisions, potentially increasing market value and reducing losses. Nonetheless, the limitations of the research should be considered. The variability in model performance across different kernels suggests that the classification accuracy may be influenced by the choice of kernel and the specific dataset characteristics. Additionally, the reliance on digital images for classification means that the model's performance is contingent on image quality and resolution, which could affect its generalizability.

Future research could explore expanding the dataset to include more diverse fruit samples and different environmental conditions, enhancing the model's robustness and generalizability. Additionally, combining SVM with other machine learning techniques, such as ensemble methods, could potentially improve classification consistency. Integrating this model into an automated system for real-time ripeness detection could be a valuable practical application, warranting further investigation and development.

4. Conclusion

The research showed that the SVM model is effective for classifying Noni fruit ripeness, with the best results achieved using the RBF kernel. The RBF kernel outperformed the Linear and Polynomial kernels, achieving the highest accuracy of 86.18%, precision of 88.71%, recall of 84.62%, and F1-score of 86.61%. These results suggest that the RBF kernel is better at capturing the non-linear patterns in the data, leading to more accurate classification. However, the presence of some misclassifications indicates that there is still room for improvement, particularly in distinguishing "ripe" fruits from "not ripe."

The research answered the main objective of evaluating different SVM kernels for ripeness classification, confirming that the RBF kernel provides the most accurate results. This supports the hypothesis that using certain kernel functions can significantly enhance the model's ability to differentiate between classes. Additionally, the findings demonstrated that using a combination of color and texture features effectively contributes to accurate classification, highlighting the importance of feature selection in machine learning tasks related to agriculture.

This study contributes to the field of agricultural technology by providing a detailed analysis of SVM kernel performance for fruit ripeness classification. The comparison across different kernels offers valuable insights for selecting the optimal kernel for similar classification problems. The integration of color and texture features into the model adds to the body of knowledge on feature engineering in agricultural machine learning applications, providing a foundation for further advancements in automated fruit classification.

Future research should aim to expand the dataset to include more diverse samples and varying environmental conditions to improve the model's generalizability. Exploring the combination of SVM with other algorithms, such as ensemble methods, may enhance classification performance further. Additionally, implementing the model into a real-time ripeness detection system could provide a practical solution for automated fruit sorting, offering significant benefits for quality control in the agricultural industry.

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