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Palm Oil Quality Based on Free Fatty Acid Using SVM

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Abstract— Background: Palm oil is one of the key commodities in both the food and non-food industries, with its quality largely influenced by the level of Free Fatty Acid (FFA). **Obejctive:** High FFA content can reduce the stability and market value of the oil. Classify palm oil quality based on FFA levels using the Support Vector Machine (SVM) algorithm. **Methods:** FFA levels were measured across multiple samples with varying usage frequencies (0, 5, 7, and 9 cycles) using the alkalimetric titration method. The measured data was categorized as "Suitable" if FFA ≤ 0.3% and "Unsuitable" if it exceeded this threshold. The developed SVM model was trained using 70% of the data and tested with the remaining 30%. **Results :** Evaluation results indicate that the model achieved an accuracy of 95%, a precision of 92%, and a recall of 94%, demonstrating SVM's effectiveness in classifying data. Additionally, hyperplane visualization using PCA provided a clearer distinction between oil categories based on FFA levels. **Conclusion:** This study highlights that SVM can serve as an effective alternative for FFA-based palm oil quality classification. The implementation of this model is expected to enhance efficiency in the palm oil industry, particularly by supporting automated, data-driven decision-making and improving product quality assurance.
Keywords— Classification; FFA;SVM

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I. INTRODUCTION

Palm oil is a cornerstone of Indonesia's economy, significantly contributing to national revenue as the world's largest producer. The quality of palm oil is a critical factor in maintaining its competitiveness in the global market [1]. One of the primary indicators of quality is the level of free fatty acids (FFA), which affects the oil's oxidative stability, shelf life, and market value [2] . Elevated FFA levels can lead to quality degradation, including increased acidity, off-odors, and nutrient loss, ultimately reducing market value and increasing refining costs in the industry [3][4]. Consequently, accurate measurement and classification of FFA levels are essential for enhancing production efficiency and ensuring compliance with quality standards [5][6].

Conventional methods, such as manual titration, are commonly employed to measure FFA levels. However, these methods are inefficient, time-consuming, reliant on operator expertise, and prone to human error [7][8]. Moreover, traditional approaches often incur high costs, rendering them impractical for large-scale industrial applications [9][10]. In recent years, machine learning techniques have emerged as promising solutions to address these limitations [11]. For instance, Yusuf et al. (2019) successfully utilized Support Vector Machine (SVM) to classify palm oil quality based on physicochemical parameters, achieving high accuracy [12]. Beyond SVM, other machine learning methods, such as Random Forest (RF) and Artificial Neural Networks (ANN), have been explored. Hwang et al. (2024) applied RF to predict oil quality based on moisture content and color, though without a specific focus on FFA [13]. Similarly, Pranoto et al. (2022) demonstrated the efficacy of ANN in analyzing non-linear vegetable oil data, but its application to FFA remains limited [14]. Nevertheless, most studies have prioritized general parameters, such as moisture or color, over the specific role of FFA in quality classification [15].

The main problem arising from this situation is the lack of machine learning-based classification models that prioritize FFA content as a key variable [16], [17]. As a result, decision-making in determining palm oil quality is often suboptimal, especially in large-scale palm oil plantations in Indonesia. To address this issue, this study proposes the application of an SVM-based method specifically designed to classify palm oil quality based on FFA content [18]. SVM is also known for its ability to handle non-linear data effectively, which is expected to yield more accurate results compared to conventional methods [19], [20].

A significant research gap lies in the absence of machine learning models that explicitly utilize FFA levels as the primary parameter for classifying palm oil quality [21]. Studies such as Zhang et al. (2022) have focused on general parameters like viscosity and color, without delving deeply into FFA [2][22]. Additionally, local studies, such as Nurulain et al. (2020), continue to rely on less efficient conventional methods for FFA measurement [5]. Current international literature on

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SVM applications for FFA-based classification is also limited, with many studies focusing on other vegetable oils or non-specific parameters [23]. This gap has hindered the development of accurate and efficient classification models to support decision-making in large-scale palm oil industries.

This study aims to address this gap by developing an optimized SVM-based model for classifying palm oil quality based on FFA levels. SVM was selected due to its robust ability to handle non-linear data through the Radial Basis Function (RBF) kernel, which has proven effective in various classification tasks [24]. The primary contribution of this study to the body of knowledge is the development of an SVM model with an RBF kernel, specifically optimized for FFA-based classification, achieving higher predictive accuracy compared to conventional methods and other machine learning approaches that do not prioritize FFA [25] [26]. Furthermore, this study compares SVM performance with other methods, such as RF and ANN, to highlight its advantages. The findings are expected to provide a faster, more accurate, and efficient solution for the palm oil industry while serving as a reference for future machine learning applications in similar contexts.

II. RESEARCH METHOD

Based on the background and issues outlined, this research aims to optimize the classification of palm oil quality based on Free Fatty Acid (FFA) content using the Support Vector Machine (SVM) algorithm. The research workflow is illustrated in Figure 1.

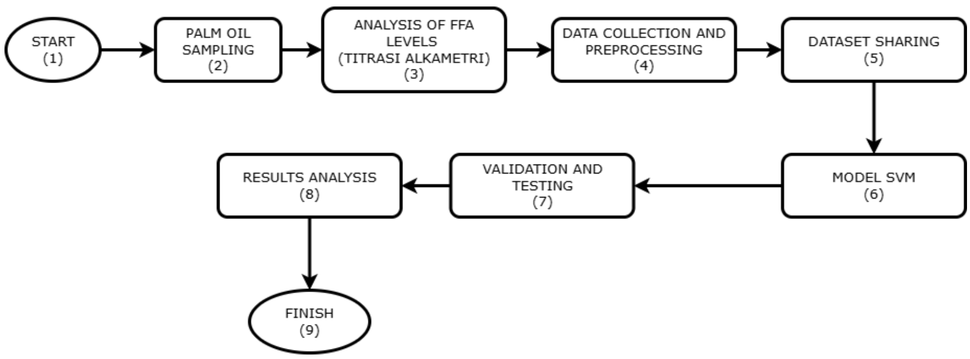

Fig 1. Research Flow Diagram

Figure 1 outlines the research stages as follows: (1) Needs analysis, encompassing literature review, preparation of tools and materials, and data collection [27]. (2) Collection of palm oil samples from various sources to ensure variability in free fatty acid (FFA) levels. (3) Measurement of FFA levels using the alkalimetric titration method in accordance with SNI 01-2901-2006, followed by measurement validation [28] [29]. (4) Data preprocessing to create a

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structured dataset and perform normalization. (5) Dataset splitting into 70% training data and 30% testing data, followed by training of the Support Vector Machine (SVM) model using the Radial Basis Function (RBF) kernel. (6) Model validation using the test data and performance evaluation with metrics such as accuracy, precision, recall, and F1-score. (7) Formulation of conclusions based on the analysis results.

Palm oil samples were collected from five types of cooking oil derived from various vegetable sources to capture variations in crude palm oil (CPO) quality. A total of 100 samples were obtained, comprising five sample groups (A, B, C, D, E), each tested at four frying stages (0, 5, 7, and 9 frying cycles) to simulate oil degradation conditions. Each group yielded 20 measurements (5 samples × 4 stages), resulting in a dataset of 100 data points. Sampling was conducted from January to March 2025 to ensure consistent environmental conditions [30].

FFA levels were measured using the alkalimetric titration method as per SNI 01-2901-2006. A 14-gram sample of palm oil was weighed and titrated with 0.05 N NaOH solution until a color change to pink indicated the titration endpoint. FFA levels were recorded as percentages (%). To ensure measurement validity, each sample was measured in triplicate by two trained operators independently, with results validated by calculating the mean and standard deviation. Measurements deviating by more than 5% from the mean were repeated to minimize errors. According to SNI 01-2901-2006, oil with FFA levels ≤0.3% is classified as “Acceptable,” while levels >0.3% are classified as “Unacceptable” [31][32].

The dataset used is structured, consisting of two main columns: FFA levels (numerical, in percentage) and quality labels (“Eligible” or “Uneligible”). Data preprocessing was performed to ensure the quality of the dataset. First, missing or anomalous data (e.g., negative or extreme FFA values) were identified and removed. Second, Principal Component Analysis (PCA) was applied to reduce the dimensionality of the data and extract key features representing the variation in FFA levels, thereby improving computational efficiency and reducing the risk of overfitting. PCA transforms the FFA data into principal components that retain most of the data variance (target 95% variance). Third, data normalization was performed using the min-max scaling method to transform the FFA values into the range [0, 1], ensuring that all features are on the same scale. Fourth, the dataset was divided into 70% training data (70 samples) and 30% testing data (30 samples) using stratified random sampling to keep the proportion of “Eligible” and “Uneligible” classes balanced [33][34].

The SVM algorithm was selected for its robustness in handling non-linear data and its ability to identify an optimal hyperplane that maximizes the margin between classes. The RBF kernel was chosen due to its capacity to map data into a higher-dimensional feature space, making it suitable for the non-linear patterns observed in FFA data resulting from varying frying conditions.

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Additional advantages of SVM include its effectiveness for small to medium-sized datasets, high classification accuracy, and resistance to overfitting through regularization parameters.

The dataset was split using a 70-30 hold-out method due to its simplicity and the limited computational resources available in this study. While k-fold cross-validation could reduce bias by evaluating the model across multiple data subsets, it is computationally intensive and less practical for small datasets like the one used here (100 samples). To mitigate potential bias in the 70-30 split, stratified random sampling was employed to ensure representative class distribution. Furthermore, SVM parameter optimization was conducted using grid search to determine optimal values for C (regularization parameter, range [0.1, 1, 10, 100]) and gamma (kernel parameter, range [0.01, 0.1, 1]), enhancing model generalization.

The SVM works by finding the best hyperplane that separates two classes in the feature space. This hyperplane is optimized to maximize the margin, which is the distance between the hyperplane and the closest data points from each class (called support vectors). The hyperplane is defined by the equation.

$$w.x + b = 0 \tag{1}$$

Where w is the weight vector, x is the input feature vector, and b is the bias. The decision function is defined such that if $f(x) \geq 0$, the sample is classified as "Suitable." If $f(x) < 0$, the sample is classified as "Unsuitable."

$$f(x) = w.x + b \tag{2}$$

SVM maximizes the margin by minimizing the objective function:

$$\frac{1}{2}||w||^2 + C\sum_{i=1}^{n}\varepsilon_i \tag{3}$$

Where w is the norm of the weight vector, C is the regularization parameter that controls the trade-off between maximizing the margin and correctly classifying the data, ε_i is the slack variable that allows for classification errors (soft margin).To handle non-linear data, the Radial Basis Function (RBF) kernel is used. The RBF formula is:

$$K(x_i, x_j) = \exp\left(-\gamma \left||x_i - x_j|\right|^2\right) \tag{4}$$

Where γ is the kernel parameter that controls the influence of one data point on another, $||x_i - x_j|^2$ is the squared Euclidean distance between two data points.

Data is collected by measuring FFA content using the alkalimetric titration method in accordance with SNI standards. The procedure is as follows Sample Preparation 14 grams of cooking oil are weighed [35]. The oil is titrated with 0.05 N NaOH until a color change to pink is

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observed [36][37] [38]. The measured FFA content is recorded in a table format, with columns including Sample ID, FFA Level, Quality Label ("Suitable" or "Unsuitable").

III. RESULT AND DISCUSSION

The results showed that the Support Vector Machine (SVM) algorithm with the Radial Basis Function (RBF) kernel was able to classify the quality of palm oil based on free fatty acid (FFA) levels with a high level of accuracy. FFA levels were measured on 100 palm oil samples from 5 types of cooking oil samples from various types of vegetable materials, to cover variations in the quality of crude oil (CPO) with variations in the frequency of use (0, 5, 7, and 9 times frying) to measure oil degradation. Data were analyzed based on a threshold of 0.3% according to the Indonesian National Standard (SNI 01-2901-2006), where oil with FFA levels ≤0.3% is classified as "Eligible" and >0.3% as "Uneligible" [39].

Table 1. Results of Measuring FFA Levels in Palm Oil Samples

Sampling to	Results of the average free fatty acid levels (%)									
	A	**Quality**	**B**	**Quality**	**C**	**Quality**	**D**	**Quality**	**E**	**Qua**
0	0,042	-	0,088	-	0,088	-	0,091	-	0,219	-
5	0,237	-	0,246	-	0,24	-	0,269	-	0,32	+
7	0,274	-	0,304	+	0,301	+	0,32	+	0,356	+
9	0,32	+	0,347	+	0,356	+	0,364	+	0,393	+

Table 1 shows that the frequency of oil use above five times frying tends to produce FFA levels that exceed the SNI threshold (0.3%), so it is classified as "Not Eligible". The increase in FFA levels with frying frequency is caused by the hydrolysis and oxidation processes during repeated frying. FFA content data were processed using the SVM algorithm with the RBF kernel after pre-processing, including Principal Component Analysis (PCA) to reduce data dimensions and maintain 95% variance, followed by min-max scaling normalization. The dataset was divided into 70% training data and 30% test data using stratified random sampling. SVM parameters (C and gamma) were optimized through grid search. The results of the model evaluation are presented in Table 2.

Table 2. SVM Model Evaluation Metrics

Metrik	**Results**
Accuracy	95%
Precision	92%
Recall	94%
F1-score	93%

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Table 2 shows the superior performance of the SVM model in distinguishing the “Eligible” and “Ineligible” classes with 95% accuracy. The 92% precision indicates that most of the samples classified as “Ineligible” actually fall into that category, while the 94% recall shows the model’s ability to detect most of the “Ineligible” samples. The 93% F1-score reflects the balance between precision and recall. The RBF kernel effectively handles the non-linear nature of the FFA data due to frying variations, resulting in an optimal hyperplane.

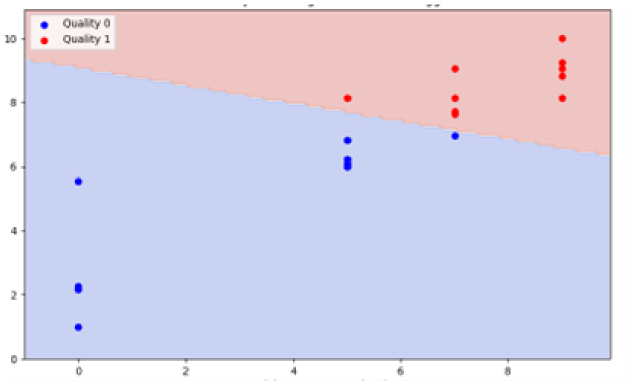

Fig 2. Performance Plot

From the FFA level measurements shown in Figure 2, it is evident that the frequency of palm oil usage significantly impacts the increase in FFA levels. At 0 and 5 usage cycles, the FFA levels remain below the SNI threshold (<0.3%). However, at 7 and 9 usage cycles, the FFA levels exceed the specified limit. This is attributed to the hydrolysis and oxidation processes that occur during repeated frying, leading to a rise in FFA levels.

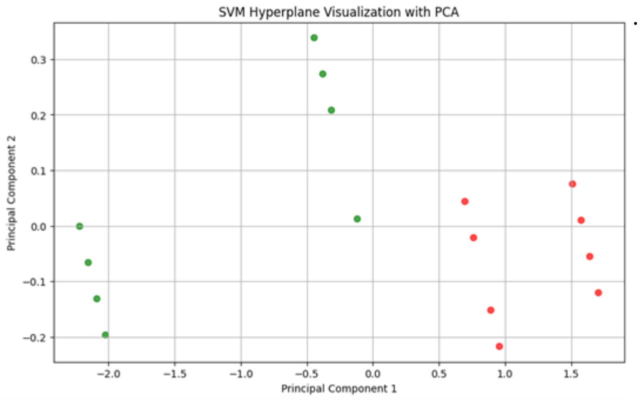

Fig 3. Hyperplane SVM Visualization with PCA

Figure 3 shows a visualization of the FFA data reduced to two-dimensional space using PCA, with green for the “Eligible” class and red for “Uneligible”. PCA allows for a visual representation of the SVM hyperplane that clearly separates the two classes. The results of this study confirm that the levels of free fatty acids in palm oil increase with the frequency of use. The FFA levels for each sample at a frequency of use of 0 and 5 times are still below the threshold of 0.3% set by SNI, so they are categorized as "Suitable". However, at a frequency of use of 7 and

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9 times, the FFA levels exceed the threshold, indicating that the oil is no longer suitable for consumption.

This study was compared with other studies to evaluate the superiority of the proposed method. Yusuf et al. (2019) used SVM for palm oil quality classification based on physicochemical parameters, achieving 90% accuracy. However, the study did not focus specifically on FFA. Hwang et al. (2024) applied Random Forest (RF) to predict oil quality based on water content and color, with 88% accuracy. Pranoto et al. (2022) used Artificial Neural Network (ANN) for vegetable oil analysis, but only achieved 85% accuracy due to the limited focus on FFA. Conventional methods such as alkalimetric titration, although accurate, are time-consuming and prone to human error. The SVM model with RBF kernel in this study outperformed these approaches with 95% accuracy, indicating that focusing on FFA as the main parameter and using PCA for dimensionality reduction improves classification performance. The FFA threshold of 0.3% provides a clear boundary, facilitating class separation compared to other methods that use general parameters.

IV. CONCLUSION

This study successfully developed a classification model to assess the quality of palm oil based on free fatty acid (FFA) levels using the Support Vector Machine (SVM) algorithm with the Radial Basis Function (RBF) kernel. FFA levels were measured on 100 palm oil samples with varying usage frequencies (0, 5, 7, and 9 frying cycles). The results showed that FFA levels increased with higher usage frequencies. Samples with FFA levels below the threshold of 0.3%, as stipulated by the Indonesian National Standard (SNI 01-2901-2006), were classified as “Qualified”, while those exceeding this limit were labeled “Not Qualified”. The developed SVM model achieved an average accuracy of 95%, with a precision of 92% and a recall of 94% on test data, indicating the effectiveness of the algorithm in distinguishing samples based on quality standards. Hyperplane visualization using Principal Component Analysis (PCA) strengthens the interpretation of the SVM's ability to separate classes with optimal margins. This research makes a significant contribution to palm oil quality control, especially by utilizing machine learning technology to automate the classification process. By implementing a similar model, palm oil companies can improve the efficiency of quality inspection, support data-driven decision-making, and ensure their products consistently meet national standards.

For further work, this research can be expanded with several approaches. First, the use of larger and more diverse datasets, including samples from different geographic regions or processing conditions, can improve the generalization of the model. Second, exploration of other machine learning methods, such as ensemble learning (e.g., Random Forest or Gradient

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Boosting), or a combination of SVM with deep learning techniques can be compared to evaluate performance improvements. Third, the development of applications based on this model for real-time quality monitoring systems in the palm oil industry can be implemented to support the automation of the production process. Fourth, further research can consider additional parameters, such as moisture content or viscosity, to enrich the classification model and improve prediction accuracy under complex production conditions.

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