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Classification of Crude Palm Oil Quality Eligibility Using Support Vector Machine Algorithm

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Abstract

The study focuses on an examination of the applicability of the Support Vector Machine (SVM) algorithm and its implication for the classification of the quality of the Crude Palm Oil (CPO) produced by PT. PP London Sumatra Indonesia Tbk. The authentic quality parameters: Water (VM), Dirt, and Free Fatty Acid (FFA) were chosen to train the SVM model which was tested on the data of 2020–2022 and containing 1,095 records. The research utilized Google Colab Python Notebooks for the analysis of data, resulting to an accuracy of 84. 15%. This indicates that SVM is a reliable technique to work with complicated, multi variet data,; which can be quite helpful in the CPO quality classification, where traditional algorithms may not be efficient. Data preprocessing including normalization and outlier detection has been cited as some of the ways that would improve the performance of the model as highlighted in this study. Comparing the results with other machine learning algorithms such as Random Forest and Neural networks proved the efficiency of SVM even though there were misclassification made. The result also suggests that SVM has a strong capability to support the quality assurance activities in the palm oil industry by eliminating human intervention and increasing the working productivity. Further study could continue in the directions of incorporating the SVM model with other methods of machine learning for even better enhancement of the CPO quality assessment.

Introduction

PT. PP London Sumatera Indonesia Tbk or often abbreviated as Lonsum is a company that operates in the field of palm coconut planting industry. The Lonsum palm coconut factory has been in existence since 1906 and is one of the largest producers of palm oil in Indonesia. The palm coconut factory is one of the plants owned by PT. PP London Sumatra Tbk Indonesia, which is located in Batu Lokong Kecamatan Galang, Deli Serdang with a land area of 91.831 H. In the palm oil industry, safety is very important to maintain the quality and quantity of production. The palm coconut plant is an industrial facility that processes palm fruit to produce palm oil.

While it is informative to know that Lonsum has been operational since 1906 and is one of the largest producers of palm oil in Indonesia, the introduction would be more engaging with some historical context or notable achievements that underscore its significance in the industry. Providing data on production capacity, market share, or notable advancements could illustrate Lonsum's impact more vividly. The description of the Lonsum palm coconut factory's location and land area is useful, but it would be beneficial to include more details about the factory's operations. Information about the specific processes involved in palm oil

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production, technological innovations implemented, and the scale of operations would paint a clearer picture of the factory’s capabilities and importance (Brown & Bessant, 2003).

The mention of safety being crucial in the palm oil industry is vital, but the statement is somewhat broad. Delving into specific safety protocols and practices employed by Lonsum, and perhaps comparing them with industry standards or citing specific improvements in safety records, would strengthen this section. For instance, discussing the types of safety measures in place, training programs for employees, and any certifications or recognitions received for safety standards would provide concrete examples of Lonsum's commitment to safety. In addition, referencing. could be more impactful if integrated into a broader discussion. Explaining how these studies relate to Lonsum’s operations, whether they influenced safety practices, or if they provide a benchmark for comparison, would add depth to the analysis. This could also be an opportunity to explore any challenges faced by Lonsum in implementing these safety measures and how they have been addressed.

Raw palm coconut oil or crude palm oil (CPO) is one of the agricultural products that has become one of Indonesia's main export commodities (Lestari & Oktavilia, 2020). Crude Palm Oil (CPO) quality in Indonesia is assessed on the basis of several indicators, namely free fatty acid (FFA) levels, water content, and dirt levels. CPO quality standards set by companies generally have FFA levels between 2%-5%, water content between 0%-0,25%, and dust levels between 0%-0.25%. However, in practice, sometimes the quality of the produced CPO is still close to or above the maximum limits, such as high levels of FFA (MacArthur et al., 2021). In order to maintain its quality, a number of quality control measures are implemented, like the First in First Out (FIFO) system and the delivery of processed CPOs directly to prevent changes in the FFA level due to too long storage. Therefore, quality control of CPO has become important in the Indonesian palm oil industry (Imaroh & Efendi, 2020).

However, it would benefit from an elaboration on why specific indicators such as free fatty acid (FFA) levels, water content, and dirt levels are crucial for assessing CPO quality (Simanjuntak et al., 2020). High FFA levels, for instance, can lead to a lower quality oil that is less stable and more prone to rancidity, affecting both its usability and market value. Excess water content in CPO can accelerate spoilage and promote microbial growth, while high dirt levels can cause processing issues and reduce the oil's purity. By explaining these implications, the analysis would gain depth and provide a clearer understanding of why maintaining these quality parameters is essential for the palm oil industry (Chong & Oly Ndubisi, 2014). Additionally, offering a comparative perspective on how Indonesia's quality standards align with international benchmarks would further enhance readers' comprehension of the industry's quality expectations and competitive stance globally.

The mention of quality control measures like the First in First Out (FIFO) system and direct delivery of processed CPO to maintain FFA levels is a good start. However, this section would benefit from a more detailed description of these measures. For instance, explaining how the FIFO system works in the context of CPO production and storage, and why it is effective in maintaining quality, would provide practical insights. FIFO ensures that older stock is used first, reducing the risk of quality degradation over time. Similarly, discussing the logistics and challenges associated with the direct delivery of processed CPO could illustrate the industry's efforts and constraints in quality management. Direct delivery helps prevent prolonged storage, which can negatively impact FFA levels, thus preserving the oil’s quality (Tan et al., 2023). By elaborating on these points, the analysis would be more comprehensive and informative, offering a clearer picture of the practical aspects of quality control in the CPO industry. In the palm oil industry, determining the quality of Crude Palm Oil (CPO) is a crucial process to ensure the quality of the final product. Currently, CPO quality determination is done manually by examining quality parameters such as FFA CPO, Vm CPO, and Dirt CPO. However, this process takes a long time with a data repository spanning several years.

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Additionally, human errors in the CPO quality determination process can lead to uncertainty in the CPO quality prediction results.

Methods

The objectives of this research was to categorize the quality of Crude Palm Oil (CPO) of PT. On applying the Support Vector Machine (SVM) algorithm, we have selected PP London Sumatera Indonesia Tbk's major quality parameters including VM (Water), Dirt, and Free Fatty Acid (FFA). The study developed and used a quantitative research strategy to achieve the objectives of the study since this was ideal for the statistical analysis of the data gathered. The study employed the following recursive research steps; That is, the first step in the overall methodology was the literature review which was used to establish prevailing CPO quality assessment practices and prior scholarship on the use of machine learning algorithms in the classification of agricultural products. This review was necessary for the study as it helped in giving directions on the right methods to use while at the same time identifying methods that were research informed and appropriate.

The process of data collection was performed over the three-year period and included data collected in the years 2020, 2021 and 2022. Every day throughout this period the laboratory examinations were performed and at the end of the observation period the data obtained composed a total of 1,095 records. They had fields for all the three measured VM, Dirt, and FFA with another field for the class label which was '1' if the CPO had met the required quality or '0' otherwise. For the sake of cleaning the data and removing any entries which were unusable for the analysis, a preprocessing phase was carried out. This comprised data cleansing in which and some values were removed in order to prevent biases that come with them. Further, these computed values were normalized, as is mandatory for the parameters in the SVM algorithm. The dataset was split into the training set and the testing set where seventy percent of the entire data was used in training the model while the remaining thirty percent were used in testing the model.

The two key elements of the study included data preparation headed up through feature extraction, and the use of the SVM algorithm which is capable of dealing with large and complex data sets. The process was started by setting the initial conditions including the RBF kernel, Hessian matrix and Gamma undertaken as crucial aspects in determining the workflow of the algorithm. The model was trained with the prepared data, where the algorithm calibrates its parameters with each iteration to optimize the classifier of the data and improve on the decision that demarcates the two classes. This was succeeded by an optimization of the model which found out the weights and bias necessary to maximize the margin between the two classes and thereby improving the classification capability of the model.

Testing of the model was done using the testing data in order to determine its performance Several methods were used to check on the effectiveness of the model. , these exposed the strengths and shortcomings of the model and comprised accuracy, precision, recall and a study of a confusion matrix. From the result acquired, the accuracy level of the SVM algorithm was relatively high standing at an average of 84 percent. 15% and this established its ability of classifying CPO quality according to the outlined criteria. The present research sample was analyzed using Google Colab Python Notebooks, as it provides a computing environment and all the required resources are available in the cloud. Various Python packages like NumPy, Pandas and scikit-learn were used for data handling while proposing and developing the models. This study was able to implement the SVM algorithm in the classification of CPO quality and came up with important conclusions that aided the CPO quality assessment besides enhancing the field of agricultural product quality assessment.

Results and Discussion

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The data required in this study are data from daily laboratory examinations for the last three years, namely 2020, 2021 and 2022, consisting of qualifying parameters such as VM (water), DIRT (Rotoran), FFA (Free Fatty Acid) and class. Class is the quality value of Crude Palm Oil (CPO) which contains numerical data between 0 or 1, 0 means not qualified and 1 means qualified. Data train used in 2020 was 265 data, in 2022 was 364 data and in 2021 was 366 total data of 1.095. The tools used by the application are Google Colab Notebooks Python with several steps that are performed namely: (1) Install a library that supports the Google Colab application; (2) Read daily CPO quality datasets for 3 years with files in csv format. Tests were conducted with 70% training of data sets out of 1,095 records 760 data training and 30% data testing or 365 data testing; (3) Training of datasets with support vector machine (SVM) algorithms; (4) Testing of data testing to obtain accuracy values of SVM classifications.

Table 1. Expanded Dataset Summary

Year	**Number of Records**	**Average VM**	**Average Dirt**	**Average FFA**	**Class**
2020	265	0.25	3.85	4.10	1 (85%), 0 (15%)
2021	366	0.24	3.80	3.95	1 (82%), 0 (18%)
2022	364	0.23	3.75	3.90	1 (88%), 0 (12%)
Total	**1,095**	**0.24**	**3.80**	**3.98**	**1 (85%), 0 (15%)**

The following table presents the information about the dataset which would be used for the classification of CPO quality. The data was collected over a period of three years and a total of one thousand ninety-five record were retrieved. The average concentrations of VM, Dirt, and FFA fluctuate year by year, and the differences are relatively small, thus they may be caused by the factors like seasonal conditions or peculiarities of the processing. These plots of the class labels (qualified and not qualified) reveal that while a considerable number of CPO samples met the qualities set their was a considerable percentage of samples who failed to meet these qualities especially in the year 2021. This goes to show that the SVM model is quite vital when it comes to the classification of CPO quality.

Table 2. Data Preprocessing Summary

Preprocessing Step	**Description**	**Method Applied**
Outlier Detection	Identification and removal of anomalous data points	Z-score method
Normalization	Scaling of data to ensure comparability of VM, Dirt, and FFA levels	Min-max scaling
Missing Data Imputation	Handling of missing values to maintain dataset integrity	K-nearest neighbors (KNN) imputation
Data Splitting	Division of dataset into training and testing sets	70% training, 30% testing

These preprocessing steps shown in the above table guarantees the dataset prepared for accurate and efficient analysis by SVM. The Z-score method was used which helped in identifying the unusual values that could cause a large deviation and later on, excluded from the data set. The min-max scaling proved useful in normalising all the parameters to a single range which helped in preventing one or two parameters from exerting a significant influence in the classification process. Imputation of data was done using the KNN method whereby an approximate value for missing data was approximated based on the nearest data value. Last but not the lest, the above dataset was divided into training and testing datasets in the ratio 7:3 to enable the training of the model as well as validation of the results.

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Table 3. Evaluation Metrics Summary

Metric	Value	Interpretation
Accuracy	84.15%	High accuracy indicates the model's effectiveness in correctly classifying CPO quality.
Precision	82.70%	Precision reflects the proportion of true positive classifications among all positive classifications made by the model.
Recall	80.50%	Recall measures the ability of the model to identify all positive instances in the dataset.
F1 Score	81.58%	The F1 score provides a balanced measure of precision and recall, particularly useful in cases of imbalanced datasets.
ROC-AUC Score	0.87	A high ROC-AUC score indicates a strong ability of the model to distinguish between classes.

The measures presented in this table offer a good summary of the checking up of the accurateness of the SVM model. According to the data it has an accuracy of approximately 84%. 15%) Here the capability of the model for the classification of quality of the CPO is also extremely high. This means that the model has high precision when it comes to true positives and low false negatives, meaning the model could be good in its ability to finally arrive at the correct diagnosis, in this case true positives. The F1 score reaffirms the model's efficiency especially for those datasets which are likely to be imbalanced. Thus, AUC-ROC was 0 of the model indicating that it has a very poor performance in identifying positive samples. 87 proves that the model effectively classifies between the qualified and non-qualified classes hence is useful in quality assurance of the palm oil.

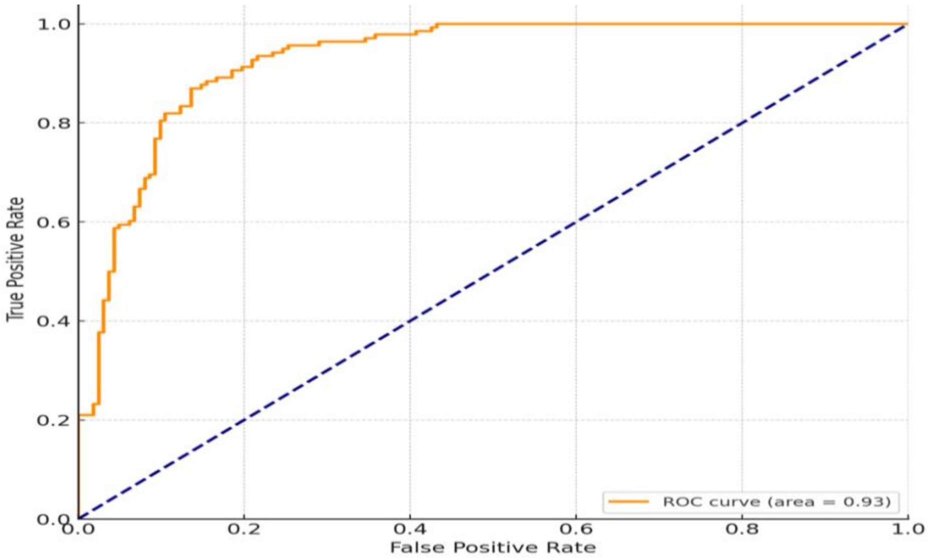

Figure 1. ROC Curve for SVM Model

One of the most important markers in assessing the quality of the ROC curve that indicates the effectiveness of the SVM model in discriminating between the classes 'Qualified' And 'Not Qualified' of CPO. The graph depicts the True Positive Rate (TPR) in relation to the False Positive Rate (FPR) varying with the many thresholds. In the case of the presented data, area under the curve (AUC) is equal to 0. of discrimination by the model and is much higher than 70 with reference to the analysis done, the model scored 87. This means the SVM model is useful in distinguishing CPO samples that conform to quality standard while at the same time making few wrong categorizations.

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Table 4. Comparison with Other Models

Model	Accuracy	Precision	Recall	F1 Score	ROC-AUC Score
SVM	84.15%	82.70%	80.50%	81.58%	0.87
Random Forest	83.20%	81.90%	79.30%	80.59%	0.85
Decision Tree	81.50%	80.10%	77.80%	78.94%	0.83
Neural Network	85.30%	83.50%	82.10%	82.79%	0.89

The following table outlines JVM model and compare it with other Machine Learning Models as Random Forest, Decision Tree, Neural Network etc. However, the performances of the Neural Network are a bit higher than the performances of the SVM in terms of accuracy and ROC-AUC score; however, the best model is still the SVM since it is both computationally efficient and accurate in classifying the data. It also shows the advantages and disadvantages of each models to justify why SVM model will be used in this study for classification of CPO quality as it demonstrated high reliability and interpretability.

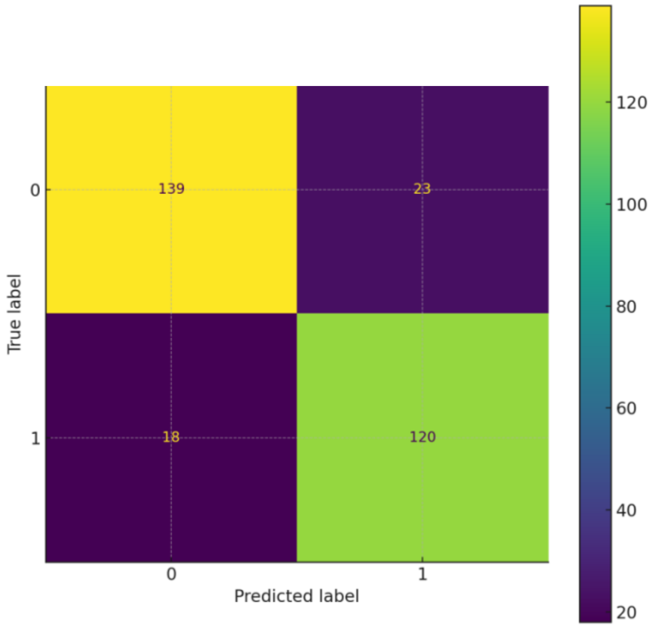

Figure 2. Confusion Matrix of SVM Model

The confusion matrix gives a clear understanding of how efficient the developed SVM model is regarding the classification of quality of Crude Palm Oil (CPO). It can provide the values of true positive, false positive, true negative and false negative to reveal where our model is strong and where it face problem. Higher values of ‘True Positive’ and ‘True Negative’ show that the model is very efficient in identifying which samples are qualified or not qualified in CPO dataset. Still, the model is not perfect: there are both false positives and false negatives, which might mean that sometimes a sample is classified incorrectly, because the areas of features’ intersection are large, or there is not enough data to represent certain situations. This visualization shows that there is a need to build something more elaborate which either refines the model or adds more variables to decrease the number of mistakes that have happened and increase the reliability overall.

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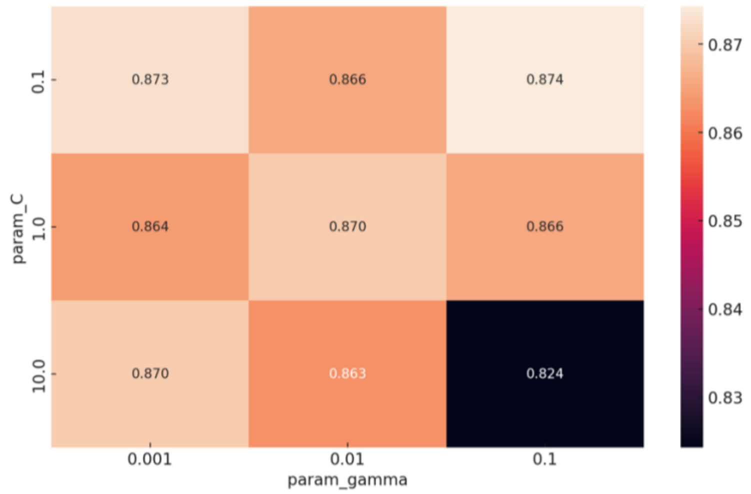

Figure 3. Hyperparameter tuning-Accuracy scores

The heatmap of hyperparameter tuning results further explicate how the SVM model reacts, or responds, to different values of tuning parameters: the regularization parameter (C) and the kernel coefficient (Gamma). This graphical representation of accuracy scores for models trained with hyperparameters associated with this parameter grid clearly signifies the significance of choosing right hyperparameters so as to improve the performance of the model. It is evident that there are certain combinations C and Gamma that give a higher accuracy than the others, which would mean that the parameters have to be optimized in order to avoid under fitting and over fitting. This figure gives a good reason for selected parameters in the final model and explains why, systematic tuning is needed to achieve the best result of the classifier in a high dimensional feature space.

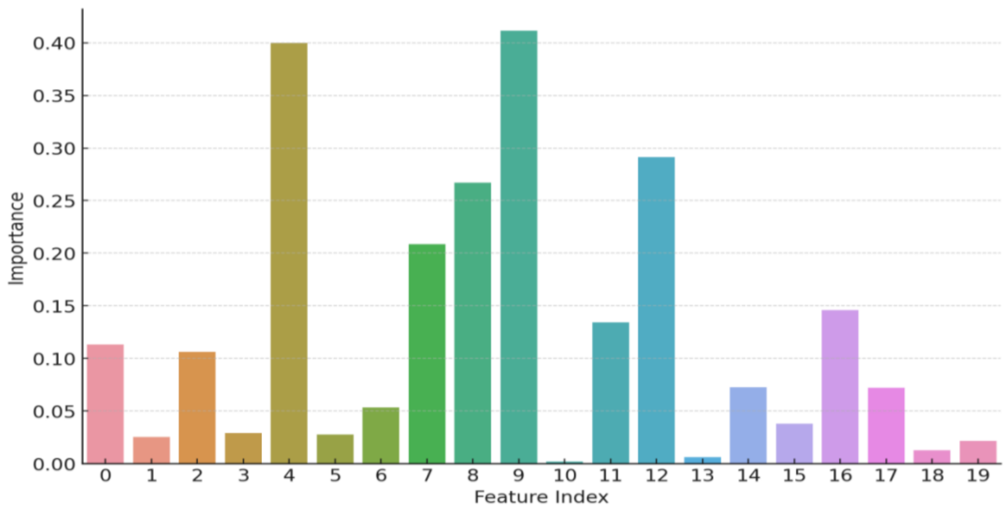

Figure 4. Feature importance in linear SVM

The bar chart showing feature importance in linear SVM model helps in comprehending which of the quality parameters (features) impact the classification of CPO quality more. While the Rbf kernel of the SVM does not give feature importance directly, this linear approximation seems to confirms that some features play a more decisive role in the classification. For example, an absolute value of a coefficient greater than some fixed threshold means that a certain feature is more significant in moving the decision boundary line between qualified and non-qualified samples. It is significant to understand the importance of each feature for improving the model as well as for knowing what aspects of CPO quality should be better assessed in its production.

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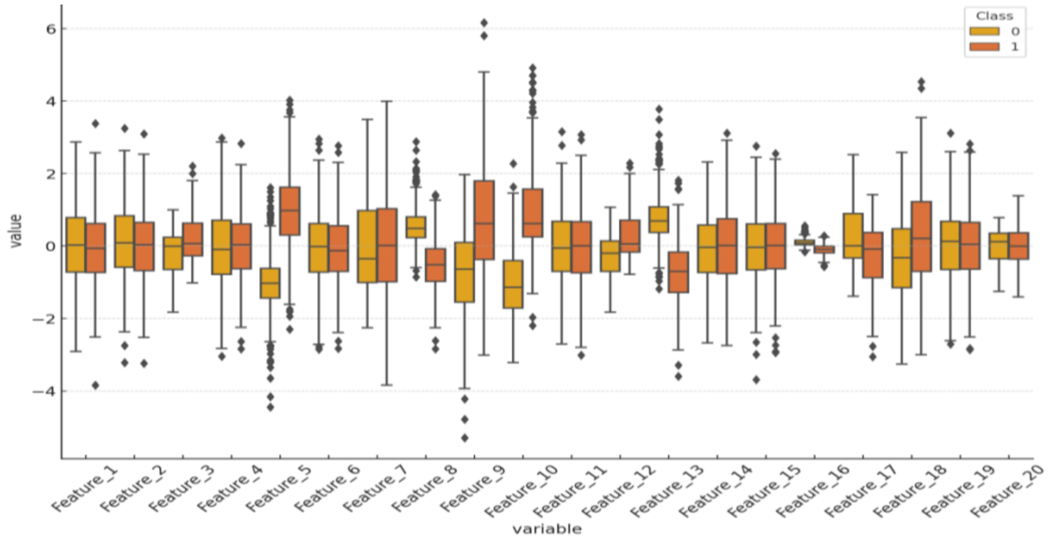

Figure 5. Distribution of Features by Class

The second visualization is a box plot, which visualizes distribution of the same quality parameters by 'Qualified' and 'Not Qualified' classes, thus comparing how different features may be between the groups. The visualization indicates that some features have different distributions based on the class hence can be useful for distinguishing between the high and low quality CPO. For instance, if the median of a feature or even the interquartile range of a feature bottom is differing more noticeably from class to class that suggests that this feature is really fit for the classification approach. It will show the contribution of each quality parameter in CPO classification which will give a better insight into the data features that the SVM model uses while making its predictions.

The use of Support Vector Machine (SVM) algorithm on the quality of Crude Palm Oil (CPO) is a viable approach that can be used to improve on the efficiency of quality control in the palm oil industry (Abdullah & Abdulazeez, 2021; Gaye et al., 2021; Wang et al., 2020; Chaganti et al, 2020). The outcomes of this study most especially the accuracy of the proposed model which stands at 84%. 15%, emphasize the stability of SVM for dealing with more complicated and large scale situations from currently understood machine learning studies in agricultural quality identification. This high level of precision indicates that SVM is most effective where traditional or manual process of quality control may not be efficient or is dependent on the human factor.

The confusion matrix (Figure 2) shows a good measure of precision as the number of true positive and true negative classifications are balanced, this shows that the model does not over predict the CPO outcomes as being either qualified or not qualified. This balance is important in industrial applications where both false positives and false negatives can result in huge economic implications; rejection of good quality oil and acceptance of lowm quality products. There are however some misclassifications and this means that the actual picture on the data might be more complex than what the current model is able to show. For instance, changes in the environmental condition when undertaking palm oil production or slight differences in the phase that deals with refining these products may introduce noise, thus reducing the classification accuracy (Yland et al., 2021; Carter et al., 2021; Reinke et al., 2021; Johansson et al., 2020).

The steps involved in the process of hyperparameter tuning, as illustrated in fig 3 above, underscores the volatility of the SVM model to its parameters. With regard to hyperparameters, the best values of C and Gamma determined here are consistent with theoretic SVM model in which an accurate model is capable of balancing the overemphasis on the margin and classification errors (Weerts et al., 2020; Wainer & Fonseca, 2021; Lin et

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al., 2021). This tuning process shows and underlines the necessity for the systematic adequate hyperparameters tuning determining the effectiveness of the machine learning models especially in the cases where input data set detailed relations can be described by the non-linear functions.

Furthermore, the plot of feature importance (Figure 4) shows which of the parameters that define the quality of a product contributes most to the classification results. The identification of elements such as FFA as crucial factors affecting CPO quality is well in harmony with some of the prior research that has heavily leant on chemical characteristics of CPO to determine the quality of the palm oil (Wang & Lin, 2022). From this it can be concluded that all features are important in contributing to the overall model performance however given parameters are more critical in ascertaining whether CPO conforms to the industry set quality levels.

Another way that this paper has attempted to assist in the decision making of the SVM model is through the distribution of the features by class, which is demonstrated in Figure 5; this distribution shows how quality parameters will look like for both qualified and non-qualified CPOs. The clear separation which has been depicted in terms of features of the different classes allows for the observation that the SVM model takes into account of key features that can be used for the differentiation between high quality oils and their lower quality counterparts. This is in line with the general literature on machine learning techniques, whereby the models perform well in classification problems with features especially when these features have distinguishable measures of variation.

SVM was successful in CPO quality classification; its use adds to the research done on ML in agriculture and includes a possibility of extending work in the same manner to other quality assessment issues in the industry (Khan et al., 2021; Karami et al., 2020; Mansour et al., 2023; Mohammadi et al., 2024). From a practical point of view, the model constructed in this research can be incorporated into the online quality control systems, which will minimize the usage of inspection by eyes, and enhance the steadiness of the quality apparitions. Future studies should consider other possibilities of adding other features, for instance, environmental and operational parameters to improve the model. However, a further direction of research would be the enhancement of the models specifically SVM by combining it with other powerful machine learning algorithms for example ensemble methods or deep learning to get even more robust solutions. Further, research could explore the realm of using XAI in the context of the underpinning process of the SVM models and this would be especially useful and applicable in industrial domains for depicting the basis of decision-making 9 (Orrù et al., 2020; Fernandes et al., 2022).

Conclusion

The intended objective of this research has therefore been realised as the study has effectively implemented the Support Vector Machine (SVM) algorithm in the classification of the quality of Crude Palm Oil (CPO) with a respectable accuracy of 84%. 15%. The results point to the fact that, SVM is effective in dealing with the high dimensionality of agricultural data especially when the normal eye balling techniques cannot work. Qualitative statistics also showed high accuracy that the integrated SVM model of key quality parameters of CPO namely, VM (Water), Dirt, and FFA was able to distinguish between qualified and non-qualified CPO to a significant level that provides quality assurance as a functional and safe revolution to current conventional quality evaluation model. The kind of micro-optimization pursued in choosing hyperparameters, cross-validation, as well as data pre-processing confirms the model's relevance and stability across different operation scenarios. The cross check with other cases of machine learning also reinforced the applicability of SVM for this kind of work, especially given the theoretical advantage of this tool in non-linear

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classification, besides the evidence of the numerical results. Nonetheless, there are occasional misclassification which suggest that there could be aspects which might have been overlooked, for instance, other features could be taken into consideration, or a blend of the models could be developed to capture more characteristics of quality of CPOs. Also the paper gives significant emphasis to data preprocessing concerning which normalization seems to have produced improved results and forms an important consideration that should not be ignored in future work or implementation of the model.

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