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International Society of Ocean, Mechanical and Aerospace Scientists and Engineers

Journal of Ocean, Mechanical and Aerospace
-Science and Engineering-
30th March 2025. Vol.69 No.1

March 30, 2025

Comparison of Machine Learning Algorithms for Palm Oil Fresh Fruit Bunch (FFB) Ripeness

Riri Nasirly [a*], Fadli Arsy [a], Rohatul Qolby [a]

[a)] *Industrial Engineering, Institut Teknologi Perkebunan Pelalawan Indonesia, Indonesia*

*Corresponding author: ririnasirly@itp2i-yap.ac.id

Paper History

Received: 16-January-2025
Received in revised form: 01-March-2025
Accepted: 30-March-2025

ABSTRACT

Determining the maturity level of FFB is crucial because it directly affects the quality and quantity of palm oil produced. Ripe FFB has high oil content, ensuring better-quality palm oil. Traditional methods include visual inspection, manual sampling, and physical testing, which are labor-intensive and subjective and can result in inconsistencies and errors. Machine learning algorithms can analyze datasets quickly and accurately, while also identifying patterns and features that are not easily visible to humans. Therefore, the aim of this study is to examine and evaluate the effectiveness of machine learning algorithm classifiers in determining oil palm FFB ripeness. The algorithms used in this research for classification analysis are Logistic Regression, Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), Neural Networks (NN), and Naïve Bayes. In this research, the analysis was carried out using the Orange data mining tool, which carried out data analysis and data visualization. The results of performance evaluation was tested, and assessment (cross-validation accuracy estimation), ROC (Receiver Operating Characteristic) analysis, and confusion matrix. The best models were Neural Network, Logistic Regression and SVM. Naïve Bayes appears to have lower performance. The results using the prediction widget show that logistic regressing has the best accuracy.

KEYWORDS: *FFB grading, Machine learning algorithm, cross validation, Confusion matrix.*

1.0 INTRODUCTION

Oil palm fresh fruit bunches (FFB) are the source of CPO. Classifying the ripeness level of FFB presents a challenge during the production process. The purpose of this classification is to determine the maximum quality of CPO [1]. According to [2], a classification process for FFB ripeness verifies the quality of CPO and overall marketability. Harvesting plays a crucial role in producing high-quality palm oils, as it directly impacts the oil content. To obtain the high oil content, harvesting must occur when the fruit reaches its optimal maturity level, approximately 151–180 days after the flowers bloom [3]. In fact, palm oil companies with thousands of trees face challenges in harvesting because they have different stages of maturity.

Each tree produces FFB with varying maturity, making the detailed harvest schedule ineffective. In addition, the industry continues to employ conventional methods. Generally, workers who lack training or experience carry out the manual and traditional process of harvesting, sorting, and assessing palm oil FFB [1],[4-5].

Human vision is a frequently employed method for determining the maturity of FFB in oil palm plantations. This method involves the examination of clusters and the classification of them based on their color and the quantity of loose fruits on the ground near the tree [1],[6-9]. This method is time-consuming and laborious, and it may lead to an inaccurate classification of ripeness. This can result in a decrease in the efficacy of the palm oil refining process, a lower quality of palm oil, and a loss of profits [7]. Hence, the classification procedure for determining the ripeness level of FFB requires innovation in order to efficiently accomplish the appropriate ripeness level.

Several studies have been conducted by researchers to identify methods for determining the ripeness of FFB. A computer vision technique was employed to quantify oil palm fresh fruit bunches (FFBs) through the analysis of video frames [10]. The results were validated through the application of the confusion matrix method. The results indicated that counting accuracy could achieve 100.00%. The accuracy is influenced by the color of the FFB and the ambient light intensity. The examination of the confusion matrix revealed an average counting accuracy of 79.35%.

Thermal scanning was implemented by [4] to evaluate the ripeness of FFB. The exact temp of each FFB sample was determined by subjecting it to thermal scanning with a thermal imaging camera. Their research consistently demonstrated a decrease in the average ∆Temp of oil palm FFBs from under-ripe to over-ripe [4]. A statistically significant difference in the means across the maturation categories was indicated by the ANOVA test results. It revealed a significance value of less than 0.05 for ΔTemp. The classification analysis was conducted using the ΔTemp of the FFBs as a reference point, and a variety of methods including: Mahalanobis Discriminant Analysis (MDA), Neural Network (NN), Linear Discriminant Analysis (LDA), and k-Nearest Neighbor (kNN), were employed. The NN method achieved the greatest overall accuracy rates of 99.1% and 92.5%. An inductive sensor was employed by [3] to collect data on the maturation of FFB.

According [11] utilized an optical spectrometer to collect data regarding the ripeness of FFB. Classification analysis utilizes machine learning techniques, specifically Support Vector Machines (SVM) and K-Nearest Neighbors (kNN) algorithms. A study by [12] utilized a LiDAR scanning system to evaluate the ripeness of palm oil fresh fruit bunches (FFB). According [7] determined the ripeness of FFB through color assessment. The FFB color test is based on the image capture process. The fuzzy inference system determines parameters from the matrix and employs the processed image as an input value. The system achieves an accuracy of 73.07% on the training dataset and 71.4% on the testing dataset [7]. The study by [9] and [13] employs classification methods that integrate color features. The color characteristics serve to differentiate the ripeness of oil palm fresh fruit bunches (FFB). The classification procedure employs the average value derived from color features in the L*a*b color space, utilizing Linear Discriminant Analysis (LDA) as the machine learning technique.

Alfatni et al. [14] accomplish image processing and analysis through computer vision and external assessment systems, following established procedures that include image acquisition, pre-processing, segmentation, feature extraction, and feature classification. A real-time system for classifying the ripeness of FFB has been developed and executed [2],[15] to improve the proposed solution regarding processing time and performance. Supervised classifiers, including support vector machines (SVM), k-nearest neighbors (kNN), and neural networks (NN), were utilized and assessed through ROC and AUC metrics [14],[16]. Although SVM classifiers demonstrate robustness, neural networks show enhanced performance, largely attributed to the presence of inherent data noise. The application of the NN algorithm in fruit texture analysis demonstrates the highest precision [16-17].

Most studies evaluating the ripeness level of oil palm fresh fruit bunches (FFB) utilize image data. This study also employs image data, with its novelty being the classification analysis conducted using the Orange data mining tool. This study aims to build a classification model by comparing several classification algorithms, including logistic regression, support vector machines (SVM), k-nearest neighbors (k-NN), neural networks (NN), and Naïve Bayes.

2.0 MATERIALS AND METHODS

In this study, the data used consists of images representing the ripeness levels of FFB (Fresh Fruit Bunches). The methodology begins with data collection and concludes with the selection of the best predictor and classification method. The workflow of the research is illustrated in Figure 1.

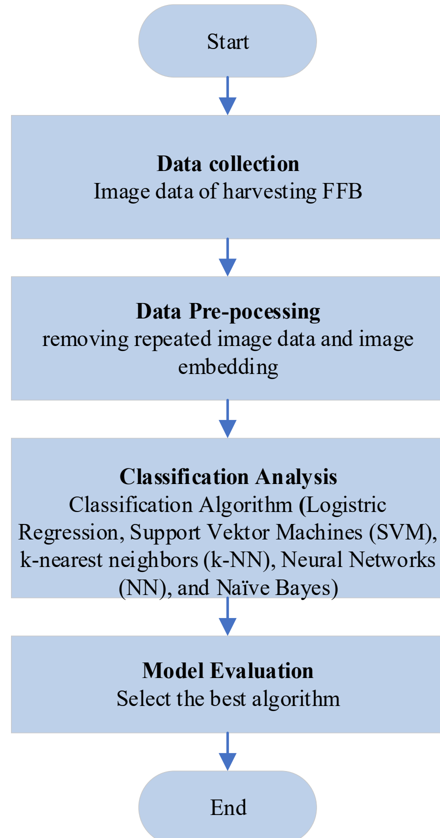

Figure 1: Workflow of the research

2.1 Data Collection

The ripeness level of FFB data used in developing this model consists of images data. The data was divided into two categories: training data and testing data. The training data was sourced from Kaggle. Kaggle is a dataset repository that serves as a platform for sharing ideas, gaining inspiration, competing with other data scientists, learning new information and coding techniques, and exploring various real-world applications of data science [18]. The training data is categorized into several categories: unripe, ripe, overripe, rotten, and empty bunches. Some examples of FFB images in categories are presented in Figure 2. The initial dataset obtained consists of 332 images, which will be used to train the classification model. The testing data was collected directly taken in Lubuk Dalam, Pangkalan Kerinci, Pelalawan. A total of 10 testing images were used as input predictors for the classification model.

2.2 Data Pre-processing

The data pre-processing stage involves several steps to ensure the dataset is ready for use in the model training process. The pre-processing steps include:

1. Data reduction. From the initial 332 training data images, duplicates were removed, resulting in 200 clean and usable images. The distribution of training and testing data is detailed in Table 1.

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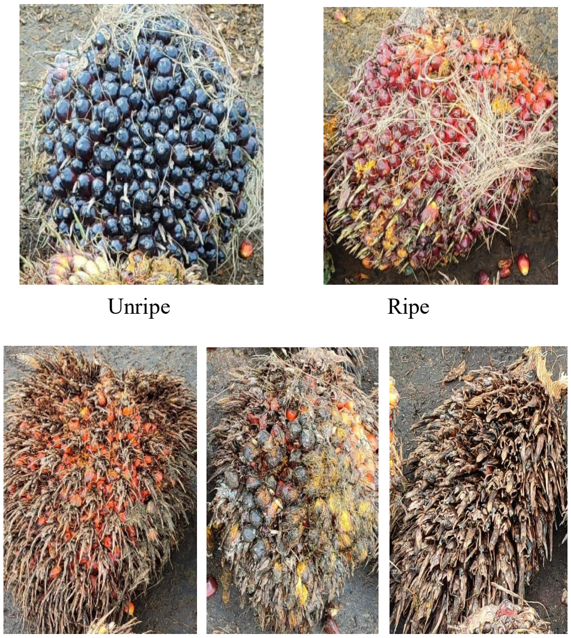

Unripe Ripe

Overripe Rotten Empty bunch

Figure 2: Example images

Table 1: Dataset of oil palm FFB

Classes	Number of Training data	Testing data
Unripe	14	2
Ripe	85	2
Overripe	55	2
Rotten	20	2
Empty bunch	26	2
Total	200	10

2. Image embedding. All images in the dataset will be processed using the Orange Data Mining tools. Orange is software for machine learning based on Python and provides sequences for data mining and visualizing data [19]. Since machine learning algorithms cannot directly process images, an Image Embedding step is performed first. This process converts each image into a vector that represents its features.

2.3 Classification Analysis

Classification analysis in this research was carried out using the Orange data mining tools. The computational process of learning from data is also called a machine learning algorithm. Supervised learning, where the model understands its input and output data for prediction, and unsupervised learning, which uncovers inherent structures or hidden patterns from the input data, are the two main techniques used [20-21].

The algorithms used in this research for classification analysis are logistic regression, SVM, k-NN, NN, and naïve Bayes. The model selection was based on several previous studies of oil palm FFB maturity classification. The model evaluation was used for the area under the curve (AUC), classification accuracy (CA), precision, recall, ROC analysis, and confusion matrix [22-25].

The following is an overview of the algorithms used to build classification models:

1. Logistic Regression
   Logistic regression can be used to classify observations into one of two classes or into one of many classes by calculating their probability is one of the most important analytical tools. l tools. The process stage is to classify the data by considering the variables at the extreme ends and creating a distinguishing logarithmic line [26].
2. Support Vector Machines (SVM)
   Based on statistical learning theory, Support Vector Machines (SVM) is divided points into one of two groups for binary classification. For linearly separable data, SVM identifies the hyperplane that maximizes the training sample margins and class boundaries. However, when the data is linearly inseparable, SVM maps samples into a higher-dimensional space to create a well-defined hyperplane through a mechanism known as a kernel function [17].
3. k-Nearest Neighbors (k-NN)
   The K-NN classification method conducts class-weighted frequency analysis to ascertain the class of an image by identifying k similar images from the training set. This categorization is activated by the majority vote of k-nearest neighbors, utilizing Euclidean distance in feature space to ascertain the number of neighbors employed. This can be adjusted to ascertain the ideal k value for classification purposes, eliminating the necessity for training [26].
4. Neural Networks (NN)
   Neural networks are models frequently used in machine learning and AI. This model imitates how nerves work in sending and receiving signals. This process converts complex signals into one simple decision. Hence, a neural network combines multiple outputs into a single output [22].
5. Naïve Bayes
   The method relies on the Bayes' theorem for probability. This theorem makes the underlying assumption that the influence of a particular class's attribute values is independent of the values of other attributes, a concept known as the conditional independence of the class [17].

2.4 Model Evaluation

This study's model evaluation employed a comprehensive approach, comparing various performance metrics. Specifically, the analysis included the Area Under the Curve (AUC), Classification Accuracy (CA), precision, recall, ROC analysis, and confusion matrix. Subsequently, the testing data was analyzed using the prediction widget, and the results from the best classification algorithm will be compared.

3.0 RESULT AND DISCUSSION

3.1 Data selection Process

The first stage in carrying out the classification process is a data selection process, also called data selection. Figure 3 illustrates the data selection process using the Orange data mining tools. It can be seen that the total image data used was 200 with 5 categories.

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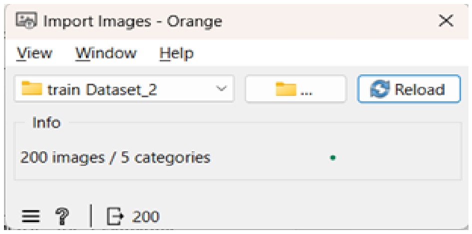

Figure 3: Selection dataset

The classification process begins with importing image data, which is divided into two subsets: training dataset and testing dataset. Training dataset used to train the model, otherwise testing dataset used to evaluate the model's performance. In the first stage, FFB images are imported and converted into numerical vectors through the Image Embedding process. Embedding models, such as InceptionV3 or VGG, are used to generate numerical features that represent the visual characteristics of each image.

3.2 Data Mining Process

The Orange data mining tools use data mining to test the classification model, compare models, and select the most accurate model for classification analysis. Figure 4 shows the data mining process flow using the Orange data mining tools.

The widget data table, which displays the dataset in a spreadsheet, yields 200 data points, 2048 features, and 5 meta-attributes. The following distance widget is used to compute the matrix of pair-wise distance, and hierarchical clustering is used to display a dendrogram constructed from the input distance matrix. The following algorithm was run on the models, testing and scoring (cross-validation accuracy estimation), ROC (Receiver Operating Characteristic) analysis, and confusion matrix. Prediction widget used for evaluate the model's performance.

3.3 Result Analysis

Table 2 displays the results of the classification analysis of oil palm FFB. The research conducted a classification analysis of oil palm FFB using 5 models. Cross-validation was used with 10 folds and was stratified to ensure a balanced distribution of classes in each fold. The training set size was 80% of the data. AUC is used to measure the model's ability to differentiate classes [22-23]. The greater the AUC, the better the classification results used [22-27].

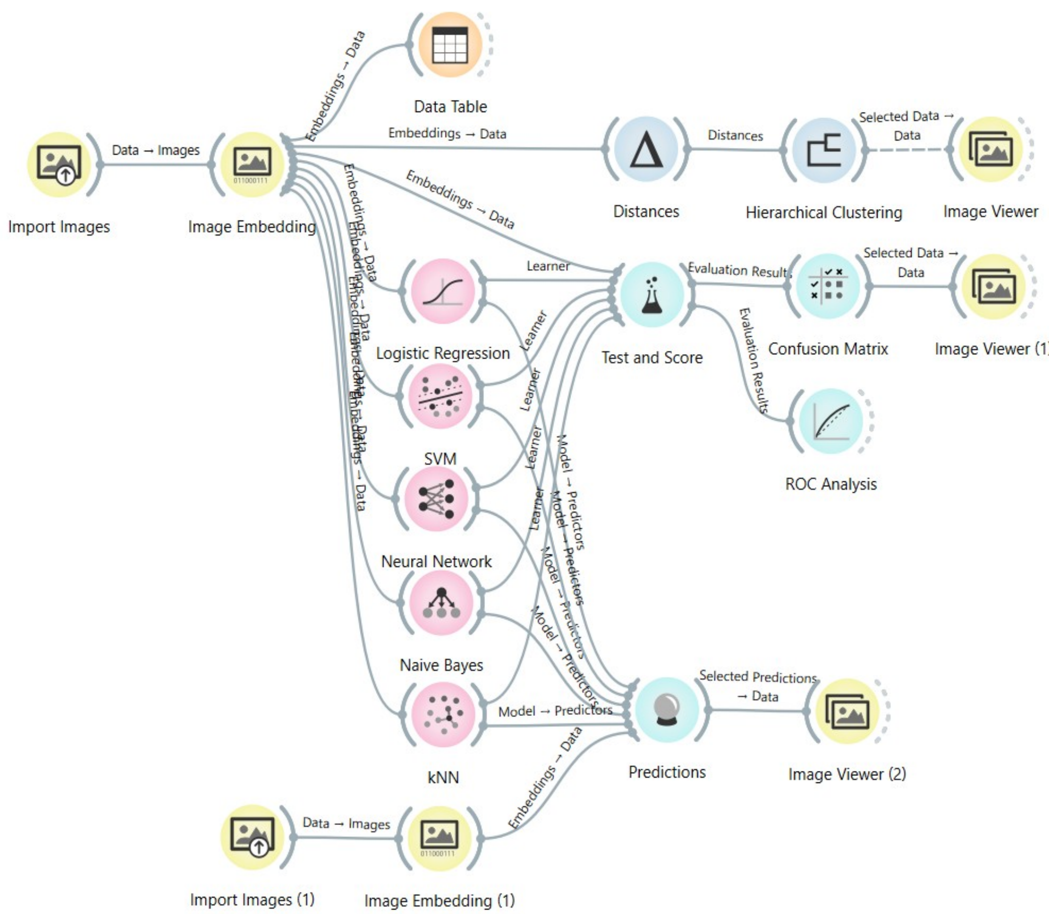

Figure 4: Process flow using Orange

JOMAse | Received: 16-January-2025| Accepted: 30-March-2025 | [(69) 1: 39-48]
Published by International Society of Ocean, Mechanical and Aerospace Scientists and Engineers, www.isomase.org., ISSN: 2354-7065 & e-ISSN: 2527-6085

Table 2: Classification analysis using 5 models

Model	AUC	CA	Prec	Recall
Logistic Regression	0.959	0.840	0.843	0.840
SVM	0.965	0.775	0.808	0.775
Neural Network	0.960	0.865	0.864	0.865
Naive Bayes	0.878	0.535	0.763	0.535
kNN	0.912	0.770	0.784	0.770

Neural Network and Logistic Regression are the best models based on AUC, classification accuracy (CA), precision (Prec), and recall. SVM had the highest AUC but lower accuracy, suggesting that this model may be more suitable for cases where AUC is the primary metric. kNN showed good performance but not as good as Neural Network or Logistic Regression. Naive Bayes was the lowest performing model and less effective for this dataset.

Neural networks have excellent performance in almost all the criteria, making them suitable for image analysis that requires complex models [23]. The Logistic Regression is simpler and more stable than Neural Network, and has near-optimal performance without high complexity [28].

Comparing the performance of classification models carried out using the Receiver Operating Characteristic (ROC) Graph. This graph represents TPR (true positive rate) versus FPR (false positive rate) at different classification thresholds. Substantially lowering the classification threshold will classify more items as positive [29]. There are two metrics based on the values obtained from the ROC curve. The two metrics are sensitivity and specificity. Sensitivity which measures the proportion of correctly classified FFB Ripeness and Specificity which measures the proportion of non-FFB Ripness classified correctly [30].

ROC analysis separates the results based on classification targets, which include unripe, ripe, overripe, rotten and empty bunch can be seen in Figure 5 - 9. The performances of the three best models are SVM, logistic regression, and NN.

The curves closer to the top left corner are preferable, as they have low FPR and high TPR. The worse models have curves closer to the diagonal line (meaning they perform almost the same as random sampling). Naïve Bayes (pink/magenta) appears to have lower performance than the other models, as its curve is closer to the diagonal.

The Confusion Matrix is a metric for evaluating performance in machine learning classification tasks [17]. Analysis of the results will be carried out on the 3 best models for this confusion matrix analysis. Confusion matrix results for neural networks can be seen in Figure 10, Logistic Regression can be seen in Figure 11 and SVM can be seen in Figure 12.

It can be seen in Figure 10, the Neural Network model works quite well with many correct predictions. The most frequently correctly classified classes were empty bunch (96.2% accuracy), ripe (88.2% accuracy), and unripe (85.7% accuracy). The most common error occurred between overripe and ripe, which may be due to the similarity in visual characteristics. Despite some misclassifications, the model remains quite reliable with most of the data being correctly classified.

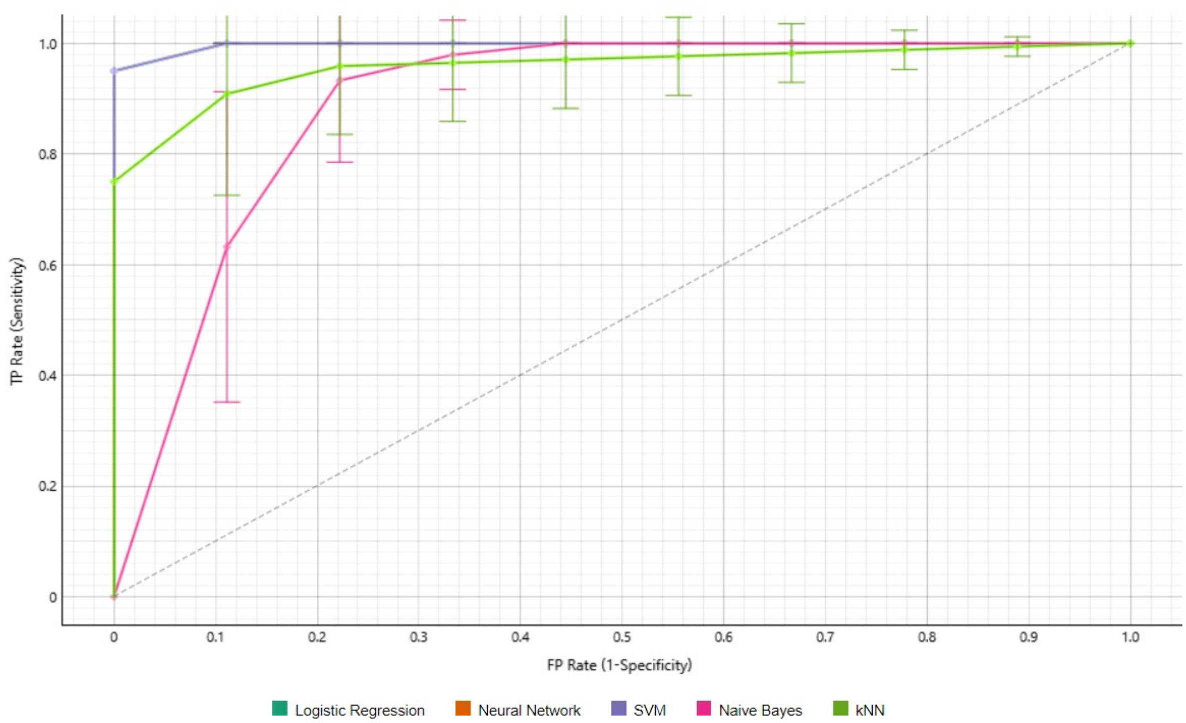

Figure 5: ROC analysis for the un-ripe class

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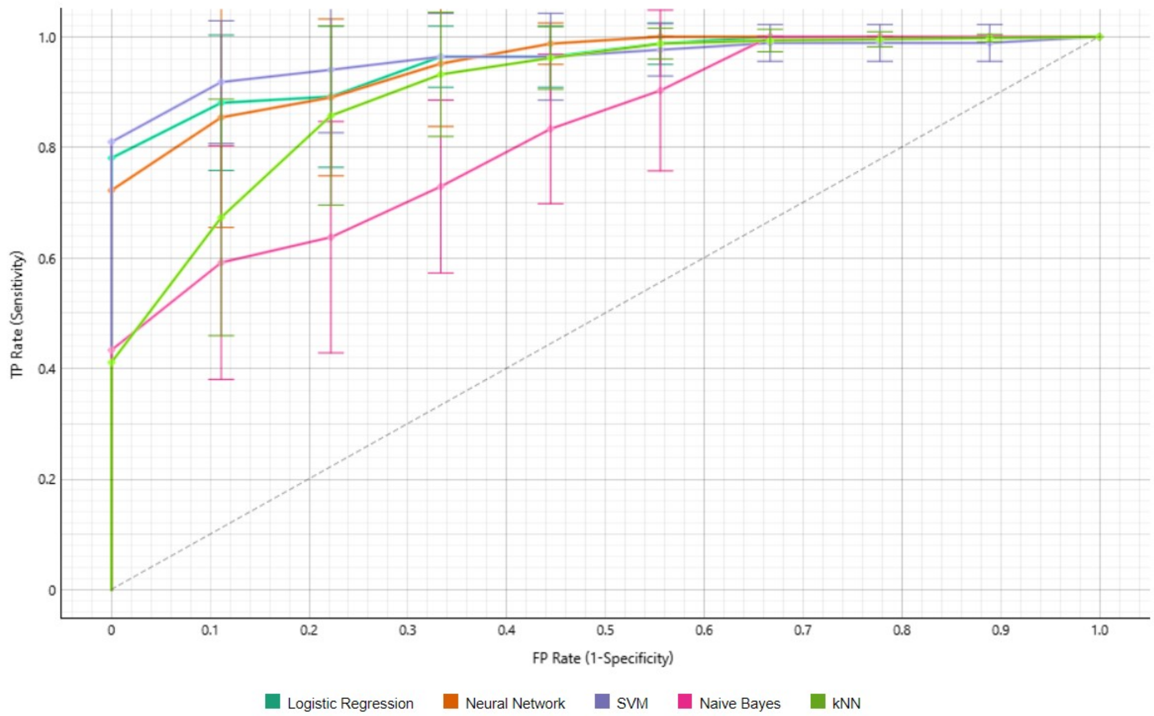

Figure 6: ROC analysis for the ripe class

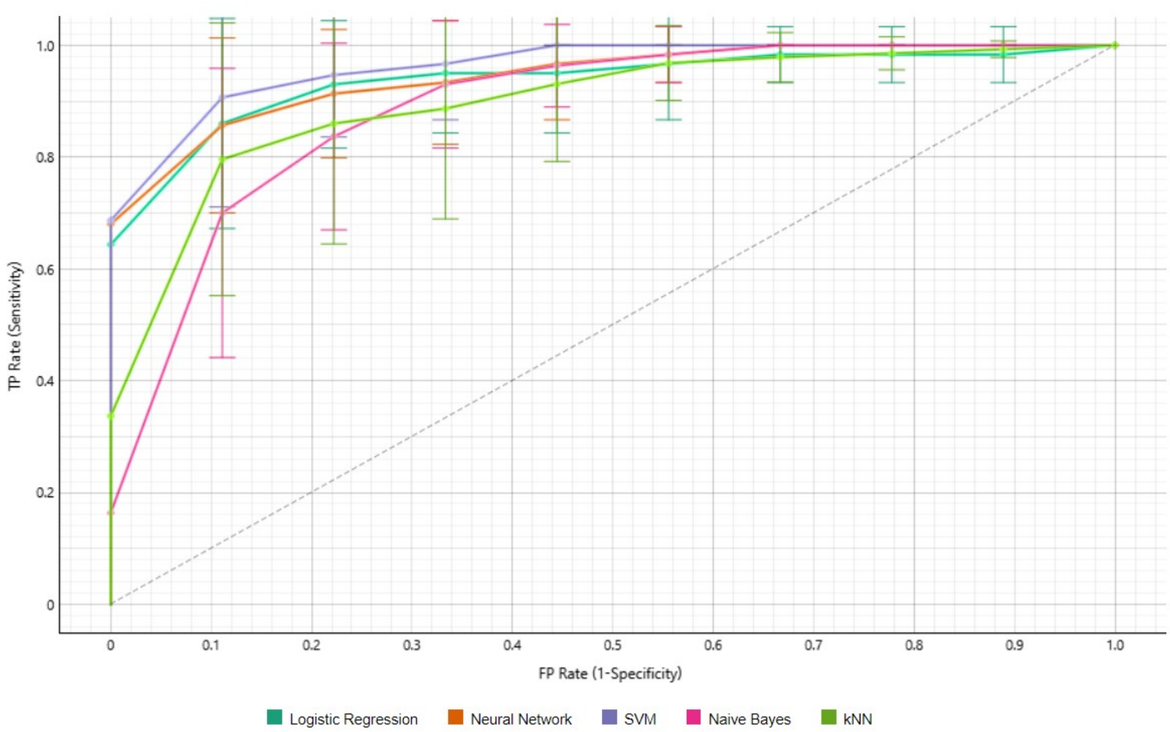

Figure 7: ROC analysis for the over-ripe class

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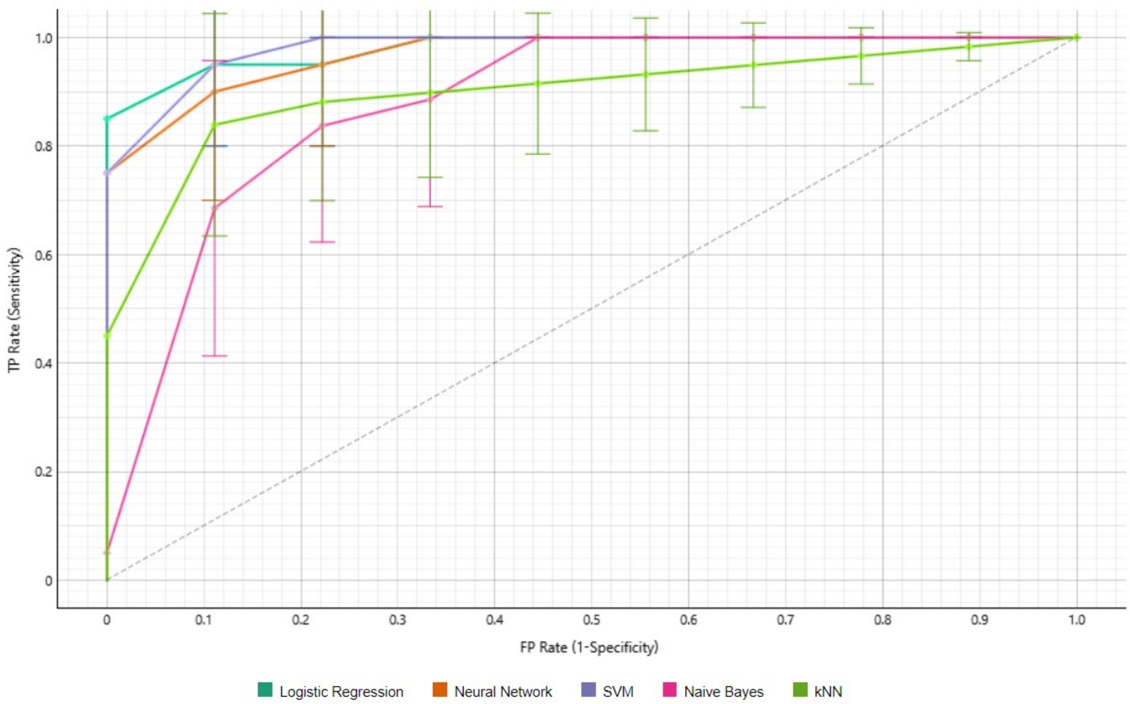

Figure 8: ROC analysis for the rotten class

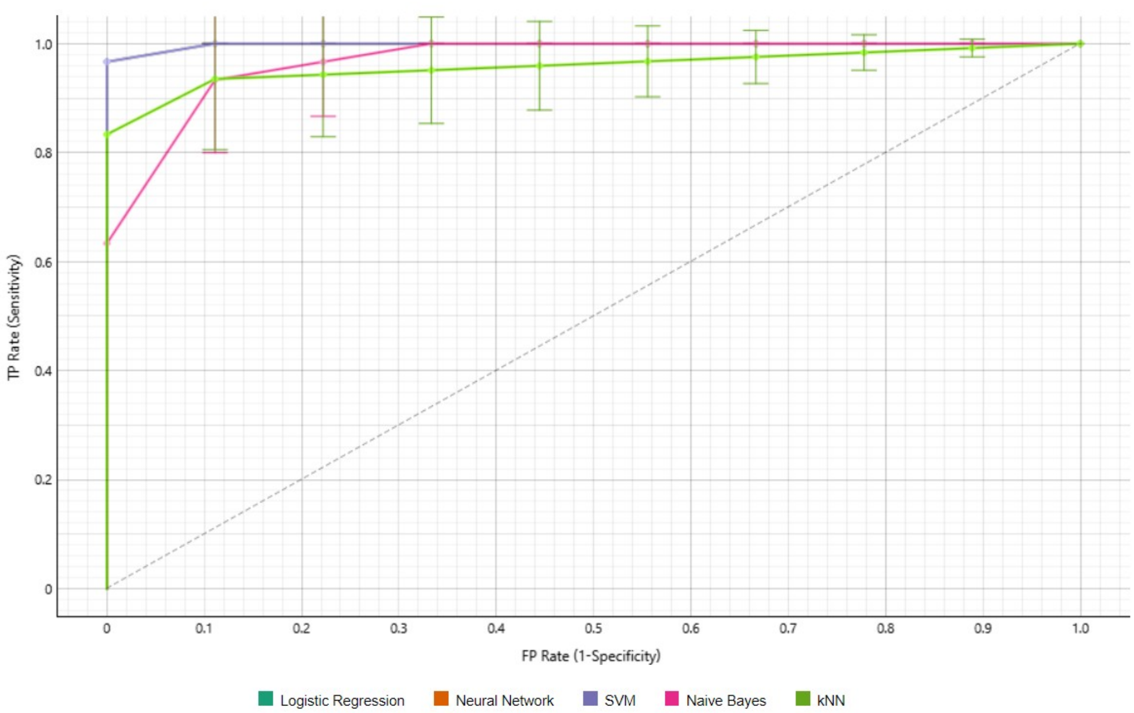

Figure 9: ROC analysis for the empty bunch class

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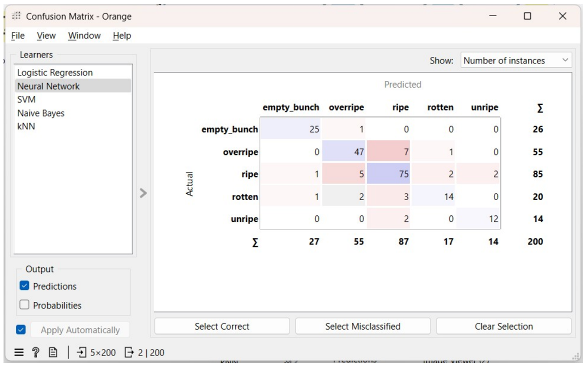

Figure 10: Confusion matrix for Neural Network

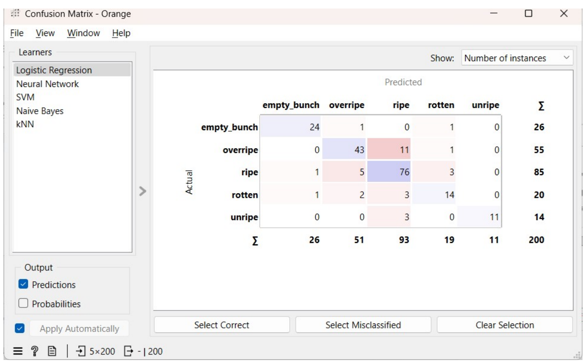

Figure 11: Confusion matrix for Logistic Regression

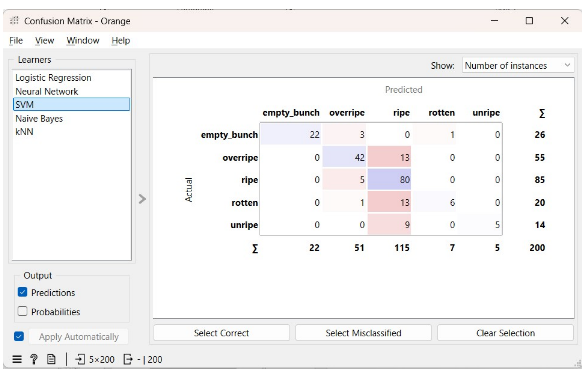

Figure 12: Confusion matrix for SVM

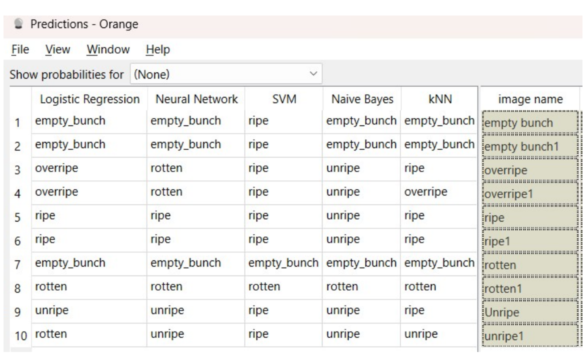

Figure 13: Prediction result

It can be seen in Figure 11, the Logistic Regression model performed well in classifying palm fruits, with high accuracy in the Empty Bunch (92.3%) and Ripe (89.4%) classes. However, this model tends to have errors in distinguishing Overripe from Ripe and Rotten from Ripe. Compared to the Neural Network, this model has slightly more errors in the Overripe and Rotten classes.

In Figure 12 depicted the SVM perform the best in classifying the majority class, particularly Ripe, with 80 samples correctly classified (94.1%). The misclassification of Overripe was slightly more than the Neural Network (13 samples misclassified as Ripe). The model was better at distinguishing the Rotten class than Logistic Regression and Neural Network, with only 6 samples misclassified.

The next step was the testing process with testing data containing images with similar categories but which have not previously been given to the model. The actual data was taken directly in Pelalawan. The testing process begins with the same steps, namely Image Embedding. After that, the classification process will use a model with the same algorithm that has been trained to test whether the model is running well. For the validation method, Prediction is used. It is intended that the model predicts the given dataset based on the dataset during the training process.

Testing data consists of 10 FFB image data that have been grouped based on existing calcifications and have been validated by experts. Furthermore, the prediction results can be seen in Figure 13. Based on Figure 13, it can be seen that from 10 test data, Logistic regression has 2 misclassified and Neural network has 3 misclassified. Thus it can be concluded that Logistic Regression provides the most accurate prediction, with only a few errors in 10 test data.

This is interesting because Neural Network has a higher metric in overall evaluation (Test & Score), hence it is still worth considering the best model for a larger number of datasets. Logistic regression is simpler than Neural Network, therefore less overfitting. In addition, it has a small difference between recall and precision, which helps avoid too many False Positives or False Negatives. Logistic Regression works well on small datasets and representative features, resulting in more stable predictions [28].

The common misclassified for all models can be seen in Figure 14. The test data shows rotten but the prediction result shows empty bunch. But visually with the existing features the image looks like an empty bunch. This shows that training with the existing dataset generally gives reasonable results.

3.4 Discussion

The data used in this study combines data from Kaggle as training data and actual data in Pelalawan as testing data. The total number of training data samples is more than the number of testing data. This difference gives different results in deciding the best model seen from the test and score results and prediction. In the case of determining FFB ripeness level, adding more samples allows for better generalization and classification.

On the other hand, the application of input data pre-processing provides information related to repetitive testing data images. Therefore, the repetitive data was removed and 200 data were used as testing data. This process was aided by the hierarchical clustering and view image widget that helped detect repetitive data.

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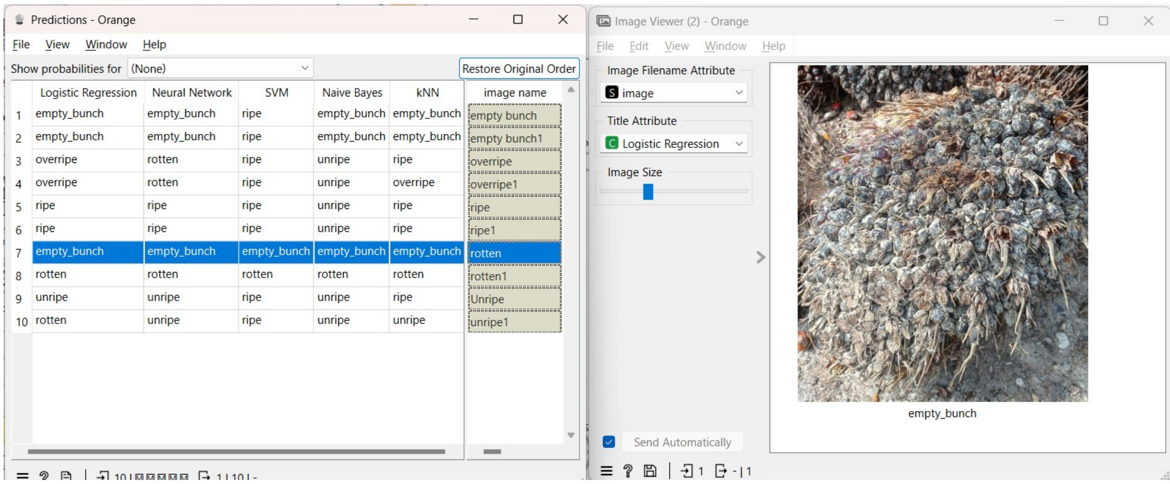

Figure 14: Common misclassified and image viewer

Performance evaluation was conducted through rigorous testing and assessment, including cross-validation accuracy estimation, Receiver Operating Characteristic (ROC) analysis, and confusion matrix analysis. These methods were used to provide a comprehensive understanding of the model's predictive capabilities. This research revealed the best models of using the Neural Network, Logistic Regression and SVM. This research demonstrates how image analysis, using neural network models (NN) based on image feature data, can determine the ripeness level of FFB. Several studies [4], [16], and [17] have chosen the neural network (NN) algorithm due to its superior accuracy. Based on the AUC value and also ROC analysis, the Support Vector Machines (SVM) in this study is the most robust model in line with other research [16]. A noteworthy aspect involves utilizing the prediction widget with testing data as input. Specifically, the application of the prediction widget to test data offers an intriguing perspective. The model with the best prediction rate is actually Logistic Regression.

4.0 CONCLUSION

The previously discussed research results suggest that Orange data mining can effectively classify the ripeness levels of FFB. Based on a comparison of several algorithms, it was found that the Neural Network, Logistic Regression and SVM are three best models. Naïve Bayes appears to have lower performance. The results using the prediction widget show that logistic regressing has the best accuracy. To improve the performance of palm oil FFB ripeness classification, it is recommended to add a larger amount of test data so that the level of accuracy becomes more accurate.

ACKNOWLEDGEMENTS

The authors are grateful to the Direktorat Riset Teknologi dan Pengabdian Kepada Masyarakat (DRTM) for facilitating training in writing scientific articles.

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JOMAse | Received: 16-January-2025| Accepted: 30-March-2025 | [(69) 1: 39-48]
Published by International Society of Ocean, Mechanical and Aerospace Scientists and Engineers, www.isomase.org., ISSN: 2354-7065 & e-ISSN: 2527-6085