Comparison of Machine Learning Techniques for Grade Classification of Exported Cavendish Bananas

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***Abstract*—The development of artificial intelligence technology has multiplied and penetrated all fields. One example is using artificial intelligence in a classification technique to determine the grading of bananas based on their quality. Banana grading is divided into three output classes: export quality, local quality, and defects. The banana classification input data is obtained by measuring the length and weight of the bananas and their color, which refers to their ripeness. The machine learning algorithm obtains test results by dividing three types of dataset separation ratios, namely 60% training data, 40% testing data (60:40), 70% training data, 30% testing data (70:30), and 80% training data, and 20% testing data (80:20). The Support Vector Machine (SVM) algorithm gets the best accuracy results of 0.84 at 80:20 ratio conditions. Based on the test results, the classification process with the highest accuracy uses the SVM algorithm. Thus, it is recommended for use as a classifier in classifying cavendish bananas for export purposes.**

Keywords— Machine learning, Dataset, Grading Banana, Export Quality

I. Introduction

Bananas are one of the most widely traded fruits in the world, with a significant contribution to the global economy and food security [1]. Banana exports involve several stages, from planting and harvesting to transportation and distribution, and require strict quality control standards to ensure customer satisfaction and safety. One crucial step in the export process is sorting bananas based on their quality, size, and ripeness to meet market demand and regulations [2].

Traditionally, banana sorting has been done manually, based on visual and tactile cues such as color, shape, and firmness. However, this approach is time-consuming, labor-intensive, and prone to errors and inconsistency, thus reducing productivity and increasing costs [3]. Computer vision and machine learning techniques have emerged as promising alternatives to automate the sorting process, providing fast, accurate, and objective measurements of banana characteristics [4].

Several efforts have been made to implement computer vision technology and combine it with instrumentation systems for banana classification [5], which uses Mazen [6] dataset. However, it is not practical for export usage. This paper compares machine learning techniques to determine banana grading with a machine learning algorithm to categorize them into export, local, or defective classes. The proposed method is to classify bananas based on quality, ripeness, and size so they can be sorted and shipped according to customer orders. We used machine learning models, such as Decision Tree (DT), Support Vector Machine (SVM), Naive Bayes (NB), Random Forest (RF), and Linear Regression (LR), to classify bananas. We simulated the performance of our Algorithm on our own collected dataset and labeled them into grades with numbers 1-8 adjusted for the level of banana ripeness. We also added length and weight data and then shuffled the data. The Algorithm was validated using evaluation metrics such as accuracy, precision, recall, and F1 score.

The remainder of this paper is organized as follows. Section 1 explains the proposed system's components and algorithms, including grading color techniques and machine learning models—section 2 presents Literature Review, and Section 3 presents Methodology 4. Present experimental results and discuss the comparison methods. Finally, in Section 5, the Conclusion and suggest future research directions.

II. Background And Related Work

Olaniyi et al. proposed an intelligent banana grading system [3]. In their system, a pattern recognition approach was adopted to extract features from the color of the bananas. The extracted features were then trained on a backpropagation neural network and tested on a feedforward neural network. A recognition rate of 97% was obtained from their system. Other researchers also adopted texture feature selection to propose a better system.

One key aspect of the fruit export process is accuracy in determining fruit ripeness and compliance with predetermined standards [7]. Sorting fruit ripeness and categorizing it into established export standards can be time-consuming and labor-intensive if the classification process is done manually [8]. Classifying various types of fruits and vegetables is difficult due to some similarities in shape, size, and color [9]. Experts or trained personnel typically examine fruits,

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vegetables, and plants before being harvested and released to the market. Color and texture are factors these individuals consider when assessing quality. Several potential human errors are associated with manual inspection and classification [10].

Image processing techniques and algorithms have been successfully applied in many fields, such as satellite imaging, medical research, and agriculture. Since agriculture is a basic human need, image processing techniques are used to detect and analyze plants, separate them based on color, shape, texture, and disease detection, and classify them accurately. Most state-of-the-art agricultural technologies use machine learning algorithms, especially in harvest prediction and intelligent irrigation systems [11]. Most matured machine learning techniques are divided into supervised and unsupervised learning. Examples of supervised learning algorithms are Naïve Bayes (NB), Discriminant Analysis (DA), Support Vector Machine (SVM), Convolutional Neural Network (CNN), and K-Nearest Neighbor (KNN). On the other hand, K-Means Clustering, Gaussian Mixture Models (GMMs), and Fuzzy Clustering are unsupervised machine learning algorithms [12].

Therefore, non-destructive approaches to banana ripeness assessment are highly needed. Image processing approaches are another non-destructive technique involving enhancement, segmentation, feature extraction, and classification. Image refinement is used to make images better for easier further image processing operations [13]–[15]. Machine vision systems or computerized image analysis methods are successful techniques for evaluating the quality of various fruits [16].

Since there are many methods for machine vision classification [16][17], a methodological comparison to evaluate the performance of machine learning [18], especially on the quality classification of bananas, consisting of three output categories: export, local, and reject quality. To our limited knowledge, this approach in fruit classification is practically necessary for real-world applications.

III. Methodology

A. Asian Standard for Banana Export Quality

The data for length measurement based on ASEAN [2] standards is indicated in Table 1.

TABLE 1. STANDARD SIZE CODE FOR BANANA

Size Code	Length of Finger (mm)	Diameter (mm)
1	> 200	> 40
2	> 180-200	> 35-40
3	> 160-180	> 32-35
4	> 140-160	> 28-32
5	120-140	25-28

For defects caused by spots on bananas, the labeling consists of 0-5% spots (few), 5-10% spots (medium), and >10% spots (many). For spot codification, 0-5% is given the number 1. For 5-10%, it is given the number 2; for the>10% range, it is given the number 3. As for weight, it follows the measurement of the length and diameter of the banana. The length measurement is given a grade value ranging from 1 to 5, as shown in Table 1. Meanwhile, the color grade is given a number from 1 to 8. The color grade can be seen in Figure 1. Based on these criteria, parameters are obtained to classify the data according to their groups, as shown in Table 2, and the color grade criteria are shown in Fig 1.

TABLE 2. REQUIREMENT DATASET

Defect	Grade Color	Grade Size	Grade Quality
0-5 %	2-4	1	Export
5-10%	1,5-7	2-3	Local
> 10%	8	4-5	Reject

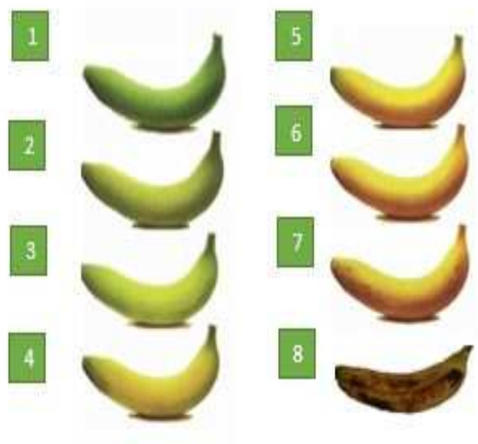


Fig. 1. Grade Color For Cavendish Banana, source = Sunpride.com

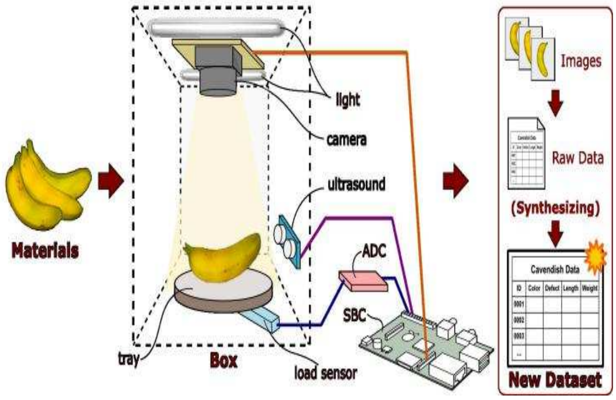
B. Instrument Measurement And Algorithm

Data is collected by observing and measuring banana objects in the Test Chamber, as shown in Figure 2a. This Test Chamber aims to observe the physical changes in banana objects during the ripening process. Figure 2b shows a scheme for collecting data during the ripening process. A camera sensor is used to collect data on color and defects of bananas, which has a resolution of 5 MP. This camera is connected serially to a single-board computer (SBC). In collecting this data, the Raspberry Pi 4.0 is used as the SBC, which can acquire and process data. The output of data collection from this camera is recorded data in the form of images.

TABLE 3. HARDWARE SPECIFICATION FOR DATA COLLECTION

NO	Device	Specification
1	Controller (Raspberry Pi 4)	Broadcom BCM2711, quad-core Cortex-A72 (ARM v8) 64-bit SoC @ 1.5GHz, 8GB LPDDR4 SDRAM
2	Camera (OV5647)	CSI (Camera Serial Interface) with Resolution: 5 MP
3	Length Sensor (Ultrasound, HC-SR04)	Working area: 2cm-4m, Precision : 3 mm
4	Load Sensor (High Precision Loadcell)	Load 5 Kg, precision/error 0.05%,
5	Converter Module SparkFun Qwiic Scale NAU7802	24-bit Dual-Channel ADC, with Operating Voltage: 3.3V (NAU7802: 2.7 - 5.5 V)

(a)



(b)

Fig. 2. (a). Test Chamber Banana Cavendish; (b). Scheme for Collecting Data

As for the length and weight measurements, an ultrasound sensor and loadcell are used, respectively, with the specifications shown in Table III. The ultrasound sensor is connected directly to the digital Input/Output pins on the SBC. As for loadcell readings, a converter module from analog to a digital signal (ADC) is used, which is connected to SBC via I2C communication. The signal read from the load cell is very weak, so it needs to be strengthened by this ADC. Analog signal data in the form of voltage will then be converted into digital signal data with 24-bit resolution.

Data collection by SBC was carried out every 1 hour during the banana ripening process, and 568 banana sample data were obtained. This sample data is then synthesized to produce new data with the aim that this dataset has more data variations. This synthetic data must meet two requirements [17] to resemble the original data statistically, formally, and structurally. The data synthetic method is Gaussian Copula using the normal distribution shape for the banana's weight and length parameters. Furthermore, this synthetic data will generate a new dataset of 1000 pieces of data. Preprocessing by adding data to the dataset aims to increase the accuracy of the training model.

Flow diagram for banana grade classification shown in Fig. 3:

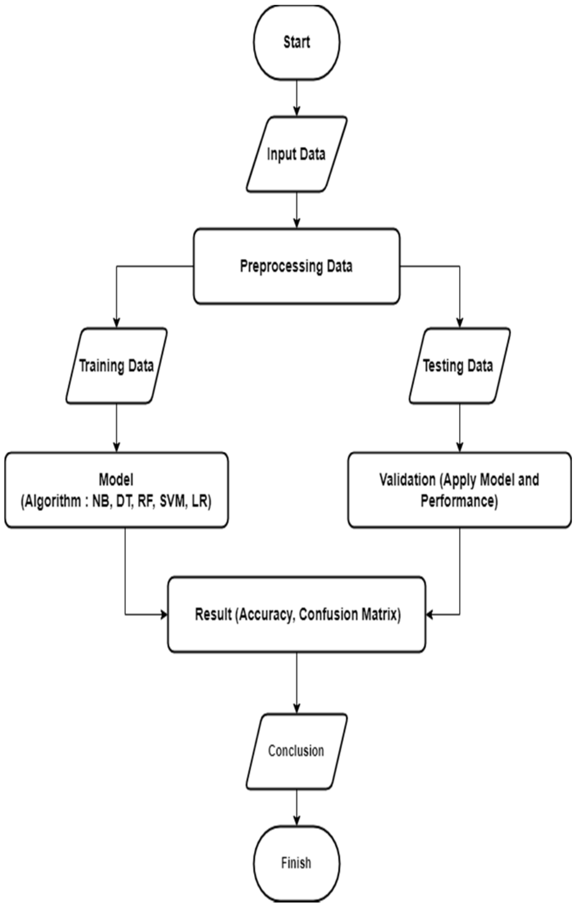


Fig. 3. Classification Process Flowchart Using Machine Learning

Here is the explanation of the algorithm diagram:

1. Start
2. Choose the datasets to be used
3. Perform data preprocessing by normalizing the min-max and then plotting the correlation of the input data using a heatmap.
4. Sort the training and testing data. For this step, the dataset is divided into 60% training data and 40% testing data, 70% training data and 30% testing data, and 80% training data and 20% testing data.
5. In the training data section, continue by creating a model using machine learning algorithms such as NB, DT, RF, SVM, and LR.
6. After completion, obtain the accuracy and training time required for the training process.
7. In the testing data section, after obtaining the model, continue by applying the model and testing the methodology's performance.
8. Then, obtain the test accuracy value, testing time, and confusion matrix value as an evaluation.
9. Conclusion
10. Finish

C. Dataset and Preprocessing

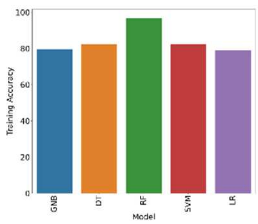
The dataset consists of 1000 data points with three input variables: length, weight, and color, with one output class: banana quality. For the Length variable, the data range is between 10-30 cm, while for weight, the data range is between 0.2-5 kg. There are eight types of grade colors, which are encoded with numbers 1-8. The output class consists of 3 banana grades, namely 1 for export quality, 2 for local quality, and 3 for the defective/rotten category. The dataset underwent preprocessing by normalizing both input and output data and performing correlation analysis on input data using a heatmap. Then, the data was split to separate the training and testing data with a composition of 60:40, 70:30, and 80:20.

TABLE 4. DATASET

No	Weight _gr	Length _mm	Grade_ color	Defect	Grade _sz	Grade Qualit y
1	125	201	6	1	1	1
2	125	197	8	3	1	3
3	118	184	7	1	2	1
4	122	187	5	2	2	2
5	115	173	7	3	3	3
6	109	166	7	1	4	3
7	123	186	5	2	2	2
8	130	202	6	2	1	1
9	110	170	8	3	3	3
10	119	183	7	3	2	3
…	…	…	…	…	…	…
1000	115	171	4	2	3	2

IV. RESULT AND ANALYSIS

The test results for the 60:40 ratio composition consist of accuracy, confusion matrix, time training, and time testing. Figure 4 shows the accuracy data from the classification results of the five methods used: NB, DT, RF, SVM, and LR.



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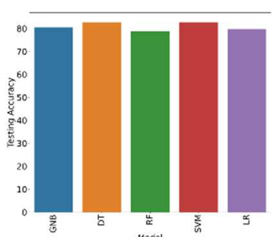
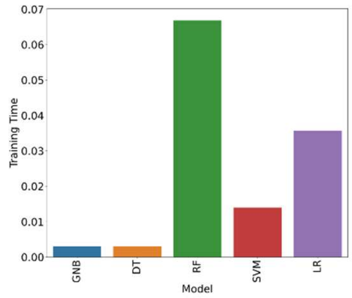


b

Fig. 4. Evaluation Results 60:40 dataset of Machine Learning Classification Accuracy Results: a) training accuracy; b) testing accuracy

The method that produces the highest accuracy is the DT and SVM methods, with a score of 0.8275, while the lowest is the RF method, with 0.7875.

Figure 5 shows the timing for time training and time testing. For the fastest training time obtained from the NB and DT methods with a value of 0.0029 seconds, the Random Forest method was obtained with a value of 0.0668 seconds for the longest time.



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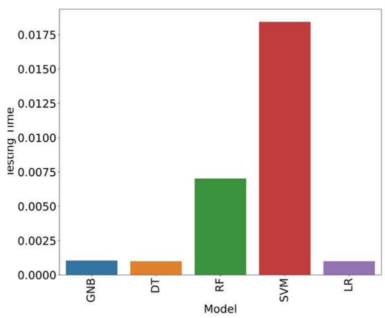


b

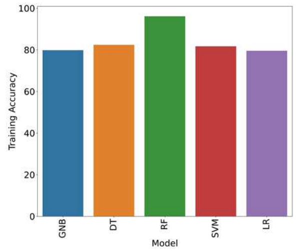
Fig. 5. Evaluation Result 60:40 dataset of machine learning classification results based on time: a training time; b test time

Table 5 shows the overall data from the test results with a ratio of 60:40, including the accuracy and confusion matrix, as well as training and testing time.

TABLE 5. VALIDATION TEST WITH DATASET COMPOSITION OF 60:40

Evaluation and Time	Machine Learning Methods				
	GNB	DT	RF	SVM	LR
accuracy	0.8050	0.8275	0.7875	0.8275	0.7975
precision	0.8340	0.8276	0.7835	0.8276	0.8015
recall	0.8050	0.8275	0.7875	0.8275	0.7975
f1-score	0.8129	0.8275	0.7849	0.8275	0.7972
train time	0.0029	0.0029	0.0668	0.0139	0.0356
test time	0.0010	0.0009	0.0070	0.0184	0.0010

The evaluation results of the 70:30 dataset comparison are shown in Fig 6 to Fig 7. Fig 6 a and 6 b show the comparison of training accuracy among the five methods used, namely Naïve Bayes (NB), Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM), and Linear Regression (LR) for training and test condition. The highest value was obtained from the Random Forest training, and the highest test score was obtained from SVM. The smallest value was obtained from the Naïve Bayes and Linear Regression methods. The results are similar to Tarek et al. research [18], which compares all of the method's performance. Based on the 70:30 composition, the highest accuracy score for training was obtained using the RF method, while the highest accuracy score for testing was obtained using SVM with a score of 0.8366.



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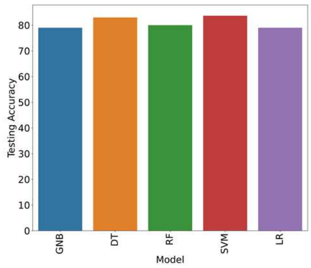
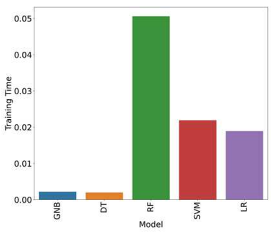
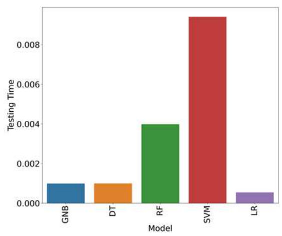


b

Fig. 6. Evaluation Results 70:30 dataset of Machine Learning Classification Accuracy Results: a) training accuracy; b) testing accuracy

Figure 7 shows the time required for the training and testing processes. Figure 7a shows the training time, while Figure 7b shows the testing time. DT obtained the fastest training time with a score of 0.0019 s, while LR obtained the fastest testing time with respective times of 0.0005 s. RF obtained the longest training time with a score of 0.0501 s; for testing, the longest time was indicated by SVM with 0.0094 seconds.





a b

Fig. 7. Evaluation Result 70:30 dataset of machine learning classification results based on time: a training time; b test time

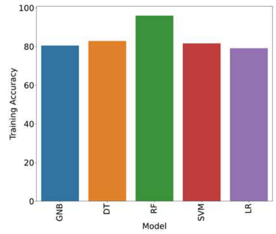
The complete data can be found in Table 6, which shows the test results, including accuracy, time, and confusion matrix data for testing with a composition of 70% training and 30% testing data.

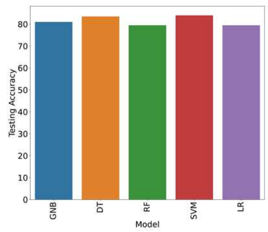
TABLE 6. VALIDATION TEST WITH DATASET COMPOSITION OF 70:30

Evaluation and Time	Machine Learning Methods				
	GNB	DT	RF	SVM	LR
accuracy	0.7900	0.8300	0.8000	0.8366	0.7900
precision	0.8302	0.8287	0.7997	0.8403	0.7974
recall	0.7900	0.8300	0.8000	0.8366	0.7592
f1-score	0.8000	0.8293	0.7996	0.8382	0.7909
train time	0.0022	0.0019	0.0501	0.0219	0.0189
test time	0.0009	0.0009	0.0039	0.0094	0.0005

Based on the 80:20 composition, the highest accuracy score for training was obtained using the random forest method, while the highest accuracy score for testing was obtained using SVM with a score of 0.84. DT obtained the fastest training time, and the slowest was RF, while DT obtained the fastest testing time with a score of 0.0019 seconds, and SVM obtained the slowest testing time with a score of 0.0059 seconds.

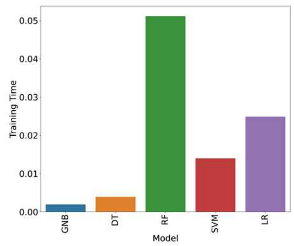
The graph details are shown in Figures 8 and 9.

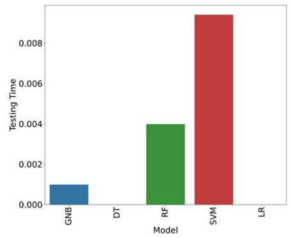




a b

Fig. 8. Evaluation Result 80:20 of Machine Learning Classification Accuracy Results: a) training accuracy; b) testing accuracy





a b

Fig. 9. Evaluation Result 80:20 dataset of machine learning classification results based on time: a training time; b test time

The overall test results consisting of accuracy, the time required for the training and testing process, and the confusion matrix for testing with a composition of 80% training data and 20% testing data can be seen in Table 7.

TABLE 7. VALIDATION TEST WITH DATASET COMPOSITION OF 80:20

Evaluation and Time	Machine Learning Methods				
	GNB	DT	RF	SVM	LR
accuracy	0.8100	0.8287	0.7950	0.8400	0.7950
precision	0.8394	0.8336	0.7979	0.8398	0.7967
recall	0.8100	0.8350	0.7950	0.8400	0.7950
f1-score	0.8175	0.8341	0.7962	0.8398	0.7936
train time	0.0019	0.0039	0.0512	0.0139	0.0249
test time	0.0009	0.0019	0.0021	0.0059	0.0074

V. Conclusion

After comparing the methodologies for banana data with specific grade levels, it was found that the highest accuracy was achieved using the SVM method, with an accuracy level of 84%. It is expected to be used for automatic classification in the future. For further research, it is hoped that deep learning methods can improve accuracy and solve banana grading problems by considering the number of epochs, hidden layers, and optimization methods. Additionally, a Hybrid Classifier between ripening grade and quality grade can be used so that ripening data referring to color can be combined directly with numerical data from length and weight measurements and classified directly.

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