Detection of Sugar Apple (Annona squamosa L.) Ripeness Based on Physical and Chemical Properties Using the K-Nearest Neighbor (k-NN) and Random Forest Algorithm

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Abstract. West Nusa Tenggara is one of the very high sugar apples producing regions every year. Post-harvest handling of sugar apples or srikaya fruits presents several challenges, one of which is judging the quality of the fruit by its ripeness. A lot of research has been done on fruit classification using one or two parameters using machine learning. Physical and chemical properties such as aroma, moisture content, total dissolved solids, texture, and weight loss are typically indicators for judging fruit ripeness. The purpose of this study is to use the k-Nearest Neighbor (k-NN) and random forest algorithms to determine the ripeness of sugar apples based on their physical and chemical properties and to measure the accuracy of the algorithms. The methods used in this study are k-NN classification methods and random forests, and their performance is measured using a confusion matrix. The parameters observed were physical properties (weight loss and texture) and chemical properties (moisture content, total dissolved solids, and gas content) and the number of test samples varied from 20%, 30% and 40%. Results were achieved to determine the ripeness of sugar apples, and the random forest method achieved 100% of accuracy for various number of test samples. On the other hand, the accuracy of the k-NN method decreases as the number of test samples increases i.e. 100%, 100%, 50% for each variant of the test sample, respectively. Therefore, it can be concluded that determining the ripeness of sugar apples by random forest method is better.

Keywords: detection, physical and chemical properties, ripeness based, sugar apple

1 Introduction

West Nusa Tenggara (NTB) is one of the places that produces sugar apple fruit with a fairly high every year. The sugar apple tree grows scattered in various parts of the NTB such as East Lombok, Sumbawa and Bima. The sweetness of the fruit and the distinctive aroma make this fruit in high demand. In the post-harvest handling of sugar apple fruit, there are several problems, one of which is determining the quality of the fruit. Aroma is often the primary indicator of fruit ripeness and quality. Determination of fruit maturity can be done using an electronic nose (e-nose). Nose E is an arrangement of sensors to detect gases produced by fruit, for example mango [1][2]. Physical and chemical properties such as moisture content, weight loss, TDS, and texture can also

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affect the quality of the fruit, as sugar apple fruit has a high-moisture content, affecting its physical and chemical properties.

Many studies have discussed the classification of fruit maturity and rot based on one or two parameters using machine learning. Machine learning is a branch of artificial intelligence that allows computers to learn from data. It can more efficiently handle solvable problems such as classification, regression, clustering, and anomaly detection in various domains. Methods used for classification in agriculture include linear regression, logistic regression, decision trees, support vector machines (SVMs), Naïve Bayes, k-Nearest Neighbors (k-NNs) and Random Forest [3][4][5][6].

The algorithms used in this study are k-NN and random forest. A k-Nearest Neighbor Classifier (k-NN) is a method of classifying objects based on training data that is closest to them. Training data is projected onto a multidimensional space where each dimension represents a feature of the data. The dimensional space is divided into parts based on the training data classification [7][8]. Random forest is a classification method that evolves the decision tree method based on the selection of random attributes at each node to determine the classification [9][10].

Therefore, the aim of this study was to determine the ripeness of Sugar apple fruit based on physical characteristics (texture and weight loss) and chemical characteristics (gas content, moisture content, total dissolved solids) using k-NN and Random Forest algorithms. We evaluated the accuracy of these algorithms in classifying Sugar apple fruit maturity in various number of testing data.

2 Materials and methods

This study was conducted between March and April of 2022. The primary research object in this study is half-ripe sugar apple fruit. The k-Nearest Neighbor (k-NN) and Random Forest methods were used to process the data; these methods are included in the classification method. The dataset contains recorded gas data from sensors TGS2600, MQ3, MQ4, MQ2, and MQ8 with units (ppm), as well as average moisture content, total dissolved solids, texture, and weight loss. The data was then tested using a confusion matrix with different numbers of test samples, namely 20%, 30%, and 40%. The Python programming language is used to process data.

2. 1. Research Stage

There are six steps in the implementation of this study, Sorting and measuring sugar apple fruit, preparing and calibrating tools, measuring initial gas level, testing of moisture content, texture, total dissolved solids (TDS), and weight loss, Implementing classification method, and System Testing, respectively.

a. Sorting and measuring sugar apple fruit
   Sugar apple is sorted to select sugar apple with a consistent level of maturity, i.e. ripeness levels that are ready for harvest but retain a firm texture. Sugar apple comes in three sizes: small, medium, and large. There were 9 sugar apple fruit samples in total. The sugar apples were then weighed, measured for length and width, and stored at room temperature.

b. Preparing and calibrating tools
As shown in Fig. 1, a gas sensor circuit is constructed using the TGS 2600, MQ3, MQ4, MQ2, and MQ8 sensors, which are connected to the Arduino Mega 2560 via a 5V DC voltage source. At the time of recording, the sensors are mounted on the lid of the container used to capture sugar apple gas, as shown in Fig. 2. The sensor is tested and calibrated after it has been assembled to obtain a stable gas number.

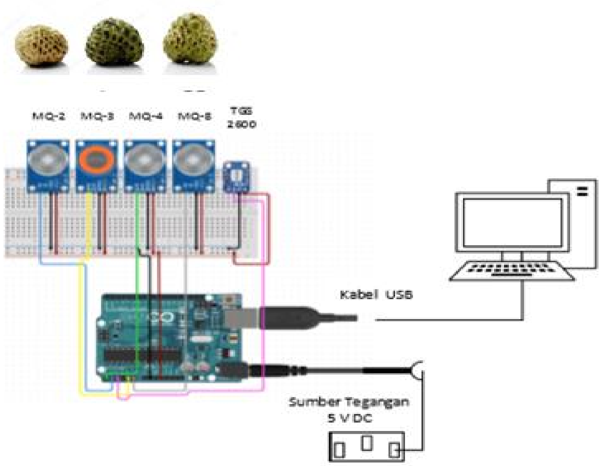


Fig. 1. Gas Sensor Circuit Schematic Diagram

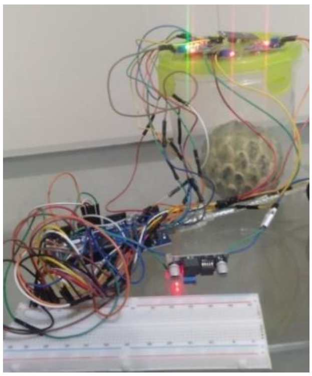


Fig. 2. Sensor Circuit When Recording Gas Data

c. Measuring gas level
Before recording the sugar apple gas data, the gas is first measured in an empty container to determine the set point that will be used as a reference for the initial gas value. After that, the recording lasted 3 minutes. The PuTTY application is used to store the data read by these sensors. Then, clean the data and convert the gas data from ADC to parts per million (ppm). The gas data (ppm) is then averaged for each sensor and used as input dataset.

d. Testing of moisture content, texture, total dissolved solids (TDS), and weight loss

Following the collection of gas data, the sugar apple was examined for moisture content, texture, TDS, and weight loss. The obtained data is then averaged and used as an input dataset in conjunction with the recorded gas data.

e. Implementing classification method
   The k-NN method and random forest were used in Python programming with the Scikit-learn library to process gas recording data for each sensor, moisture content, texture, TDS, and weight loss. Previously, the training and input data were labeled to identify the new object.
f. System testing
   The Confusion matrix was used for system testing, with the number of test samples varying between 20%, 30%, and 40%. There are two types of tuples: positive tuples and negative tuples. The confusion matrix generates four indications, with true positive (TP) referring to positive tuples correctly labeled by the classifier and true negative (TN) referring to positive tuples correctly labeled by the classifier. False positives (FP) are incorrectly labeled negative tuples, while false negatives (FN) are incorrectly labeled positive tuples [11]. It is critical to assess system performance using the k-NN and Random forest algorithms to determine accuracy, precision, sensitivity, and specificity.

3 Results and discussion

This section discusses the result of physical properties (weight loss and texture) and chemical properties (moisture content, total dissolved solids, and gas content) used as variable as dataset. Then we evaluate the performance of implementing k-NN and Random Forest in detecting sugar apple ripeness.

3. 1. Weight Loss

Weight loss is one of the indicators of the fruit's quality. The increase in weight loss in fruits is one sign that the quality of freshness is beginning to deteriorate. Fig. 3 depicts the weight loss calculation results.

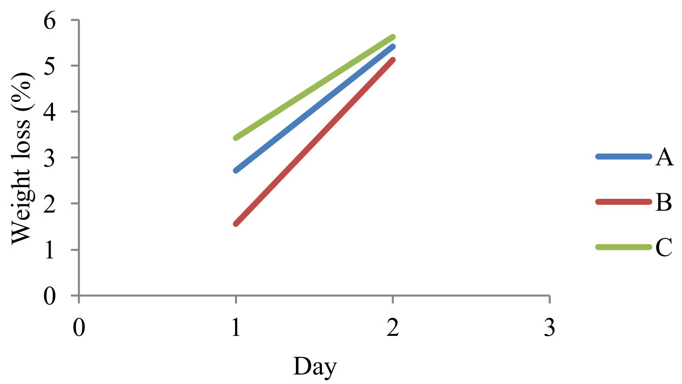
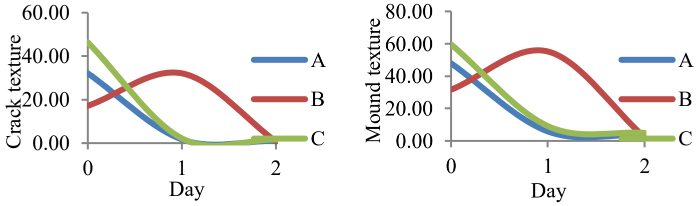


Fig. 3. Sugar Apple Weight Loss Chart

Based on Fig. 3, weight loss increased in sugar apple fruit, both large (A), medium (B), and small (C). Weight loss occurs because of the transpiration of fruit water and the evaporation of gases produced by the breakdown of glucose into carbon dioxide during storage [12]. Internal factors such as metabolism, respiration, and transpiration, as well as external factors such as temperature and RH, influence a food product's high and low weight loss.

3. 2. Texture

Texture measurements were taken on sugar apple mounds and crevices for this study. The sugar apple mound is the skin that protrudes from the sugar apple, and the slit is the space between the mounds.



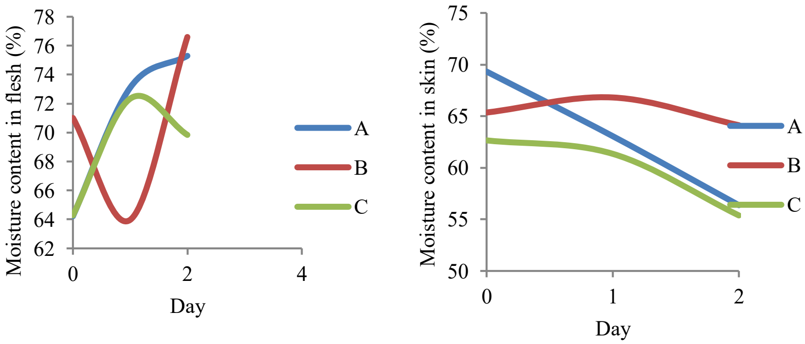
(a) (b)

Fig. 4. Texture Graphics on Sugar apple Mounds and Cracks

According to Fig. 4 (a) and (b), the average value of sugar apple texture has decreased from day to day, both in fruit (A), (B), and (C) (C). However, because the sugar apple samples tested had different textures, the texture of the sugar apple in the gap in the fruit (B) on day 2 was higher than on day 1. The texture of the fruit will decrease as the level of fruit maturity increases (soft). Fruit softening is caused by the hydrolysis of starch or fat or the breakdown of insoluble protopectin into soluble pectin. The sugar apple skin mounds have a higher or harder texture than the sugar apple skin slits [13].

3. 3. Moisture Content

Moisture content refers to the amount of water in agricultural products. The moisture content of the sugar apple fruit flesh and skin was tested in this study.



(a) (b)

Fig. 5. Graph of Moisture Content in Sugar apple Flesh and Skin

According to Fig. 5, (a), the average moisture content of sugar apple flesh fluctuates and tends to increase from day 0 to day 2. Fig. 5. (b) shows how the moisture content of the sugar apple skin fluctuated and decreased. Because the skin is the outermost part of the sugar apple fruit, the decrease in moisture content is directly related to the environment. As a result of the transpiration process of water in the sugar apple fruit through the skin, transpiration increases. Water loss in sugar apple skin is influenced by humidity, air temperature, atmospheric pressure, and the fruit's surface area, in addition to transpiration. Skin tissue is the outermost layer of plant organs that serves as a protective layer. In addition to experiencing changes in color and texture, the natural nature of skin tissue can regulate gas exchange, water expenditure, and sensitivity to the environment physically, biologically, and chemically [12]. Sugar apple fruit has a relatively high moisture content, which causes it to rot and damage. The high moisture content in the fruit allows microbes and other bacteria to grow in it, which can reduce the product's quality [14].

3. 4. Total Dissolved Solids

Total dissolved solids (TDS) are a measurement of the total amount of inorganic and organic substances in a liquid. According to Fig. 6, the average TDS value fluctuated. TDS increased from day 0 to day 2, but TDS decreased on day 1 in fruit (B) because the surface area of fruit on day 1 was smaller, causing the respiration rate to be slower than in other fruits. The rising TDS value indicates that the sugar content of the fruit is rising. The more ripe the fruit, the higher the TDS content. As a result of the respiration process, the sugar content increases and the acid content decreases when the fruit is ripe. Sugar apple fruit is a climacteric fruit, which means that as it ripens, the sugar content rises while the acid content falls. The hydrolysis of carbohydrates into glucose and fructose compounds causes an increase in the value of TDS in fruit [15].

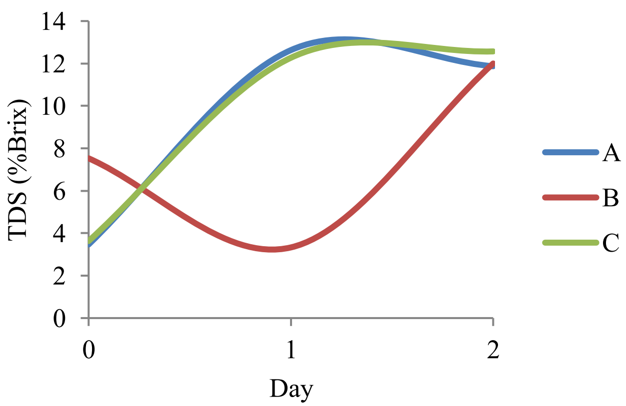


Fig. 6. Sugar apple Total Dissolved Solids Chart

3. 5. Gas Levels

a. Data collection

Data collection begins with a 5-minute recording of set points; set point measurements are taken when the gas measurement container is empty. The average of the measured ADC is then calculated using the data set points. Table 1 shows the average set point results for each sensor.

Table 1. Gas Sensor Set Point Average Value

Variable	Sensors				
	TGS 2600	**MQ-3**	**MQ-4**	**MQ-2**	**MQ-8**
Rated average ADC value	117	270	254	252	158

Following the recording of the set point data, the gas data on the sugar apple fruit is recorded. Each sugar apple sample was monitored for three minutes. During the recording process, the measured data is still in the form of ADC data. Table 2 displays the raw measurement data. Following that, data cleaning is performed to facilitate the next process. The Python programming language and the Pandas library are used in this data cleaning.

Table 2. Raw Data of Sugar apple Gas Measurement Sample C Day 2

Index	**=~ PuTTY log 2022.03.15 08:34:23 ~=~=**
1.	TGS MQ-3= 287 MQ-4= 417 MQ-2= 256 MQ-8= 190
2.	TGS2600= 160 MQ-3= 286 MQ-4= 416 MQ-2= 254 MQ-8= 188
3.	TGS2600= 156 MQ-3= 287 MQ-4= 417 MQ-2= 256 MQ-8= 190
4.	TGS2600= 167 MQ-3= 291 MQ-4= 421 MQ-2= 257 MQ-8= 193
5.	TGS2600= 162 MQ-3= 287 MQ-4= 417 MQ-2= 253 MQ-8= 190
6.	TGS2600= 155 MQ-3= 288 MQ-4= 418 MQ-2= 253 MQ-8= 190
7.	TGS2600= 153 MQ-3= 295 MQ-4= 424 MQ-2= 260 MQ-8= 197
. . .	. . .
450	TGS2600= 199 MQ-3= 430 MQ-4= 584 MQ-2= 299 MQ-8= 340
451	TGS2600= 204 MQ-3= 434 MQ-4= 588 MQ-2= 303 MQ-8= 343
452	TGS2600= 197 MQ-3= 429 MQ-4= 583 MQ-2= 297 MQ-8= 337
453	TGS2600= 204 MQ-3= 434 MQ-4= 588 MQ-2= 302 MQ-8= 343
454	TGS2600= 202 MQ-3= 433 MQ-4= 587 MQ-2= 301 MQ-8= 342

b. Data Cleaning

The data cleaning process begins with reading the data and then dividing it so that only the measured ADC value from each sensor is retrieved. The result is a data table of size M x N, where M represents the number of data rows and N represents the number of columns, which are TGS2600, MQ3, MQ4, MQ2, and MQ8. As a result, each new table is M x 5, shown in Table 3. Pandas is the library used in this process [1]. As shown in Fig. 7, the measured ADC data after cleaning experienced an increase and irregular fluctuation during recording for 3 minutes.

Table 3. ADC Measurement Data for Cleaning Sample C Day 2

Index	tgs26	mq3	mq4	mq2	mq8
3	156	287	417	256	190
4	167	291	421	257	193
5	162	287	417	253	190
6	155	288	418	253	190
7	153	295	424	260	197
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
346	199	430	584	299	340
347	204	434	588	303	343
348	197	429	583	297	337
349	204	434	588	302	343
350	202	433	587	301	342

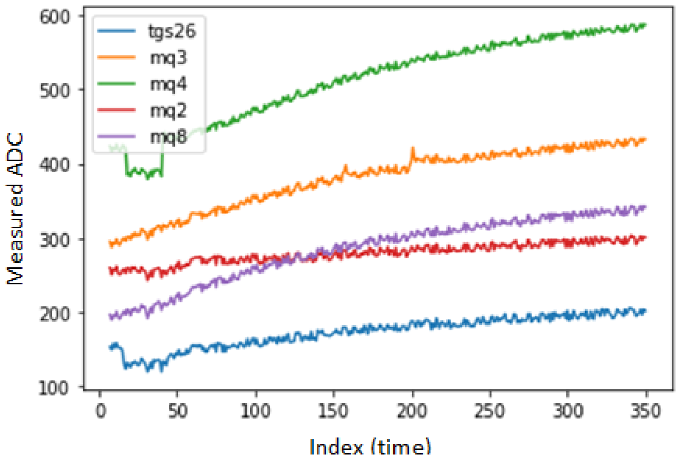


Fig. 7. ADC measurement graph of the data cleaning result of Sample C Day 2

c. Normalization and Data Conversion

Prior to conversion, normalization is performed to ensure that the initial value of each measured sensor is 0. The next step is to convert the ADC data to ppm data. The measurement range of each sensor, the set point, the measured ADC value, the ADC 1023 scale, the maximum input voltage Vmax 5 V, and the DAC value are all required for the conversion. Equations (1) and (2) are used to convert observational data (2). This data was normalized and converted using the Python programming language and the NumPy library.

$$dADC = ADC_t - SP_{ssr} \quad (1)$$
$$\Delta ADC = dADC - min\ (dADC) \quad (2)$$

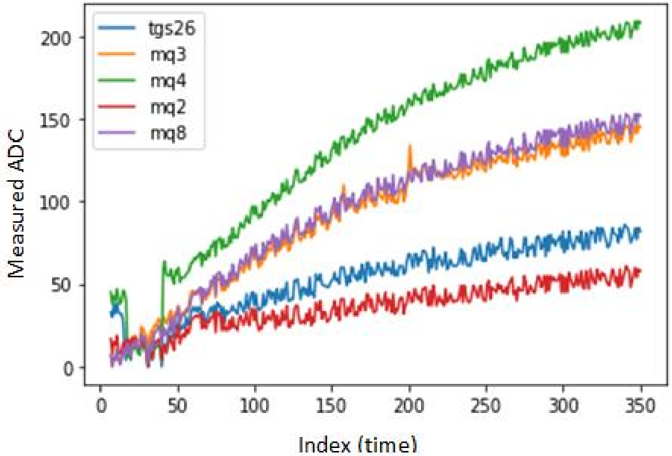


Fig. 8. Graph of Normalization of Measured ADC Value of Sample C Day 2

Fig. 8 represents the graph shows the ADC value recorded for 3 minutes has increased. The initial value is between 0 and 1. Each sensor's measured ADC value falls between 0 and 200.

Table 4. ADC Conversion Data to ppm C Sample Day 2

Index	tgs26	mq3	mq4	mq2	mq8
7	33	7	45	17	7
8	30	0	38	8	0
9	38	6	43	15	6
10	32	4	40	13	4
11	39	11	47	19	11
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
450	79	142	205	56	150
451	84	146	209	60	153
452	77	141	204	54	147
453	84	146	209	59	153
454	82	145	208	58	152

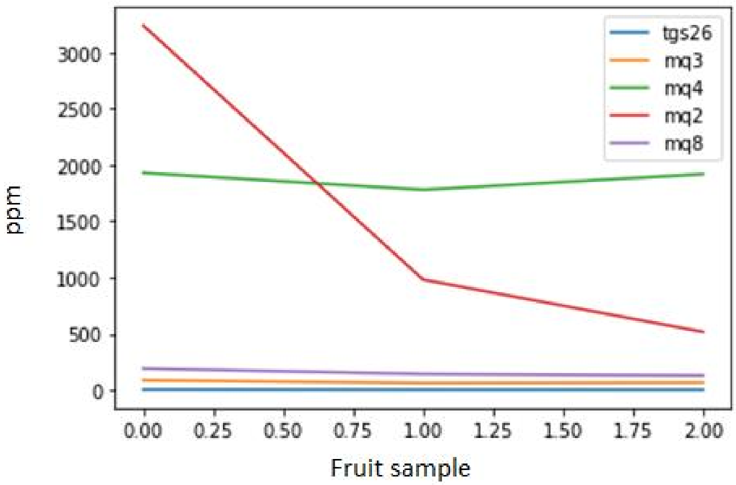


Fig. 9. Graph of Average Value of Gas Data Conversion Results for Day 2

Fig. 9 shows that the ppm value measured by the MQ2 and MQ4 sensors is higher than that of the other sensors. The MQ2 sensor is sensitive to flammable gases and smoke, whereas the MQ4 sensor is sensitive to natural gas and methane.

d. Average Gas Data for Each Sensor

Fig. 10 illustrates the average data from each sensor's conversion from measured ADC to ppm units. The letter R indicates that the sugar apple fruit is stored at room temperature, while the letters (A, B, and C) indicate that the fruit is large, medium, or small. While the numbers 0-2 are the fruit storage code of the day.

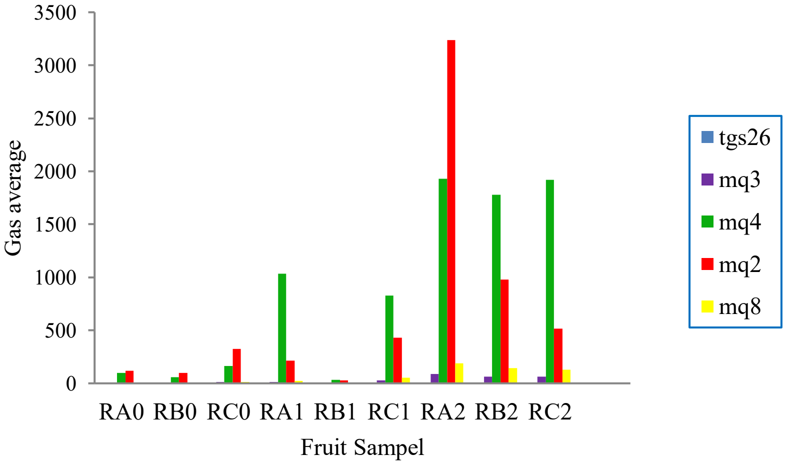


Fig. 10. Graph of Average Gas Content (ppm)

Fig. 10 shows that the gas produced by the MQ4 and MQ2 sensors has a very high value when compared to other sensors. The MQ4 sensor detects natural gas and methane gas with high sensitivity. The MQ2 sensor, on the other hand, can detect the concentration of combustible gases and smoke in the air [16]. The sensors used are not designed to detect gas in sugar apples. A single sensor can record a variety of gases, including methane gas, CO, hydrogen, alcohol, LPG gas, and others.

The amount of gas produced increased from day 0 to day 2. This means that when the sugar apple fruit ripens on the second day, it has the highest gas concentration; the aroma produced by the sugar apple fruit is also very strong when ripe; and the gas produced during ripening is suspected to be ethylene gas because ethylene gas is a volatile gas. The high respiration rate and high concentration of ethylene produced by post-harvest fruit can hasten the spoilage process in fruits. Ethylene production contributes to the appearance of damage, and ethylene is very active in stimulating hydrophobic enzymes like pectin esterase, amylase, invertase, cellulase, and chlorophyllase [17].

3. 6. Confusion Matrix of k-NN Method and Random Forest

Tables 5–10 show the test results of the sugar apple ripeness detection system in the form of a confusion matrix with test data of 20%, 30%, and 40% obtained after classifying using the k-NN algorithm and random forest.

Table 5. Confusion Matrix k-NN method test data 20%

Predictive value	Actual Value	
	Raw (1)	**Ripe (2)**
Raw (1)	1	0
Ripe (2)	0	1

Table 6. Confusion Matrix Random Forest method test data 20%

Predictive value	Actual value	
	Raw (1)	**Ripe (2)**
Raw (1)	1	0
Ripe (2)	0	1

Table 7. Confusion Matrix k-NN method test data 30%

Predictive value	Actual Value	
	Raw (1)	**Ripe (2)**
Raw (1)	1	0
Ripe (2)	0	2

Table 8. Confusion Matrix Random Forest method test data 30%

Predictive value	Actual Value	
	Raw (1)	**Ripe (2)**
Raw (1)	1	0
Ripe (2)	0	2

Table 9. Confusion Matrix k-NN method test data 40%

Predictive value	Actual Value	
	Raw (1)	Ripe (2)
Raw (1)	0	2
Ripe (2)	0	2

Table 10. Confusion Matrix Random Forest method test data 40%

Predictive value	Actual Value	
	Raw (1)	Ripe (2)
Raw (1)	2	0
Ripe (2)	0	2

Tables 5 and 6 show that with 20% test data, the k-NN method and random forest can both detect 1 unripe fruit and 1 ripe fruit. The k-NN method and random forest were both able to detect 1 unripe fruit and 2 ripe fruits using 30% test data. The k-NN method detected 0 unripe and 2 ripe fruits from the 40% test data, while the random forest method detected 2 unripe and 2 ripe fruits. This means that the more test data collected, the riper fruit detected. That the more test data there is, the more likely there will be errors in classifying test data, but there is also a chance that more test data will be correctly classified. The higher the accuracy value, the more correct test data in the classification [18].

The Accuracy (Acc), Precision (Pr), Sensitivity (Se), and Specificity (Sp) values are calculated based on the confusion matrix value. Fig. 11 - 14 illustrates the obtained results.

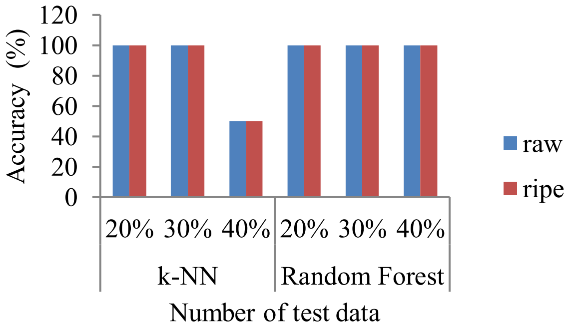


Fig. 11. Accuracy of k-NN and Random Forest in different testing data

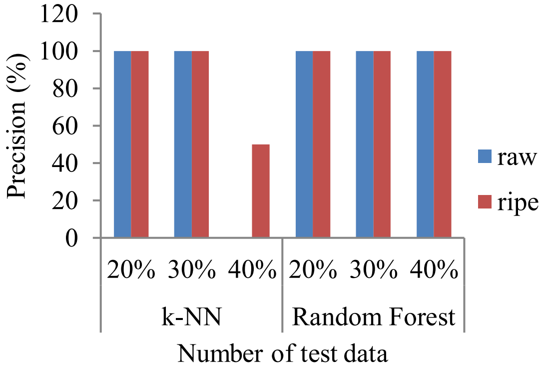


Fig. 12. Precision of k-NN and Random Forest in different testing data

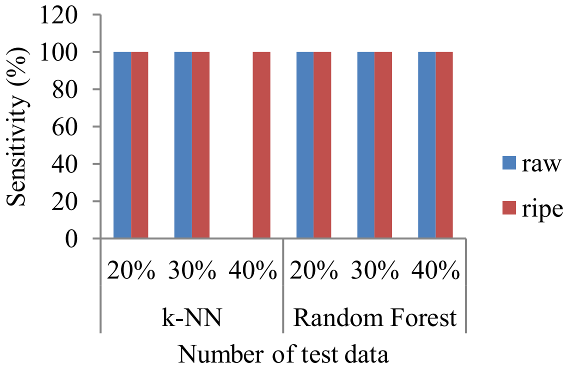


Fig. 13. Sensitivity of k-NN and Random Forest in different testing data

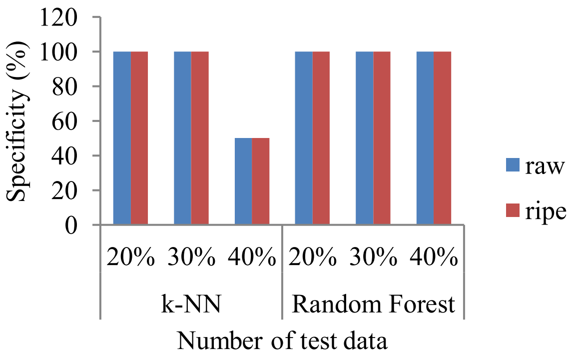


Fig. 14. Specificity of k-NN and Random Forest in different testing data

According to Fig. 11, the k-NN and random forest methods with 20% and 30% test data have the same accuracy of 100% in predicting raw and ripe fruit, respectively, whereas the 40% test data results in a lower accuracy of the k-NN method, namely 50%. Fig. 12 shows that the k-NN method and random forest with 20% and 30% test data both have 100% precision results, except for the k-NN method with 40% test data, which has a precision value of 0% detecting unripe fruit and 50% detecting ripe fruit. The results of sensitivity/recall using the random forest method with test data of 20%, 30%, and 40% in detecting raw and ripe fruit, namely 100%, are shown in Fig. 13, while the k-NN method with test data of 20%, 30%, and 40% is shown in Fig. 14. The sensitivity result in detecting ripe fruit is 100%, except for the 40% test data in detecting unripe fruit, which has a sensitivity result of 0%. The percentage of specificity with test data of 20% and 30% in detecting unripe and ripe fruit using the k-NN method and random forest is 100% in Figure 14, except for the k-NN method with 40% test data having a specificity of 50%. on sugar apple fruit is greater than the k-NN method's accuracy value, namely the random forest method of 100% versus the k-NN method of 50%.

Accuracy, Precision, Sensitivity, and Specificity obtained using the random forest method with 40% test data have a higher value than the k-NN method. Random forest has several advantages, including high accuracy, high resistance to outliers and noise, faster processing than bagging and boosting, and simplicity and ease of parallelization [9]. While the k-NN method is very simple, it works by determining the shortest distance between the query instance and the training sample [18]. The random forest method achieves a high level of accuracy, 57% [1]. The classification results of several studies using the random forest method have a high level of accuracy [19].

The purpose of this system is to detect ripeness of sugar apple fruit based on texture samples, weight loss, moisture content, total dissolved solids, and gas content. Test data variations of 20%, 30%, and 40% have been achieved. They were able to detect the ripeness of the sugar apple fruit using the 9 sugar apple samples, although the k-NN algorithm with 40% test data had lower accuracy than the other test data, but the random forest algorithm had 100% accuracy. The results of the tests show that identification with three variables, namely shape, color, and texture, has a higher level of accuracy than identification with only one or two variables [20]. This means that the higher the level of accuracy obtained, the more diverse the variables used for classification.

4 Conclusion

The detection of ripeness in sugar apple fruit based on texture samples, weight loss, gas content, moisture content, and total dissolved solids was accomplished using the k-NN algorithm and random forest with variations in the number of test samples, namely 20%, 30%, and 40%. For each variation in the number of test samples, the random forest method was found to provide 100% accuracy. While the k-NN method's accuracy decreases as the number of test samples increases, namely 100%, 100%, and 50% for each variation of the test sample. As a result, the Random Forest method for determining the maturity level of sugar apple fruit is superior.

References

1. M. Murad, S. Sukmawaty, A. Ansar, R. Sabani, and S. Hidayat. *JTIM J. Teknol. Inf. dan Multimed.* 3, 186-194, (2021). doi: 10.35746/jtim.v3i4.169.
2. N. Aghilinategh, M. J. Dalvand, and A. Anvar. *Food Sci. Nutr.* 8, 4919–4928 (2020) doi:10.1002/fsn3.1788.
3. Y. Heryadi. Gava Media Yogyakarta. 1-11 (2020).
4. P. S. Priya, N. Jyoshna, S. Amaraneni, and J. Swamy. *Mater. Today Proc.* 33, 4900–4906 (2020) doi: 10.1016/j.matpr.2020.08.445.
5. B. Dhiman, Y. Kumar, and M. Kumar. *Multimed. Tools Appl.* 81, 16255–16277 (2022) doi: 10.1007/s11042-022-12652-2.
6. M. Surya Kiran and G. Niranjana. *Int. J. Innov. Technol. Explor. Eng.* 8, 1470–1473 (2019) doi: 10.35940/ijitee.F1300.0486S419.
7. M. H. Hanafi, N. Fadillah, and A. Insan. *It J. Res. Dev.* 4, 10–18 (2019) doi: 10.25299/itjrd.2019.vol4(1).2477.
8. M. A. Souza, G. D. C. Cavalcanti, R. M. O. Cruz, and R. Sabourin. *Pattern Recognit.* 85, 132–148 (2019) doi: 10.1016/j.patcog.2018.08.004.
9. Luthfiana Ratnawati and Dwi Ratna Sulistyaningrum. *J. Sains Dan Seni Its*. 8, 1-7 (2019).
10. A. Primajaya and B. N. Sari. *Indones. J. Artif. Intell. Data Min.* 1, 27 (2018) doi: 10.24014/ijaidm.v1i1.4903.
11. D. Yunita. *J. Inform. Univ. Pamulang*. 2, 103 (2017) doi:10.32493/informatika.v2i2.1512.
12. Sartika, R. Departemen Agronomi Dan Hortikultura. 1-77 (2010).
13. W. Mudyantini, E. Anggarwulan, and P. Rahayu. *Agric*. 27, 23, (2016). doi:10.24246/agric.2015.v27.i1.p23-29.
14. N. Yousif *et al. J. Phys. Ther. Sci.* 9, 1–11 (2018). doi:10.1016/j.neuropsychologia.2015.07.010%0
15. Hidayah, N. N. Departemen Fisika, Fakultas Matematika dan Ilmu Pengetahuan Alam. 1-10 (2009).
16. Sarmidi and R. Akhmad Fauzi. *Manaj. Dan Tek. Inform.* 3, 51–60, (2019).
17 N. Iqbal, N. A. Khan, A. Ferrante, A. Trivellini, A. Francini, and M. I. R. Khan,. *Front. Plant Sci.* 8, 1–19 (2017). doi: 10.3389/fpls.2017.00475.
18. S. B. Y. Firmansyah. *Inform. Jur. Tek. Tinggi, Sekol. Inform. Manaj. Komputer, D A N Purwokerto, Amikom*. 1-9 (2015).
19. H. Santoso. *J. Penelit. Kelapa Sawit*. 28, 133–146 (2020). doi: 10.22302/iopri.jur.jpks.v28i3.116.
20. A. Zaenuddin. *International Journal of Engineering Reasearch & Teechnology (IJERT)*. 9, 177–182 (2020).