Non-Destructive Classification Model of Pineapple Sweetness Level

Nunu Nugraha Purnawan[1], Dwi Vernanda[2*], Tri Herdiawan Apandi[3], Zatin Niqotaini[4]
[1,2,3] Prodi Sistem Informasi, Jurusan Teknologi Informasi dan Komputer, Politeknik Negeri Subang, Subang, Indonesia
[4]Prodi S1 Sistem Informasi, Fakultas Ilmu Komputer, Universitas Pembangunan Nasional Veteran Jakarta, Jakarta, Indonesia
Email: [1,]nunu@polsub.ac.id, [2*]nanda@polsub.ac.id, [3]tri@polsub.ac.id, [4]zatinniqotaini@upnvj.ac.id

Abstrak– Penelitian ini berfokus pada pengembangan model klasifikasi tingkat kemanisan buah nanas secara non-destruktif dengan menggunakan teknologi Internet of Things (IoT) dan algoritma K-Nearest Neighbor (KNN). Tujuan utama dari penelitian ini adalah untuk menentukan tingkat kemanisan buah nanas tanpa merusak buah, yang merupakan masalah umum pada metode pengukuran kemanisan tradisional seperti menggunakan refraktometer yang memerlukan sari buah nanas. Penelitian ini memberikan kontribusi signifikan dengan menawarkan metode non-destruktif berbasis teknologi IoT dan machine learning yang lebih efisien, akurat, dan ramah terhadap kualitas buah. Kabupaten Subang dipilih sebagai lokasi pengambilan sampel karena merupakan salah satu daerah penghasil nanas terbesar di Jawa Barat. Terdapat tiga pasar utama untuk distribusi nanas di daerah tersebut, yaitu supermarket, industri pengolahan, dan pasar tradisional, yang masing-masing memiliki standar tingkat kemanisan yang berbeda. Sebanyak 500 buah nanas digunakan dalam penelitian ini, dengan 450 sampel digunakan untuk data latih dan 50 sampel sebagai data uji. Penelitian ini menggunakan sensor warna TCS230 yang dihubungkan dengan Arduino Uno R3 untuk menangkap data RGB dari kulit nanas pada jarak tertentu. Nilai RGB yang diperoleh kemudian diproses menggunakan algoritma KNN untuk memprediksi tingkat kemanisan buah nanas berdasarkan kategori Brix: tinggi (14-17 Brix), sedang (10-13 Brix), dan rendah (<10 Brix). Setelah nilai RGB diperoleh, data tersebut diolah untuk menghasilkan klasifikasi tingkat kemanisan nanas yang valid. Pengujian dilakukan dengan menggunakan confusion matrix, yang memberikan metrik seperti akurasi, presisi, dan recall. Hasil penelitian menunjukkan bahwa model KNN yang dikembangkan berhasil mengklasifikasikan nanas dengan akurasi 72%, yang berarti sebagian besar prediksi yang dihasilkan oleh model sesuai dengan tingkat kemanisan nanas yang sebenarnya. Pendekatan non-destruktif ini memberikan keuntungan signifikan dibandingkan metode tradisional, karena tidak hanya menjaga integritas buah nanas, tetapi juga lebih efisien dalam hal waktu dan sumber daya. Dengan mengintegrasikan IoT dan machine learning, penelitian ini berkontribusi dalam memberikan solusi praktis, akurat, dan inovatif bagi petani dan pelaku industri untuk meningkatkan kualitas produk serta efisiensi distribusi ke berbagai pasar.

Kata Kunci: Algoritma K-Nearest Neighbor (KNN), Internet of Things (IoT), Klasifikasi, Nanas, Non-destruktif.

Abstract– This research focuses on developing a non-destructive model for classifying the sweetness level of pineapples using Internet of Things (IoT) technology and the K-Nearest Neighbor (KNN) algorithm. The main goal of this research is to determine the sweetness level of pineapples without damaging the fruit, which is a common issue with traditional sweetness measurement methods, such as using a refractometer that requires pineapple juice. This study provides a significant contribution by offering a non-destructive method based on IoT technology and machine learning, which is more efficient, accurate, and preserves the quality of the fruit. Subang Regency was selected as the sampling location because it is one of the largest pineapple-producing regions in West Java. There are three main markets for pineapple distribution in the area: supermarkets, processing industries, and traditional markets, each with different sweetness level standards. A total of 500 pineapples were used in this study, with 450 samples used for training data and 50 samples for testing. The study employed a TCS230 color sensor connected to an Arduino Uno R3 to capture the RGB data from the pineapple's skin at a certain distance. The obtained RGB values were then processed using the KNN algorithm to predict the sweetness level of the pineapples based on Brix categories: high (14-17 Brix), medium (10-13 Brix), and low (<10 Brix). After the RGB values were acquired, the data was processed to generate a valid classification of the pineapple's sweetness level. Testing was conducted using a confusion matrix, which provided metrics such as accuracy, precision, and recall. The results showed that the developed KNN model successfully classified the pineapples with an accuracy of 72%, meaning that most of the predictions made by the model matched the actual sweetness levels of the pineapples. This non-destructive approach offers significant advantages compared to traditional methods, as it not only preserves the integrity of the fruit but is also more efficient in terms of time and resources. By integrating IoT and machine learning, this research contributes to providing a practical, accurate, and innovative solution for farmers and industry players to improve product quality and distribution efficiency to various markets.

Keywords: Algoritma K-Nearest Neighbor (KNN), Classification, Internet of Things (IoT), Non-destructive, Pineapple,.

1. INTRODUCTION

Fruits play a vital role in agriculture, serving as a primary source of livelihood for millions of people worldwide. Ensuring the quality of fruits for consumption is critical, particularly for fruits like pineapples, which are not only a key nutritional source but also hold significant commercial value. In West Java, Subang Regency stands out as the largest producer of pineapples, with farmers and sellers striving to maintain the quality of the fruit for optimal distribution to meet the nutritional demands of the community and the needs of various industries. Pineapple distribution in Subang is directed to three primary markets: supermarkets, pineapple processing industries, and traditional markets. Each market has its own standards for pineapple sweetness, with supermarkets preferring pineapples with a Brix level between 14-17, processing industries seeking a range of 10-13 Brix, and traditional markets accepting pineapples with a Brix level under 10[1].

Currently, the assessment of pineapple sweetness is carried out through subjective methods, where farmers and sellers rely on visual inspection of the fruit's skin color and aroma. This approach leads to inaccurate results, as it is based on personal perceptions, which vary from one individual to another. Additionally, to obtain precise sweetness measurements, traditional methods require extracting juice from the pineapple, resulting in fruit wastage and long processing times. The physical properties of pineapples, including size, shape, crown form, texture, color, water content, sugar, acid, and fat, can provide valuable insights for classifying the sweetness level of the fruit in a more efficient and non-destructive manner[2].

Non-destructive methods for determining fruit quality, particularly sweetness, are increasingly in demand due to their ability to avoid waste and preserve fruit integrity. Although deep learning algorithms are now being used for classification in some studies, machine learning algorithms, particularly K-Nearest Neighbor (KNN), continue to show high accuracy in non-destructive fruit classification. Previous research has focused on destructive methods, such as slicing the pineapple and testing the juice to determine the Brix value, which is impractical and wasteful. For example, a study on melon sweetness detection utilized local binary pattern feature extraction and KNN classification, achieving an accuracy rate of 80% using 360 training images and 90 test images. Another study employed infrared spectroscopy to determine the ripeness of durian fruit using KNN, with an accuracy of 83.15%. These methods, however, either require physical damage to the fruit or specialized equipment, making them less accessible for widespread use, particularly among farmers and sellers in resource-limited settings [3].

This research seeks to address these limitations by developing a non-destructive method for classifying the sweetness level of pineapples using an Internet of Things (IoT) approach combined with the KNN algorithm. The study will utilize an Arduino Uno R3 and TCS2300 color sensor to capture the color of the pineapple skin, which will then be processed to predict the Brix value and classify the sweetness level. Unlike previous methods, this approach eliminates the need for fruit extraction or subjective visual inspection, thus reducing waste, time, and resource consumption[5].

The primary objective of this study is to develop an efficient, non-destructive classification system for pineapple sweetness using IoT devices and machine learning. The contribution of this research lies in the integration of IoT technology with machine learning algorithms to provide a practical solution that can help farmers and sellers determine the optimal sweetness level of pineapples for different markets, ultimately improving distribution efficiency and product quality. By offering an affordable, rapid, and accurate method for classifying pineapple sweetness, this research aims to revolutionize the way pineapples are assessed and distributed, benefiting both the agricultural sector and the broader pineapple industry [8].

This study will answer the problems faced by pineapple farmers and sellers, the existence of a system to classify the level of sweetness of pineapples using the KNN algorithm by utilizing IoT devices including Arduino Uno R3 and TCS2300 color sensors so that this classification is carried out non-destructively, namely knowing the level of sweetness of pineapples without damaging and wasting a lot of time.

2. RESEARCH METHODS

This research focuses on developing a non-destructive classification system for pineapple sweetness levels by leveraging IoT technology and the K-Nearest Neighbor (KNN) machine learning algorithm. The research methodology is divided into several stages, each of which is described in figure 1 detail below, alongside the application of solutions and supporting literature for the methods used.

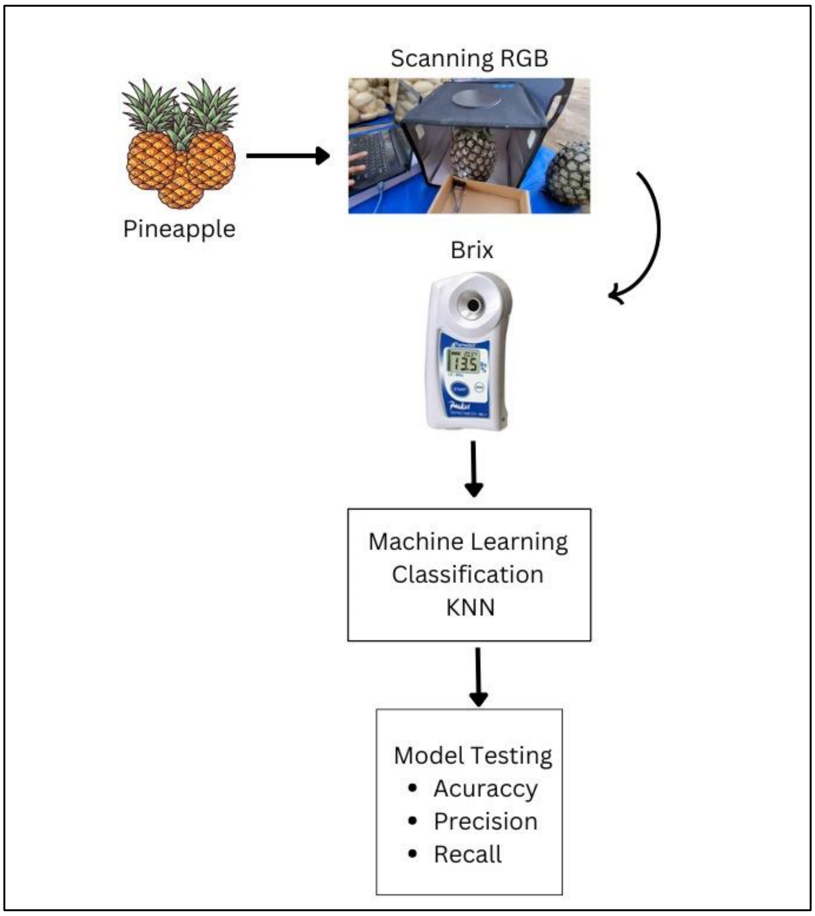

Figure 1. Research methods

1. Pineapple Sampling

Pineapples were collected from Subang Regency, a major pineapple-producing area in West Java. A total of 500 pineapples were selected for the study, covering a range of sizes, colors, and ripeness levels to ensure diversity in the dataset. Of these, 450 samples were used for training the model, while 50 samples were reserved for testing. This sampling approach ensures a balanced and representative dataset for model development.

2. RGB Data Acquisition

To classify the sweetness level, the color of the pineapple skin was captured as an indicator of ripeness and sweetness. This was performed using the TCS230 color sensor connected to an **Arduino Uno R3 microcontroller**. The TCS230 sensor was chosen for its ability to capture precise RGB values under controlled lighting conditions. The sensor was calibrated to maintain consistent measurement distances and eliminate the impact of ambient lighting.

The pineapples were placed in a controlled scanning environment, as shown in the diagram, to reduce noise in RGB readings. The RGB values captured from the skin were recorded and stored in a structured dataset for further processing.

Literature Review: Color as an indicator of fruit ripeness and sweetness has been widely studied. Research on melons and coffee fruits using RGB color extraction has shown that color data can be a reliable input for classification algorithms [1][2]. The use of the TCS230 sensor has also been validated in prior studies for its effectiveness in agricultural applications.

3. Brix Value Measurement

The sweetness level (Brix value) of the pineapple was measured using a **digital refractometer**. This step was carried out to provide labeled data for training and testing the KNN algorithm. The Brix values were categorized into three levels:

- **High sweetness:** 14-17 Brix (suitable for supermarkets)
- **Medium sweetness:** 10-13 Brix (preferred by processing industries)
- **Low sweetness:** <10 Brix (distributed to traditional markets)

This step established the ground truth for the classification process.

Literature Review: The use of Brix measurement as a standard for sweetness is common in fruit quality research [3]. However, destructive methods like refractometer testing are labor-intensive and result in fruit waste, which this study aims to address.

4. Machine Learning Classification using KNN

The captured RGB values and their corresponding Brix levels were used to train the **K-Nearest Neighbor (KNN)** classification model. The KNN algorithm was chosen for its simplicity, efficiency, and robustness in small-to-medium-sized datasets. The key steps in this stage include:

- **Data Preprocessing:** Normalizing the RGB values to ensure uniform scaling.
- **Training the Model:** The model was trained using 450 samples, with the RGB values as input features and Brix categories as the output labels.
- **Hyperparameter Tuning:** The optimal value of ‘K’ (number of neighbors) was determined through cross-validation to maximize model accuracy.

Literature Review: KNN is widely used in agricultural classification tasks due to its high interpretability and effectiveness with RGB data. Previous studies on fruit ripeness and sweetness classification using KNN reported accuracies of 80-85%, supporting its suitability for this research [4][5].

5. Model Testing and Validation

The trained model was tested using the remaining 50 samples. The evaluation was conducted using a **confusion matrix**, which provided key performance metrics:

- **Accuracy:** The proportion of correctly classified samples to the total samples.
- **Precision:** The proportion of true positive predictions to the total predicted positives for each class.
- **Recall:** The proportion of true positive predictions to the total actual positives for each class.

These metrics provide a comprehensive assessment of the model’s performance.

Literature Review: The confusion matrix is a standard evaluation tool for classification models, allowing for detailed analysis of errors across classes [6].

6. IoT Integration and Implementation

The final step involved the integration of the IoT device for practical use. The TCS230 sensor and Arduino Uno R3 microcontroller were programmed to capture RGB data, which was then fed into the trained KNN model. This system allows for real-time classification of pineapple sweetness levels without damaging the fruit, making it a practical tool for farmers and sellers.

Advantages of IoT in Agriculture: IoT-based solutions have proven to be transformative in agriculture by enabling real-time monitoring, data collection, and analysis. The use of IoT in this research aligns with the broader trend of smart agriculture, which aims to enhance productivity and reduce waste

2.1 Sample

Pineapple fruit samples were obtained from pineapple plantations in Cijambe District, Subang Regency with the queen variety which has a sweetness level of 4 brix - 17.5 brix. A total of 500 pineapples were used as samples to take RGB values and sweetness levels, namely (brix), 450 pineapples as training data and 50 pineapples as test data.

2.2 IoT

At this stage, the study used sensor technology and IoT devices to collect RGB data from the color of pineapple skin. The tools used include the TCS230 color sensor paired with the Arduino Uno R3. RGB (Red, Green, Blue) of each pineapple was measured using this tool at a distance of 5 cm from the bottom of the pineapple. This RGB measurement is useful for classifying the sweetness level of pineapple in the next stage [9]. The IoT Scanning RGB prototype can be seen in Figure 2 Prototype.

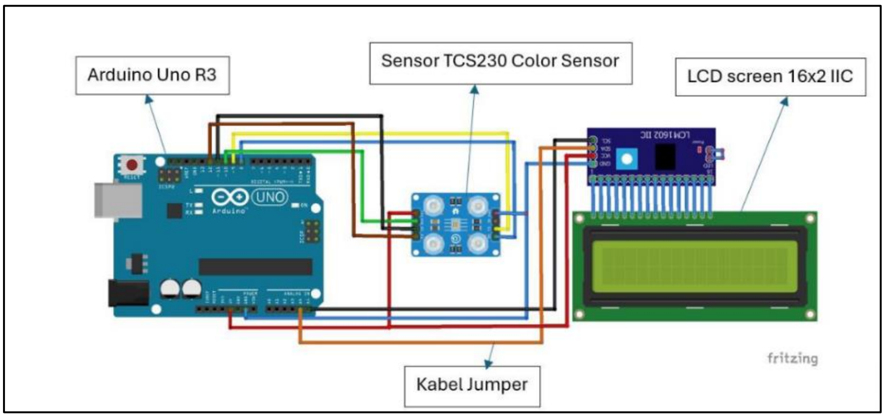

Figure 2. Prototype

2.2 Scanning RGB

After collecting the pineapples, the next step is to determine the RGB value of each fruit. RGB is a representation of the color components taken from the surface of the pineapple using the TCS230 sensor. Each RGB value will later be used as input for the classification algorithm (KNN) [10]. The purpose of this process is to obtain physical data that can be further processed and correlated with the sweetness level of pineapple.

2.3 Calculate Brix

After the RGB measurement is complete, the pineapple juice is taken to measure the sweetness level or Brix value [11]. This measurement was done using a refractometer, a tool that can calculate the sugar content in pineapple juice. The Brix value will help in validating the sweetness prediction results generated by the KNN algorithm.

The Brix measurement divides the sweetness level of pineapple into three categories:

- **High sweetness (14-17 Brix)** : Distributed to supermarkets.
- **Moderate sweetness (10-13 Brix)** : Distributed to the fruit processing industry.
- **Low sweetness (<10 Brix)** : Distributed to traditional markets.

2.4 KNN

Collecting Training Data

Collect data from pineapples that have known ripeness labels, such as unripe, medium ripe, and ripe. This data can be physical measurements (pineapple skin color, weight, size), sensory data (aroma, taste), or image data (picture of a pineapple).

Extracting Features

From the existing pineapple data, extract the relevant features to determine ripeness, for example:

1. Pineapple skin color (using image processing)
2. Sugar content (using sensors)
3. Skin texture
4. Water content

Determination of K Value

In KNN, the main parameter is the K value, which is the number of nearest neighbors that will be considered to determine the new pineapple class. This K value can be adjusted according to needs, for example if K = 3, then the 3 nearest neighbors will be analyzed.

Distance Calculation

The KNN algorithm calculates the distance between the new pineapple data to be classified and all existing training data. This distance is usually calculated using the Euclidean distance, which measures how far the new data is from the existing data based on predetermined features. [12]

Evaluation and Validation

After the KNN model is developed, the testing phase is carried out using a confusion matrix to measure model performance. Some evaluation metrics used:

- Accuracy: The percentage of correct predictions out of all predictions.

- Precision: The ability of the model to identify correct predictions out of the total positive predictions.

- Recall: How well the model can find all positive cases from the available data.

This process aims to ensure that the developed model is able to provide precise and accurate classification results in determining the sweetness level of pineapple.

3. RESULTS AND DISCUSSIONS

In this chapter, the research results obtained from the methods described in the previous chapter are analyzed in detail. The results include RGB measurement data of pineapple samples, Brix values obtained from pineapple juice, and classification results using the K-Nearest Neighbors (KNN) algorithm. A comprehensive discussion is provided regarding the accuracy, advantages, and disadvantages of the approach used, including an explanation for the obtained accuracy of 72%.

3.1 Data Collection

The dataset was collected from 500 pineapples sourced from plantations in Cijambe District, Subang Regency. The RGB data of the pineapple skin was captured using IoT devices, specifically a TCS230 color sensor integrated with Arduino Uno R3. The use of this setup ensured consistency in data collection under controlled lighting conditions.

The Brix values, representing the sweetness level of pineapple, were measured using a refractometer. Pineapple juice was extracted from a section of the fruit located 5 cm from the base. The Brix values were then categorized into three levels: sweet A (14-17 Brix), sweet B (10-13 Brix), and sweet C (<10 Brix).

A combined dataset of 450 training samples and 50 test samples was created, consisting of RGB values, corresponding Brix values, and labels representing sweetness categories (A, B, C). This dataset serves as the foundation for training and validating the KNN classification model.

Figure 3. Implementasi IoT

After the RGB of pineapple skin is known, the next step is to determine the sweetness value of pineapple using a refractometer, pineapple juice is taken from the pineapple flesh which is 5 cm from the base of the pineapple. The following is the determination of the brix value of pineapple juice.

Figure 4. Sweetness Level Measurement

A total of 450 RGB and brix data of pineapple fruit were collected in one file for further use in classification.

Tabel 1. Dataset

Nanas	Red	Green	Blue	Brix	Label
1	136	126	129	15,3	A
2	120	150	154	13,2	B
3	102	118	125	14,7	A
4	85	118	119	13,7	B
5	110	139	136	5,3	C
6	74	105	109	14,1	A
7	109	136	146	5,6	C
8	113	145	146	6,4	C
9	112	90	95	9,8	C
10	106	112	98	12	B
11	129	148	150	16,1	A
12	86	128	144	7,9	C
13	97	112	156	9,2	C
14	111	107	125	11,6	B
15	142	151	114	16,8	A
16	126	134	118	14,5	A
17	140	137	120	17	A
18	96	104	117	12,3	B
19	112	129	95	10,4	B
20	112	86	98	6,9	C
21	148	148	125	16,3	A
22	87	151	114	5,4	C

The image above is a pineapple dataset, which contains features to describe the physical characteristics, namely the RGB value and sugar content of each pineapple sample. Each row in this dataset represents one pineapple sample with several columns describing these features. The first column is the identification number or sequence of each pineapple sample. Next, there are three columns representing the color intensity values of the red, green, and blue components, which indicate the color of the pineapple skin or flesh. These colors may be measured using digital methods to obtain information about the physical condition of the fruit. [13]

In addition, there is a "Brix" column that describes the sugar content of the pineapple on the Brix scale, which is often used as an indicator of the ripeness or sweetness of the fruit. The higher the Brix value, the sweeter the pineapple. Finally, the "Label" column shows the quality class of the pineapple, which is grouped into categories A, B, or C.

3.2 Data Processing and KNN Implementation

The dataset was processed using RapidMiner to develop and validate the KNN model. The visual process flow consisted of:

1. Reading the dataset from Excel files.
2. Assigning roles for features (RGB values) and target labels (Brix categories).
3. Applying the KNN algorithm to train the model using 450 training samples.
4. Testing the model using 50 test samples to evaluate its predictive performance.

KNN was chosen for its simplicity, efficiency, and proven accuracy in handling classification tasks in similar agricultural applications. The RGB values provided a reliable non-destructive indicator for sweetness classification.

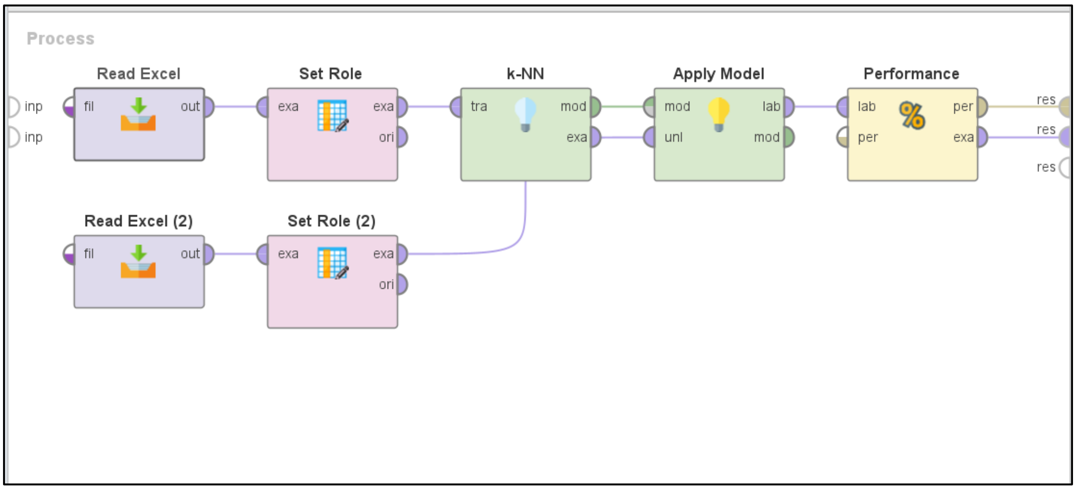

Figure 5. Process Flow

The figure above shows a process flow of a visual interface-based machine learning application, which may come from a platform like RapidMiner or similar tools. The process starts with two "Read Excel" steps that are used to read data from two separate Excel files. This imported data is then processed through the "Set Role" node, where the role of each column in the dataset is defined. Typically, this involves setting the columns as features (attributes) and targets (labels) to be predicted. Once the data roles are defined, the process moves on to the k-nearest neighbors (k-NN) classification algorithm. At this stage, the training data is used to build a predictive model [14].

3.3 Confusion Matrix Tabel View

Table View   Plot View

accuracy: 72.00%

	true A	true B	true C	class precision
pred. A	17	5	0	77.27%
pred. B	10	31	5	67.39%
pred. C	2	6	24	75.00%
class recall	58.62%	73.81%	82.76%	

Figure 6. Confusion Matrix

The table above is the result of testing the performance of the K-Nearest Neighbors (KNN) model using Rapid Miner to classify the ripeness level of pineapple based on its sweetness level, which is divided into three categories: sweet A, sweet B, and sweet C. In this table, the columns show the actual labels of the data (True Labels), while the rows show the predictions generated by the model (Predicted Labels).

The main diagonal in the table represents the number of correct predictions, that is, when the model predicted that a pineapple was in the correct category according to the actual data. For example, there were 17 pineapples that should have been categorized as sweet A and were correctly predicted by the model as sweet A. Similarly, there were 31 pineapples that should have been sweet B and were correctly predicted, and 24 pineapples that should have been sweet C and were also correctly classified [15].

3.4 Confusion Matrix Plot View

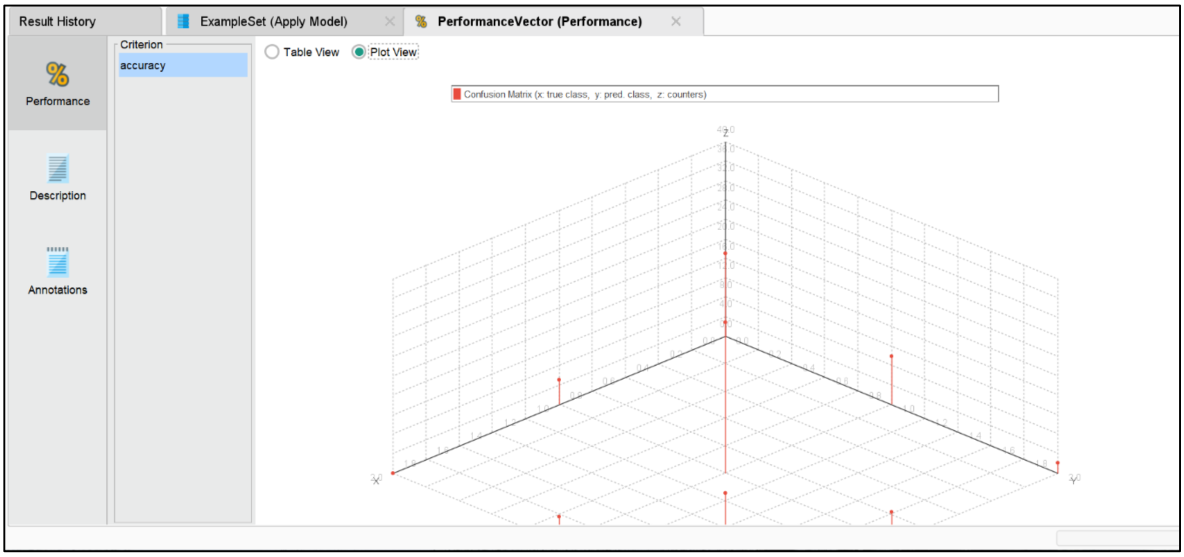

Figure 7. Plot View

The image above is a 3D plot visualization of the Confusion Matrix that illustrates the relationship between model predictions and actual labels for a three-class classification. In this graph, the X-axis represents the true class, the Y-axis represents the class predicted by the model (predicted class), and the Z-axis shows the number of cases or data that fall into each combination of the actual and predicted classes.

Each red dot that appears on the graph represents the number of predictions in each category, with the height of the dot on the Z-axis representing how much of the data matches that combination of the true and predicted classes. If the model is working perfectly, then most of the dots will be along the diagonal, where the true and predicted classes are the same (e.g. True A is predicted as A)[16].

3.5 Performance Vector

PerformanceVector

```
PerformanceVector:
accuracy: 72.00%
ConfusionMatrix:
True:   A       B       C
A:      17      5       0
B:      10      31      5
C:      2       6       24
```

Figure 8. Performance Vector

The performance results of the classification model are presented through a PerformanceVector, including a Confusion Matrix and an accuracy level of 72.00%. This accuracy indicates that from all the test data, 72% of the predictions generated by the model are correct. This means that most of the model classifications are in accordance with the actual data, although there are some classification errors.

The Confusion Matrix in this figure explains in detail how the model predicts three categories, namely A, B, and C. In category A, there are 17 pineapples that are correctly classified as A. However, there are some errors that occur, where 5 pineapples that are actually in category B are incorrectly predicted as A. However, no pineapples from category C are incorrectly classified as A, indicating that the model is more accurate in avoiding prediction errors for this category [17].

For category B, 31 pineapples were correctly classified as B by the model. However, there were a number of errors where 10 pineapples that were actually in category A were incorrectly predicted as B, and 5 pineapples from category C were also incorrectly classified as B.

4. CONCLUSION

This study successfully developed a non-destructive classification model for pineapple sweetness levels using IoT technology and the K-Nearest Neighbor (KNN) algorithm. The research addressed the problem of inefficiency and waste caused by traditional destructive sweetness measurement methods by introducing a non-destructive approach. The RGB values obtained from pineapple skin using the TCS230 color sensor served as the input for the classification model, while the sweetness levels were categorized using the Brix scale into high, medium, and low categories based on market segment requirements. The findings demonstrate that the developed KNN-based classification model achieved an accuracy of 72%, successfully classifying pineapples into their respective sweetness levels in alignment with market needs. Specifically, the model effectively differentiated between high-sweetness pineapples suitable for supermarkets, medium-sweetness for processing industries, and low-sweetness for traditional markets. Although there is room for improvement in classification accuracy, the results show that the proposed method is practical and efficient for large-scale applications. This research directly answers the problem formulation by providing a solution that maintains the integrity of the fruit while reducing the time and resources required for sweetness classification. It eliminates the need for fruit destruction, which is a limitation of traditional methods, and highlights the feasibility of integrating IoT technology into agricultural practices. The use of IoT devices like the TCS230 sensor and Arduino Uno R3, combined with machine learning techniques, offers a scalable and efficient alternative for farmers and industry players to ensure product quality and meet diverse market demands. In summary, this study contributes to the advancement of non-destructive methods in agriculture by providing an innovative solution for pineapple sweetness classification, demonstrating its potential to improve efficiency, reduce waste, and optimize the distribution process. Future research can build upon these findings by enhancing classification accuracy through the inclusion of additional features or exploring more advanced algorithms.

REFERENCES

[1] M. Rizzo, M. Marcuzzo, A. Zangari, A. Gasparetto, dan A. Albarelli, “Fruit ripeness classification: A survey,” *Artificial Intelligence in Agriculture*, vol. 7, hlm. 44–57, Mar 2023, doi: 10.1016/J.AIIA.2023.02.004.

[2] F. Tangguh Admojo, “Klasifikasi Aroma Alkohol Menggunakan Metode KNN,” *Indonesian Journal of Data and Science* , vol. 1, no. 2, hlm. 34–38, 2020.

[3] R. Manaek, Richardus Eko Indrajit, dan Erick Dazki, “Klasifikasi Kualitas Buah Pisang Berdasarkan Waktu Panen dan Tingkat Kematangan Menggunakan Metode SVM & KNN,” *SATIN - Sains dan Teknologi Informasi*, vol. 9, no. 2, hlm. 01–11, Des 2023, doi: 10.33372/stn.v9i2.1000.

[4] A. Ilmi, M. Hanif Razka, D. S. Wiratomo, dan D. S. Prasvita, *Klasifikasi Tingkat Kematangan Buah Apel Berdasarkan Fitur Warna Menggunakan Algoritma K-Nearest Neighbor dan Ekstraksi Warna HSV*. 2021. [Daring]. Tersedia pada: https://www.kaggle.com/mbkinaci/fruit-images-for-object-detection

[5] V. C. Wijaya dan F. Utaminingrum, “Deteksi Tingkat Kemanisan Buah Melon melalui Ekstraksi Fitur Local Binary Pattern dengan Klasifikasi K-NN berbasis Raspberry Pi 4,” *Jurnal Pengembangan Teknologi Informasi dan Ilmu Komputer*, vol. 6, no. 1, hlm. 52–57, 2022.

[6] S. Ditcharoen *dkk.*, “Improving the non-destructive maturity classification model for durian fruit using near-infrared spectroscopy,” *Artificial Intelligence in Agriculture*, vol. 7, hlm. 35–43, Mar 2023, doi: 10.1016/J.AIIA.2023.02.002.

[7] P. Astuti, U. Nusa Mandiri Jln Jatiwaringin Raya No, K. Cipinang Melayu Kecamatan Makasar, J. Timur, dan C. Author, “Klasifikasi Kualitas Buah Apel Dengan Algoritma K-Nearest Neighbor (K-NN) Menggunakan Bahasa Pemrograman Python,” 2024. [Daring]. Tersedia pada: https://www.kaggle.com/

[8] B. Gupta, G. Madan, dan A. Quadir Md, “A smart agriculture framework for IoT based plant decay detection using smart croft algorithm,” *Mater Today Proc*, vol. 62, hlm. 4758–4763, Jan 2022, doi: 10.1016/J.MATPR.2022.03.314.

[9] W. W. Anggoro dan I. R. Widiasari, “Perancangan dan Penerapan Kendali Lampu Ruangan Berbasis IoT (Internet of Things) Android,” *Jurnal Teknik Informatika dan Sistem Informasi*, vol. 8, no. 3, 2021, [Daring]. Tersedia pada: http://jurnal.mdp.ac.id

[10] F. Aliefuddin Hamzah, R. Wahyusari, P. Studi Informatika, dan S. Tinggi Teknologi Ronggolawe ab, “J I I F K O M (J u r n a l I l m i a h I n f o r m a t JIIFKOM (Jurnal Ilmiah Informatika & Komputer) STTR Cepu Perbandingan Perbaikan Citra Magnetic Resonance Imaging (MRI) Menggunakan Ruang Warna RGB, HSV dan YCbCr Dengan Metode Histogram Equalization dan Contrast Streching.”

[11] V. C. Wijaya dan F. Utaminingrum, “Deteksi Tingkat Kemanisan Buah Melon melalui Ekstraksi Fitur Local Binary Pattern dengan Klasifikasi K-NN berbasis Raspberry Pi 4,” 2022. [Daring]. Tersedia pada: http://j-ptiik.ub.ac.id

[12] A. Setiawan, “Perbandingan Penggunaan Jarak Manhattan, Jarak Euclid, dan Jarak Minkowski dalam Klasifikasi Menggunakan Metode KNN pada Data Iris,” *Jurnal Sains dan Edukasi Sains*, vol. 5, no. 1, hlm. 28–37, Mei 2022, doi: 10.24246/juses.v5i1p28-37.

[13] Hanka K dan Santosa B, “Analisis Kualitas Bahan Baku Tebu Melalui Teknik Pengklasteran dan Klasifikasi Kadar Gula Sebelum Giling (Studi Kasus Pabrik Gula PT. XYZ),” *JURNAL TEKNIK ITS*, 2021.

[14] R. Maulidiah, M. Muchtar, N. Aisyah Fitri, I. Asriani, M. Putri Yasmine, dan P. Studi, “Pengelompokan Data Pertumbuhan dan Kontribusi Ekonomi Indonesia Menurut Provinsi Menggunakan Metode K-Means Clustering,” *Jurnal Teknologi Sistem Informasi dan Sistem Komputer TGD*, hlm. 436–444, 2023, [Daring]. Tersedia pada: https://ojs.trigunadharma.ac.id/index.php/jsk/index

[15] H. Mubarok, S. Murni, dan M. M. Santoni, *Penerapan Algoritma K-Nearest Neighbor untuk Klasifikasi Tingkat Kematangan Buah Tomat Berdasarkan Fitur Warna*. 2021.

[16] Anissa Ollivia Cahya Pratiwi, “Klasifikasi Jenis Anggur Berdasarkan Bentuk Daun Menggunakan Convolutional Neural Network Dan K-Nearest Neighbor,” *Jurnal Ilmiah Teknik Informatika dan Komunikasi*, vol. 3, no. 2, hlm. 201–224, Jul 2023, doi: 10.55606/juitik.v3i2.535.

[17] I. P. Putri, “Analisis Performa Metode K-Nearest Neighbor (KNN) dan Crossvalidation pada Data Penyakit Cardiovascular,” *Indonesian Journal of Data and Science (IJODAS)*, vol. 2, no. 1, hlm. 21–28, 2021.