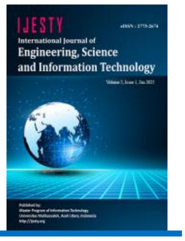
International Journal of Engineering, Science and Information Technology
Volume 5 No. 1 (2025) pp. 272-277
ISSN 2775-2674 (online)
Website: http://ijesty.org/index.php/ijesty
DOI: https://doi.org/10.52088/ijesty.v5i1.710
Research Paper, Short Communication, Review, Technical Paper



Identification of Papaya Ripeness Using the Support Vector Machine Algorithm

Rizki Minta Maito*, Mukti Qamal, Fajriana

Department of Informatics, Faculty of Engineering, Universitas Malikussaleh, Aceh, Indonesia

**Corresponding author Email: rizki.200170203@mhs.unimal.ac.id*

The manuscript was received on 1 March 2024, revised on 15 April 2024, and accepted on 1 January 2025, date of publication 9 January 2025

Abstract

Papaya is a tropical fruit that is commonly consumed and found in Indonesia. The ripeness level of papaya is typically assessed based on its colour. However, farmers and consumers often make mistakes identifying the fruit's ripeness. This research aims to design an application capable of determining the ripeness level of papaya based on colour images using Red, Green, Blue (RGB) and Hue, Saturation, Value (HSV) features and applying the Support Vector Machine (SVM) algorithm for ripeness classification. The dataset consists of images of California papayas, with 150 samples. The outcome of this study is a digital image application that can classify papaya ripeness into three categories: raw, half-ripe, and fully ripe. The evaluation used 80% of the data for training and 20% for testing. The results show an accuracy of 80%. With this relatively high level of accuracy, it can be concluded that the SVM algorithm is reliable for classifying papaya ripeness levels of Papayas.

Keywords: *Algorithm, RGB, HSV, Support Vector Machine, Papaya.*

1. Introduction

The papaya fruit, scientifically named Carica papaya L., is a tropical fruit native to Central America and commonly found in the Pacific region and tropical areas [1]. Papaya fruit contains nutrients that are highly beneficial for the body [2]. Papaya harvesting is done when the fruit reaches 8–9 months of age [3]. The papaya plant is a fruit plant rich in nutrients, including high levels of vitamin A (3.65 mg) and vitamin C (78 mg) per 100 grams. Papayas can be processed into various foods such as juice, candied papaya, or pudding [4].
The consistent demand for papaya has become an opportunity for farmers to expand papaya cultivation and optimize the quality of the products produced, ensuring the market value of papaya varieties is fully maximized [5].
The high level of papaya production reflects the significant consumer interest in this fruit. With the increasing production of papayas, a system is needed to classify the ripeness of the fruit more efficiently for farmers. Farmers, traders, and consumers still rely on traditional methods, primarily using human visual observation, which is limited in accurately identifying colours due to various factors [6]. The identification process through visual observation results in suboptimal outcomes due to the limitations of human vision [7].
Research on the classification of papaya ripeness has already been conducted [8]. In the study, the classification of papaya types and ripeness levels was performed using image processing. The image features used in the study are based on colour features, specifically Hue, Saturation, and Intensity (HSI) and the YCbCr colour model. The classification was performed using the Support Vector Machine (SVM) method, achieving a matching accuracy of 65%.
This research was conducted to test the accuracy performance of implementing the Support Vector Machine (SVM) algorithm to determine the ripeness level of papaya. The study also utilizes colour features such as red, green, blue (RGB), hue, saturation, and Value (HSV). This study aims to distinguish methods for identifying the ripeness stages of papaya. This research uses three ripeness categories: ripe, semi-ripe, and unripe. As a result, the output from this study is more varied compared to previous research.

2. Literature Review

2.1. Classification

Classification is evaluating data objects and grouping them into specific categories from available categories. This process involves training the available data to be categorized for new data. Classification is an activity that teaches a target function, which organizes each attribute for every provided class category [9]. The confusion matrix tests and estimates which objects are correctly and incorrectly classified.

Some conventional clustering methods that are commonly used include discriminant analysis and logistic regression. With the significant growth of large-scale data, known as big data, there is a need for methods to process such big data efficiently and accurately. Classification applied through technology with the help of computer systems involves several algorithms, such as Naïve Bayes, Support Vector Machine (SVM), Decision Tree, Fuzzy, and Artificial Neural Networks (ANN) [10].

2.2. Machine Learning

Machine learning is a discipline that concentrates on developing and designing systems and analyzing algorithms that enable computers to learn. It also refers to the skill of learning without being explicitly programmed, allowing systems to improve automatically through experience [11]. Machine Learning is a subset of Artificial Intelligence (AI) that optimizes system performance by analyzing sample and historical data [12].

2.3. Support Vector Machine

Vector Machine (SVM) was initially introduced by Vapnik in 1992 as a structured approach to pattern recognition in statistical learning theory [13]. Support Vector Machine (SVM) is a machine learning technique for data analysis and pattern recognition, specifically applied to classification tasks [14]. SVM has two main objectives: to optimize the accuracy of correctly labelled data and to ensure that the classification can be generalized to new, unseen data [15]. In this research, the Support Vector Machine (SVM) used is based on the Radial Basis Function (RBF) kernel) with a Multiclass SVM approach, as it involves four labels: raw, semi-ripe, and ripe. The modelling approach is One-Versus-One (OVO), where each label is compared against one another individually.

Gaussian RBF (Radial Basis Function):

$$\mathbf{K}(\mathbf{x_{i,}}\ \mathbf{x_j} = \mathbf{exp}(-\Upsilon \left|\left|\mathbf{x_i} - \mathbf{x_i}\right|\right|^{\mathbf{2}}) \quad \text{.......}(1)$$

Prediction Function:

$$f(x) = \sum \alpha_n^i \alpha_i y_j K\left(X_i X_j\right) + b \quad \text{.......}(2)$$

$x_{i,}$ = Test data vector of the i-th

x_j = Training data vector of the i-th

$\left|\left|x_i - x_j\right|\right|$ = Euclidean Distance

2.4. RGB (Red, Green, Blue)

RGB stands for Red, Green, and Blue and is known as an additive colour model, where colours are created by adding different light intensities in these three primary colours [16]. RGB is a colour feature combining red, green, and blue to generate new colours [17]. Red, Green, and Blue RGB is a colour model that produces a broad spectrum of colours by blending red, green, and blue in different proportions [18].

2.5. HSV

HSV consists of three main components: Hue, Saturation, and Value. Hue indicates colour attributes such as redness, greenness, and others. Saturation describes the purity or intensity of the colour, while Value indicates the brightness level of the colour, with values ranging from 0 to 100%. A value of 0 represents black, and as the Value increases, the colour becomes brighter with more variations. The Hue component in the HSV image represents colour based on the wavelength of visible light, such as red, orange, yellow, green, blue, and purple [19].

2.6. Image Processing

Digital image processing can be defined as manipulating images to enhance their quality, making them easier for humans or computers to understand. The image may be in the form of a photo or video. By leveraging this digital information, object classification can be applied to the image [20]. Image processing is a branch of Artificial Intelligence that utilizes digital image formats to solve various problems. The methods used in image processing may involve mathematical computations at the pixel level or geometric aspects. Each image object has distinct characteristics that can be measured mathematically, such as colour differences, texture, or shape, which allow for distinguishing one object from another [21].

2.7. Confusion Matriks

A confusion matrix is a tool used to assess the performance of a classification model by comparing the predicted classifications with the actual labels. This technique provides information about the number of correct and incorrect predictions and the types of errors that occur by comparing the model's predicted results with the actual data [22].

The formula for accuracy is:

$$\textbf{Accuray} = \frac{\textbf{Number of Correct Predictions}}{\textbf{Total Number of Prediction}} \textbf{ x } \mathbf{100\%} \qquad \text{(3)}$$

The formula for precision is:

$$\textbf{Precision} = \frac{\textbf{True Positive (TP)}}{\textbf{True Positive(TP)+False Positive(FP)}} \qquad \text{(4)}$$

The formula for the recall is:

$$\textbf{Recall} = \frac{\textbf{True Positive (TP)}}{\textbf{True Positive(TP)+False Negative(FP)}} \qquad \text{(5)}$$

The formula for the recall is:

$$\mathbf{F-1\ Score} = \mathbf{2}.\frac{\textbf{Presisi.Recall}}{\textbf{Presisi+Recall}} \qquad \text{(6)}$$

3. Research Methods

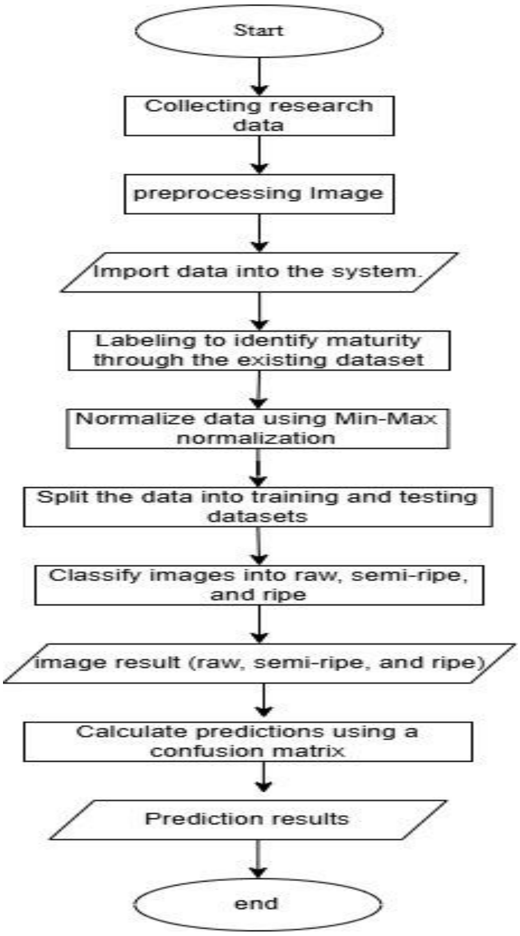


Fig 1. Research Workflow

The research steps based on Figure 1 are as follows:

1. Collecting Research Data
   This stage outlines how the researcher collects data and the purpose of data collection. This research gathered data by directly capturing papaya fruit images from a papaya plantation in Sibuhuan.
2. Preprocessing Image
   After data collection, the image preprocessing stage is carried out, where images are cropped to ensure neatness, background removal is performed, and resizing is done to align the images. RGB colour features are extracted into HSV.
3. Import Data to System
   After the image preprocessing stage, data is imported into the system to train the model, which the machine will study using the Support Vector Machine. The trained data will generate patterns that determine the system's success, which will be evaluated using test data.
4. Labeling Dataset
   The next stage is data labelling, which aims to assign appropriate categories to the data for machine learning and to facilitate data processing. Labelling makes it easier for the system to understand and recognize the problem to be solved. Labelling in this research serves to classify the ripeness of papaya fruits. The labels used in this study are categorized into three groups: raw, semi-ripe, and ripe.

5. Dataset Normalization
   Data normalization is a stage to align data for more excellent uniformity. In this research, data normalization was performed using Min-Max normalization. This method requires the data's minimum and maximum values to be normalized so that the resulting values fall from 0 to 1. This step ensures that the data does not have a wide range, making it easier to process.
6. Data Splitting
   Data splitting divides the dataset into two parts: training data and testing data. The data is split using 80% training and 20% testing data. This step allows the system to learn patterns from the training data and apply them to the testing data.
7. Image classification
   Image classification is performed with three labels: raw, semi-ripe, and ripe. Classification is done using the Support Vector Machine (SVM) method. Initially, the training data is classified, and the learned patterns from the training data are applied to the test data, resulting in raw, semi-ripe, and ripe classifications.
8. Evaluate
   At this stage, the data that has been tested will undergo prediction calculations, along with precision, recall, and F1-Score, using a Confusion Matrix. This evaluation step is performed to assess the success of the system that has been developed.

Another method used for collecting data and information is a literature review, which examines various sources such as journals, books, and articles related to this research. Data is then collected using a smartphone camera, and the images are stored in JPG format.

4. Results and Discussion

4.1. System Analysis

The system analysis is conducted to identify the research needs and the challenges faced during the research process. The system developed is an identification system for determining the ripeness of papaya fruit using the Support Vector Machine (SVM) algorithm to train the data and using colour features in Red, Green, Blue (RGB), and Hue, Saturation, Value(HSV) for the identification of papaya fruit colour. The system is built using MATLAB programming. After obtaining the RGB and HSV values, classification is done using the Support Vector Machine (SVM) algorithm. After training the data, testing is carried out to show the classification results for the ripeness of the fruit, which are raw, semi-ripe,

4.2. Design System

The system design is created using Unified Modeling Language (UML). System design assists users in visualizing the system's functionality. The first step in system planning is creating a use case diagram, developing an activity diagram, and then making a sequence diagram to identify the ripeness of papaya fruit using the Support Vector Machine (SVM) method.

4.3. Preprocessing Image

This stage involves cleaning, transforming, and organizing the data to make it suitable for modelling.

1. Image Cropping: Image cropping removes unnecessary parts of the papaya fruit image.
2. Resizing involves changing the image's dimensions, including its width and height. This is done to ensure that all photos have the same size,
3. Colour Conversion: Color conversion is performed by extracting colour features from red, green, blue (RGB), hue, saturation, and Value (HSV).
4. Normalization: Normalization adjusts the colour feature values to the range [0,1] to ensure uniformity in the data's scale.

4.4. Support Vector Machine Calculation

In this research, the SVM applied uses the RBF Kernel to build the model and make predictions on the ripeness level of papaya fruit. The study also utilizes Multiclass SVM with a One-Versus-One (OVO) approach, as there are three label categories to be predicted.
Below are the results of the tested data:

Table 1. Result of tested data

R	G	B	H	S	V	Label	Prediction
0,841455	0,89662	0,856214	0,092137	0,316833	0,863394	1	Raw
0,707384	0,777473	0,771412	0,400179	0,22667	0,754573	1	Raw
0,885716	0,962488	0,92618	0,143132	0,134538	0,926751	1	Raw
0,885716	0,962488	0,92618	0,143132	0,134538	0,926751	1	Raw
0,784314	0,887418	0,860095	0,302634	0,200565	0,854038	1	Raw
0,714803	0,854368	0,821594	0,409615	0,346454	0,822016	1	Semi -Ripe
0,918221	0,976331	0,916176	0,157507	0,204832	0,941362	1	Raw
0,912372	0,988576	0,969885	0,120134	0,071729	0,952055	1	Raw
0,797458	0,893302	0,826947	0,248226	0,323319	0,859749	1	Ripe
0,658827	0,804883	0,785923	0,534825	0,389449	0,774099	1	Semi -Ripe
0,908837	0,930524	0,858008	0,054571	0,401747	0,911131	2	Ripe
0,870414	0,932555	0,709839	0,149328	0,850661	0,898222	2	Semi -Ripe
0,857435	0,916442	0,793158	0,127163	0,553778	0,884013	2	Semi -Ripe
0,878202	0,924196	0,811598	0,105053	0,516422	0,892028	2	Ripe
0,811261	0,866461	0,788312	0,146435	0,49499	0,834946	2	Semi -Ripe

0,86376	0,890815	0,789224	0,091512	0,554709	0,866191	2	Semi -Ripe
0,861172	0,916999	0,673168	0,16002	0,950617	0,886832	2	Semi -Ripe
0,834121	0,886368	0,822792	0,102169	0,431347	0,854434	2	Semi -Ripe
0,794801	0,828634	0,668337	0,169915	0,857889	0,802625	2	Semi -Ripe
0,070938	0,101001	0,082377	0,138056	0,53084	0,094262	2	Raw
0,935453	0,951665	0,794818	0,08052	0,610604	0,93767	3	Ripe
0,934538	0,965157	0,836758	0,067007	0,488432	0,938668	3	Ripe
0,912142	0,9515	0,767855	0,089873	0,711736	0,920156	3	Ripe
0,932873	0,964858	0,732125	0,109972	0,816234	0,936468	3	Ripe
0,918557	0,955474	0,749331	0,108415	0,760332	0,928335	3	Ripe
0,929351	0,947194	0,880226	0,05421	0,313079	0,929773	3	Ripe
0,948315	0,983028	0,873145	0,051541	0,392675	0,953132	3	Ripe
0,922144	0,935994	0,809234	0,060919	0,573846	0,92133	3	Ripe
0,913251	0,937243	0,837607	0,049525	0,485389	0,912534	3	Ripe
0,903504	0,935593	0,733491	0,139722	0,757967	0,908161	3	Ripe

4.5. System Implementation

The system implementation phase involves testing the model with the data from which the developed model was trained. The system can be executed once it functions appropriately and aligns with the design specifications. The image below shows the system's results after all the stages.

1. Papaya Raw ripeness
   The papaya raw ripeness identification results using the Support Vector Machine method are presented in Fig. 2 below.

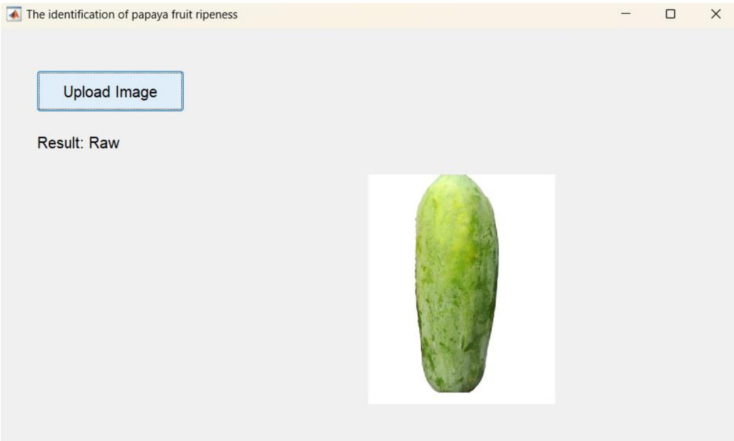


Fig. 2 The prediction results for raw papaya

2. The results for semi-ripe papaya
   The results of papaya semi-ripe identification using the Support Vector Machine method are presented in Fig. 3 below.

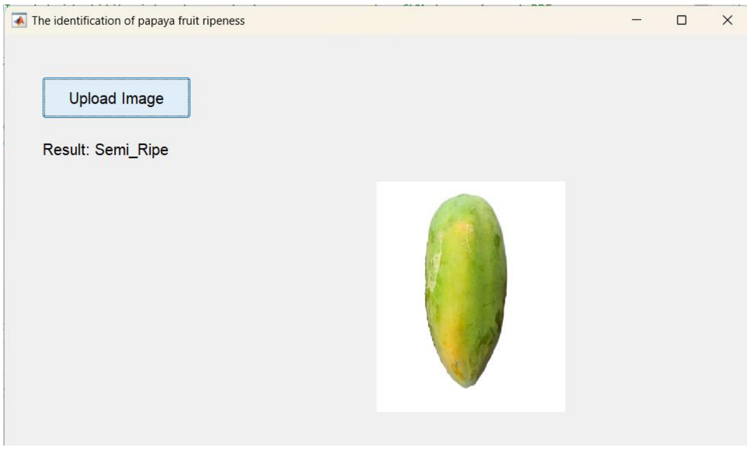


Fig. 3. The prediction results for ripe papaya.

3. The results for ripe papaya
   The results of papaya ripe identification using the Support Vector Machine method are presented in Fig. 4 below.

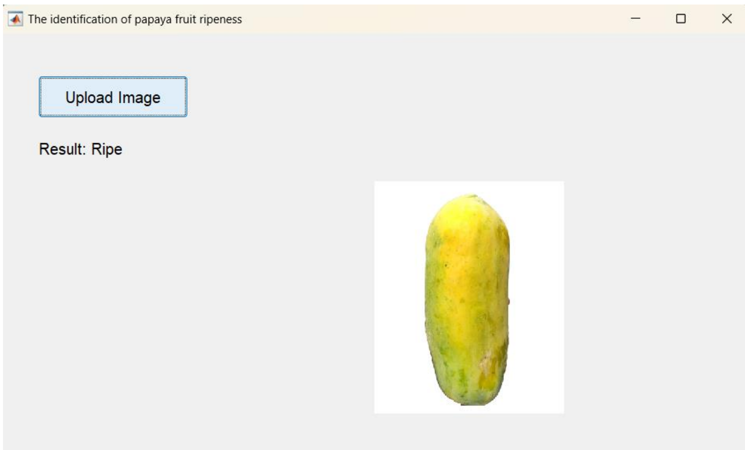


Fig. 4. The prediction results for ripe papaya

4.6. Prediction Results

Predictions were made using a Confusion Matrix by calculating the prediction results, precision, recall, and F1-Score. The dataset used consists of 30 test data points of papaya fruits. Seven were correct for the prediction of raw ripeness, and three were incorrect. The prediction of semi-ripe ripeness yielded seven correct and three incorrect results, while the prediction of ripe ripeness had 10 correct test data points.

Table 2. Test Data Results

Labels	Raw Ripeness	Semi-Ripeness	Ripe Ripeness
Raw Ripeness	7	2	1
Semi-Ripeness	1	7	2
Ripe Ripeness	0	0	10

The accuracy, precision, recall, and F1-Score obtained after calculating using the Confusion Matrix are as follows:

Table 3. Prediction Result

Labels	Precision	Recall	F1-Score
Raw Ripeness	87.5%	70%	77%
Semi-Ripeness	77.7%	70%	73.6%
Ripe Ripeness	76.9%	100%	83.3%

The table above represents the papaya ripeness identification prediction results using the Support Vector Machine (SVM) method, calculated using the Confusion Matrix formula. For raw papaya predictions, the precision is 87.5%, recall is 70%, and the F1-Score is 77%. For semi-ripe papaya predictions, the precision is 77.7%, recall is 70%, and the F1-Score is 73.6%. Meanwhile, for ripe papaya predictions, the precision is 76.9%, recall is 100%, and the F1-Score is 83.3%. The overall accuracy achieved is 80%

Based on the prediction table, which has been calculated using the Confusion Matrix formula, the following diagram is produced:

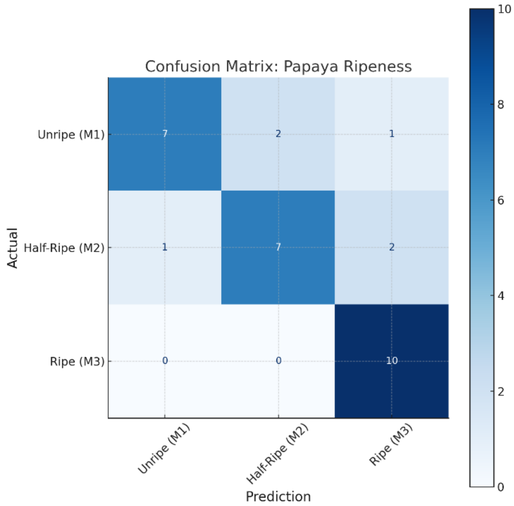


Fig 5. Confussion matrix Diagram

5. Conclusion

1. The Support Vector Machine (SVM) algorithm demonstrates strong performance in predicting papaya ripeness.
2. The training data in the system employs the Support Vector Machine (SVM) algorithm along with colour features Red, Green, Blue (RGB) and Hue, Saturation, and Value (HSV). The prediction accuracy for the tested data is 80%.
3. The prediction accuracy for the data that has been tested is 80%.
4. The prediction results for precision, recall, and F1-Score using the Confusion Matrix are as follows: Precision for raw papaya predictions, the precision is 87.5%, recall is 70%, and the F1-Score is 77%. For semi-ripe papaya predictions, the precision is 77.7%, recall is 70%, and the F1-Score is 73.6%. Meanwhile, for ripe papaya predictions, the precision is 76.9%, recall is 100%, and the F1-Score is 83.3%.

References

[1] M. E. Al Rivan and G. R. Sung, “Identifikasi Mutu Buah Pepaya California (Carica Papaya L.) Menggunakan Metode Jaringan Syaraf Tiruan,” *Jurnal Sisfokom (Sistem Informasi dan Komputer)*, vol. 10, no. 1, pp. 113–119, Apr. 2021, doi: 10.32736/sisfokom.v10i1.1105.

[2] E. Ellif, S. H. Sitorus, and R. Hidayati, “Klasifikasi Kematangan Pepaya Menggunakan Ruang Warna Hsv Dan Metode Naive Bayes Classifier,” *Coding Jurnal Komputer dan Aplikasi*, vol. 9, no. 01, p. 66, Apr. 2021, doi: 10.26418/coding.v9i01.45906.

[3] M. L. Firdhaus, F. Romadlon, and F. M. Wibowo, “Akurasi Estimasi Brix pada Tingkat Kematangan Pepaya Menggunakan Nilai RGB Berbasis Aplikasi Mobile,” *Industria: Jurnal Teknologi dan Manajemen Agroindustri*, vol. 8, no. 2, pp. 79–86, Aug. 2019, doi: 10.21776/ub.industria.2019.008.02.1.

[4] L. Ardhia Wardani, I. G. P. S. Wijaya, and F. Bimantoro, “Klasifikasi Jenis Dan Tingkat Kematangan Buah Pepaya Berdasarkan Fitur Warna, Tekstur Dan Bentuk Menggunakan Support Vector Machine,” *Jurnal Teknologi Informasi, Komputer dan Aplikasinya (JTIKA)*, vol. 4, no. 1, Mar. 2022.

[5] D. P. N. Kinding, “Analisis Kelayakan Finansial Pada Usahatani Pepaya Calina / California Indonesia (Carica papaya. L),” *Perwira Journal of Science & Engineering*, vol. 1, no. 1, pp. 24–33, Feb. 2021, doi: 10.54199/pjse.v1i1.18.

[6] M. E. Al Rivan and G. R. Sung, “Identifikasi Mutu Buah Pepaya California (Carica Papaya L.) Menggunakan Metode Jaringan Syaraf Tiruan,” *Jurnal Sisfokom (Sistem Informasi dan Komputer)*, vol. 10, no. 1, pp. 113–119, Apr. 2021, doi: 10.32736/sisfokom.v10i1.1105.

[7] R. Kurniawan, “Klasifikasi Tingkat Kematangan Buah Pepaya Berdasarkan Warna Kulit Menggunakan Sensor Warna Tcs3200,” *Journal ICTEE*, vol. 4, no. 1, p. 1, Mar. 2023, doi: 10.33365/jictee.v4i1.2692.

[8] W. L. Ardhia, “Klasifikasi Jenis Dan Tingkat Kematangan Buah Pepaya Berdasarkan Fitur Warna, Tekstur Dan Bentuk Menggunakan Support Vector Machine,” *JTIKA (Jurnal Teknologi Informasi, Komputer, dan Aplikasinya)*, vol. 4, no. 1, Mar. 2022.

[9] A. Nata and S. Suparmadi, “Analisis Sistem Pendukung Keputusan Dengan Model Klasifikasi Berbasis Machine Learning Dalam Penentuan Penerima Program Indonesia Pintar,” *JOURNAL OF SCIENCE AND SOCIAL RESEARCH*, vol. 5, no. 3, p. 697, Oct. 2022, doi: 10.54314/jssr.v5i3.1041.

[10] P. R. Sihombing and A. M. Arsani, "Comparison Of Machine Learning Methods In Classifying Poverty In Indonesia In 2018," *Jurnal Teknik Informatika (Jutif)*, vol. 2, no. 1, pp. 51–56, Jan. 2021, doi: 10.20884/1.jutif.2021.2.1.52.

[11] I. Daqiqil Id, *MACHINE LEARNING : Teori , Studi Kasus dan Implementasi Menggunakan Python* , 1st ed. Pekan Baru: UR PRESS , 2021.

[12] M. Qamal, D. Hamdhana, and M. Martin, "Sistem Pakar Untuk Mendiagnosa Penyakit Angina Pektoris (Angin Duduk) Dengan Metode Forward Chaining Berbasis Web," *TECHSI - Jurnal Teknik Informatika*, vol. 12, no. 1, p. 86, Apr. 2020, doi: 10.29103/techsi.v12i1.2150.

[13] N. L. P. C. Savitri, R. A. Rahman, R. Venyutzky, and N. A. Rakhmawati, “Analisis Klasifikasi Sentimen Terhadap Sekolah Daring pada Twitter Menggunakan Supervised Machine Learning,” *Jurnal Teknik Informatika dan Sistem Informasi*, vol. 7, no. 1, Apr. 2021, doi: 10.28932/jutisi.v7i1.3216.

[14] Y. Afrillia, L. Rosnita, and D. Siska, “Analisis Sentimen Ciutan Twitter Terkait Penerapan Permendikbudristek Nomor 30 Tahun 2021 Menggunakan TextBlob dan Support Vector Machine,” *G-Tech: Jurnal Teknologi Terapan*, vol. 6, no. 2, pp. 387–394, Oct. 2022, doi: 10.33379/gtech.v6i2.1778.

[15] D. A. Pisner and D. M. Schnyer, "Support vector machine," in *Machine Learning*, Elsevier, 2020, pp. 101–121. doi: 10.1016/B978-0-12-815739-8.00006-7.

[16] N. Astrianda, "Klasifikasi Kematangan Buah Tomat Dengan Variasi Model Warna Menggunakan Support Vector Machine," *VOCATECH: Vocational Education and Technology Journal*, vol. 1, no. 2, pp. 45–52, Apr. 2020, doi: 10.38038/vocatech.v1i2.27.

[17] M. Afriansyah, J. Saputra, Y. Sa'adati, and Valian Yoga Pudya Ardhana, "Optimasi Algoritma Nai?ve Bayes Untuk Klasifikasi Buah Apel Berdasarkan Fitur Warna RGB," *Bulletin of Computer Science Research*, vol. 3, no. 3, pp. 242–249, Apr. 2023, doi: 10.47065/bulletincsr.v3i3.251.

[18] M. Afriansyah, J. Saputra, Y. Sa'adati, and Valian Yoga Pudya Ardhana, "Optimasi Algoritma Nai?ve Bayes Untuk Klasifikasi Buah Apel Berdasarkan Fitur Warna RGB," *Bulletin of Computer Science Research*, vol. 3, no. 3, pp. 242–249, Apr. 2023, doi: 10.47065/bulletincsr.v3i3.251.

[19] A. N. Dzulhijjah, S. Anraeni, and S. Sugiarti, "Klasifikasi Kematangan Citra Labu Siam Menggunakan Metode KNN (K-Nearest Neighbor) Dengan Ekstraksi Fitur HSV (Hue, Saturation, Value)," *Buletin Sistem Informasi dan Teknologi Islam*, vol. 2, no. 2, pp. 103–110, May 2021, doi: 10.33096/busiti.v2i2.808.

[20] S. Santi, C. Susanto, M. Muhardi, M. Patasik, and N. Nurlina, "Penerapan Algoritma K-Nearest Neighbor (KNN) Dalam Pengklasifikasian Tingkat Kematangan Buah Nangka Berdasarkan Citra Warna Kulit," *Digital Transformation Technology*, vol. 4, no. 1, pp. 685–692, Aug. 2024, doi: 10.47709/digitech.v4i1.4550.

[21] Ristiana Betris Tosi, Helena dorothea Mbura, and Yampi R Kaesmetan, "Implementasi CNN Dalam Mengidentifikasi Kematangan Cabai Berdasarkan Warna," *Indonesian Journal of Education And Computer Science*, vol. 2, no. 1, pp. 34–42, Apr. 2024, doi: 10.60076/indotech.v2i1.385.

[22] A. Anggara, N. Nurdin, and R. Meiyanti, "Sentiment Analysis of the MK Decision Trial of the Result of the 2024 President and Vice President General Election on Social Media X Using the Support Vector Machine Method," *International Journal of Engineering, Science and Information Technology*, vol. 4, no. 4, pp. 125–134, Oct. 2024, doi: 10.52088/ijesty.v4i4.591.