The application of machine learning algorithms for assessing the maturity level of palm fruits as the prominent commodity in the Western-Southern Area of Aceh

Rizki Agam Syahputra[1], Fajar Okta Widarta[2*]
[1,2] Industrial Engineering Department, Universitas Teuku Umar, West Aceh, Aceh, Indonesia
*Corresponding author: fajaroktawidarta@utu.ac.id

ARTICLE INFO

Article history
Submission: 6th September 2023
Revised: 10th May 2024
Accepted: 18th May 2024

Keywords
Palm fruit
Maturity detection
Self Organizing Map (SOM)

https://doi.org/10.22219/oe.2024.v16.i1.102

ABSTRACT

The potential of palm oil plantations in Aceh is substantial, with the province ranking eighth in Indonesia for palm oil cultivation. Aceh boasts a vast oil palm plantation area of 470.8 thousand hectares, comprising 44% of Aceh's total plantation land. Palm fruit quality directly impacts palm oil production, emphasizing the need for consistent maturity levels. To address this, computer algorithms, especially machine learning, have been applied. This study introduces the Self-Organizing Map (SOM) Algorithm for palm fruit maturity determination. SOM's reliability in capturing dataset topology offers a diverse classification process, revolutionizing palm fruit maturity detection and optimizing palm oil production. This study uses 40 dataset consisted of 20 mature and 20 unmature palm fruit image as the basis data which then converted into RGB and HSV value with Matlab engine. The result of the study indicates that the SOM algorithm is capable of classifying the maturity detection with 100% precision result. The SOM algorithm is synthesized in a Graphical User Interface that is capable of reading and classifying the input data into the output cluster.

1. Introduction

The potential of palm oil plantations in Aceh is significant. Aceh holds the eighth position among Indonesian provinces with the largest oil palm plantation areas. The province boasts a substantial total oil palm plantation area of around 470.8 thousand hectares, accounting for approximately 44% of the entire plantation area within Aceh. This presence underscores the province's substantial contribution to the palm oil industry. Especially prominent in the southwestern region of Aceh, oil palm plantations prevail as a major agricultural enterprise. These plantations are categorized into both smallholder ventures and larger-scale operations. In West Aceh, for instance, the oil palm plantation area spans about 10,967.51 hectares, yielding a substantial production output of 13,852.80 tons in the year 2021 (BPS Aceh, 2022).

Essentially, the quality and quantity of palm oil generated from these plantations largely depend on the maturity level of the palm fruits. Maintaining a consistent and optimal maturity level of harvested palm fruits enhances the quality and volume of the resulting palm oil. Conversely, inadequate fruit quality can lead to higher levels of Free Fatty Acid (FFA) content when processing the fruits into Crude Palm Oil (CPO). Fruits harvested when overripe may have the potential to yield higher Fresh Fruit Bunch (FFB) quantities (Sintia, Sitio, Hasibuan, & Parinduri, 2022). Conversely, harvesting FFB under immature or sub-optimal ripe conditions typically results in lower oil yields, typically below 20%. In contrast, optimal ripe conditions can lead to significantly higher oil yields, ranging from 24% to 26% (Akbar, Wibowo, & Santoso, 2023).Such considerations underline the importance of monitoring and ensuring fruit quality for maintaining product standards (Pryo & Sudrajat, 2017).

To harness this potential and address challenges related to palm oil production, The utilization of computer algorithm is seen as the best method to obtain optimum solution (Syahputra el al. 2022),

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especially in the usage of innovative methods including computer vision and machine learning. In the field of agriculture, the technologies have been used to classify fruit maturity levels, optimize production processes, and enhance product quality. Several prior studies have been conducted to apply technology, particularly machine learning, as a maturity detection system. These include classifying the maturity level of coffee beans, limes, and bananas using RGB and HSV colour features through the K-Nearest Neighbor method (Paramita et al., 2019; Raysyah et al. 2021; Samantha, 2022), identifying the maturity level of oil palm fruit using Laser Speckle Imaging (Fitrya, Wirman, & Fitri, 2018), determining oil palm fruit maturity based on RGB and HSV colors using K-Means Clustering (Himmah et al., 2020), and classifying tomato ripeness based on color and shape using the Support Vector Machine method (Abdullah & Pahrianto, 2017).

Additionally, the combination pre-trained classification model combined with Support Vector Machine (SVM) in a research developed by Michael (2022) demonstrates an accuracy of 96% in image-based coffee maturity classification. Similar technology can not only classify fruit maturity levels but also taste of the classified object (Arum et al., 2021; Barkah et al., 2020). And in addition a study reported successful construction of an electronic nose (e-nose) based on fruit maturity identification system using a series of SnO_2 semiconductor gas sensors and artificial neural networks (Soedarmaji & Ediati, 2011).

However, unlike previous studies, this research proposes the utilization of the Self-Organizing Map (SOM) Algorithm to determine the maturity level of the studied oil palm fruit. SOM, is an unsupervised neural network method wherein a self-organizing process begins by randomly selecting node weights on the Kohonen input layer (Asri & Wulanningrum, 2021). Compared to other methods, the SOM algorithm is considered to have a higher level of reliability in capturing the dataset's topology for a more diverse classification process (Chaudhary et al., 2014; Jamil et al., 2022). SOMs are trained on large datasets containing various parameters related to palm fruit texture and color. These parameters are measured using sensors and cameras vision in the field. The SOM algorithm processes this data, mapping it onto a grid-like structure. Each grid node represents a specific fruit maturity level (Binder & Löffler-Wirth, 2014). As new data is collected, the SOM continues to learn and refine its map. When a palm fruit is assessed, the SOM assigns it to the closest matching node, determining its maturity level with high accuracy. This automation greatly accelerates the assessment process, allowing for more efficient harvesting decisions. In summary, SOMs have revolutionized palm fruit maturity detection, enhancing the efficiency and quality of palm oil production. This technology exemplifies the transformative potential of machine learning in agriculture, offering sustainable solutions for the palm oil industry and contributing to its continued growth.

Therefore, in this paper, SOM is employed as a pivotal tool for assessing palm fruit maturity levels. For the pretraining and testing model, this paper collects 40 data set of palm fruit with the specification on the *Tenera* variety by using camera imagery vision. The originality of the paper stem from tailoring the machine learning models specifically to the characteristics of palm fruits grown in the Western-Southern area of Aceh, which is the Tenera Variety. This might involve considering unique environmental factors, soil compositions, or specific cultivar variations that influence fruit maturity. In addition, this research focus on interpreting the SOM representations to extract meaningful insights into the factors driving palm fruit maturity in the Aceh region. This emphasis on interpretability enhances the practical utility of the research findings for stakeholders and decision-makers. Moreover, The SOM algorithm processes this data, creating a structured map where each node corresponds to a specific maturity level. When new fruit samples are assessed, the SOM accurately categorizes them by assigning them to the nearest node on the map.

The output of this research is a systematic assessment tool that is capable of detecting the level of oil palm fruit maturity based on the input provided to the designed algorithm, the algorithm is then translated in a form of a Graphical User Interface (GUI) for an efficient and easier use. This data-driven automation is expected to accelerate the assessment process, enabling precise and efficient maturity determination, a critical factor for optimizing palm oil production and ensuring high-quality yield.

2. Methods

The obtain an effective result of the paper, thus the paper employs a framework thinking depicted as follow:

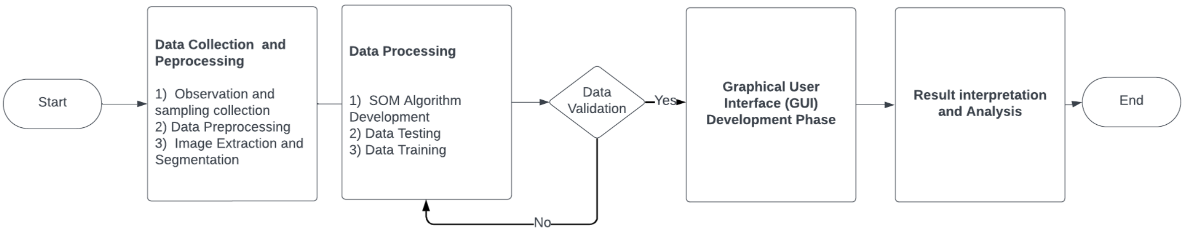
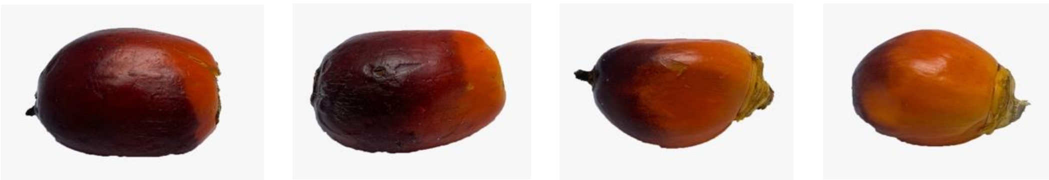


Fig. 1 Research framework.

Data collection and pre-processing

This research requires dataset consisting of 40 oil palm fruits, with a classification of 20 mature and 20 unmature palm fruit sample. A dataset size of 40 samples provides a sufficient amount of data to draw meaningful conclusions without being overly complex. It allows for statistical analysis and hypothesis testing to assess the effectiveness of the machine learning algorithm in accurately classifying palm fruit maturity levels. By having an equal number of mature and immature palm fruit samples (20 each), the dataset ensures a balanced representation of both classes. This balance is essential for training the machine learning algorithm to recognize and distinguish between different maturity levels effectively (Muraina, 2022). While a larger dataset would provide more data points for model training, 40 samples are sufficient to capture the essential variability in palm fruit maturity levels within the specific context of the research area (Western-Southern area of Aceh). As long as the dataset is representative of the population, it can yield meaningful insights and reliable model performance (Kiang, Fisher, Hu, & Chi, 2005).

The fruit sample is obtained based on the Tenera variety of oil palm which are gathered from a local plantation and palm oil factory in the western part of Aceh. The collected data will then undergo a pre-processing stage. Pre-processing involves capturing images using a CMOS sensor camera in RAW file format. To obtain high-quality visual results, image capture takes place in a controlled mini photo studio environment.



(a) Mature (b) unmature

Figure 2. Dataset sample (a) for mature and (b) for unmature palm fruit

After the pre-processing stage, the image results are converted into RGB (Red, Green, and Blue) and HSV (Hue, Saturation, and Value) components in the Segmentation and Feature Extraction stage. This stage aims to separate objects from the background, making it easier to analyze objects in order to recognize objects that heavily rely on visual perception. Image segmentation is performed using thresholding methods to set the background values to zero or black, and then displaying the segmented image as binary, RGB, and HSV images. In this case the image can be calculated with the equation:

$$T = (Fmax + Fmin) \quad (1)$$

where F_{max} is the maximum intensity value in the image and Fmin is the minimum intensity in the image. If f(x, y) is the pixel intensity value at position (x, y) then the pixel is changed to white or black depending on the following conditions.

$$f(x,y)\begin{cases}1, if f(x,y)\geq T\\0, if f(x,y)<T\end{cases} \quad (2)$$

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ISSN-p: 2085-1431
ISSN-e: 2654-5799

Data Processing

This research utilizes the SOM algorithm for the process of classifying the maturity level of oil palm fruit. SOM is one of the supervised learning algorithm methods used in classifying an object by comparing it with the majority of existing attributes and training samples. In this case, the SOM algorithm is developed as follow:

a. SOM Architectural Development
The results of image segmentation and extraction is presented as the input database in the classification process, and the output of the model will present a classification result of the input image in the model. The SOM architecture in this research was built by using Matlab R2021 software. The system architecture design in this research can be seen in the diagram in Figure 3 below:

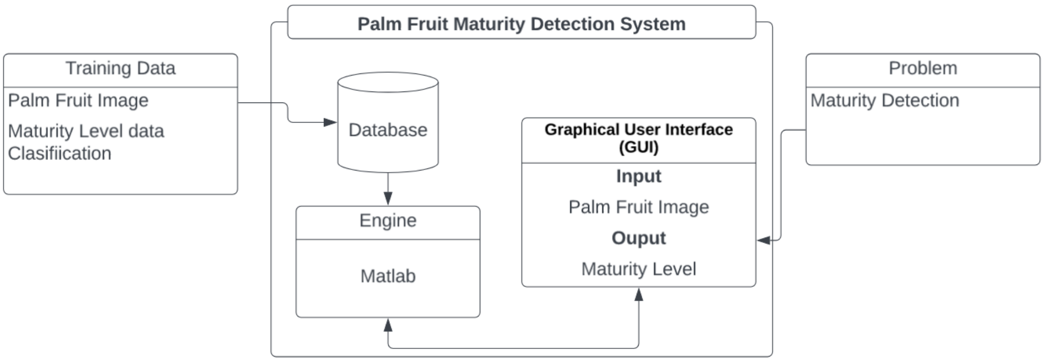

Fig. 3 Architectural system.

b. Data Testing and Training
In the data training process. A total of 40 datasets that have passed the pre-processing stage are needed in the data training and testing process. Both the training and testing processes will go through the preprocessing and feature extraction stages before entering the classification stage. Both processes at this stage will go through an accuracy validation process which compares the level of accuracy of the training and test results with the number of input datasets (Chaudhary et al., 2014).Various researchers employ different evaluation metrics based on the objective of the research. We describe the most widely and commonly used evaluation metrics in the field of object detection and classification which is precision. Precision is mathematically stated as (Ukwuoma et al., 2022):

$$Precision \ = \frac{TP}{TP + FP} \times 100\% \tag{3}$$

Where TP (true positive) indicating that the predicted out- come corresponds to the actual outcome, FP (false positive) indicating that the predicted outcome does not correspond to the actual outcome.

Graphical User Interface (GUI)

GUI design functions to produce an interface in the form of a control system that can show the output produced from the results of testing and training data input into the system. The GUI at this stage is also designed using the Matlab R2021 application.

3. Results and Discussion

SOMs are trained on large datasets containing various parameters related to palm fruit, including color spectrum of each dataset. The parameters is measured using camera and classified into Red (R), Green (G), Blue (B), Hue (H), Saturation (S), and Value (V) with two segmentation (mature and unmature). In this early stages, the classification of the mature, unmature indicator were sorted manually based on actual fruit ripeness and harvest time condition.

Therefore, after the data set has been classified and preparation, the SOM algorithm processes this data, mapping it onto a grid-like structure. Each grid node represents a specific fruit maturity level. The result of RGB and HSV extraction is presented in Table 1.

Table 1 Feature extraction

No	R	G	B	H	S	V	Classification
1	0.31766	0.12484	0.10409	0.50516	0.71284	0.31803	Mature
2	0.27341	0.12581	0.10850	0.53824	0.65396	0.27372	Mature
3	0.30343	0.12964	0.10495	0.47388	0.68788	0.30360	Mature
4	0.30150	0.12820	0.10524	0.40999	0.68022	0.30188	Mature
5	0.29174	0.12936	0.09771	0.44319	0.68715	0.29212	Mature
6	0.34621	0.14979	0.10935	0.26864	0.70192	0.34664	Mature
7	0.41358	0.15798	0.09238	0.21872	0.76600	0.41378	Mature
8	0.30194	0.12439	0.10709	0.44940	0.68847	0.30203	Mature
9	0.33569	0.14155	0.12252	0.41360	0.68176	0.33599	Mature
10	0.24685	0.10989	0.08793	0.47063	0.67225	0.24702	Mature
11	0.57239	0.32553	0.06787	0.09149	0.87118	0.57239	Unmature
12	0.55366	0.25815	0.05739	0.10643	0.87481	0.55370	Unmature
13	0.57004	0.31411	0.07850	0.08230	0.86617	0.57012	Unmature
14	0.43964	0.18689	0.07674	0.23542	0.79531	0.43986	Unmature
15	0.55493	0.29511	0.06044	0.07911	0.89024	0.55493	Unmature
16	0.56673	0.30587	0.06990	0.07897	0.86887	0.56675	Unmature
17	0.51079	0.23804	0.06495	0.09266	0.85915	0.51083	Unmature
18	0.57435	0.27576	0.07246	0.10513	0.85351	0.57447	Unmature
19	0.47201	0.20891	0.07988	0.20040	0.79748	0.47210	Unmature
20	0.53129	0.29060	0.05869	0.08052	0.89167	0.53129	Unmature
21	0.29451	0.11134	0.09232	0.47259	0.72671	0.29500	Mature
22	0.37668	0.13919	0.08507	0.33291	0.74877	0.37676	Mature
23	0.30083	0.12511	0.11368	0.52635	0.67870	0.30106	Mature
24	0.31862	0.12359	0.09771	0.49648	0.70253	0.31894	Mature
25	0.31392	0.12478	0.10350	0.41297	0.71919	0.31413	Mature
26	0.31687	0.13706	0.11445	0.54350	0.67445	0.31738	Mature
27	0.32178	0.13812	0.11135	0.46055	0.67739	0.32240	Mature
28	0.33696	0.12752	0.08693	0.42595	0.72683	0.33712	Mature
29	0.35726	0.14988	0.11037	0.37558	0.69319	0.35793	Mature
30	0.34124	0.13721	0.10178	0.45415	0.68652	0.34139	Mature
31	0.62812	0.32762	0.09413	0.07365	0.85514	0.62812	Unmature
32	0.54336	0.27954	0.05865	0.08349	0.88986	0.54337	Unmature
33	0.57927	0.33062	0.07953	0.08877	0.86226	0.57929	Unmature
34	0.60877	0.32862	0.04497	0.08549	0.92031	0.60877	Unmature
35	0.46904	0.19342	0.05667	0.18228	0.84743	0.46923	Unmature

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ISSN-p: 2085-1431
ISSN-e: 2654-5799

No	R	G	B	H	S	V	Classification
36	0.55245	0.28840	0.04124	0.07999	0.92174	0.55245	Unmature
37	0.63357	0.34112	0.05621	0.08304	0.91032	0.63358	Unmature
38	0.64227	0.36097	0.05799	0.08424	0.90666	0.64227	Unmature
39	0.55744	0.31058	0.04743	0.08987	0.91091	0.55750	Unmature
40	0.60403	0.29155	0.05519	0.09365	0.89678	0.60405	Unmature

Based on Table 1, each node produces different RGB and HSV color spectrum. Whereas in R, G and V feature, the palm fruit in the mature class category tends to produce a lower color value (0.24-0.41 for R, 0.10-0.51 for G, and 0.24-0.41 for V) compared to the unmature segment. Meanwhile, for the B, H, and S feature, the mature fruit produce higher color value (0.8-0.10 for B, 0.26-0.59, and 0.6-0.76). Therefore, this value presents a level of uniqueness between each node for the SOM algorithm to classify.

The data training and testing in SOM Algorithm in this paper is constructed by using Matlab engine with 40 data set consisted of 20 data for training and 20 data for testing. Based on the matlab calculation, the shortest distance between each node in data training in SOM is presented in Table 2.

Table 2 Group distance in data training process

No	Mature Class (1)	Unmature Class (2)	Group Class	No	Mature Class (1)	Unmature Class (2)	Group Class
1	0.0221	0.1621	1	11	0.2551	0.0363	2
2	0.0208	0.2300	1	12	0.2069	0.0398	2
3	0.0093	0.1849	1	13	0.2434	0.0249	2
4	0.0150	0.1913	1	14	0.0519	0.0000	2
5	0.0241	0.1945	1	15	0.2353	0.0121	2
6	0.0155	0.1447	1	16	0.2377	0.0174	2
7	0	0.0519	1	17	0.1593	0.0000	2
8	0.0092	0.1882	1	18	0.2189	0.0174	2
9	0.0155	0.1679	1	19	0.0858	0.0397	2
10	0.0208	0.2429	1	20	0.2201	0.0121	2

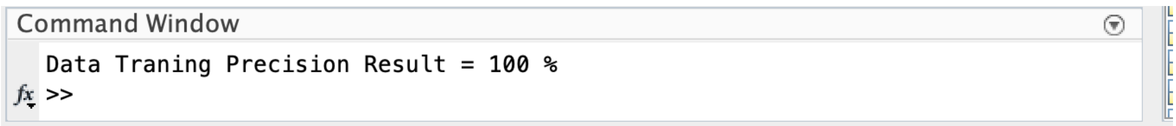

Fig. 4 Data training precision result.

Figure 4 shows the result of the data training error result, which indicates 100% precision and 0 error between each node. In the data testing process, the shortest distance between each node in data testing with SOM algorithm is presented in Table 3.

Table 3 Group distance in data training process

No	Mature Class (1)	Unmature Class (2)	Group Class	No	Mature Class (1)	Unmature Class (2)	Group Class
1	0.0417	0.1963	1	11	0.2877	0.0661	2
2	0.0462	0.1098	1	12	0.2194	0.0067	2
3	0.0181	0.2118	1	13	0.2583	0.0282	2
4	0.0204	0.1835	1	14	0.3059	0.0763	2

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No	Mature Class (1)	Unmature Class (2)	Group Class	No	Mature Class (1)	Unmature Class (2)	Group Class
5	0.0303	0.1799	1	15	0.1111	0.0572	2
6	0.0262	0.1983	1	16	0.2516	0.0413	2
7	0.0273	0.1924	1	17	0.3228	0.0867	2
8	0.0518	0.1552	1	18	0.3384	0.1007	2
9	0.0238	0.1542	1	19	0.2593	0.0420	2
10	0.0221	0.1722	1	20	0.2695	0.0509	2

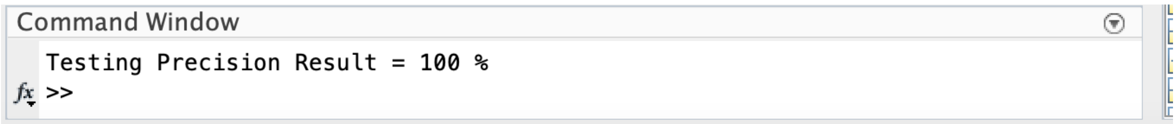
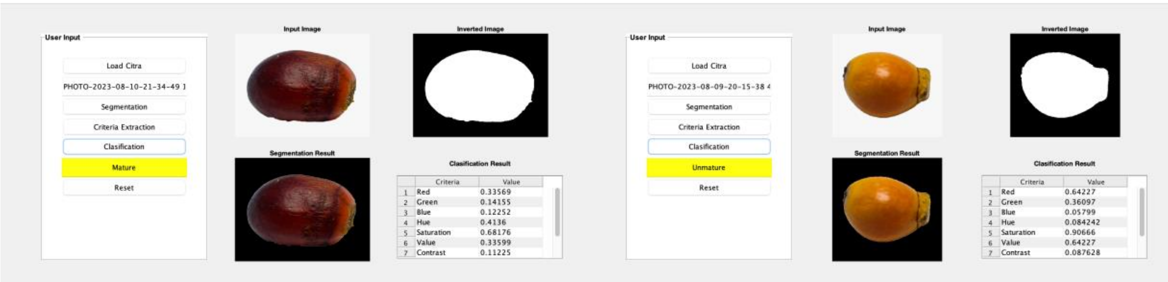


Fig. 5 Data training precision result.

Figure 5 explains the data testing result gained from the training process. Therefore, based on the data testing and testing result, both process present satisfactory outcome with 100% precision result. This result indicates that the algorithm is capable to classify and object data based on the dataset used in both processes. Furthermore, for easier classification and usage, the algorithm is presented in Graphical User Interface (GUI). The GUI simplifies the process of assessing fruit ripeness, making it accessible and efficient. The GUI typically comprises user-friendly components such as buttons, text fields, and images. Users can input data, such as images of fruit, or relevant parameters like colour or size. The GUI interfaces with algorithms, in this case Self-Organizing Maps (SOMs) to process the data. The algorithm analyses the input to determine fruit maturity levels based on predefined criteria from the dataset from the sample of mature and unmature image. The GUI design for classifying maturity level of palm oil fruit is presented in Figure 6.



(a) Mature (b) unmature

Figure 6. GUI design and result fo (a) for mature and (b) for unmature palm fruit

Therefore, the results of SOM classification are displayed directly on the GUI, providing users with a clear indication of fruit ripeness. Figure 6. (a) shows the result of maturity detection where a sample of a mature palm fruit is used as the input. The GUI analyses the segmentation of the input image, providing criteria result and maturity level as the final output. While Figure 5. (b) displays the result of maturity level, where unmature sample image is loaded and resulted to a un mature classification as an output.

The result of the paper indicates that the Self-Organizing Maps (SOM) algorithm offers valuable insights into the application of advanced technology in agricultural practices. While there may not be direct related research specifically focusing on using SOM for palm fruit maturity assessment in the Aceh region, the findings can be discussed in the context of broader research on machine learning applications in agriculture and palm oil production. Research in agricultural science has increasingly explored the potential of machine learning algorithms for various tasks, including crop yield prediction, disease detection, and quality assessment. Studies by Santos, Silva, Matos, Moura, & Dompieri (2021) and (Mokarram, Najafi-Ghiri, & Zarei, 2018) has demonstrated the effectiveness of machine learning techniques, including SOM, in analysing agricultural data and improving decision-making processes. In the context of palm oil production, research by Khan, Kamaruddin, Ullah Sheikh, et al., (2022) and Khan, Kamaruddin, Sheikh, Yusup, & Bakht (2022) has investigated the use of machine learning algorithms for predicting oil palm yield and optimizing cultivation practices. These studies highlight the relevance of machine learning in addressing challenges specific to the palm oil industry, such as yield variability and resource optimization.

The application of SOM in assessing palm fruit maturity aligns with the broader trend of leveraging data-driven approaches to enhance agricultural productivity and sustainability. SOM's ability to identify underlying patterns and relationships within complex datasets makes it well-suited for capturing the diverse factors influencing palm fruit maturity, such as environmental conditions, soil composition, and genetic variations.

Furthermore, the research results on palm fruit maturity assessment using SOM can contribute to ongoing efforts to improve harvesting practices and optimize oil yield in palm oil plantations. By accurately assessing fruit maturity levels, farmers and plantation owners can make informed decisions regarding the timing of harvest, thereby maximizing oil production efficiency and quality.

Overall, while there may not be direct related research specifically focusing on SOM for palm fruit maturity assessment in the Aceh region, the findings of this research can be situated within the broader context of machine learning applications in agriculture and palm oil production. They underscore the potential of advanced technology to address key challenges facing the agricultural sector and pave the way for more efficient and sustainable practice

4. Conclusion

Given to the problems in palm oil production and current development of computer technology in the post-harvest handling. This paper attempt to develop an assessment tool to determine the maturity Level of Palm Fruits in the southern west region of Aceh. This paper analyzes 40 sample images of palm oil fruit from the *Tenera* variety as the data set of the assessment tool.

The SOM neural modelling and methods of digital image analysis identified the palm oil fruit maturation classes and supported the decision-making processes during the harvest and post-harvest handling. The SOM network successfully and graphically identified two classes of the composted material. The analysis showed that it was enough to obtain information about the color of composted matter to identify its maturity. In addition, the algorithm is then translated into a Graphical User Interface (GUI) to streamlines the maturity determination process, offering precision and efficiency to farmers and plantation owners in the Western-Southern area of Aceh. As a result, the proposed method is of utilitarian significance because it can be used for automated assessment of the degree of maturity of organic and as a tool supporting the decision-making process during production.

Moving forward, future research should continue the refinement and validation of the GUI in collaboration with local communities and industry partners. The collaboration will be essential for its successful implementation and adoption. Furthermore, ongoing research efforts should focus on expanding the functionality and scalability of the GUI to address evolving challenges and opportunities in the dynamic field of palm oil production. Through concerted efforts and innovation, the research paves the way for sustainable growth and prosperity in the Western-Southern area of Aceh's palm oil industry.

In addition, to better advances the machine learning focus on the paper, future works should consider on collecting a more extensive and diverse dataset. This dataset can encompass various maturity parameters, including visual aspects, size, chemical composition, and other relevant factors. With a richer dataset, the SOM model can provide more accurate and detailed results. Additionally, Research can focus on integrating the SOM model with automated fruit processing systems. In such a system, fruits can be automatically scanned, identified, and classified based on their maturity levels using the SOM model. This would provide a more efficient and accurate approach to mass fruit processing.

Acknowledgments

We would like to express my heartfelt gratitude to the University of Teuku Umar, LPPM-PMP University of Teuku Umar, PT Scofindo Nagan Raya, and The Ministry of Research and Education of the Republic of Indonesia for their invaluable support in making this research possible.

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