

VISUAL DETECTION OF OIL PALM MATURITY LEVERAGING SIMPLE EVOLVING CONNECTIONIST SYSTEM

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Received: 10 September 2025, Revised: 24 April 2026, Accepted: 12 May 2026

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ABSTRACT

Detecting the ripeness of oil palm fruit bunches is a crucial process in the palm oil industry to ensure the quality and quantity of oil extracted. Conventional methods still rely on subjective and inefficient manual observation. This study proposes a visual detection system using the Simple Evolving Connectionist System (SECoS) algorithm to identify the ripeness of oil palm bunches based on visual images. This model utilizes color, texture, and shape characteristics extracted from images and processed through an adaptive and evolving neural network structure. The results demonstrate that SECoS is capable of high detection accuracy and adapts to new data patterns. This system has the potential to be applied in precision agriculture practices. The model achieved an average accuracy of 91.3%, with the highest accuracy of 94% in the "Ripe" category in the final test based on 300 dataset. This demonstrates that parameter optimization is crucial in improving the model's ability to adapt to variations in oil palm bunch image data. Accuracy improvements were evident in both training and validation data. However, not all categories achieved optimal results, with accuracy for the "empty bunch" labels (89%) and "unripe" labels (88%) being relatively lower than for the other categories.

Keywords : Oil Palm Bunches, Detection, Accuracy, SECoS, Image Processing.

1. Introduction

Palm oil is a strategic commodity in Indonesia, contributing significantly to the economy and energy sectors (Purnomo et al., 2020; Al-Khowarizmi et al., 2023; Wijaya & Amin, 2026). Accurately determining the ripeness level of the fruit bunches is crucial for increasing palm oil yield and quality (Lai et al., 2023; Nurfitriah & Rakhmawati, 2024; Lubis & Jelita, 2025). Picking underripe or overripe fruit bunches can reduce oil yield and quality, as production success is heavily influenced by the quality of the bunches (Goh et al., 2025). Therefore, high-quality palm fruit bunches will yield high-quality palm oil. (Salambue & Shiddiq, 2019) detecting palm fruit at the wavelength values of the front and back images are not different, from this study only extracting features in the image and converting them into RGB results. Meanwhile (Asming et al., 2022) conducted research on the detection of oil palm plantations by utilizing satellite images/images to distinguish oil palm plantations and did not use artificial neural network algorithms and successfully achieved an accuracy of 98.2857%.

However, many ripeness detection processes are still performed manually based on visual observations by farmers or field workers (Tian et al., 2020). This method is subjective, inconsistent, and inefficient. With the advancement of technology, approaches based on image processing and artificial intelligence have become promising alternatives to minimize the tendency to rely on visual observation for labor (Frank et al., 2019). In this regard, many efforts and processes have been undertaken to implement technology for detecting ripeness of oil palm bunches, such as the use of mobile robots and applications on various platforms. These innovations can be used to minimize human error in carrying out tasks or in making decisions regarding the ripeness of oil palm bunches, which can affect productivity. One way to implement an integrated system is by using technology in the form of an accurate oil palm bunch ripeness detection system.

Detection certainly requires training data and testing data in the form of nominal data, numeric data, images, videos, and even mathematical functions. (Kasnavi et al., 2018)(Tapeh & Naser, 2023)(Albahra et al., 2023). However, the success and success of detection cannot be

separated from the algorithm process that runs according to the learning process in supervised learning (Dogan & Birant, 2021). The most basic detection algorithm in data mining is the multilayer perceptron (MLP) (Mohammed et al., 2020). As done by (Lee et al., 2022) Detecting oil palm tree diseases by comparing several Artificial Intelligence (AI) algorithms such as MLP and Support Vector Machine (SVM) on images/images where the average accuracy is 80% and states that MLP is superior in data utilization. (Juman et al., 2016) research proposed a comparison of Artificial Condition Networks and SVM capable of detecting new tree trunks in oil palm heads with an accuracy of 91.7%. However, his research also explained that with the presence of the Dario sensor tool, the comparison of the two methods succeeded in achieving 100% accuracy (Lubis, n.d.).

Therefore, the MLP algorithm is certainly very good at detecting data in data mining. However, MLP training and testing data involves iterations and epochs on each input vector in the neural network. (Rezaeipannah et al., 2021). This raises the question that the algorithm processes during training and testing data take a long time, so the MLP algorithm has been developed by (Rahmat et al., 2016) Evolving MLP (eMLP) is also often referred to as Simple Evolving Connectionist System (SECoS) (M. Watts & Kasabov, 2000)(Ghobakhlou et al., 2003). SECoS is no longer a running process like MLP (Syah & Al-Khowarizmi, 2021). Where the process of developing the hidden layer and output layer is carried out to avoid epochs in the input vector process (M. J. Watts, 2014). Various studies have been conducted with SECoS such as in (Al-Khowarizmi & Suherman, 2021). It can be seen that SECoS carries out the training and testing process by developing nodes in the hidden layer. With the process that has been developed by (MJ Watts & Worner, 2004) Using the normalized Hamming distance. Therefore, in several tests, the average distance formula that excels in finding distance proximity is the normalized Euclidean distance. (Al-Khowarizmi et al., 2017).

Much research has been conducted in recent years on detecting the ripeness of oil palm bunches to ensure that harvested palm oil meets accurate and precise ripeness standards. This research will attempt to implement a method and implement an Android-based application capable of detecting the ripeness of oil palm bunches for use by workers. This is relevant to the importance of managing harvests according to ripeness, resulting in high-quality oil. One approach that can be adapted is the SECoS, an artificial neural network system capable of adaptive learning and development over time. SECoS is known to be efficient, lightweight, and highly suitable for real-time applications or environments with constantly changing data. The SECoS approach has been widely applied in research in several cases, such as isolated venom recognition and skin cancer image classification. The purpose of using SECoS is to design and evaluate a digital image-based classification system for oil palm fruit bunch ripeness.

This research uses oil palm fruit mark data, categorized as empty, overripe, ripe, rotten, underripe, and unripe, with 300 data sets, each containing 50 data sets. The data will be used for application as data for SECoS. In the process, the data will be trained with three layers of neurons: an input layer with a linear transfer function; an evolving layer; and an output layer with a simple saturated linear activation function. In this case, normalized Euclidean distance will be proposed to determine the activation function based on the value $1 - D_n$.

2. Material and Method

The methodology in this study is to produce an optimal algorithm for detecting palm oil cluster images using the SECoS algorithm. This study conducted training and testing data on palm oil bunch images obtained from palm oil plantation partners. Dataset collection in this study is the initial step and is labeled in Figure 1 below.

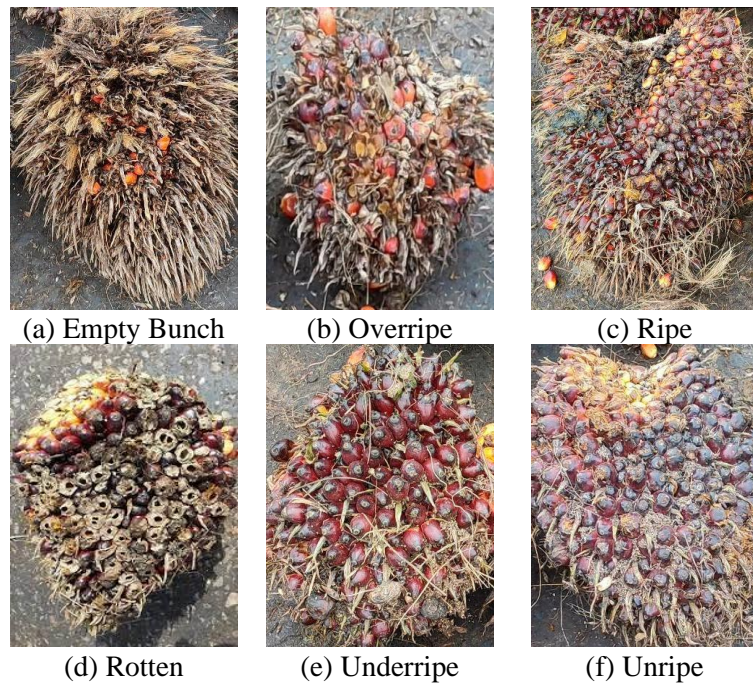


Fig. 1. Research Dataset

Figure 1 represents the available dataset, comprising 300 images: 50 unripe, 50 overripe, 50 ripe, 50 rotten, 50 underripe, and 50 unripe. Next, the SECoS model was trained and tested by extracting features from the images to generate numerical values. SECoS has a network that extends to the hidden layer and can also be used in the output layer. The SECoS network can be seen in Figure 2.

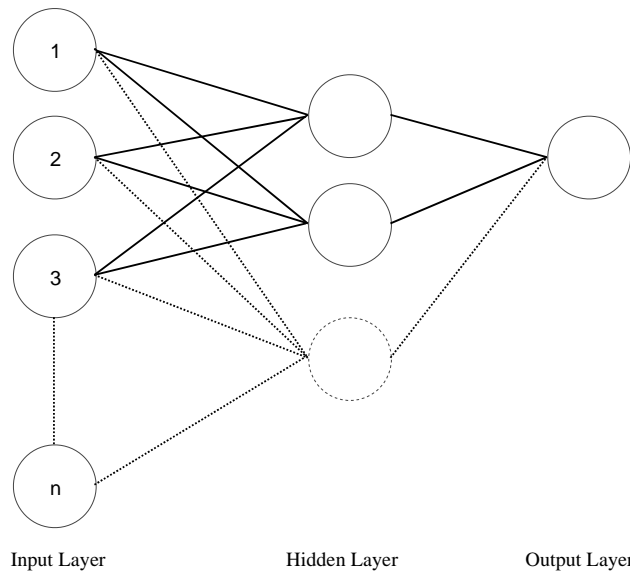


Fig. 2. SECoS Network

Figure 2 shows the SECoS feedforward network consisting of three layers. The input layer is a transfer function to another function, the hidden layer is an evolving layer, and the output layer is the result. Feedforward networks generally have an activation function, but SECoS uses a linear activation function called activation A at the evolving layer, node n, which is determined by equation (1). (Kasabov, 2007):

$$A_n = 1 - D_n \tag{1}$$

A_n is the activation function of node n and D_n is the distance value between the input vector and the incoming weight vector at the target node. D_n Generally, normalized Hamming distance is used, but in this study, it is in accordance with those who have carried out optimization with the normalized Euclidean distance formulation to obtain good results in learning (Nababan et al., 2017)(Al-Khowarizmi et al., 2017). The normalized Euclidean distance formulation in equation (2).

$$D_n = \sqrt{\sum_{i=1}^K \frac{|I_i - W_i|^2}{k}} \quad (2)$$

In equation (2) K is the number of nodes at the input position of the SECoS network, I is the value inputted in the input vector. W is the weight matrix in the evolving layer (Marshall et al., 2005). Next, learning was conducted using the SECoS method on a dataset of oil palm images. The SECoS network's trajectory is as follows (M. J. Watts, 2014):

1. input vector I into the feedforward network.
2. If the activation value is maximum (A_{max}) from nodes smaller than the sensitivity threshold (S_{thr}), then:
 - a. Add new node to hidden layer
If not:
 - a. Calculate the error value between the output vectors O_c and *output vector* O_d .
 - b. If the error value is greater than the threshold error coefficient (E_{thr}) or the desired node output is not supported, then add a new node, if not then update the connection weight on the winning hidden node.
3. This step is required for each input vector without any epoch..

A node needs to be added if the input weights are initialized according to the input vector I and the output weights are initialized according to the output vector O_d . The feedforward process from the hidden layer to the output layer can be done in two ways. The first method uses the One-of-N propagation method, where propagation is only carried out by the hidden node with the highest activation value. Modification of the input weights at the winning node j is carried out according to equation (3) below (M. J. Watts, 2016):

$$WW_{ii,jj}(tt + 1) = WW_{ii,jj}(tt) + \eta\eta_1 II_{ii} - WW_{ii,jj}(tt) \quad (3)$$

While the weight modification comes out of the node j done according to equation (4):

$$WW_{jj,pp}(tt + 1) = WW_{jj,pp}(tt) + \eta\eta_2 AA_{jj} \times EE_{pp} \quad (4)$$

So, from the explanation of the methodology, a general architecture is formed as a research path for the use of AI algorithms in palm oil, which is depicted in Figure 3.

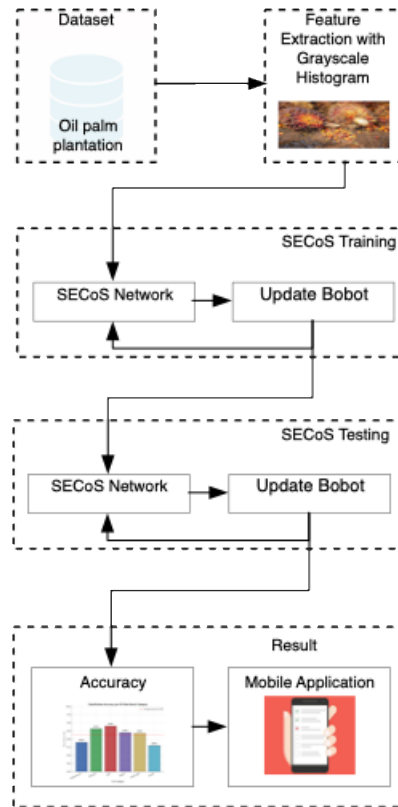


Fig. 3. General Architecture

Figure 3 shows the general architecture of the research, which begins with collecting datasets from oil palm plantations. After obtaining the dataset, features were extracted using a grayscale histogram to convert the image data into numerical data. The next step was training with SECoS and testing with SECoS. The final result, accuracy, was then transmitted to a mobile application to facilitate the classification of oil palm signs.

3. Result and Discussion

The implementation of the Palm Oil Bunch Maturity Detection System with the SECoS Model is carried out by utilizing digital images of oil palm bunches as the main data which are then processed through pre-processing, feature extraction, and ripeness level prediction stages. The SECoS model was chosen because of its ability to learn adaptively and continue to develop as new data is added, so that this system is not only able to classify ripeness levels based on visual patterns such as fruit color and texture, but also can adapt to variations in dynamic field environmental conditions. With this system, the process of determining the harvest period which previously relied heavily on the subjective experience of field workers can be done more objectively, quickly, and accurately. Data accuracy is of course formed based on the data. The data comes from images extracted by applying a grayscale histogram. The feature extraction process is based on figure 4.

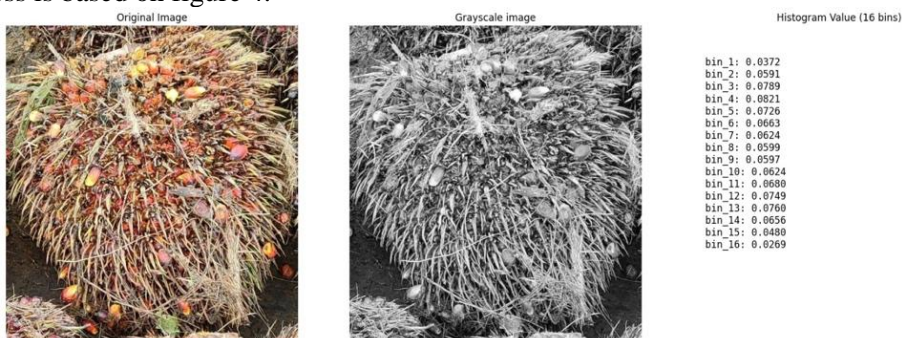


Fig. 4. Grayscale histogram of oil palm bunches

Figure 4 generates numerical data that will be processed using the SECoS method. In the context of detecting oil palm bunch ripeness, SECoS uses adaptive data learning, eliminating fuzzification, making the SECoS model more computationally efficient. This research will use binary image data, allowing the SECoS model to maintain the adaptation of the Evolving Fuzzy Neural Network in the evolving layer. SECoS will consist of three main layers: an input layer for linear transfer, an evolving layer for adaptive data representation, and an output layer for activation.

The classification decision for the ripeness level of the bunch is then obtained using the argmax function on the output values generated during the SECoS training process, following the prototype-based ECoS algorithm. For each data sample, the winning evolving neuron is determined based on the minimum distance. If the distance exceeds a threshold, a new neuron is added and its weights are initialized from the training data. Otherwise, the winning neuron is updated using a learning rule. The implementation results on oil palm bunch image data demonstrate that the SECoS model is capable of detecting ripeness levels effectively. The training results graph shows a consistent increase in accuracy, reaching over 90% in the final epoch, as well as a decrease in loss values to a minimum. This demonstrates SECoS's ability to provide an adaptive, efficient, and interpretable solution to support decision-making related to oil palm bunch harvesting. This can be seen in Figure 5 below.

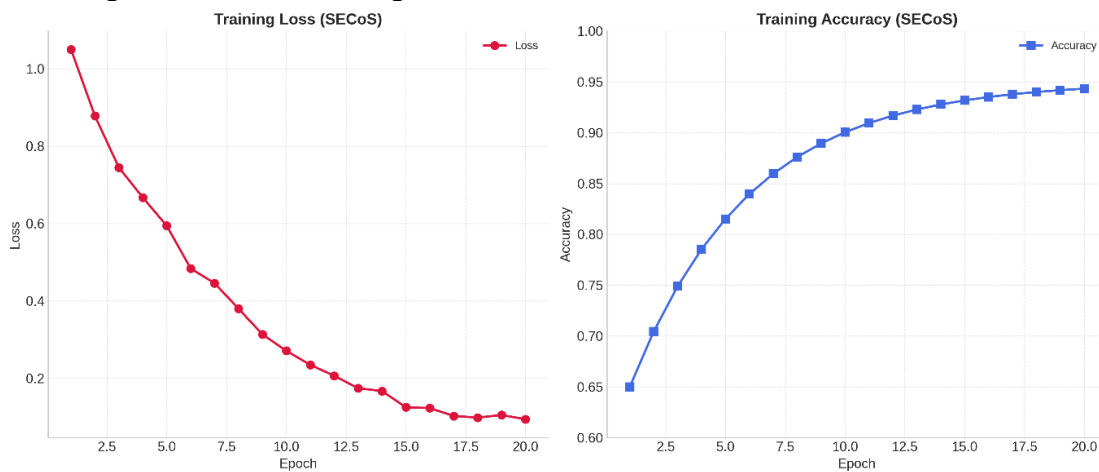


Fig. 5. Training Loss and Accuracy

Figure 1 shows that the performance of the SECoS algorithm during training on the oil palm bunch ripeness detection system showed a significant decrease in training loss, from a relatively high initial value to nearly 0.1 in the 20th epoch. This indicates that the SECoS model is capable of effectively learning by minimizing prediction errors on the training data. The training accuracy showed a consistent increase, from around 65% in the initial epoch to over 94% in the 20th epoch. The decreasing trend in loss, which coincides with the increasing accuracy, indicates that the model can effectively recognize oil palm bunch image patterns, resulting in increasingly accurate ripeness classification. This is consistent with the testing with the test data in Table 1. The testing used 300 test data sets, divided into six labels, with each label tested with 50 image data sets to assess the accuracy of the model. The following are the test results based on the test data in Table 1.

Table 1 - Testing Results of Test Data

No	Label	Number of Test Data	MAPE (%)
1	Empty Bunch	50	89
2	Overripe	50	93,2
3	Ripe	50	94
4	Rotten	50	92
5	Underripe	50	91,8
6	Unripe	50	88

Based on the test results presented in Table 1, consisting of six classes of oil palm bunch labels, it can be seen that the model's accuracy level varies for each label. The Ripe Class label achieved the highest accuracy of 94%, indicating that the model is able to recognize the characteristics of oil palm bunches that are in optimal ripeness. Then for the Overripe label with an accuracy of 93.2% and Rotten with an accuracy of 92%, which shows fairly consistent detection performance in categories with relatively clear visual characteristics. Meanwhile, lower accuracy was found for the Underripe class (91.8%), Empty Bunch (89%), and Unripe (88%). These results indicate that categories with more subtle visual differences or similar to other categories such as Unripe and Empty Fruit, tend to be more difficult for the model to detect. In terms of model performance, with an average of 91.3%, the model performed relatively well in predicting oil palm bunch ripeness. The following is a visual depiction in graphic form of the test results, shown in Figure 6.

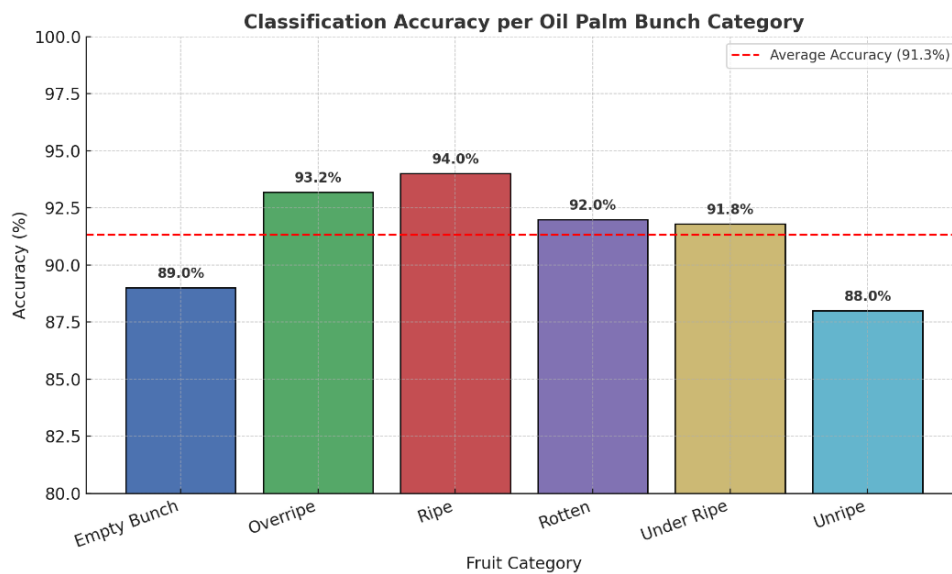


Fig. 6. Accuracy Graph

The application includes a mobile-based application used by oil palm plantation workers to facilitate the detection of oil palm ripeness. The next step shows the interface of the SECoS Palm Oil application, designed to digitally detect the ripeness of oil palm fruit. The application has several main menus. The first menu is Maturity Detection, which analyzes the ripeness of oil palm bunches using the SECoS model through image input. Next, there is the Detection History menu, which displays information on the results of previous ripeness analyses. The next menu is the Location Map, which displays the locations of oil palm fruit detections within the plantation area, making it easier to map field conditions. Finally, there is the Harvest Schedule menu, used to manage and schedule harvest times based on the ripeness detection results. The application displays the results of the oil palm bunch ripeness detection. The detection results are shown in Figure 7.

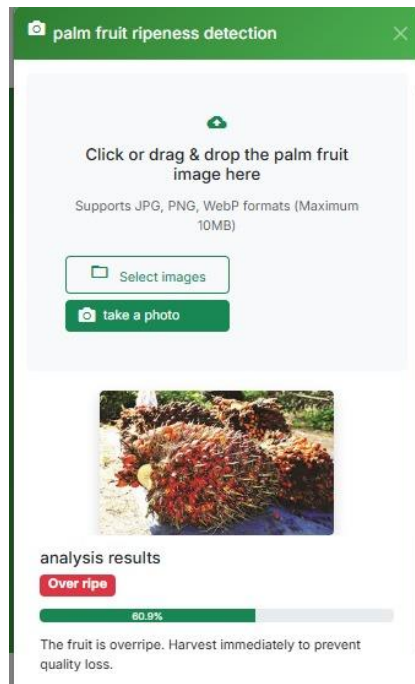


Fig. 7. Capture Image Menu Display

Figure 7 shows the analysis results from the Palm Oil SECoS application in the Detection Results menu. At the top, you can see a photo of the oil palm bunch that will be analyzed by the SECoS algorithm. The system then displays the predicted ripeness information. According to the application, the palm bunch is categorized as overripe, with a detection accuracy of 60.9%. Furthermore, the system records the analysis time, August 20, 2025, at 2:17 PM, and stores the GPS coordinates of the image capture location at 3.5595, 98.7007. This display demonstrates how the application not only provides ripeness classification results but also provides information with accuracy, time, and location, making it easier for users to evaluate harvests and record data in a structured manner. The detection history menu displays the history of oil palm bunch ripeness detection results. The following is a display of the detection history in Figure 8.

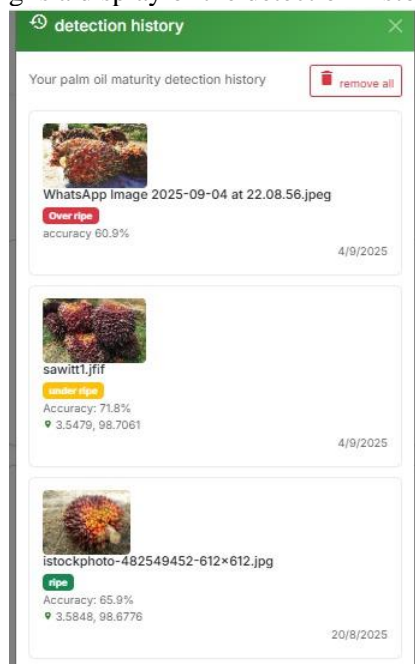


Fig. 8. Location Map Menu Display

Figure 8 displays the interface of the oil palm bunch ripeness detection application. The detection history menu includes a Filter by Ripeness feature that allows users to display detection history based on ripeness categories: All, Rotten, Unripe, Ripe, and Overripe. Below this, you can see the detection results, in the form of photos of the oil palm fruit bunches that have been analyzed by the system.

4. Conclusion

Based on the test results, the accuracy of the Simple Evolving Connectionist System (SECoS) model in detecting the ripeness of oil palm bunches showed a significant improvement after training. In the validation phase using test data, the model achieved an average accuracy of 91.3%, while in the final test, the highest accuracy reached 94% for the "Ripe" category. This indicates that the parameter optimization process plays a crucial role in improving the model's ability to adapt to variations in oil palm bunch image data. Although accuracy improvements were seen in both training and validation data, not all categories achieved optimal results. Accuracy for the "Empty Bunch" (89%) and "Unripe" (88%) labels was relatively lower than for the other categories. This may be due to visual similarities between classes and the limited amount of training data for these categories. Overall, SECoS performance remained stable and consistent in testing, with an average accuracy of 91.3% across the six ripeness categories. The resulting SECoS predictive model can be used by palm oil plantation operators to support more timely harvesting decisions, thereby minimizing losses due to substandard bunch harvests. Therefore, the implementation of this system has the potential to improve operational efficiency, palm oil production quality, and reduce reliance on manual assessments that are prone to subjectivity. For further research, development can focus on increasing the number and diversity of image datasets, as well as the application of additional optimization techniques such as attention mechanisms or transfer learning to improve accuracy in low-level classes.

Acknowledgement

Thanks are expressed to Directorate of Research, Technology, and Community Service, Directorate General of Higher Education, Research, and Technology, Ministry of Higher Education, Science and Technology, the Republic of Indonesia for funding this research through the Research and Community Service Program for the 2025 Fiscal Year with Contract Number: 003/II.3-AU/UMSU-LP2M/C/2025.

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