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Developing prediction model for ripeness level of melon (*Cucumis melo* L.) based on acoustic impulses using artificial neural network (ANN)

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Abstract

Khuriyati, N. & Kasih, A. N. (2026). Developing prediction model for ripeness level of melon (*Cucumis melo* L.) based on acoustic impulses using artificial neural network (ANN). *Bulg. J. Agric. Sci., 32*(4), 982–990

Non-climacteric fruits such as melons are often difficult to assess for ripeness due to the lack of obvious physical changes upon ripeness. Currently, melon producers rely on visual assessment, which requires specialized expertise and involves inefficient, destructive test methods. Thus, a non-destructive approach like acoustic impulse is crucial for ripeness classification. This study aims to develop a melon ripeness prediction model based on an acoustic impulse test. A total of 120 Honey Globe *melons* (*Cucumis melo* var. inodorus) were measured for acoustic properties (dominant frequency, magnitude, zero moment power, and short-term energy), using a knocker to obtain acoustic parameter data. The acoustic parameter data were processed using an artificial neural network (ANN) with the Backpropagation method, and model performance was evaluated using a confusion matrix. The model showed excellent performance with an R^2 value of 94.46% and accuracy, precision, and recall rates of 98.33%, 97.37%, and 97.37%, respectively.

Keywords: acoustic impulse response; artificial neural network; confusion matrix; melon; ripeness level

Introduction

Melon *(Cucumis melo* L.) is a seasonal fruit crop that has high economic value and is often grown as part of horticultural agriculture. In Indonesia, melons are very popular because of their delicious taste and good nutritional content (Annisa and Gustia, 2018). Melons are one of non-climacteric fruit, which means that they cannot continue their ripening process after being picked from the parent plant or have a reduced respiration rate. This type of fruit produces very small amounts of endogenous ethylene and does not respond to external ethylene treatment. Therefore, melons should be harvested when they are just ripe and have reached the optimal level of ripeness for consumption, as they will not experience significant changes in ripeness, such as skin discoloration, after the harvesting process (Rizzo et al., 2023). Due to its non-climacteric nature, determining the ripeness level of melons visually becomes more difficult compared to other climacteric fruits. On the other hand, melon producers currently rely on subjective judgment and special expertise to determine the ripeness level of melon fruit. This method has disadvantages, including variations in results due to human visual limitations, fatigue levels, and differences in perception of fruit quality. In addition, to ensure an accurate ripeness level, farmers often conduct destructive testing by taking fruit samples to measure the Brix value, which is an indicator of sugar content in the fruit, using a refractometer. This damages the fruit and reduces fruit availability. Therefore, there is a need for an objective and non-destructive method for determining the ripeness level of melon fruit, known as non-destructive testing.

Non-destructive testing is a technique applied in industry, sciences, and innovations to assess the characteristics

of materials, components, or systems without causing internal damage (Sanchez et al., 2020). This approach is highly beneficial because its analytical process does not alter or harm the tested object, thus enhancing product reliability, preventing accidents, and reducing costs compared to destructive testing methods (Phey et al., 2020).

One example of a non-destructive technique that can be applied is acoustic impulse testing. This method is based on the principle that the density and surface condition of a material affects the speed of sound waves moving through it. This technique has the advantage of being able to penetrate the object's surface and identify any cracks or internal damage within the object being tested (Albert Wei et al., 2020). This technique is beneficial for providing accurate information about the quality of melons, including internal damage or ripeness level. The acoustic impulse test yielded the best prediction when magnitude was used to determine fruit firmness (Khuriyati et al., 2024). Research conducted by Agusta and Ahmad (2016) shows that acoustic parameters such as dominant frequency, zero moment power, and short-term energy are closely related to the harvest age of fruits. Other studies also state that acoustic parameters have a significant correlation with physicochemical properties such as the firmness of melon flesh and total soluble solids content, which can help determine the optimal harvest time (Pamungkas and Bintoro, 2021).

One method that can be used to identify the level of fruit ripeness is artificial neural networks. An Artificial Neural Network (ANN) inspired by biological neural networks, captures both linear and non-linear relationships between inputs and outputs (Pishro et al., 2021), learns and adapts through continual signal stimulation, and is ideal for processing large, complex datasets, making predictions, and taking action (Kariri et al., 2023). ANN training using variables such as attenuation value, fruit age, and density has been successful in predicting the physicochemical quality properties of melon fruit (Izdihar et al., 2023), demonstrating the ANN's capability in handling diverse and intricate datasets. Additionally, in fruit ripeness identification, ANNs have demonstrated impressive accuracy rates: 97.86% for apples (Sabzi et al., 2022), 94.5% for durians (Rivai et al., 2021), and 97.75% for bananas (Mazen and Nashat, 2019), highlighting their effectiveness in creating accurate, user-friendly models for complex systems with large inputs.

The objectives of this study are to develop a predictive model for melon ripeness levels based on acoustic parameter values using artificial neural networks, and to analyze the effectiveness of the prediction model using a confusion matrix for classifying melon ripeness levels.

Material and Methods

Materials

Honey Globe *melons (Cucumis melo* var. inodorus) used in this study were obtained from the *Greenhouse* Fablab Jogja melon garden, Field Research Center of Universitas Gadjah Mada, Kulonprogo, Indonesia. A total of 120 melon samples were used with three ripeness levels: *unripe*, *ripe*, and *overripe*. The ripeness level of melon fruit was determined based on the value of total soluble solids. Unripe melon fruit has a minimum limit of total soluble solids value lower than 14 Brix, ripe melon fruit has a total soluble solids value ranging from 14 – 17 Brix, and overripe melon fruit has a total soluble solids value greater than 17 Brix.

Non-destructive measurement of acoustic parameter

Acoustic impulse parameter testing was conducted using a self-designed knocker and laptop. Based on research by Pamungkas and Bintoro (2021), the knocker operates by knocking the surface of the fruit with a rubber ball driven by a spring, resulting in a knocking sound. During the measurement of acoustic parameter data, the melon was placed on a table and knocked by the knocker positioned perpendicular at a distance of approximately ±1cm from the fruit's surface (Figure 1). Knocking on the melon's surface was performed at 3 points (A, B, C), as indicated in Figure 2, and repeated 3 times at each point for each sample with different ripeness levels. The resulting knocking sound were recorded in WAV format using Audacity 3.2.1 software with a project value of 44100 Hz, with a knocking duration of 1 second. The sound recordings were analyzed using Matlab R2021b software

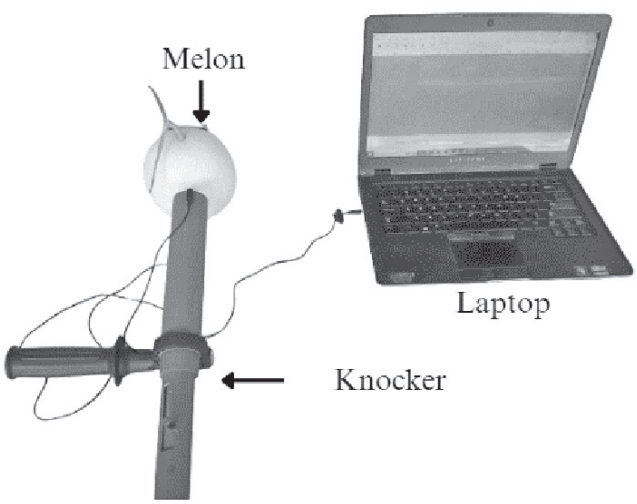


Fig. 1. Measurement of acoustic properties
Source: Authors' own elaboration

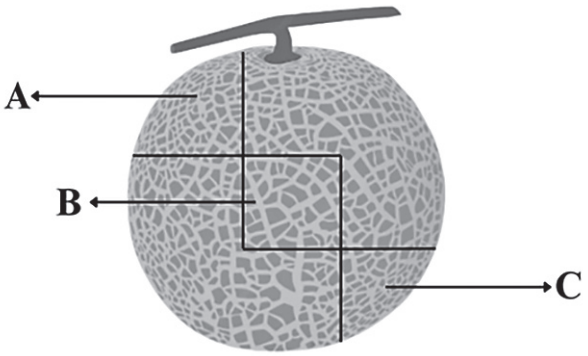


Fig. 2. Knocking location
Source: Authors' own elaboration

to obtain the values of impulse acoustic parameters such as dominant frequency (f), magnitude (M), zero moment power (Mo), and short-term energy (STE).

Artificial Neural Network modelling

Artificial Neural Networks (ANN) were used to form a predictive model for melon ripeness levels with the backpropagation training algorithm. The backpropagation (BP) algorithm is one of the most popular learning methods for neural networks. Backpropagation is a supervised learning technique that attempts to minimize the error of the network by moving down the gradient of the error curve (Hamid et al., 2011). This technique assists with computing the inclination of a misfortune work regarding all the loads in the system (Sekhar et al., 2020). The process involves data preparation, and training the ANN by determining its structure, activation function, epochs, and learning rate, where each step selects the results that yield the smallest Mean Squared Error (MSE) value. The MSE value can determine the performance of the prediction results based on testing the training architecture model by observing the smallest MSE. The range of MSE is (0, +∞) the smaller the MSE value, the higher the accuracy of the prediction model. The perfect value of MSE is 0, indicating that the prediction model is perfect (Jierula et al., 2021). After the training stage, validation and verification (testing) processes were conducted using new data to determine the accuracy of the training results. The output of the ANN model represents the ripeness level of the melon, which was then evaluated using a confusion matrix to measure the model's performance.

Two models were built: Model A, which uses 4 inputs and 1 output, and Model B, which uses 7 inputs and 1 output. The inputs used in Model A include acoustic parameters such as dominant frequency, magnitude, zero moment power, and short-term energy, while Model B uses both acoustic parameters and physicochemical property parameters such as firmness, total soluble solids, and moisture content. The output for both models is the classification of melon ripeness levels. The approach taken in this study began with the development of Model A to evaluate the predictive ability based solely on acoustic parameters. Afterward, Model B was developed to survey whether the expansion of physicochemical parameters could improve the accuracy of predicting melon ripeness level. Therefore, the focus of this research is not on the comparison between Model A and Model B, but rather on assessing the effectiveness of Model A in predicting the physicochemical properties of melons. The design of the artificial neural network (ANN) architecture used in this study can be seen in Figure 3.

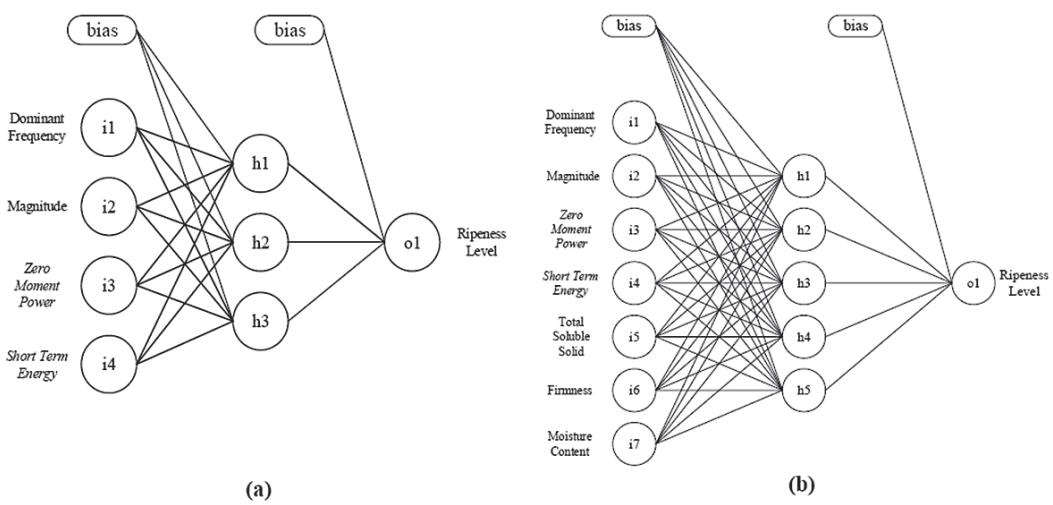


Fig. 3. ANN architecture design (a) model A and (b) model B
Source: Authors' own elaboration

Results and Discussion

The alteration of acoustic parameters

Change in acoustic parameters at different ripeness levels (unripe, ripe, overripe) can be observed in Figure 4. The results of the acoustic test generally show a trend closely related to the fruit ripening process, where frequency dominant, magnitude, and zero moment power show a trend of values inversely proportional to the ripeness level of the fruit (unripe, ripe, overripe) or a decreasing trend with fruit ripening. Meanwhile, short-term energy shows a trend of values directly proportional to the ripeness level (unripe, ripe, overripe) or an increasing trend. Fruit ripening decreases the dominant frequency as the fruit flesh becomes softer (Karthickumar et al., 2018). This also enhances the fruit's ability to absorb sound and reduces the intensity of tapping sounds by decreasing the magnitude value, which is directly proportional to the change in zero moment power (Mo) value, because more energy is absorbed and transferred by the fruit, resulting in reduced reflected energy (Agusta and Ahmad, 2016). Each acoustic test parameter shows a very high correlation with the ripeness level of melon fruits. Changes in acoustic test parameters in melon fruits are closely related to changes in fruit firmness.

Artificial Neural Network training

A total of 120 melon samples were used as the dataset, which was divided into three parts: training data, validation data, and testing data, with a ratio of 80% (n = 96), 10% (n = 12), and 10% (n = 12) of the total available data, respectively. The training, validation, and testing data were randomly selected using the RapidMiner Studio software.

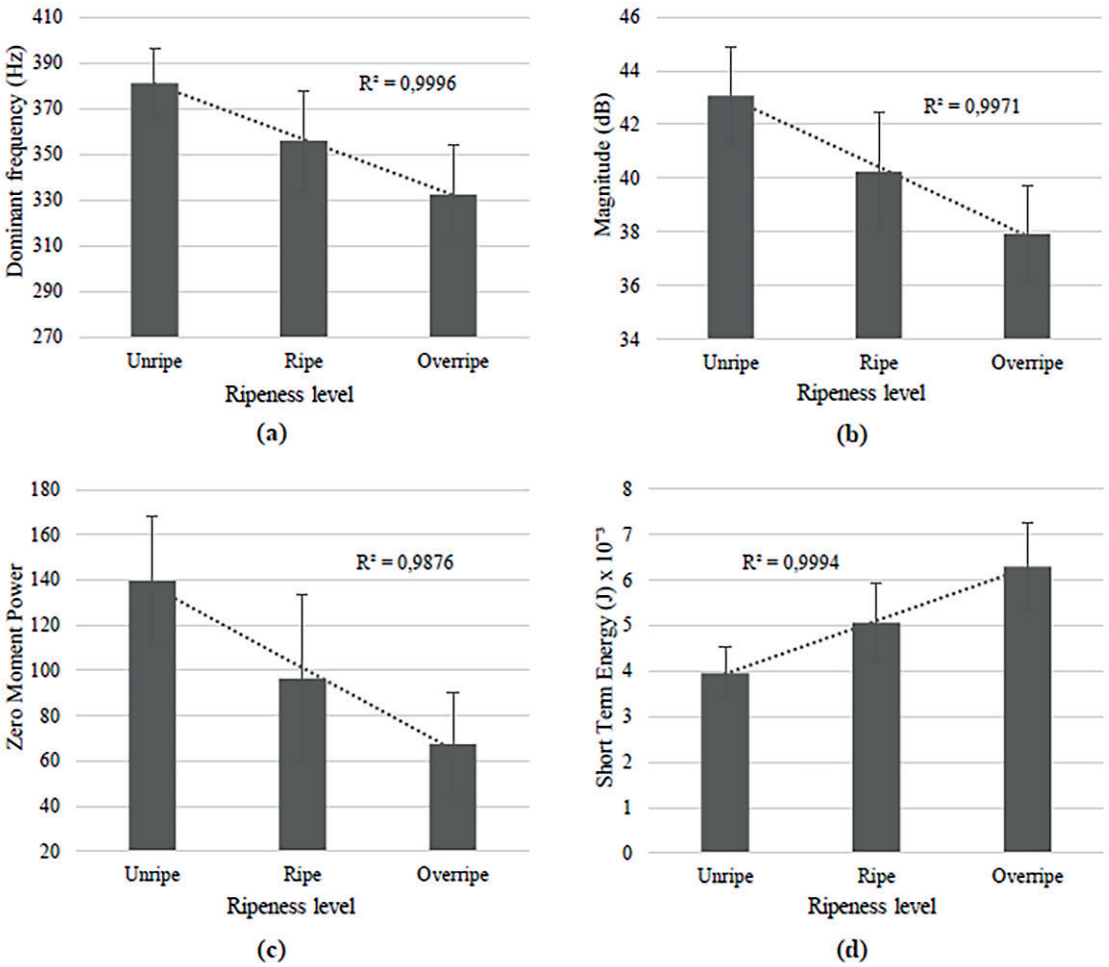


Fig. 4. Diagram of the value of (a) dominant frequency, (b) magnitude, (c) zero moment power, (d) short term energy on melon fruit ripeness level

Source: Authors' own elaboration

Data normalization is conducted as a preprocessing step. It is performed using the min-max normalization method, which transforms the data into specific ranges such as [0.1] or [-1.1], to eliminate the domination of some of the features over others in machine learning (Muhammad Ali, 2022). The purpose of data transformation is to ensure that all data falls within this range, because the original data may have different ranges of values. This normalization process also ensures that the data values are compatible with the activation function used during the training process.

Training of the hidden layers was performed twice for 1 and 2 hidden layers. The architecture that produces the lowest error value or smallest Mean Squared Error (MSE) was used for the second stage of training, which is the activation function training. Activation functions play an important role in deep learning models by introducing non-linearity to the neuron outputs, allowing the network to learn complex patterns and non-linear relationships in the data, as well as determining the network output by mapping the inputs to a desired range of values (Ramadevi et al., 2024). The training of activation functions was carried out using a combination of two functions for the input-hidden layer (ih) and hidden-output layer (ho) activation functions, consisting of logsig, purelin, and tansig. There were 9 combinations of activation function combinations. The combination that yields the smallest MSE or error value was used for the third stage of training, which is epoch training.

Epoch training was conducted with 5 variations of the number of epochs. Epoch is the number of repetitions of the learning process carried out by machine learning (Hastomo et al., 2021). The training epoch represents a complete repetition of the parameter update that involves the complete training dataset at one time (Alzubaidi et al., 2021). An epoch is a repetition or iteration of the process performed to achieve a predefined target (Suhartanto et al., 2019). Limiting the iterations is necessary to prevent the learning process from continuing indefinitely for a long time when the network has not yet achieved the expected performance. The epoch that yields the smallest MSE or error value was used for the fourth stage of training, which is the learning rate training. Learning rate training was carried out with 5 variations. The learning rate is defined as the step size of the parameter updating (Alzubaidi et al., 2021). The learning rate that yields the smallest MSE or error value became the most optimal model and was selected for further analysis. The training of ANN in both models can be seen in Table 1.

The results of the ANN training that yielded the lowest MSE values for both models can be seen in Table 2. The training results of the network in Model A indicate that the optimal ANN architecture has a network structure of 4-7-1, with the tansig activation function in the hidden layer and purelin in the output layer, trained with 9000 epochs and a learning rate of 0.7. Meanwhile, the training results of the network in Model B show that the optimal ANN architecture has a network structure of 7-4-1, with the tansig activation function in the hidden layer and purelin in the output layer, trained with 3000 epochs and a learning rate of 0.9. In both models, the selected ANN architecture has one hidden layer. This aligns with the understanding that a network with one hidden layer is generally sufficient to adequately map between input and target (Nurmahaludin, 2014). There is no definite rule to determine the ideal number of neurons in the hidden layer.

Table 1. Training of the ANN model

ANN Model	1 Hidden Layer Structure	2 Hidden Layer Structure	Activation Function	Epoch	Learning Rate
Model A	4-3-1	4-2-2-1	logsig-logsig logsig-purelin logsig-tansig purelin-logsig purelin-purelin purelin-tansig tansig-logsig tansig-purelin tansig-tansig	1000 3000 5000 7000 9000	0.1 0.3 0.5 0.7 0.9
	4-4-1	4-4-2-1			
	4-5-1	4-6-3-1			
	4-6-1	4-6-4-1			
	4-7-1	4-7-4-1			
	4-8-1	4-8-7-1			
	4-9-1	4-9-7-1			
Model B	7-4-1	7-4-2-1			
	7-5-1	7-6-4-1			
	7-6-1	7-7-4-1			
	7-7-1	7-8-5-1			
	7-8-1	7-9-4-1			
	7-9-1	7-9-7-1			

Source: Authors' own elaboration

The reliability of the ANN was evaluated through the R-squared (R^2) value, as shown in Table 2. Model A has an R^2 value of 0.94. This indicates that in explaining the variance of ripeness prediction values, Model A can explain 94%, which means that the constructed networks have learned well and are capable of displaying outputs consistent with the target data. The R^2 value shows the proportion of variance between predicted and actual values (Nouayti et al., 2024). The positive values of the R^2 range in the interval [0, 1], with 1 meaning perfect prediction in a model (Chicco et al., 2021). Based on the R-squared values generated by Model A, it can be seen that the development of a melon ripeness prediction model using acoustic parameters (Model A) has achieved a very high level of accuracy, reaching 94%. This value is only slightly lower than Model B, which combines acoustic parameters and physicochemical properties, with an R-squared value of 98%.

Evaluating model ANN

Confusion matrix is a visual evaluation tool, which is represents the prediction result of the predicted class versus actual class values (Valero-Carreras et al., 2023). A confusion matrix present information about how often a certain behavior is detected correctly and how often it is classified as another behavior (Ruuska et al., 2018). The use of the confusion matrix in measuring the performance of both models includes accuracy, precision, and recall of the generated models. The dataset used consists of 120 data points with three classes: unripe (1), ripe (2), and overripe (3). The matrix diagram shows that the prediction results of the verification data are quite successful in classifying the ripeness levels of melons, as indicated by the distribution of colors along the diagonal of the confusion matrix (Figure 5).

In Model A, there are 38 data predicted as unripe (1), 38 data predicted as ripe (2), and 44 data predicted as overripe (3). Among the 38 data predicted as unripe (1), there is one prediction error where the data belongs to the ripe class (2), but the model predicts it as unripe (1). Meanwhile, among the 38 data predicted as ripe (2), there is one prediction error where the data should belong to the overripe class (3), but the model predicts it as ripe (2). In Model B, there are 36 data predicted as unripe (1), 39 data predicted as ripe (2), and 45 data predicted as overripe (3). However, among the 39 data predicted as ripe (2), there is one prediction error. The data should belong to the unripe class (1), but the model predicts it as ripe (2). The accuracy, precision, and recall

Table 2. ANN model training results

ANN Model	Structure	Activation Function (ih;oh)	Epoch	Learning rate	MSE			R^2
					Training	Validation	Testing	
Model A	4-7-1	tansig;purelin	9000	0.7	0.0276	0.1048	0.1048	0.94
Model B	7-4-1	tansig;purelin	3000	0.9	0.0043	0.0018	0.0018	0.98

Source: Authors' own elaboration

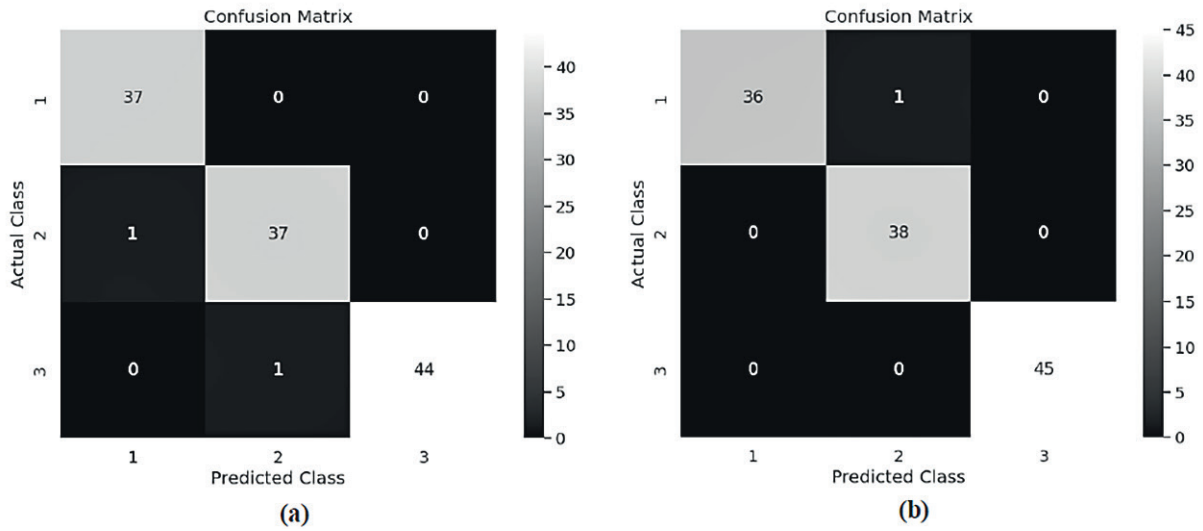


Fig. 5. Confusion matrix of (a) model A and (b) model B

Source: Authors' own elaboration

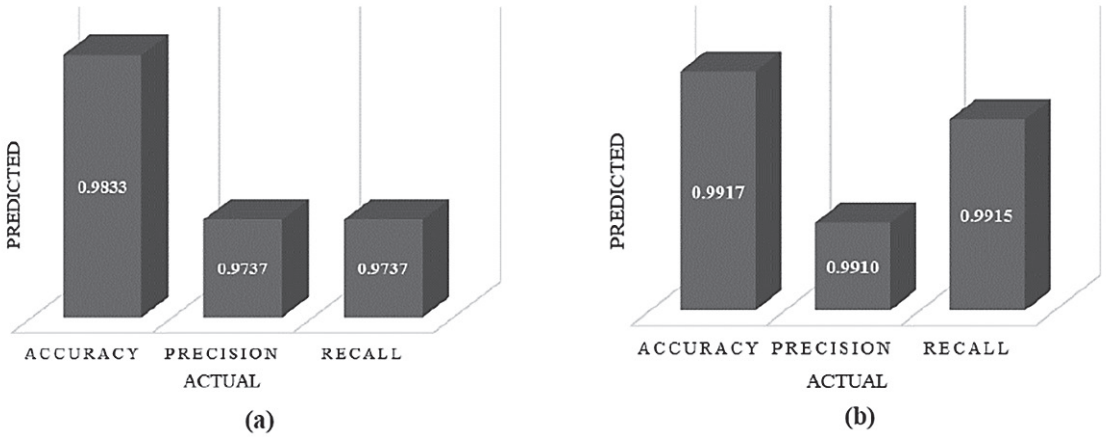


Fig. 6. Accuracy, precision, and recall of (a) model A and (b) model B
Source: Authors' own elaboration

values are obtained from the confusion matrix table formed. The measurement results of accuracy, precision, and recall in the models can be seen in Figure 6.

The accuracy results of Model A and Model B show a very good level of accuracy in classification, with Model B reaching 99.17% while Model A reaching 98.33%. The accuracy of a model describes how precise the model is in classifying data. Model A has a precision of 97.37%, while Model B has a precision of 99.10%, which shows how precisely the model provides predictions that match the requested data (Valero-Carreras et al., 2023). The recall values for Model A and Model B are 97.37% and 99.15%, respectively, which describes the ratio between the number of samples classified as positive to the total number of actual positive samples (Hicks et al., 2022). Based on (Figure 6), the performance of both Model A and Model B can be considered good because all the mean parameter values of the constructed artificial neural network models are above 80% (Nainggolan and Sinaga, 2023). Although Model B achieves higher levels of accuracy, precision, and recall compared to Model A, this study demonstrates that Model A, which is built solely on acoustic parameters, performs well with very high accuracy, precision, and recall values. This indicates that acoustic parameters are sufficiently effective in forming a ripeness prediction model without the need to incorporate physicochemical property parameters.

Conclusion

The ANN model that utilizes acoustic parameters (Model A) has demonstrated excellent performance in predicting the ripeness level of melon fruits, with an R-squared value of 94.46% between the calculated and predicted ripeness levels. This indicates that the model can effectively utilize four input parameters consisting of dominant frequency, magnitude, zero moment power, short-term energy, hardness, and one output parameter, which is the ripeness level of melon fruits, for ripeness prediction. Additionally, the formed model exhibits a high accuracy of 98.33%, precision of 97.37%, and recall of 97.37%, although these values are slightly lower compared to the ANN model using both acoustic and physicochemical parameters (Model B). This suggests that acoustic parameters alone hold potential in constructing a ripeness prediction model for melon fruits, making it an effective and efficient alternative without involving physicochemical property parameters. However, it is important to note that the acoustic parameters used are still susceptible to bias in the form of noise. Therefore, refinement of the knocker used for non-destructive data acquisition is necessary to ensure that the acquired acoustic data is not disturbed by noise.

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