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Super learner ensemble-based internal quality assessment of watermelon via integration of tapping acoustics and rind texture analysis

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Abstract

Watermelon (Citrullus lanatus) is a widely cultivated fruit recognized for its high sugar content. Accurate detection of maturity and soluble solid content (SSC) is essential to ensure optimal harvest timing, sweetness, and market value, as well as to manage resource usage efficiently. This study introduces a low-cost, portable, and non-destructive approach for maturity classification and SSC estimation in Kinnaree watermelon by integrating tapping acoustics and rind texture analysis with ensemble learning algorithms. Tapping-induced acoustic signals were analyzed to extract key resonant features, while rind texture was quantified using image processing techniques. Selected features from both data sources, combined with watermelon mass, were utilized for three-class maturity classification and SSC regression modeling. Machine learning (ML) algorithms were used to map complex and nonlinear relationships between features and watermelon quality attributes. Results demonstrated that acoustic features and fruit mass were critical for maturity classification. Visual features were essential for SSC estimation. Super learner ensemble demonstrates superior predictive accuracy compared to other models, both in classifying ripeness and predicting the SSC of watermelons. Comparative studies with earlier methods confirmed the effectiveness and competitiveness of the proposed technology for non-destructive evaluation of watermelon quality.

Keywords: *Watermelon maturity classification, Soluble solid content (SSC) estimation, Super learner ensemble, Acoustic signal processing, Image texture analysis*

1 Introduction

Watermelon (Citrullus lanatus) is a popular fruit that is consumed globally due to its sweet flavor, high water content, and nutritional benefits [1]–[3]. Watermelon is a non-climacteric fruit, meaning its internal qualities, such as sugar content and flavor compounds, do not significantly improve after harvesting (unlike climacteric fruits, such as bananas or tomatoes, which continue to ripen after harvest). Thus, the maturity level at harvesting defines the quality of watermelon products. Harvesting watermelons at their optimal ripeness stage then ensures consumer satisfaction, achieves market success, and

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reduces economic losses related to postharvest management. This highlights the need for a rapid and reliable technique to assess watermelon quality efficiently.

Consistency in taste and flavor is crucial for watermelon exports and local consumption. Premature harvesting of watermelons results in fruit with an undeveloped taste, low sugar content, and an unpleasant texture. On the other hand, Overripe watermelons have a mealy or mushy texture and a shorter shelf life. Today, in many countries, watermelon grading and quality evaluation are still mainly performed manually by humans (thumping check or visual inspection) [4], [5]. This approach is labor-intensive, time-consuming, and prone to inaccuracies due to human limitations, resulting in inefficiency in the assessment process. For these reasons, it is essential to improve the accuracy of the internal quality assessment of watermelon. Modern non-destructive detection technologies (NDT) have emerged as efficient tools for grading and quality assessment of watermelon to meet these expectations. The use of NDT allows an accurate assessment of internal qualities, including maturity, sweetness, and even internal defects, without damaging the fruit.

NDT techniques exploit the physical and chemical changes that occur during ripening, such as sugar content, moisture, pigment levels, and tissue structure [6]–[9]. Various NDT techniques have been studied for detecting the ripeness and quality of watermelons, each with its own concepts, benefits, and drawbacks. Acoustic Impulse Response relies on impacting the watermelon and capturing the vibration or sound signal using microphones or accelerometers. Research has mapped the relation between acoustic parameters and key internal qualities like maturity [10], [11], internal defects, and sugar content or SSC [12]. For example, previous studies using 100 watermelon samples demonstrated a strong relationship between acoustic indices (e.g., f^2m) and fruit firmness [13]. The results indicated that the highest correlation coefficient (r) among the indices studied was 0.739 and 0.684 for the training and test sets. Recently, acoustic-based approaches have been proposed to classify watermelon ripeness using portable signal processing and machine learning (ML) [4]. A classification accuracy of 77.3% was achieved, demonstrating the potential of this acoustic technology to detect watermelon quality.

Image processing is another non-destructive detection technique widely employed for fruit quality assessment [3], [14], [15]. Rizam et al. [16] utilized image processing technology to extract texture information from 90 samples of watermelon rind and developed ML models for classifying the maturity of watermelons. The result indicated high accuracy in the assessment, with an 86% accuracy rate. In a study by Syazwan et al. [17] RGB images of 45 watermelon samples were used to train ML models for estimating the watermelon's maturity stage, using five positions for each sample. The models achieved a maximum accuracy of 73%. Moreover, watermelon's rind texture has been used as an essential feature to develop several ML models for classifying ripeness stages and predicting SSC [2], [3]. These findings highlight the potential and reliability of image-based, non-destructive techniques for assessing watermelon quality. Recent research has also explored the integration of deep learning and IoT technologies for disease identification in cotton plants to support real-time pest and disease prevention systems [18]. Another NDT, Near-Infrared (NIR) Spectroscopy, is one of the most extensively researched and commercially used methods for determining fruit quality, especially SSC. This technology employs the interaction between light in the near-infrared area and the chemical components of the fruit. Previous studies showed that correlation coefficients (r) between predicted and observed values were around 0.80 to 0.95 [8], [19]. Other NDT techniques also demonstrated high performance on quality detection in watermelon. Laser Doppler Vibrometer (LDV) assesses surface vibrations to estimate ripeness and texture [20]. Magnetic Resonance

Imaging (MRI) offers high-resolution internal imaging [9] while X-ray can accurately detect volume and weight [21].

Challenges remain in scaling NDT methods for real-world applications owing to their high equipment costs, technical complexity, frequent calibration requirements, and sensitivity to environmental variations [7], [8]. This makes such advanced detecting systems mainly utilized by large-scale enterprises in some developed countries (e.g., Japan, South Korea, and China) [5], [6]. On the other hand, small and medium-sized producers still rely on manual inspection by human labor. This highlights a critical need to develop low-cost, scalable NDT solutions that can be easily adopted across all levels. One promising direction lies in the integration of complementary features from multiple sources, which may enhance accuracy and reliability while controlling investment budgets [22] [22], [23]. Acoustic properties combined with image processing technology can be a valuable tool. Since the physiological maturation of watermelon stops at harvest, soluble solids content (SSC) develops very little afterward, even though acoustic signals continue to change. Therefore, relying solely on acoustic data is insufficient. Rind texture, which fully matures at harvest, can help identify if a watermelon was harvested prematurely [2]. Moreover, compared to other technologies, the two technologies are simple, high-speed, and low-cost. The ease of operating the equipment enables farmers and small-scale producers to determine the optimal harvest time and estimate SSC, while also allowing consumers to assess the internal quality of watermelons before purchase.

In this study, we propose the development of a low-cost, portable, and scalable NDT detection that utilizes signal and image processing methods to assess watermelon maturity and SSC. Visual data from surface texture, combined with acoustic signals, is analyzed to classify watermelons into three classes: unripe, ripe, and overripe, and estimate SSC. ML algorithms are used as a mapping tool for model development. Furthermore, the accuracy of the proposed method is evaluated in comparison with previous approaches, demonstrating its effectiveness and competitiveness as a non-destructive technique for assessing watermelon quality. This study aims to meet the needs of small and medium-sized producers by providing a viable alternative that addresses the accuracy and budgeting gaps. Moreover, as the approach requires only a microphone and camera, it is readily scalable for implementation in portable devices, making it well-suited for practical agricultural applications.

2 Data Curation

In this section, we describe the experimental techniques and procedures used for detecting watermelon maturity and sweetness. The proposed method comprises five main steps: sample preparation, acoustic signal and image acquisition, feature extraction and selection, model development and evaluation, and efficiency comparison, as illustrated in Fig. 1.

We source watermelon samples from a local farm in Thailand. The watermelon samples were kept in a temperature-controlled laboratory. Acoustic signals were recorded from tapping responses in a noise-reduction box, while rind textures were captured under controlled lighting using a digital camera. Then, the samples were weighed, and their SSC levels were measured. Feature extraction and selection techniques were employed to inform key features for the quality detection. Subsequently, maturity classification and SSC detection models were developed using various ML techniques, and their performance was assessed. Lastly, the models produced were compared to earlier research for accuracy evaluation.

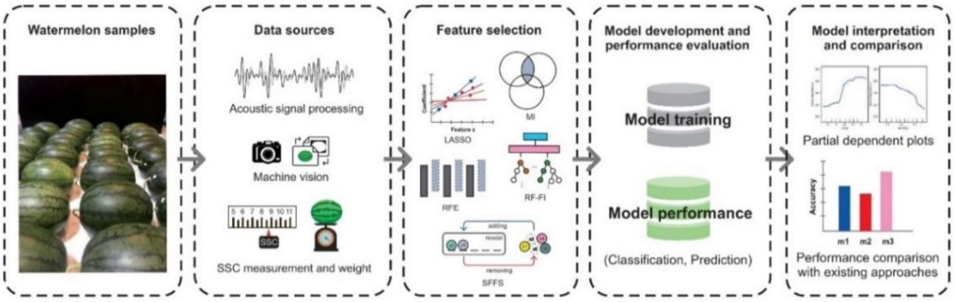

Fig. 1. An overview of the proposed framework.

2.1 Sample preparation

Samples (Kinnaree watermelons) at varying maturity levels were collected by experts to provide a wide range of maturity levels, and then were categorized into three stages (unripe, ripe, overripe). Note that the samples were sourced from two distinct seasons within the same year, with half collected during summer and the other half during winter. Only samples free from bruises or cracks were selected, resulting in a total of 400 watermelons, which were stored in a temperature-controlled laboratory maintained at 25 °C for examination.

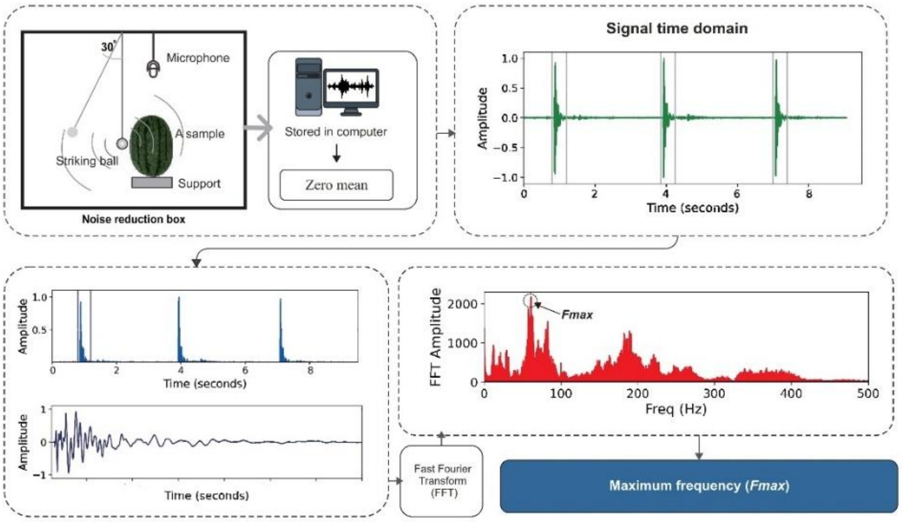

Fig. 2. Schematic diagram of the acoustic detection system.

2.2 Acoustic detection system

A device was developed as a prototype system to detect the acoustic response signals of watermelon samples upon being tapped. The system is equipped with a product support, a microphone, and a striking ball. The equipment was entirely installed inside a noise-reduction box. The ball was released from rest (initial velocity = 0) to impact one side of the sample in the central zone, producing the same contacting force in all tests. The impact ball used in this study was made of steel and had a diameter of 1 inch. As a steel striking ball has a high elastic modulus, it generates a consistent resonance frequency in response signals when hitting, due to the short contact duration [2], [4], [13]. A permanently polarized condenser microphone (RODE, smartLav+) was positioned above the sample to record the sound wave. The acoustic response signals were digitized as 24-bit WAV audio files before being stored on a computer. Fig. 2 illustrates the schematic design of the proposed experiment.

We selected the best three waves to represent the acoustic responses for each sample. However, time-domain signals do not offer insights into the frequency content of the data. These signals are often characterized by significant noise, which limits their ability to provide accurate information. To this end, the selected waves were set to a zero mean before normalization. Subsequently, all signals were subjected to a 0.1 threshold amplitude cut to eliminate background noise and then stored as 4,096 points. The Fast Fourier Transform (FFT) was applied to the signals, enabling the extraction of the frequency at the maximum amplitude value (f_{max}), considered an important feature in the frequency domain. By averaging the f_{max} values of the three waves, the f_{max} of a sample can be obtained.

Fig. 3 shows a signal diagram for a ripe watermelon. The selected window, bounded by the red dashed lines, was used for analyzing and extracting features. The response signals were all normalized; the maximum value of the time domain signal was set to 1, while the others were transformed into fractions between -1 and 1.

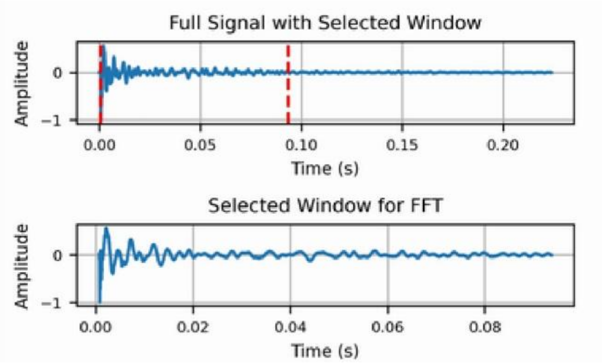

Fig. 3. Full signal and selected window for FFT.

By applying the FFT, the frequency content and amplitude of a signal were extracted. In this approach, the maximum frequency (f_{max}) was used as the critical feature representing the natural frequency of each sample. Fig. 4 compares the f_{max} of each ripeness stage in the frequency-domain signals, illustrating the decrease in natural frequency as the watermelon ripens.

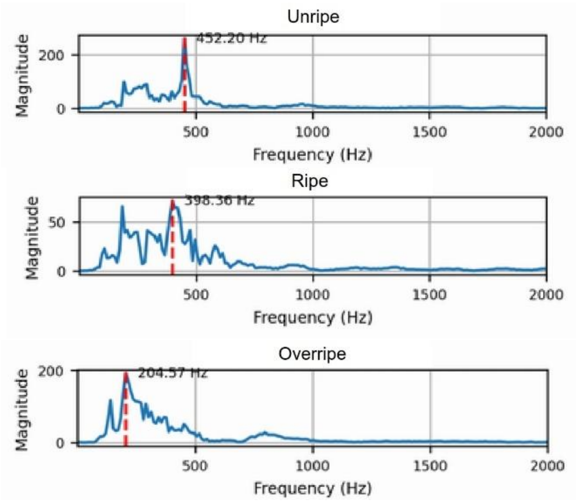

Fig. 4. Comparison of f_{max} for watermelon with different unripe/ripe/overripe stages.

2.3 Image processing system

The experimental configuration for the processing system is shown in Fig. 5. The system has three main components: a product support platform, a camera, and a light source. The components were integrated into a lighting box to control light intensity. The support platform was positioned at the bottom of the lighting box, with a Sony a5100 digital camera mounted on top of the box, encircled by a ring-shaped LED light source. The ring design of the LED modules ensured uniform light intensity, hence improving the dependability of the findings [17]. The mean light intensity recorded on the box floor was 750 lux.

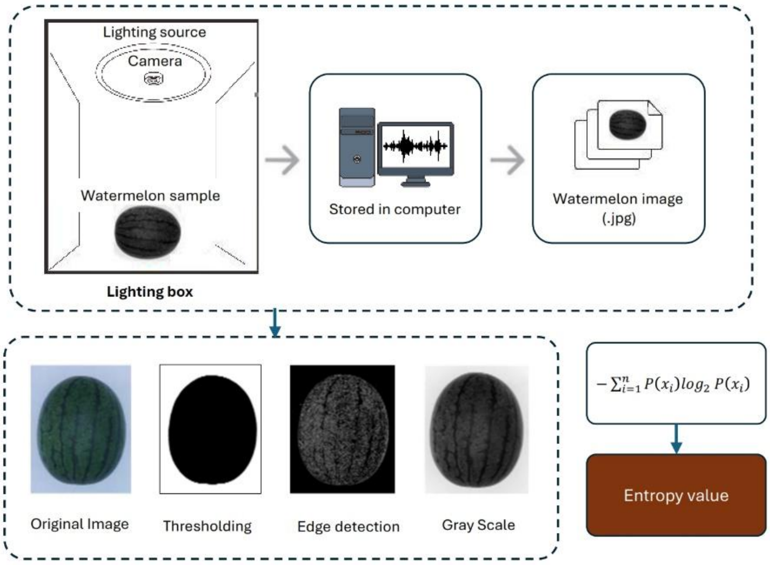

Fig. 5. Schematic diagram of image processing system.

The texture of the watermelon rind was utilized as a key feature in image processing for predicting SSC. This approach was inspired by traditional farming practices, where rind texture patterns are commonly used to estimate maturity, based on the belief that the complexity and size of the patterns increase as the fruit ripens. The literature also indicates that rind textures are crucial for categorizing watermelon's SSC [3].

To quantitatively analyze the texture patterns of watermelon rind, we utilize the entropy function, which provides a measure of stripe distribution and randomness. Entropy is a measure of uncertainty or randomness, which can be used to characterize the texture of an image and investigate the correlation between the external appearance of a watermelon and its internal quality [23], [24]. To this end, we initially detected the shape of the watermelon samples using a morphological operation. Subsequently, the image was converted to grayscale and masked, followed by the application of Canny edge detection to extract the rind pattern from the image. Finally, the entropy function was used to measure the entropy value of the image. An entropy value can be determined by combining all local entropy values throughout an image. The local entropy is calculated by multiplying the probability Distribution (p) with the base $\log_2$ as shown in equation (1):

$$Entropy(x_i) = -p(x_i)log_2(x_i) \tag{1}$$

where x_i is a class of features for an image. The range of the entropy value is between 0 and 1. The higher entropy value means more different information from the average content in an image. A general form of the entropy (H) can be expressed as equation (2):

$$H(x_i) = -\sum_{i=1}^{n} p(x_i)log_2(x_i) \quad (2)$$

Fig. 6 illustrates the maturity levels of the internal fresh color and entropy. Results show that the texture characteristics of watermelons differ across maturity levels, resulting in an increasing entropy value from unripe to overripe watermelons.

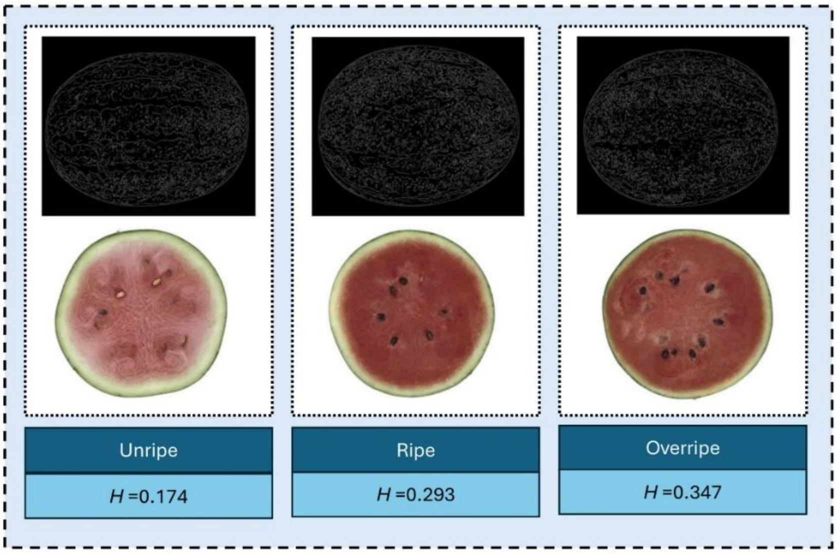

Fig. 6. Maturity levels with internal fresh color and entropy (*H*).

2.4 Ripeness classification and SSC measurement

Following the collection of tapping sound data and rind appearance, the watermelon samples underwent a weighing process. A sensory evaluation was conducted using panel tests to classify watermelon samples based on quality. This was carried out with the assistance of five experts on ripeness classification to minimize bias. Comments were recorded both before and after cutting the watermelons. Pre-cut comments were used to compare human categorization accuracy with that of classification algorithms, while post-cut comments were used to determine the sample classes. The evaluation classified 131 samples as unripe, 145 as ripe, and 124 as overripe.

After ripeness classification, the watermelons were measured for SSC using a handheld refractometer. The SSC of each sample was measured three times, and the average of these measurements was used to represent the sugar content of each sample.

3 Watermelon Maturity and SSC Detection Model

3.1 Database description and feature engineering

The previous section describes how we utilized two non-destructive technologies (signal and image processing) to extract features from watermelon samples. Three main features are obtained, including mass (m), the maximum frequency (f_{max}), and the entropy value (H) of the watermelon samples.

Not only do we use these features alone, but we also consider engineered features, expecting that it can improve the model's robustness and accuracy of the developed models. For example, firmness indices are a combined feature of the mass and the resonant frequency (commonly the first or second natural frequency) for a fruit or vegetable. It is well known that the index significantly correlates with firmness, elastic modulus, and ripeness in agricultural products. For example, an index of firmness (mf^2) was employed to predict the firmness of apples. The modification of mf^2 called $m^{2/3}f^2$, namely the elastic coefficient (EI), developed was found to have strong relations with Young's modulus and was efficiently employed for estimating the internal qualities of fruits such as watermelon, mango, and apple. Other indices like mf and m^2f^2 are also used for estimating the fruit quality. Currently, there is no clear evidence indicating whether the firmness indices are most suitable for Kinnaree watermelons. Therefore, except for m and f_{max}, this study added four firmness indices: mf, mf^2, m^2f^2, and $m^{2/3}f^2$ as candidates to develop the ML models. As a result, a total of 7 features were considered for the model development process: m, f_{max}, H, mf, mf^2, m^2f^2, and $m^{2/3}f^2$. The target output was soluble solids content (SSC). The statistical information of the input features and the target is shown in Table 1.

Table 1: The statistical information of input features.

feature	mean	std	min	max
m (kg)	2.57E+00	4.27E+01	1.789E+00	3.73E+00
f_{max} (Hz)	2.88E+02	6.21E+01	2.10E+02	4.20E+02
H	2.58E-01	8.31E-02	*1.04*E-01	*3.85*E-01
mf ($kg\cdot Hz$)	7.27E+02	1.42E+02	4.22E+02	1.23E+03
mf^2 ($kg\cdot Hz^2$)	2.15E+05	8.13E+04	8.86E+04	4.64E+05
$m^{2/3}f^2$($kg^{2/3}\cdot Hz^2$)	1.58E+05	6.17E+04	7.02E+04	3.13E+05
m^2f^2($kg^2\cdot Hz^2$)	5.48E+05	2.17E+05	1.78E+05	1.51E+06

To partition the data, we randomly separated it into the training and test sets, following common model development practices. This split was performed using a stratified approach across the two distinct seasons to ensure proportional representation in both the training and test sets. The applied approach enables robust evaluation of seasonal variability. The training set comprised 80% (320 samples) of the total database and was utilised for training the model. The remaining 20% (80 samples) of the data was set as unseen data, which served the purpose of evaluating the model's performance. Fig. 7 illustrates the correlation coefficients for the training set as a heatmap, with colors ranging from blue (negative correlation) to red (positive correlation). It was observed that a high negative correlation (-0.85) exists between ripeness and f_{max}. This indicated a strong relationship between the natural frequency and ripening stages of watermelon, as f_{max} decreases when the fruit ripens. For the interaction terms (mf, mf^2, m^2f^2, and $m^{2/3}f^2$), the correlations with ripeness decreased due to the effects of fruit mass. The entropy (H) was found to have a moderate correlation with ripeness, suggesting that variations in the watermelon's skin texture may not be reliable for ripeness classification. This limitation is likely due to the premature harvesting of watermelon samples, during which the skin texture had not yet fully developed. Consequently, ripeness showed only a moderate correlation with soluble solid content (SSC), indicating that the ripeness status did not significantly influence sugar accumulation.

In the case of SSC, moderate correlations were observed when considered individually with m or f_{max}, yielding coefficients of 0.60 and -0.70, respectively. However, when m and f_{max} were combined as firmness indices, the correlations with SSC declined. Among the evaluated features, $m^{2/3}f^2$ demonstrated the strongest correlation with a coefficient of –0.61. Moreover, the firmness-related features had high intercorrelation, with coefficients ranging from 0.82 to 0.99, suggesting that they carried overlapping information relevant to SSC prediction. Regarding entropy (*H*), which represents the rind pattern of watermelon, its correlation with SSC was 0.70, being comparable to that of f_{max}.

The correlation analysis presented suggests that the use of individual features offers limited classification and predictive capability. Consequently, incorporating multiple features is essential for enhancing the accuracy of the classification and prediction tasks. It enables the model to capture more complex and complementary patterns that are not represented by any single feature alone. The following section presents the feature selection process, which aims to identify the most informative subset of features for model development.

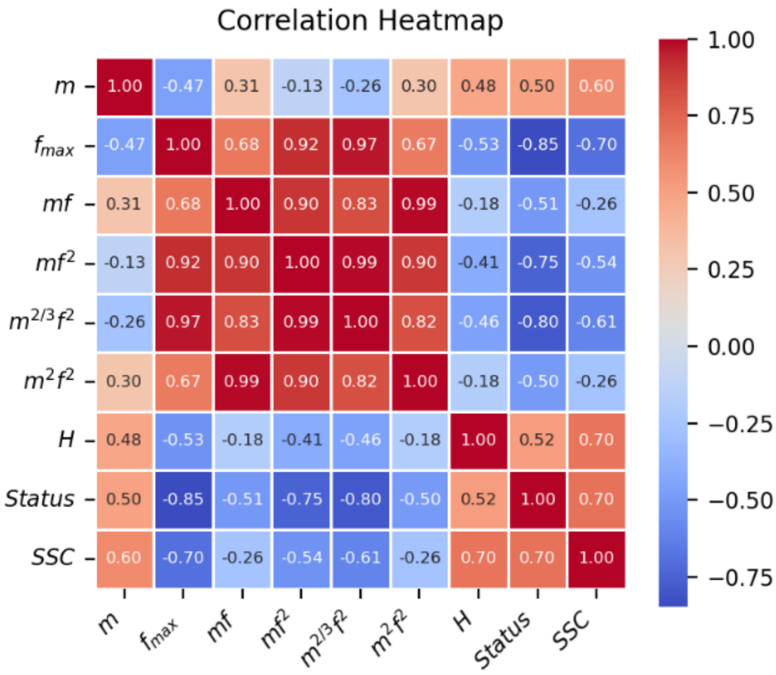

Fig. 7. The feature correlation plot.

3.2 Evaluation of important features

Not all features presented previously made a practical contribution to the model accuracy. Therefore, feature selection is necessary to identify those most strongly correlated with class discrimination and SSC prediction. This section presents techniques applied to select important features for the model development. The seven features were considered as candidates. In this study, we employ several feature selection techniques to evaluate the importance of the features, including Mutual Information (MI), Recursive Feature Elimination (RFE), Sequential Forward Floating Selection (SFFS), Least Absolute Shrinkage and Selection Operator (LASSO), Elastic Net, and Random Forest Feature Importance (RF-FI).

MI is an information theory metric that quantifies the amount of information one feature contributes to another. It captures both linear and nonlinear dependencies, helping to determine the mutual dependence of each feature and the target. Second, RFE is a wrapper-based strategy for repeatedly training a model and ranking features based on relevance. At each iteration, the least significant feature is removed, and the procedure is repeated until a certain number of features remain. RFE is good in capturing interactions between features, but it is computationally costly and sensitive to data variations. The third is SFFS, which is an improvement on basic forward selection. It starts with iteratively adding a candidate to the model to maximize a predefined criterion or minimize error. Furthermore, it performs a backward elimination step if deleting features improves performance, resulting in a flexible and adaptable technique for feature selection. The selection is stopped when no feature is added to the model. For another approach used, Lasso is a regularization approach that incorporates feature selection into its linear regression framework by penalizing the absolute values of the coefficients. This penalty tends to reduce specific coefficients to zero, thereby removing unimportant features and decreasing overfitting. However, Lasso might suffer when features are strongly correlated. Elastic Net combines the penalties of Lasso (L1) and Ridge (L2) regression to achieve a balance between the two. It is intended to handle multicollinearity more strongly than Lasso by combining feature selection with coefficient shrinking. Elastic Net allows flexibility in handling duplicate features by altering hyperparameters for each penalty. Last, RF-FI is a feature selection approach that leverages Random Forest ensemble learning techniques to assess candidate features based on their predictive potential. The features are ranked by their ability to decrease impurity or improve accuracy when permuted. Essentially, features that result in larger reductions in model error are considered more important. This approach efficiently captures non-linear relationships and interactions, offering a practical way to prioritize features.

3.3 Model development

In the classification problem, we categorized watermelon samples into three maturity levels: unripe, ripe, and overripe. For the sweetness prediction problem, we used SSC as the sugar content index. The features selected via feature selection methods were then employed for model development. We applied eight ML algorithms for comparison: Artificial Neural Network (ANN), Support Vector Regression (SVR), Decision Tree (DT), K-Nearest Neighbor (KNN), Random Forest, Gradient Boost, AdaBoost, and XGBoost. Hyperparameters were tuned to guarantee robustness and accuracy during model training.

After comparing the performance of the single ML models, Super Learner (SL) models were developed. SL is an advanced ensemble learning technique that optimally combines multiple machine learning algorithms (base learners) using cross-validated predictions. It operates in two layers: first, various base models make their predictions, then a meta-learner learns the optimal weighted combination of these predictions. This approach automatically adapts to data features, offering improved prediction accuracy and reduced bias. In this study, we selected three to four of the highest-performing algorithms among ML models for the SL model development.

We applied several performance metrics to evaluate the classification models' performance, including precision, recall, accuracy, and F1 score. They can be expressed as equation (3)-(6):

$$precision = \frac{TP}{TP+FP} \tag{3}$$

$$recall = \frac{TP}{TP+FN} \tag{4}$$

$$accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (5)$$

$$F1 = \frac{2 \times precision \times recall}{precision+recall} \quad (6)$$

where TP is true positive; TN is true negative; FP is false positive; and FN is false negative. In the SSC prediction, three metrics were used to assess the performance: the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute percentage error (MAPE), expressed as equations (7)-(9):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)} \quad (7)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (8)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (9)$$

where $\hat{y}_i$ is the estimated target, y_i is the real target value, and n is the data points.

4 Results and Discussions

4.1 Maturity classification model

Fig. 8 summarizes the features selected using different approaches. MI analysis indicates that f_{max} scored 0.65, $m^{2/3}f^2$ scored 0.52, and mf^2 scored 0.48, clearly differentiating the most influential features from those with lower importance. Meanwhile, the RFE method not only confirmed the top three features inconsistent with MI but also identified H as a valuable predictor. Both Lasso and Elastic Net produced very similar outcomes, emphasizing $m^{2/3}f^2$, mf^2, and m^2f^2 as having the strongest coefficients. The RF-FI method further validated f_{max}, $m^{2/3}f^2$, and mf^2 as key predictors. Overall, the most critical features were identified as f_{max}, $m^{2/3}f^2$, and mf^2. These features consistently demonstrated the highest importance across the applied methods, with f_{max} emerging as the most significant feature. In addition to the primary features, there are secondary features that provide supplementary classification power, including mf^2 and $m^{2/3}f^2$. The interaction terms between m and f_{max}, which represent the watermelon firmness, are expected to contribute additional information to the analysis. However, due to high collinearity between mf^2 and $m^{2/3}f^2$, as illustrated in the correlation analysis (Fig. 7), we only considered $m^{2/3}f^2$ in our analysis. Hence, the total combined features for our classification models were f_{max} and $m^{2/3}f^2$.

Based on the results, we propose an SL model with a diverse set of base models, including ANN, SVM, RF, and XGBoost. These four models not only perform well on the given data but also provide a balance between non-linear representation, ensemble diversity, and complementary predictive strengths. In other words, an ANN can capture complex non-linear patterns, while an SVM provides robust decision boundaries. The reliable ensemble method of RF emphasizes variance reduction via bagging, and the strong boosting performance of XGBoost helps handle sophisticated interactions.

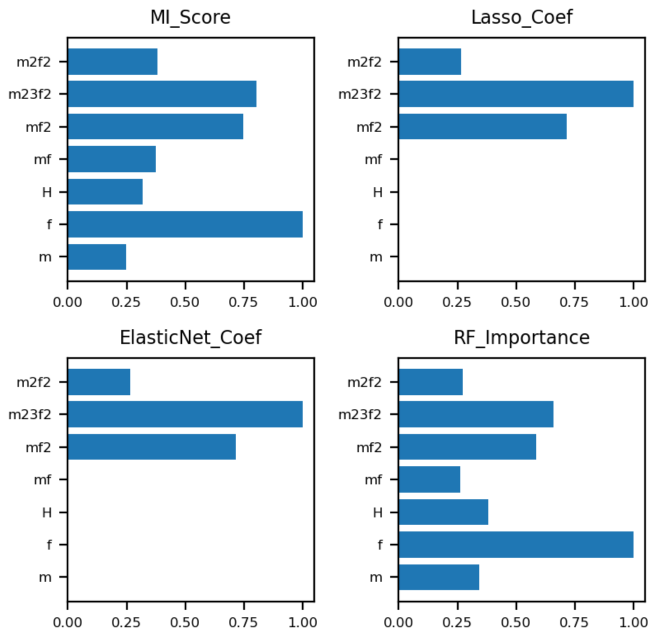

Fig. 8. Comparison of feature selection results for the maturity classification.

The meta-learner provided ensemble-level behavioral insights after finding the optimal combination. ANN and SVM had the most significant positive impact on correct-class probabilities, while RF and XGBoost provided complementary, stabilizing decisions. The classification performance of the Super learner model is shown in Table 2. The SL model has achieved an accuracy of 0.88 (88%), which is a significant improvement over our models (previous best was 80% with ANN).

Table 2: Model performances of the classification models.

Model	**Accuracy**	**Precision**	**Recall**	**F1-score**
ANN	0.80	0.80	0.80	0.80
DT	0.79	0.79	0.78	0.78
RF	0.76	0.77	0.76	0.76
AdaBoost	0.76	0.76	0.76	0.76
GBT	0.79	0.79	*0.79*	*0.79*
XGboost	0.79	0.79	0.79	0.79
SVM	0.78	0.77	0.78	0.78
KNN	0.78	0.78	0.77	0.77
Super Learner	0.88	0.89	0.88	0.88

The confusion matrix for the test set of the SL model is provided in Fig. 9 for the performance analysis. It clearly shows that most predictions fall along the diagonal, indicating that the SL is generally effective across all classes. For the Unripe class, the model correctly identifies 88.5% of the observations, suggesting that their feature representation is sufficiently distinct for accurate classification. In the Ripe class, the model exhibits a high rate with a 93.1% correction. Some false positives possibly result from shared characteristics with the Overripe class. However, the Overripe class was predicted to be at an 80% correct rate, indicating that a portion of Overripe instances are misclassified into the Ripe class. One primary reason for the misclassification may be the small sample size of the overripe class. The result suggests that further investigation is needed to distinguish these classes for future research.

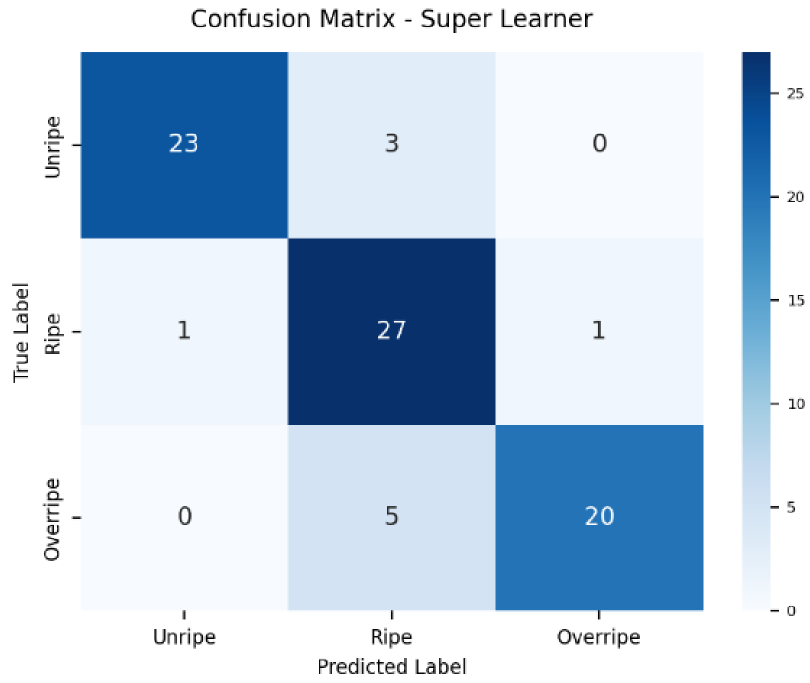

Fig. 9. Confusion matrix plot.

The confusion matrix for the test set of the SL model is provided in Fig. 9 for the performance analysis. It clearly shows that most predictions fall along the diagonal, indicating that the SL is generally effective across all classes. For the Unripe class, the model correctly identifies 88.5% of the observations, suggesting that their feature representation is sufficiently distinct for accurate classification. In the Ripe class, the model exhibits a high rate with a 93.1% correction. Some false positives possibly result from shared characteristics with the Overripe class. However, the Overripe class was predicted to be at an 80% correct rate, indicating that a portion of Overripe instances are misclassified into the Ripe class. One primary reason for the misclassification may be the small sample size of the overripe class. The result suggests that further investigation is needed to distinguish these classes for future research.

4.2 SSC detection model

Similar to the development of the classification model, our SSC detection modelling started with feature selection using six techniques. Fig. 10 illustrates the selection results, revealing important insights into the SSC prediction. Unlike the classification problem, the entropy feature (H) emerges as the most consistently influential feature across all selection methods. It demonstrated high importance scores in MI, the strongest coefficients in both Lasso and Elastic Net analyses, and the highest importance in RF. It was followed closely by the natural frequency, f_{max}, which shows strong predictive power, particularly in MI and RF analyses. However, its importance is diminished in the Lasso and Elastic Net models. Moreover, m was observed as a moderate but consistent level of importance across all methods, suggesting its reliable contribution to the model. Interestingly, the interaction terms (mf^2, $m^{2/3}f^2$, m^2f^2) generally show lower predictive power across all methods. To this end, the features considered for our predictive models were H, f_{max}, and m.

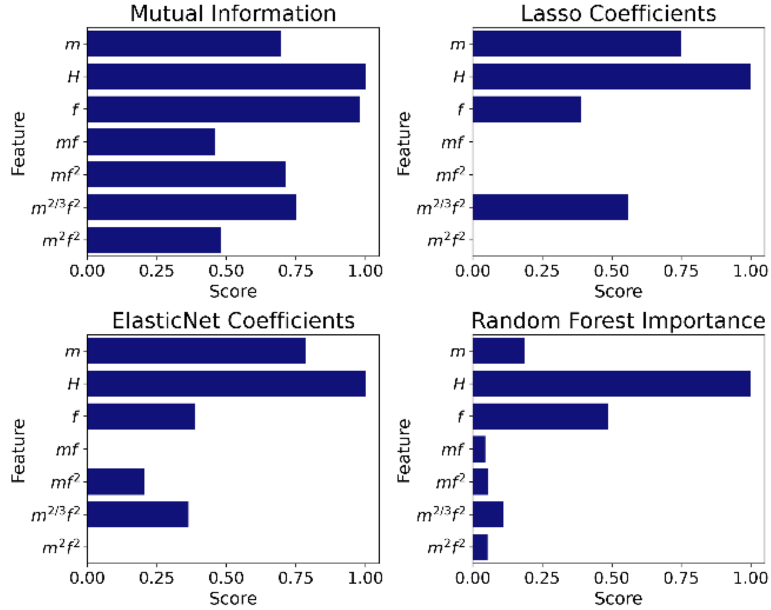

Fig. 10. Comparison of feature selection results for the SSC prediction.

Fig. 10 Comparison of feature selection results for the SSC prediction. Table 3 shows that SVM stands out as the best-performing individual model, achieving the highest R^2 (0.71), the lowest RMSE (0.84), and the lowest MAPE (6.73%). This indicates that SVR can explain the most variance in the SSC values. Random Forest and Gradient Boosting yield strong results, with R^2 values exceeding 0.69 and error metrics comparable to those of the top models. KNN, XGBoost, and Decision Tree regressors have lower R^2 and higher error rates, indicating less effective modeling of the SSC variable. The ANN model has the lowest R^2 (0.579) and the highest RMSE and MAPE, suggesting it is not well-suited to this regression problem.

Table 3: Model performances of the SSC prediction models.

Model	**R^2**	**RMSE**	**MAPE**
ANN	0.58	1.02	8.49
DT	0.61	0.98	7.97
RF	0.70	0.85	6.78
GBT	0.69	0.87	*7.06*
XGboost	0.65	0.92	7.27
SVM	0.71	0.84	6.73
KNN	0.68	0.87	7.12
Super Learner	0.72	0.82	6.55

A predictive-based SL model for SSC was developed based on the performance results. Three algorithms were selected, including SVM, RF, and GBT. The result indicates that the performance of SL was slightly higher than that of the others individually, with an R^2 of 0.72 and lower errors. Moreover, we interpreted the nonlinear relations between the three input features and SSC using partial dependence plots, as shown in Fig. 11. It is observed that the rind texture (explained by *H*) and weight (*m*) have a positive effect, especially in the middle range of the features. The natural frequency was found to have nonlinearly negative impacts on the prediction.

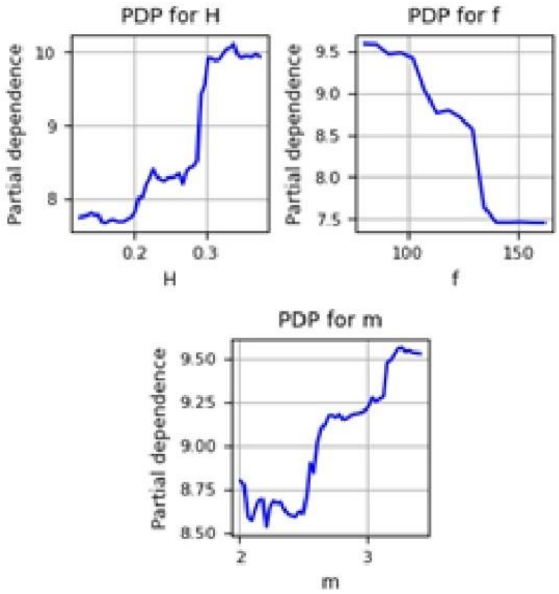

Fig. 11. Partial dependent plots of key features.

5 Performance Comparison with Previous Models

To provide a more comprehensive evaluation, the SSC prediction accuracy of the proposed method was compared with that of previous studies. The most successful model, SL, is used for the comparison. However, no study has yet applied the combined information from acoustic and image processing technologies to predict the SSC of watermelon. Therefore, existing models from other non-destructive detection techniques are used in this comparison. NIR and VIS-NIR spectroscopy technologies, carried out in the literature [21], [25], were employed. NIR and VIS-NIR spectroscopy are non-destructive technologies that have been widely applied in practice for detecting SSC of watermelon. These technologies have been efficiently used on a commercial scale as an online detection system [5]. Thus, these spectroscopy technologies are suitable for benchmarking the performance of this proposed method. The comparative result is provided in Table 4.

Table 4: Comparison of the prediction accuracy among different approaches.

Model	r	RMSE
This proposed method	0.848	0.820
Qi et al. [21] *(VIS-NIR spectroscopy)*	0.862	0.717
Jie et al. [25] *(NIR spectroscopy, 14 features)*	0.845	0.574

To be consistent with previous studies, the correlation coefficient of the test set (r) was used in this comparison. It is noted here that, in the literature, Jie et al. [25], the authors evaluated different sets of combined features. Thus, we selected the model using 14 features for this comparison, as the authors considered this set to be the optimal model. According to the table, our model achieved a correlation coefficient equal to or slightly higher than that of previous proposals, indicating a stronger linear relationship between the predicted and actual values. However, the earlier studies reported a lower RMSE, suggesting higher precision in individual predictions. These results indicate that the previous models demonstrate slightly better accuracy.

While these metrics suggest that the previous model yields more precise point predictions, our model offers significant practical advantages in terms of deployment and scalability.

Specifically, our model requires only a microphone and camera, making it more suitable for integration into mobile or portable devices. This enhances usability and accessibility, especially for local farmers and small businesses.

6 Limitations and Future Works

The proposed method relies on two- to three-dimensional space based on three external characteristics of watermelons: weight, rind texture, and tapping sound to explain maturity levels and SSC. This approach should be used for the Kinnaree watermelon cultivar, with parameter values spanning the statistical scopes provided in Table 1. The dataset in this study may not be typical of all watermelons. Additional sample sets and calibration across varieties are necessary to improve model accuracy and generalizability. Future work will focus on the model's performance stability in realistic ambient conditions, including the effects of variable, uncontrolled industrial lighting and the background noise characteristic of processing lines.

7 Conclusion

This paper presents a low-cost, portable, and scalable non-destructive testing (NDT) detection technique for assessing watermelon ripeness and soluble solids content (SSC) using signal and image processing. The watermelon's rind texture, tapping sound, and weight were used as the critical characteristics. Model mapping technologies include ML methods as well as Super learners. Two main tasks were carried out: classifying watermelon maturity and predicting soluble solids content (SSC), which is a key indicator of fruit sweetness and quality. Watermelon features were extracted through signal and image processing techniques. First, a range of machine learning models was evaluated for both tasks, including Decision Tree, Gradient Boosting, XGBoost, Support Vector Machine, KNN, Artificial Neural Network, and Random Forest. Then, Super Learner was developed among these diverse models. This research employed various ML-based feature selection techniques to carefully select key features and utilized grid search strategies to optimize the collection of hyperparameters for model development.

For the maturity classification task, the ANN model achieved the highest accuracy among individual models at 80%. However, when multiple models (ANN, SVM, RF, XGBoost) are combined into a Super learner ensemble, the accuracy improves further to 88%. The confusion matrix analysis showed that the SL model was particularly effective, with high correct prediction rates for both Unripe (88.5%) and Ripe (93.1%) classes, indicating robust performance across all maturity levels. In the SSC regression task, the SVM regressor stood out as the best single model, while the Super learner provided a slight improvement in performance. Partial dependence plots from the analysis revealed meaningful nonlinear relationships between the features of rind texture, weight, and natural frequency, and the SSC.

The comparative study with previous proposals indicated that, although our RMSE is slightly lower, the proposed method achieves a similar level of predictive correlation while offering substantial benefits in terms of portability and accessibility. These characteristics make it a strong candidate for practical deployment in fruit sorting. Given its ensemble structure, the Super learner model has low computational overhead, making its deployment highly feasible on low-cost, resource-constrained devices such as microcontrollers or smartphones.

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