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An acoustic-mechanical sensing system with multimodal machine learning techniques for in-line quality grading of watermelons

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ABSTRACT

A complete assessment of both internal and external quality parameters of watermelons is essential for export. However, small and medium-sized watermelon export enterprises often face challenges in accessing cost-effective and integrated grading systems. This study proposes an acoustic-mechanical sensing system for classifying watermelons based on both sweetness and weight. By combining weight measurement and sweetness estimation through acoustic analysis at a single station, the proposed system achieves a compact design and reduces data acquisition time. Additionally, a multimodal machine learning approach is applied to classify watermelon quality accurately. Among the tested models, the K-Nearest Neighbors model achieves the highest classification performance, with an accuracy of 97.3% and a precision of 96.6%. With its strong classification ability, integrated design, and low cost, the proposed system shows great potential for automated in-line quality grading of watermelons and other agricultural products. Unlike conventional large-scale systems that cascade individual grading functions, the integrated and cost-effective design of this system is suitable for small and medium-sized watermelon export enterprises to apply at each distributed shipping facility during intensive periods.

1. INTRODUCTION

Comprehensive quality assessment of fruits plays an essential role in their post-harvest handling and commercialization, particularly in export-oriented supply chains. For watermelons, both external and internal quality attributes are important for determining market value and consumer acceptance. External factors such as weight and visual appearance are commonly used due to their simplicity and the availability of objective measurement tools like electronic scales and visual inspection systems. However, internal attributes such as sweetness and hollow heart are even more important, as they strongly influence consumer satisfaction and directly impact the reputation of exporters (Liu et al., 2024). Despite their importance, internal quality traits are more difficult to assess in a rapid, non-destructive, and cost-effective manner.

Among the internal quality traits of watermelons, sweetness is particularly significant and difficult to evaluate accurately. In practice, it is often estimated based on the experience of growers or traders, or through destructive methods using specialized instruments such as refractometers. The experience-based approach lacks objectivity and reliability, as it depends heavily on individual skills and cannot be consistently applied. On the other hand, destructive testing provides more accurate results but is labor intensive, requires cutting the fruit, and can only be performed on a limited sample (Yu et al., 2024). As a result, it fails to represent the quality of the entire batch and is unsuitable for large-scale or real-time quality control.

To overcome the limitations of traditional methods, several non-destructive techniques have been explored for internal quality assessment of watermelons and other fruits, including machine vision, magnetic resonance imaging, spectroscopy, dielectric properties, laser Doppler vibrometer, and acoustic analysis (Mohd Ali et al., 2017; Tran et al., 2021; Yu et al., 2024; Nguyen et al., 2025). Among these, acoustic-based methods have shown promising results in terms of accuracy, cost-effectiveness, system simplicity, and evaluation speed. Zeng et al. (2014) developed a mobile application to classify the ripeness of watermelons using acoustic techniques with an accuracy of 87%. Liza Pintor et al. (2016) also used acoustic analysis on a mobile phone to classify the maturity of watermelons based on sweetness with an accuracy of 92.79%. These results made acoustic sensing a practical solution for rapid and affordable estimation of internal attributes of watermelons, such as sweetness, especially in large-scale or field-based applications.

In addition to sweetness, weight is also an important metric of watermelon quality. This is mainly due to the current practices of watermelon production, where they are harvested simultaneously across the entire field according to their planting date and the quality of a few samples assessed by farmers empirically, resulting in inconsistent quality. However, especially for export markets, both sweetness and weight are critical parameters for quality assurance (Yu et al., 2024), and grading and sorting are inevitable at the time of shipment of each batch of harvested watermelons. This demands the development of reliable solutions that can completely evaluate sweetness and weight to support more precise sorting and grading processes.

In large-scale agricultural enterprises, specialized systems for automated in-line quality grading have already been deployed (Jie & Wei, 2018). These typically involve commercial solutions with cascaded independent stations measuring various metrics such as weight and sweetness. Such systems are suitable for production where numerous products are collected in a facility and graded on a large scale and continuously. However, these systems are not so suitable for watermelon farmers because SMEs are distributed throughout the country, and their shipping facilities are small-scale and intensively operated during certain periods.

As a result, many SMEs still continue to rely on manual assessment methods in which sweetness is estimated based on human experience, and weight is measured using commercial scales. This approach lacks accuracy and consistency, and does not provide any advantages of in-line grading, which limits the ability of these enterprises to meet export standards or maintain quality control.

Therefore, it is necessary to develop an in-line grading system based on both sweetness and weight, effectively applicable at each farm or distributed shipping facilities during intensive periods. Such a system would support early quality classification at SMEs. This brings benefits to different stakeholders in the watermelon production and supply chain. Specifically, farmers can improve their income because accurate quality assessment helps increase the value of their products. SMEs can set prices more easily based on quality and export watermelons that meet the standards of target markets. In addition, the system helps remove low-quality products early, reducing storage and transportation costs. Consumers also benefit because they can trust the declared quality and enjoy watermelons that meet their expectations.

This study proposes an acoustic-mechanical sensing system for the classification of watermelons based on both sweetness and weight. A key feature of the proposed system is its integrated design, which combines sweetness and weight measurements at a single station, resulting in a compact setup and reduced data acquisition time. Additionally, a multimodal machine learning approach is employed to accurately classify watermelon quality. This integrated solution offers lower investment costs and supports automated in-line quality grading, making it suitable for SMEs. Ultimately, the proposed system contributes to the advancement of high-tech and sustainable agriculture.

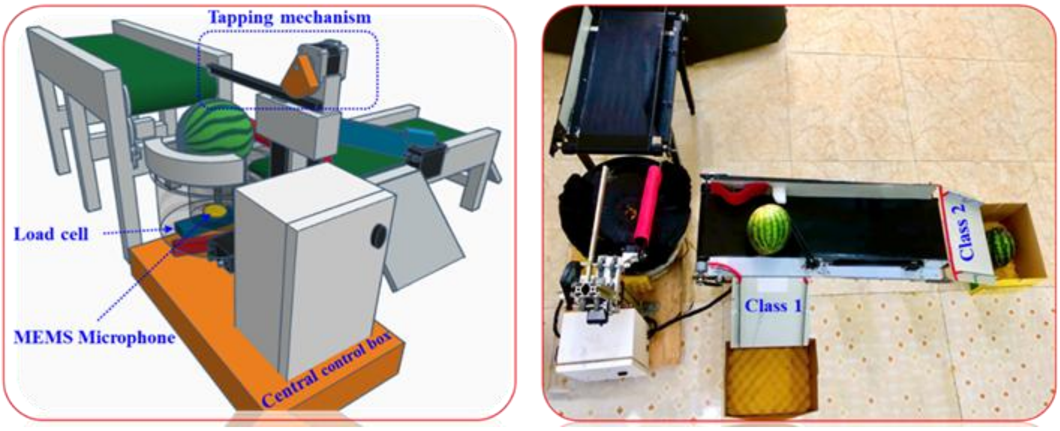
2. MATERIALS AND METHOD

2.1. Sample preparation

A total of 50 watermelons were used in this study. The watermelon variety selected was Thanh Long TN522, a commonly cultivated watermelon type in the Mekong Delta region of Viet Nam due to its short growing period (55–60 days) and strong resistance to pests and diseases (Thuc & Minh, 2022). The fruits were harvested at two different time points: day 56 and day 59 after planting. These harvest dates were chosen based on local growers' experience in selling to traders. The watermelons were grown in Hau Giang province, Vietnam. After harvesting, the fruits were transported to the laboratory, where they were cleaned thoroughly before conducting further experiments.

2.2. Proposed system

The proposed system consists of several main components, including a tapping mechanism, a fruit holder integrated with both an acoustic sensor and a weight measurement device, a central control unit, and belt conveyors with a sorting mechanism, as illustrated in Figure 1.



(a) (b)

Figure 1. The three-dimensional model (a) and prototype (b) of the proposed system

Tapping mechanism: The tapping mechanism was designed to apply a controlled tapping force to the watermelon in order to generate acoustic signals. To prevent damage to the fruit, the tapping arm was made of wood, with the tapping head consisting of a steel ball weighing approximately 30 grams, covered by a soft rubber layer. The lifting angle of the tapping head was fixed and controlled by an electric motor with a cam disk mounted on the motor shaft (Figure 1a). This design ensures that the tapping force is carefully regulated to produce reliable and reproducible acoustic responses without causing harm to the watermelons.

Fruit holder: The fruit holder is a crucial component of the proposed system. It was designed as a cylindrical structure with a MEMS microphone (model INMP441, InvenSense Inc., California, United States) embedded inside to capture the acoustic signals generated when the watermelon was tapped by the tapping mechanism. Additionally, the fruit holder was mounted on a load cell sensor (model YZC-133) paired with a signal amplification module (model HX711) to measure the weight of the watermelon during tapping and acoustic data acquisition. This integrated design enabled the assessment of sweetness and weight simultaneously at a single station, allowing the system to rapidly complete a comprehensive quality evaluation of the watermelon.

Central control unit: A Raspberry Pi 3 mini-computer was used as the central control unit in this study. It is a high-performance, low-cost device that supports various peripheral connections with a variety of communication protocols (Raspberry Pi 3 Model B+, 2025). In this study, the Raspberry Pi 3 was responsible for (1) reading input signals, (2) processing input data, estimating watermelon sweetness and weight, (3) executing the machine learning model, and (4) outputting control signals to actuators.

Belt conveyors and sorting mechanisms: Two belt conveyors were used in this study: an input conveyor that transports watermelons to the fruit holder, and an output conveyor that moves the watermelons to the appropriate collection containers. Additionally, a guide arm was mounted on the frame of the output conveyor to sort the watermelons into the correct containers after classification.

In addition to these main components, the system also employed infrared proximity sensors to detect the presence of watermelons, utilized relays to activate electric motors, 5/12 VDC power supplies, and a number of other supporting equipment.

2.3. Operation of the system

The system operates according to the following sequence: first, the belt conveyors are started, and watermelons are transported onto the input conveyor to the fruit holder. At this station, the watermelons are tapped, and the reflected acoustic signals are captured by the MEMS microphone, while their weight is simultaneously measured by the load cell sensor. The acoustic and weight data are read and processed by a Raspberry Pi 3 mini-computer to calculate the frequency with the largest amplitude (F_{max}) and the weight of each fruit. These data are then input into a machine learning model to classify the watermelons based on sweetness and weight. Finally, the guide arm on the output conveyor is activated to sort the watermelons into the appropriate containers. Figure 2 illustrates the operation flow of the system.

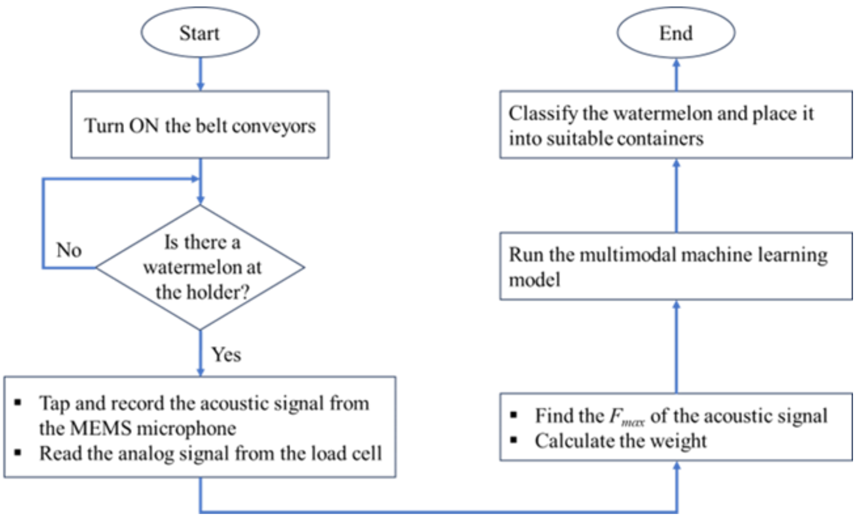


Figure 2. Operation flow of the proposed system

2.4. Reference measurement

After acquiring the acoustic signals and measuring the weights of the watermelons using the proposed system, the actual weight and sweetness of the fruits were measured using reference devices.

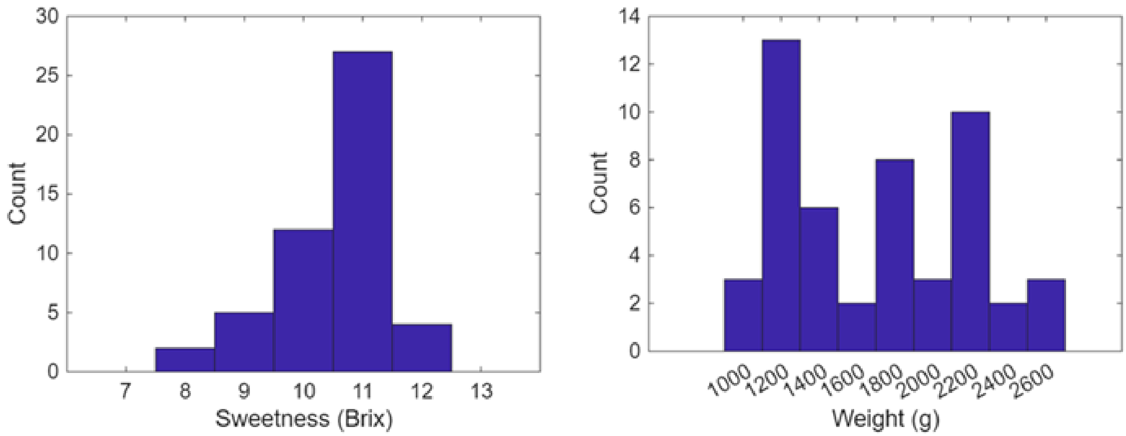
Weight measurement: A commercial kitchen scale (model GP-K1905-3000, GRAM PRES Co., Ltd., China) was used. This scale has a maximum capacity of 3000 g and a resolution of 0.1 g.

Sweetness measurement: A commercial pocket Brix-Acidity meter (model PAL-BX|ACID15, Atago Co., Ltd., Tokyo, Japan) was employed to measure the sweetness of the watermelons. This meter has a measurement range of 0 to 90 Brix, a resolution of 0.1 Brix, and an accuracy of ±0.2 Brix. The procedure for measuring the sweetness of watermelons followed the method described in (Tran et al., 2024). Table 1 presents the statistics on the sweetness and weight of the 50 watermelons used in this study.

Table 1. Statistics on the sweetness and weight of the watermelon samples

Item	Sweetness (Brix)	Weight (g)
Minimum	7.6	1094
Maximum	12.0	2628
Average	10.6	1709
Standard deviation	0.89	475.1

The sweetness values ranged from 7.6 to 12.0 Brix, with an average of 10.6 Brix and a standard deviation of 0.89 Brix, indicating moderate variability in sugar content among the samples. The weight of the watermelons varied from 1094 g to 2628 g, with a mean weight of 1709 g and a standard deviation of 475.1 g, reflecting a considerable size variation within the sample set. Figure 3 shows the distributions of sweetness and weight for the 50 Thanh Long TN522 watermelons in this study.



(a) (b)

Figure 3. Histograms of (a) sweetness and (b) weight for the 50 watermelons

In Figure 3a, the sweetness values mainly concentrate around 11 Brix, with fewer fruits at the lower and higher ends of the range. This indicates a distribution slightly slanted towards higher sweetness levels. Figure 3b illustrates the weight distribution, which spans a broad range from about 1000 g to 2600 g. The data reveal several peaks at different weight intervals, reflecting natural variability in fruit size. These distributions demonstrate the diversity in both sweetness and weight among the watermelons, highlighting the importance of an effective sorting system to ensure consistent quality.

The threshold values for classifying watermelons based on sweetness and weight vary depending on the watermelon variety and target market. Therefore, in this study, the average values were chosen as classification thresholds. Specifically, watermelons with sweetness greater than 10 Brix and weight exceeding 1700 g were classified as "Class 1", while the remaining samples were classified as "Class 2."

2.5. Classification models and evaluation

Six popular classification algorithms, including Decision Tree (DT), Discriminant Analysis (DA), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Random Forest (RF), and Neural Network (NN), were employed in this study. To identify the most effective classification model, several hyperparameters for each algorithm were tuned during the training process, as summarized in Table 2.

Table 2. Several hyperparameters for each proposed classification algorithm

Algorithm	Hyperparameter
DT	Maximum number of splits: 4, 20, 100
DA	Linear, quadratic
SVM	Linear, quadratic, cubic, Gaussian
KNN	Number of neighbors: 1, 10, 100
RF	Number of learners: 30, maximum number of splits: 369
NN	Connected layer: 1, 2, 3; layer size: 10, 25, 100

To compare and select the best-performing model among the proposed models, accuracy and precision metrics were used as evaluation criteria. This metrics were calculated based on the confusion matrix information and are defined by Equations (1) and (2).

$$Accuracy = \frac{TP + TN}{TP+FP+TN+FN} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

whereas,

- TP (True Positive): True Class 1 sample was correctly predicted as Class 1,
- FN (False Negative): True Class 1 sample was wrongly predicted as Class 2,
- FP (False Positive): True Class 2 sample was wrongly predicted as Class 1,
- TN (True Negative): True Class 2 sample was correctly predicted as Class 2.

In this study, precision was prioritized as the main evaluation criterion because misclassifying a watermelon of Class 2 quality (i.e., not meeting sweetness or weight requirements) as Class 1 would reduce customer trust if they purchase such fruit. Additionally, model size and prediction speed were considered secondary criteria when models showed comparable classification performance.

The Classification Learner application in MATLAB was used for training and testing the machine learning models. The software was run on a laptop with normal specifications, featuring a 2.40 GHz CPU and 6.00 GB RAM.

3. RESULTS AND DISCUSSION

3.1. Accuracy of the proposed weighing system

The weight measurements of the watermelons obtained using the proposed weighing system in this study were compared with those measured by a commercial scale. The statistical information is presented in Table 3.

Table 3. Statistical information on the weights of watermelons measured by the proposed weighing system and a commercial scale

Item	Commercial scale (g)	Proposed system (g)	Error (%)
Minimum	1094	1091.94	0.15
Maximum	2628	2613.80	0.63
Average	1708.98	1703.75	0.28
Standard deviation	475.10	472.07	0.12

The results showed very close agreement between the two methods. The minimum, maximum, average, and standard deviation values measured by the proposed system were all within a small margin of error (less than 1%) compared to the commercial scale. This indicates that the proposed weighing solution provides accurate and reliable measurements, making it suitable for practical application in watermelon quality assessment.

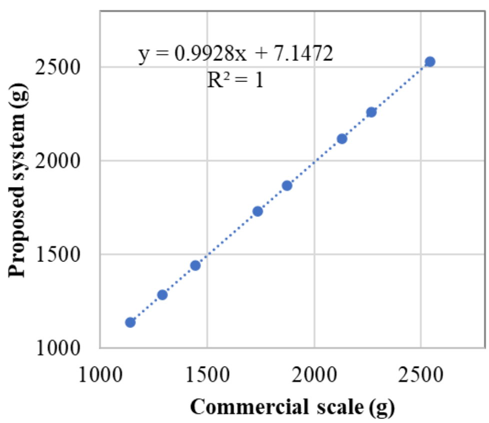


Figure 4. Relationship between the average weight of watermelon samples measured by the commercial scale and the proposed weighing system

To further illustrate this, Figure 4 shows the relationship between the average weight of watermelon samples, ranging from 1000 g to 2600 g with an interval of 200 g, measured by both methods. A coefficient of determination of 1 indicates that the weights measured by the proposed system completely fit those measured by the commercial scale.

Based on the statistical information presented in Table 3 and the scatter plot of average weights shown in Figure 4, the proposed weighing solution in this study demonstrates high accuracy and effective performance.

3.2. Correlation between frequency analysis and sweetness

To evaluate the feasibility of the acoustic recording and analysis method for estimating the sweetness of watermelons, the correlation between the sweetness measured by a destructive method with the commercial meter and the F_{max} frequency extracted from the acoustic signal of the fruit was examined and is presented in Table 4.

The sweetness values range from 7.60 to 12.00 Brix, with an average of 10.60 Brix and a standard deviation of 0.89 Brix. The F_{max} frequency varies between 211.20 Hz and 290.50 Hz, with an average of 250.32 Hz and a standard deviation of 21.38. These results show a consistent variation in both sweetness and frequency values, which supports further analysis of the correlation between the two parameters. Figure 5 shows the relationship between the average sweetness values at six points within the sweetness range and the corresponding average F_{max} frequencies for those intervals.

Table 4. Statistical information on measured sweetness and F_{max} frequency extracted from watermelon acoustic signals

Item	Measured sweetness (Brix)	F_{max} value (Hz)
Minimum	7.60	211.20
Maximum	12.00	290.50
Average	10.60	250.32
Standard deviation	0.89	21.38

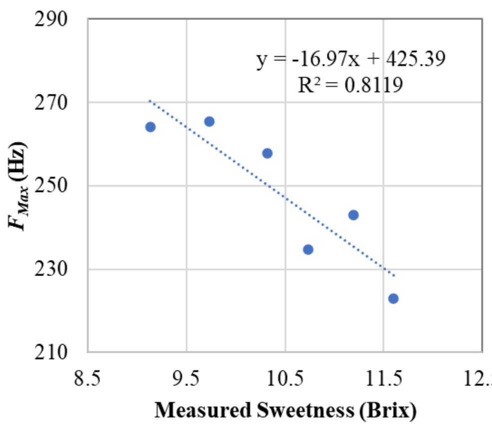


Figure 5. Relationship between measured sweetness and F_{max} frequency of watermelon samples

Figure 5 shows that as the sweetness of the watermelon increases, the Fmax frequency decreases. The coefficient of determination was 0.8119, indicating a strong correlation between sweetness and F_{max} frequency. This suggests that the F_{max} frequency extracted from the tapping signal can be used as a reliable indicator to estimate the sweetness of watermelons.

3.3. Performance of classification models

Each watermelon was tapped in the middle area, and three acoustic samples were recorded at four positions (top, bottom, left, and right). After removing several outliers, 555 samples were divided into two datasets with a 2:1 ratio for training and testing purposes. Accordingly, 370 samples were used for training, and 185 samples were used for testing.

After the training process with the 10-fold cross-validation method, the performance of the machine learning models was evaluated using the testing dataset. Figure 6 shows the confusion matrices of the best-performing models for each classification algorithm with different hyperparameters.

Table 5 presents the performance of the proposed classification models during the training and testing processes. In addition, information about the prediction speed and model size for each model is also included in this table.

Table 5. Performance of the proposed classification models

Model		DT	DA	SVM	KNN	RF	NN
Training	Accuracy	97.6	87.6	94.1	97.3	98.6	93.5
	Precision	97.7	85	89.5	97.6	98.3	92
Testing	Accuracy	96.2	88.6	95.7	**97.3**	**97.3**	94.1
	Precision	95.5	87.5	91.6	**96.6**	95.6	89.6
Prediction speed (obs/sec)		1411	1874	4237	2655	370	6214
Model size (bytes)		5953	3896	7241	23534	179634	6897

Based on Table 5, the performance of the proposed classification models was evaluated during both the training and testing phases. During training, the RF model showed the highest accuracy at 98.6% and precision at 98.3%, indicating an excellent ability to learn from the training data. The KNN and DT models also demonstrated strong training results, with accuracy above 97%.

In the testing phase, both KNN and RF models achieved the highest accuracy of 97.3%. Their precision values remained high, with KNN at 96.6% and RF at 95.6%, showing that both models are reliable.

Clear differences arise when comparing KNN and RF based on practical criteria, such as prediction speed and model size. The KNN model can predict at a speed of 2655 observations per second, which was about seven times faster than the RF model's 370 observations per second. In terms of memory usage, KNN's model size was 23,534 bytes, considerably smaller than RF's 179,634 bytes. This indicates KNN requires less storage space and provides faster prediction times, which are important factors for real-time applications and deployment on devices with limited resources like the Raspberry Pi.

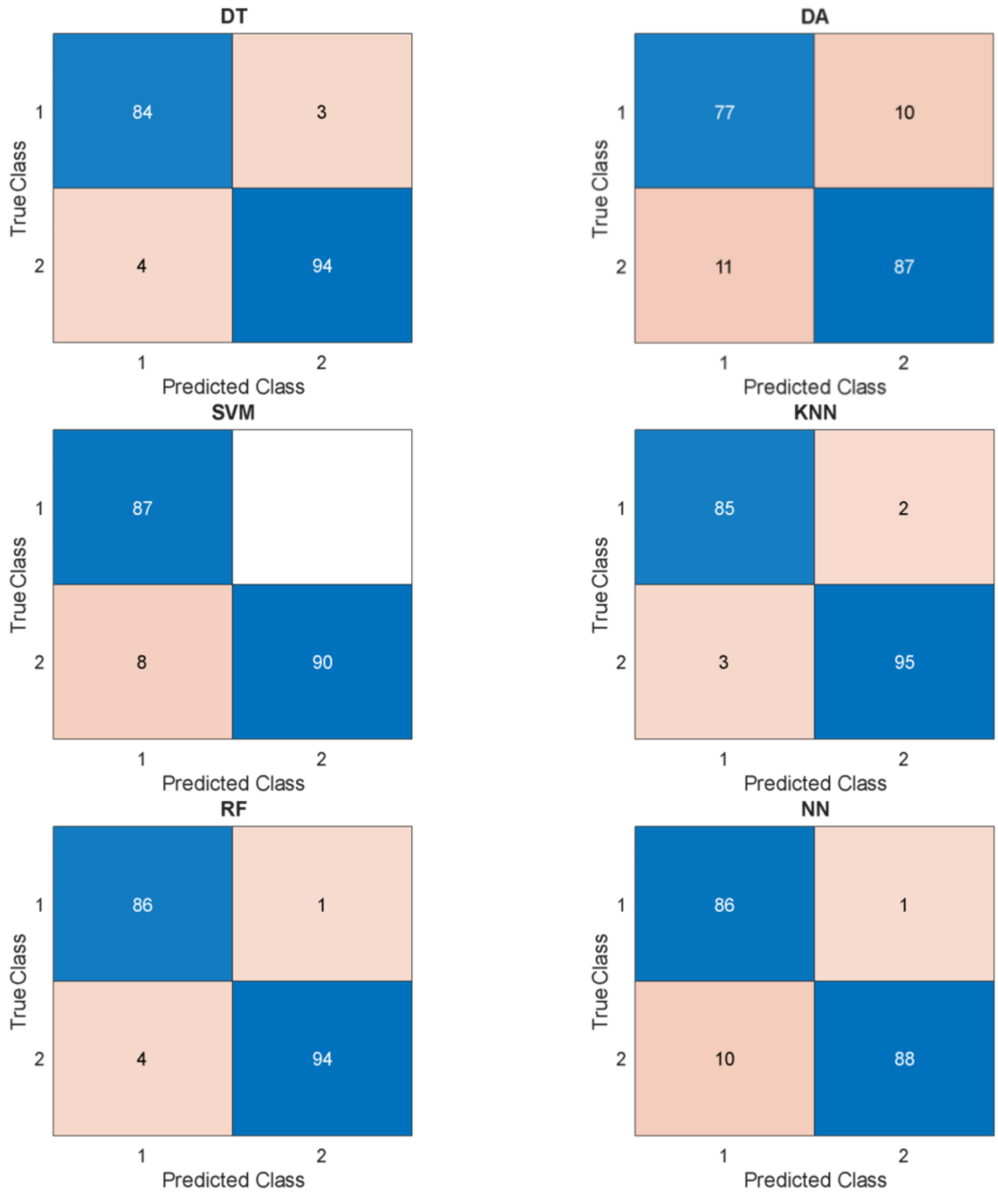


Figure 6. Confusion matrices of the six proposed classification models

Considering both accuracy and practical factors, KNN was selected as the most efficient model overall. It maintained high performance in both training and testing while offering better prediction speed and lower memory requirements than RF. This balance made KNN particularly suitable for applications in this study.

3.4. Discussion

In this study, sweetness assessment was conducted by recording the reflected sound using a low-cost MEMS microphone and analyzing the F_{max} of the recorded signal. The analysis results showed that as the sweetness increased, the F_{max} decreased. This finding is consistent with the results of previous studies. Notably, the correlation coefficient between sound frequency and sweetness in this study (R = -0.901) is also comparable to those reported by Khoshnam, F. et al. (2015) with R = -0.978, by Liza Pintor et al. (2016) with R = -0.721, and by Tran N.-T. et al. (2024) with R = -0.82. These results demonstrate that the sweetness estimation method proposed in this study is reliable and accurate.

The classification models developed in this study achieved high accuracy while maintaining small model sizes and fast prediction speeds. Such characteristics make these models suitable for deployment on embedded computers or microcontrollers, which are common in compact and cost-effective agricultural devices. Moreover, the proposed system offers significant economic and social benefits, particularly for SMEs. By enabling faster, accurate, and nondestructive quality evaluation, it can reduce labor costs, minimize product losses, and help maintain consistent product standards for export markets.

For future development, several directions are proposed, including integrating imaging technology, such as cameras, which could add the capability to evaluate external appearance, further improving overall quality assessment. Additionally, collecting larger and more diverse datasets will allow the construction of classification models with higher accuracy and better robustness. Finally, the proposed system can be extended to assess other agricultural products that can be evaluated by acoustic analysis, such as melons, durians, jackfruits, and coconuts. This expansion would broaden the applicability and impact of the proposed system in various agricultural sectors.

4. CONCLUSION

This study developed an acoustic-mechanical sensing system for watermelon quality assessment by combining weight measurement and sweetness estimation through acoustic analysis. The proposed system demonstrated high accuracy and reliability and was consistent with previous research. The KNN model used in this study showed strong performance while maintaining efficiency suitable for embedded system deployment. The integrated, cost-effective design of the proposed system makes it accessible for small and medium-sized enterprises, especially those involved in fruit export, offering significant economic and social benefits by improving quality control processes. Future work includes enhancing the system with imaging capabilities, expanding data collection to improve model robustness, and adapting the system for other agricultural products assessed through sound analysis. Overall, this study provides a promising approach for practical, efficient, and accurate quality evaluation in agricultural production.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

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