

## A REVIEW OF MUSKMELON HARVESTING TECHNOLOGY

## 甜瓜收获技术综述

Yang LI<sup>1)</sup>, Yiteng LEI<sup>1)</sup>, Luochuan XU<sup>1)</sup>, Wei DONG<sup>1)</sup><sup>1)</sup> Intelligent Signal Capture and New Generation Communication Technology Laboratory, College of Electronic Engineering, Yili Normal University, Yining, Yili 835000, China

Tel: +8615699398577; E-mail: younger1425580067@163.com

DOI: <https://doi.org/10.35633/inmateh-78-82>**Keywords:** muskmelon, maturity detection, non-destructive testing, harvesting machinery, machine learning.**ABSTRACT**

This paper systematically reviews the current status, key issues, and future directions of melon harvesting technologies. First, it outlines the industrial value of melons and the efficiency challenges associated with manual harvesting, emphasizing the necessity of developing mechanized harvesting technologies. Second, it summarizes major techniques for melon maturity detection, including non-destructive methods based on spectral, aromatic, and acoustic characteristics, while analyzing the progress in machine vision and artificial intelligence applications for fruit recognition and localization. Furthermore, the study compares the development history and typical models of melon harvesting machinery domestically and internationally, noting that partial commercialization has been achieved abroad, whereas domestic efforts remain focused on prototype design and experimentation. Finally, the paper identifies existing challenges, such as the lack of commercialized maturity detection technologies, low automation levels in harvesting machinery, and insufficient integration of intelligent systems. To address these issues, recommendations are proposed, including promoting multi-technology integration, advancing the development of harvesting robots, and creating specialized equipment tailored for precision cultivation, thereby facilitating the evolution of melon harvesting technologies toward higher efficiency and intelligence.

**摘要**

本文系统综述了甜瓜收获技术的发展现状、关键问题与未来方向。首先，概述了甜瓜的产业价值与人工采收面临的效率瓶颈，指出发展机械化收获技术的必要性。其次，梳理了甜瓜成熟度检测的主要技术，包括基于光谱、香气与声学特性的无损检测方法，并分析了机器视觉与人工智能在果实识别与定位中的应用进展。接着，对比了国内外甜瓜收获机械的研发历程与典型机型，指出国外已实现部分商业化应用，而国内仍以样机设计与试验为主。最后，总结出现有技术存在成熟度检测尚未商业化、收获机械自动化程度低、智能系统集成不足等问题，并提出推动多技术融合、加强采摘机器人研发、发展适配精细化种植的专用装备等建议，以促进甜瓜收获技术向高效、智能方向发展。

**INTRODUCTION**

Muskmelon is an annual creeping plant of the genus *Cucumis* in the Cucurbitaceae family (Molina et al., 1989). After long-term artificial selection, muskmelon has developed into a highly diverse variety, encompassing multiple variants such as netted muskmelon and hard-skinned muskmelon (Nunez-Paleniuss et al., 2008). Its flesh is rich in nutrients such as soluble sugar, vitamin C, and dietary fiber (Manchali et al., 2021; Yan et al., 2019; Manchali et al., 2020), while the seeds have a high oil content, especially rich in unsaturated fatty acids, and can be developed as a health oil source for both medicinal and edible purposes (Maran et al., 2015; Li et al., 2022). Muskmelon has growth characteristics of preferring warmth and light, and is therefore widely cultivated in temperate to tropical regions (Ma et al., 2022).

Globally, muskmelon production is highly concentrated in Asia. China, as one of the largest producers in the world, has become a core production area for high-quality thick-skinned muskmelon, with its northwestern regions such as Xinjiang and Gansu relying on their superior light and heat conditions (Xie et al., 2024). In addition, the United States (Gusmini et al., 2008), Türkiye (Kaya et al., 2024), Spain (Liu et al., 2023), and other regions are also important production areas in the global muskmelon supply system.

<sup>1</sup> Yang LI, lecturer; Yiteng LEI, Associate Professor; Luochuan Xu, PhD; Wei DONG, lecturer.

The economic value of muskmelon not only stems from the nutritional quality of the fruit itself, but also effectively extends the industrial chain and enhances added value through processing into products such as candied fruit (Wang *et al.*, 2021), fruit juice (Niu *et al.*, 2025), and fruit wine (Wang *et al.*, 2025).

The muskmelon industry also possesses significant social value. As a high-value economic crop with a short production cycle, it plays a positive role in helping farmers increase their income and alleviate poverty (Swinnen *et al.*, 2013; Yang *et al.*, 2018). In the harvesting process, the world still primarily relies on manual selective picking. Experienced workers can judge the maturity of fruits based on characteristics such as peel color, net pattern, and aroma, and ensure the integrity of the fruits through gentle handling (Sangamithra *et al.*, 2020). Although some countries have attempted to apply muskmelon harvesting machinery, a significant amount of manual assistance is still required (Brandenberger *et al.*, 2021). With the expanding market demand for muskmelons and the continuous increase in planting area, issues such as low efficiency in manual harvesting have become increasingly prominent, severely restricting the large-scale and intensive development of the muskmelon industry.

Most existing studies on muskmelon harvesting focus on a single technology, such as spectral detection or a specific type of picking machinery, lacking systematic integration. From a global perspective, this paper systematically reviews three major technical areas—maturity assessment, machine vision, and harvesting machinery—forming a technical system that covers the entire process from "detection" to "recognition" to "harvesting". On this basis, the main problems currently existing in muskmelon harvesting are analyzed, and targeted improvement suggestions are proposed, aiming to provide theoretical support for the development and optimization of muskmelon harvesting equipment.

## MUSKMELON MATURITY DETECTION TECHNOLOGY

Due to differences in geographical location, variety, and climatic conditions, the harvesting period of muskmelon varies. For example, Hami melons and Jiashi melons from Xinjiang, China, are mostly harvested from July to September each year (Zhang *et al.*, 2024). Usually, when a muskmelon ripens, it undergoes noticeable changes in appearance, aroma, and texture (Seo *et al.*, 2018; Henane *et al.*, 2024). Taking Jiashi melon as an example, its peel color transitions from dark green to yellowish-green, with a smooth and creamy surface texture, while emitting a more intense fruit aroma. Experienced fruit farmers can make a preliminary assessment of the maturity of muskmelon based on the above characteristics, but this method is relatively inefficient, and the accuracy of the assessment still needs to be improved (Sun *et al.*, 2010).

Currently, the technology and equipment for detecting the maturity of fruits such as apples (Liu *et al.*, 2024), pears (Huč *et al.*, 2020), and citrus (Sachan *et al.*, 2022) have developed rapidly and are gradually moving towards commercial application. However, for fruits like muskmelon, which have a larger fruit shape and thicker peel, non-destructive detection and grading of their internal quality still face significant challenges (Magwaza *et al.*, 2015). Through continuous exploration by scientific researchers, a method for detecting the maturity of muskmelon based on various technologies such as spectral characteristics, volatile aroma components, and acoustic features has been established.

### **Detection technology based on spectral characteristics**

Since the 1980s, near-infrared spectroscopy technology has gradually been applied in the field of food detection (Dull *et al.*, 1989), and near-infrared spectroscopy detection devices for specific fruits have also been developed one after another (Dong *et al.*, 2007; Olarewaju *et al.*, 2016). With the advancements in computer and data processing technologies, the combination of visible-near infrared spectroscopy and chemometrics has become one of the most widely used techniques in non-destructive detection of fruit quality (Wang *et al.*, 2023; Tilahun *et al.*, 2019).

The discrimination of muskmelon maturity based on spectral characteristics falls under the category of non-destructive detection technology, with its principle lying in the correlation changes between the internal material composition of the fruit and optical parameters (Osborne *et al.*, 1986). As the muskmelon gradually matures, significant transformations occur in its key chemical components such as sugar, water, and chlorophyll. These changes directly affect the absorption, scattering, and reflection characteristics of the fruit tissue towards specific wavelength bands of light (Ayesha *et al.*, 2021).

To address the need for automated grading and timely harvesting of Hami melons, Sun *et al.* employed hyperspectral imaging combined with feature wavelength selection methods for the nondestructive detection of soluble solids content (SSC) and firmness, enabling maturity discrimination.

After preprocessing the spectra with multiplicative scatter correction (MSC), feature wavelengths were selected using the successive projections algorithm (SPA), competitive adaptive reweighted sampling (CARS), and a combined CARS-SPA approach. Support vector machine (SVM) prediction models for SSC and firmness, as well as maturity discrimination models, were then developed based on the original spectra, MSC-processed spectra, and the selected feature wavelengths, as illustrated in Figure 1. The results demonstrated that the SVM prediction models for SSC and firmness constructed using the MSC-CARS-SPA method were optimal. For maturity discrimination, the SVM model based on CARS-PCA feature fusion performed equally well to the full-spectrum SNV-SVM model, achieving correct classification rates of 95% and 94% for the calibration and prediction sets, respectively (Sun *et al.*, 2017).

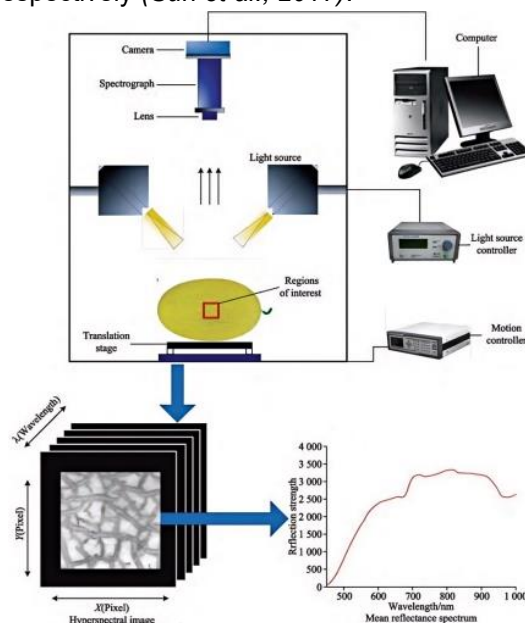


Fig. 1 - Hyperspectral technology combined with characteristic wavelength selection method

Xu *et al.* integrated deep learning with near-infrared spectroscopy to investigate key technologies for intelligent melon harvesting. Based on the Darknet platform, they proposed a YOLOResNet70 model, which achieved a mean average precision (mAP) of 89.4% and a detection speed of 61.8 frames per second (FPS) in melon target detection, outperforming comparative models. Combined with depth sensors to acquire target 3D coordinates, they further introduced a ResNet29 classification model that achieved an F1-score of 99% for maturity discrimination. Additionally, leveraging near-infrared spectroscopy, they established a partial least squares (PLS) detection model for melon rind crispness and a kinetic model, enabling non-destructive prediction of shelf life and providing a reliable basis for the zero-order reaction equation. This research provides an effective methodology for automated melon harvesting and quality inspection (Xu *et al.*, 2020).

Levoni *et al.* investigated the feasibility of time-resolved reflectance spectroscopy (TRS) for assessing the maturity and quality of melons. They performed TRS measurements on 60 'Mielue' melons within the 540-1064 nm range and categorized them into low, medium, and high maturity grades based on the absorption coefficient at 540 nm ( $\mu_a 540$ ). The results indicated that highly mature fruits exhibited yellower rinds, deeper orange flesh, higher juiciness and carotenoid content, along with elevated internal ethylene concentration and reduced firmness. A positive correlation was observed between  $\mu_a 540$  and ethylene, carotenoids, and juiciness, suggesting its utility in monitoring the melon ripening process. However, due to the limited variation in flesh color and carotenoid content among the samples, the correlation between  $\mu_a 540$  and the latter was weaker than anticipated. In conclusion,  $\mu_a 540$  measured by TRS can be employed for melon maturity sorting, though further validation across diverse cultivars is warranted (Levoni *et al.*, 2023).

Kasampalis *et al.* systematically evaluated the feasibility of visible, near-infrared, and short-wave infrared spectroscopy (350-2500 nm) combined with chemometric methods for non-destructive prediction of nutritional components in Galia-type melon fruit. Reflectance spectra were collected from three fruit regions—the stem end, equatorial zone, and blossom end—to develop prediction models using partial least squares regression (PLSR), principal component regression (PCR), and multiple linear regression (MLR). Results showed that the PLSR model based on equatorial zone spectra achieved the highest predictive accuracy, particularly for soluble solids content (SSC) and the SSC/titratable acidity (SSC/TA) ratio.

Key wavelength ranges for each nutrient were identified using genetic algorithms; for instance, critical wavelengths for SSC were found within 670-720 nm and 900-1100 nm. In conclusion, spectroscopic techniques enable rapid, non-destructive assessment of melon quality, demonstrating promising potential for postharvest grading and management (*Kasampalis et al., 2025*).

Shah et al. achieved rapid, non-destructive prediction of nitrogen, potassium, and sugar contents in melon leaves and fruits by integrating hyperspectral imaging with deep learning models. Results demonstrated that the MobileNet-v3-l model performed best for nitrogen content prediction ( $R^2=0.958$ ), whereas ResNet18 showed optimal performance for predicting potassium and reducing sugar content. The RegNet-y-8gf model achieved the highest accuracy in predicting sucrose content ( $R^2=0.958$ ). Compared to traditional RGB imaging methods, the hyperspectral-based models exhibited significant improvements across multiple evaluation metrics. This study validates the potential of hyperspectral technology for proximal field measurements under natural light conditions to predict melon harvest timing, offering an effective tool for crop phenotyping and precision agriculture management (*Shah et al., 2025*).

Spectroscopy is the most thoroughly researched direction in non-destructive testing of muskmelon maturity and holds the greatest application potential. Its core advantage lies in its ability to quantify internal chemical components and achieve high-precision discrimination when combined with machine learning models. However, this technology still faces three major limitations. First, the optical responses of different muskmelon varieties vary significantly, leading to insufficient model generalization ability. Second, hyperspectral equipment is expensive and data processing is complex, making low-cost field deployment difficult. Third, environmental factors such as illumination changes and dust on the fruit surface cause considerable interference. Currently, this technology is more suitable for post-harvest grading lines or laboratory testing, and there is still a gap before it can be applied to real-time field applications.

#### **Detection technology based on fruit aroma characteristics**

During the ripening process of fruits, the aroma of muskmelon undergoes significant changes. Research indicates that its aroma is primarily composed of various volatile components, including esters, aldehydes, alcohols, and sulfur-containing compounds (*Tang et al., 2007; Xiao et al., 2021; Hermo et al., 2023*). The volatile compound profiles produced by different varieties of muskmelon differ (*Pang et al., 2012; Gonda et al., 2016*), making the use of aroma characteristics for maturity assessment an effective detection method (*Lv et al., 2014; Allwood et al., 2014*). Currently, the technologies commonly used for identifying volatile aroma compounds in melon mainly include electronic noses and gas chromatography-mass spectrometry (GC-MS) techniques.

Brezmes et al. developed an electronic nose system based on a tin oxide gas sensor array and neural network for non-destructive monitoring of the ripeness of peaches, pears, and muskmelons by analyzing fruit volatile compounds combined with weight and surface area data. Results showed that the system achieved classification accuracies of 93% for peaches and 95% for pears, with storage duration prediction errors within one day. However, its performance was less satisfactory for muskmelons (72.9%). The study demonstrates the feasibility of electronic nose technology for rapid, non-destructive fruit ripeness monitoring, providing a technical reference for intelligent quality assessment of fruits and vegetables during postharvest handling (*Brezmes et al., 2000*).

Tang et al. employed electronic nose technology combined with principal component analysis (PCA) and linear discriminant analysis (LDA) to detect volatile compounds in multiple muskmelon cultivars at both semi-ripe and ripe stages. Results indicated that the electronic nose effectively distinguished melons of different maturity levels (with PCA achieving 100% separation) and different cultivars. Furthermore, analyzing cut fruit samples enhanced the differentiation capability among closely related varieties. This study established a rapid and objective method for evaluating muskmelon maturity and flavor profiles, providing a reliable technical basis for quality assessment and harvest grading (*Tang et al., 2010*).

Gabriel et al. developed an electronic nose detection system utilizing an MQ3 gas sensor to measure ethanol concentration (ppm) released by fruit, with data classification performed by integrating Arduino and MATLAB platforms via a fuzzy logic algorithm (Fig. 2). The results revealed distinguishable ethanol concentration ranges among unripe, ripe, and overripe melons (e.g., approximately 100–392 ppm during the ripe stage), with an overall system recognition accuracy of 80%. This study confirms the feasibility of non-destructively determining melon maturity based on ethanol volatilization levels (*Gabriel et al., 2022*).



Fig. 2 - Electronic nose muskmelon detection system

There are various varieties of muskmelon with different aromatic components. Therefore, when using an electronic nose to detect the maturity of melon, multiple pattern recognition and comparison methods should be employed to improve detection accuracy.

Zhang et al. systematically analyzed the aroma profiles of a new netted muskmelon cultivar, 'Zhenmi 5,' at six time points around the ripening stage using headspace solid-phase microextraction combined with gas chromatography–mass spectrometry. The results showed that the diversity of aroma compounds peaked five days before maturity, while ester content reached its maximum on the day of maturity. Hydrocarbons and alcohols decreased sharply within the five days preceding maturity, whereas esters continued to increase until the ripening day. The study identified the five-day pre-maturity period as a critical phase for flavor formation in 'Zhenmi 5,' providing a scientific basis for determining the optimal harvest time and quality regulation in muskmelon production (Zhang et al., 2014).

Zhao et al. conducted a comparative analysis of aroma components in three melon cultivars—the alcoholic fragrance-type thick-skinned melon 'C51,' the green grassy-type thick-skinned muskmelon 'C52,' and the thin-skinned melon 'Baiyu Mantang'—using headspace solid-phase microextraction coupled with gas chromatography-mass spectrometry. Results indicated that esters constituted the predominant aroma compounds in all three cultivars, yet their characteristic components differed significantly: 'C51' contained unique compounds such as 2-phenylethyl chloroacetate, contributing to its alcoholic fragrance; 'C52' was rich in (Z)-3-nonen-1-ol, imparting a green grassy aroma; while 'Baiyu Mantang' possessed various unique sulfur-containing compounds (e.g., allyl methyl sulfide), which are presumed to be responsible for its distinctive aroma. The study identified key aroma substances associated with different fragrance types in muskmelons, providing crucial insights for flavor quality evaluation and targeted breeding programs (Zhao et al., 2015).

Chaparro-Torres et al. compared aroma volatiles in the climacteric muskmelon near-isogenic line SC3-5-1 and its non-climacteric parental line PS at harvest using both HS-SPME/GC–MS and an INDEX/MS electronic nose system. Results showed that the concentrations of most volatile compounds (primarily esters and alcohols) were significantly higher in SC3-5-1 than in PS. Accurate discrimination between the two lines was achieved using partial least squares-discriminant analysis and selected mass-to-charge ratio ions, leading to the identification of multiple QTLs influencing aroma synthesis. GC-MS demonstrated better classification performance than the electronic nose, and most QTLs consistently detected across two growing seasons were associated with enhanced synthesis of climacteric-related aroma compounds (Chaparro-Torres et al., 2015).

The discriminant technology based on fruit aroma characteristics offers advantages such as rapid response, non-contact operation, and the ability to distinguish varieties, making it particularly suitable for post-harvest quality grading. However, this technology faces two fundamental limitations. First, the aroma composition of muskmelon is greatly influenced by variety, maturity stage, and environmental conditions, making it difficult for models to generalize across different varieties. Second, the sensitivity and selectivity of electronic nose sensors are limited, making it challenging to accurately identify characteristic maturity components in complex gas mixtures. Although GC-MS provides high accuracy, the equipment is expensive, the operation is cumbersome, and the analysis is time-consuming, which cannot meet the requirements for real-time field detection. Overall, this technology is more suitable as an auxiliary tool for post-harvest quality assessment rather than as an independent solution for rapid field maturity discrimination.

### Detection technology based on acoustic characteristics

Acoustic discrimination technology evaluates the quality of fruits by analyzing their transmission, scattering, absorption, and reflection characteristics under acoustic excitation, as well as parameters such as attenuation coefficient, propagation velocity, acoustic impedance, and natural frequency (Taniwaki et al., 2010; Choe et al., 2022). Differences in the maturity of muskmelon can lead to changes in its internal structure, which in turn affect its acoustic response, such as natural frequency, attenuation coefficient, and power spectrum peak values (Mizrach et al., 2008; Sun et al., 2010). By conducting a quantitative analysis on these parameters, a correlation model between them and maturity can be established, enabling lossless and efficient detection.

Acoustic discrimination techniques are primarily categorized into contact-based and non-contact methods. Contact-based methods typically require attaching sensors to the fruit surface. For instance, Taniwaki et al. utilized an accelerometer to measure the second resonant frequency of melons and calculated the elasticity index (EI). Studies have demonstrated that EI can be applied to predict the shelf life of melons, thereby ensuring fruit quality throughout the sales period (Taniwaki et al., 2010).

Non-contact acoustic testing technology requires the use of a microphone to detect acoustic impulse response signals, with the detection system illustrated in Figure 3. This system primarily consists of a test bench, a multi-channel signal conditioner, vibration control equipment, and a dynamic signal acquisition analyzer along with its software system (Wang et al., 2010).

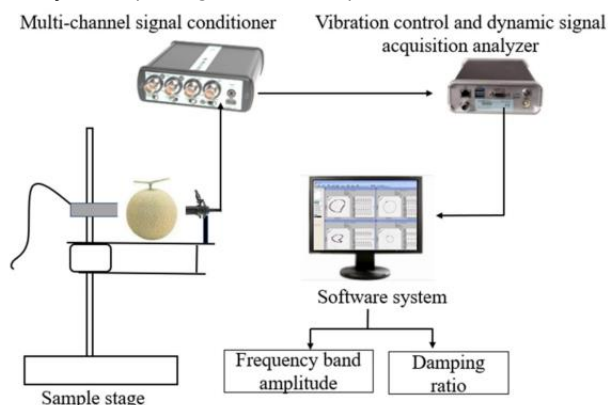


Fig. 3 - Muskmelon internal quality detection system based on acoustic pulse signals

Sugiyama et al. developed a portable muskmelon firmness tester consisting of a light-impact system and two microphone sensors. The acquired sound signals were transmitted to a computer via A/D conversion, and the transmission velocity and correlation between the two signals were calculated. Results showed a high correlation coefficient of 0.94 between the instrument's readings and destructive measurement data, demonstrating its utility for detecting overripeness in muskmelons (Sugiyama et al., 2010).

Khoshnam et al. applied acoustic impulse response technology to evaluate two melon cultivars across five maturity stages. The study involved exciting the fruit and capturing vibration signals to extract parameters such as resonant frequency and sound pressure level, which were then compared with measurements of mass, elastic modulus, soluble solids content, and sensory evaluation. Results indicated that resonant frequency decreased significantly with advancing maturity and exhibited strong correlations with both elastic modulus and soluble solids content, supporting its reliability as an indicator for distinguishing melon maturity stages. In contrast, sound pressure level demonstrated limited stability due to interference from factors such as measurement distance (Khoshnam et al., 2015).

He et al. developed a non-destructive acoustic response detection system based on impact hammer excitation and microphone sensing to assess the maturity of Hami melons. Results indicated high signal stability at the same measurement point, with no significant difference in resonant frequency observed along the equatorial region. A rubber hammer head under 6-12 N excitation yielded optimal signals. By calculating the elasticity index and damping ratio from frequency response parameters, a firmness prediction model was constructed, showing correlation and sensitivity comparable to conventional methods. A soluble solids content prediction model based on damping ratio also proved effective. Additionally, a PCR firmness model established using amplitude parameters in the 40-200 Hz frequency band and fruit mass achieved a validation set correlation coefficient of 0.795 and sensitivity of 67.70%, demonstrating applicability in non-destructive testing, though with slightly lower performance than the frequency response parameter model. This study provides a feasible acoustic-based approach for maturity detection in Hami melons (He et al., 2017).

Lv et al. developed a non-destructive maturity detection method for Hami melons based on smartphone audio recording. By analyzing tapping sound signals, acoustic features were extracted to train a support vector machine classifier. Features such as spectral centroid and frame energy effectively distinguished unripe from ripe melons, while zero-crossing rate and sub-band energy ratio enabled the discrimination of optimally ripe and overripe melons. The developed Android application achieved an overall classification accuracy of 90.9% and incorporated a user feedback mechanism for continuous optimization. Additionally, a regression model based on acoustic features allowed effective prediction of sugar content. This approach offers a portable, rapid, and low-cost solution for melon maturity assessment, suitable for both growers and consumers (Lv et al., 2019).

Choi et al. proposed a detection method based on the propagation characteristics of surface acoustic waves. The study used an exciter to generate pulsed acoustic waves on the melon surface and measured the propagation velocity of surface waves at different frequencies via a laser Doppler vibrometer. Results revealed that surface wave velocity increased with rising frequency and, at the same frequency, decreased significantly as the fruit softened during ripening. This indicates a strong correlation between surface wave velocity and the internal elasticity (maturity) of the melon, confirming the feasibility of surface acoustic wave technology for assessing melon maturity. The study provides a new theoretical foundation and practical pathway for developing objective, non-destructive fruit quality assessment instruments (Choi et al., 2020).

When acoustic vibration detection technology is applied to assess melon maturity, environmental noise and mechanical vibrations can interfere with the test signals, and the testing process tends to be time-consuming (on the order of seconds). Furthermore, impact-based methods, while commonly used, inevitably cause a certain degree of physical damage to the fruit, compromising its quality and making real-time inline inspection during production unfeasible. As a result, these approaches fall short of meeting the requirements for rapid, non-destructive melon testing. In response, researchers have begun integrating acoustic techniques with other sensing technologies to more effectively evaluate internal quality attributes of melons (Ghosh et al., 2026).

Khuriyati et al. explored the potential of combining ultrasonic and acoustic methods for non-destructive prediction of firmness and total soluble solids in Hami melons. Using a sample set of 100 fruits, parameters such as ultrasonic attenuation, acoustic frequency, and signal intensity were employed as variables to develop prediction models based on partial least squares regression, with cross-validation and blind testing performed for evaluation. Results showed that both methods performed well in predicting firmness, while neither approach yielded satisfactory predictions for soluble solids content. The findings suggest that acoustic and ultrasonic techniques hold promise for assessing melon firmness, providing key support for the development of efficient and cost-effective quality detection systems (Khuriyati et al., 2024).

Chen et al. proposed a non-destructive detection method combining acoustic characteristics and machine learning. An acoustic detection system was designed to collect time-domain signals from melons, which were normalized and processed via Fourier transform to obtain frequency-domain signals. Key features were then extracted using principal component analysis (PCA), with the first three principal components accounting for 95.22% of the variance and demonstrating separability among samples of different maturity grades. Feature variables were further refined using the stable competitive adaptive reweighted sampling (SCARS) algorithm, reducing the variable count by approximately 84.27%. Based on the optimized feature set, classification models were constructed, with the support vector machine (SVM) model achieving the best performance-reaching an accuracy of 95.74% on the validation set. The study demonstrates that the integration of acoustic technology and machine learning enables effective non-destructive testing and grading of melons (Chen, et al., 2024).

Izdihar et al. proposed a non-destructive prediction method integrating ultrasonic technology with an artificial neural network (ANN). The study used measured ultrasonic attenuation values, fruit density, and days after harvest as inputs to train an ANN model for predicting multiple physicochemical properties, including firmness and soluble solids content. Results indicated that while the normalized root mean square error was acceptable for some predictions, the  $R^2$  values on the test set were generally unsatisfactory (as low as -0.776), reflecting limited overall reliability of the model. The study underscores the challenges of applying ultrasonic-ANN-based nondestructive techniques to fruits with complex internal structures and highlights the need for further investigation into ultrasonic wave propagation mechanisms in cavity-containing fruits (Izdihar et al., 2023).

Acoustic detection technology offers outstanding advantages such as simple equipment, low cost, rapid response, and portability, making it particularly suitable for rapid field screening and farmer self-use scenarios.

Its core challenge lies in the complex internal structure of muskmelon; the correlation between acoustic response and maturity is significantly influenced by factors such as variety, size, and rind thickness, and a universal acoustic-maturity mapping model has not yet been established. In addition, issues such as environmental noise suppression, the risk of slight damage, and test consistency remain to be resolved. At present, this technology has achieved high accuracy in distinguishing three coarse maturity levels ("immature / mature / over-ripe"), but it is still unreliable for accurately predicting continuous indicators such as soluble solids content. Overall, acoustic technology holds the greatest potential for portability and low cost, but it requires variety-specific calibration and is more suitable as an auxiliary discriminant tool.

### **Application of machine vision technology in muskmelon harvesting**

In recent years, machine vision technology has advanced rapidly with continuous improvements in efficiency and accuracy (Abebe *et al.*, 2023; Tandoballa *et al.*, 2025). This technology can extract and analyze multi-dimensional features of fruits—such as color, texture, and morphology—from fruit images using deep representation learning algorithms, thereby providing a basis for decision-making during harvesting (Cubero *et al.*, 2011; Li *et al.*, 2015). Current research has shown promising results in muskmelon target recognition and quality detection through the application of artificial intelligence technologies.

Xu *et al.* proposed an automatic maturity discrimination method for muskmelons based on machine vision. The study collected images of "Xintian" melons at three maturity stages, extracting color and texture features using the RGB color model and Gray-Level Co-occurrence Matrix (GLCM), followed by feature dimensionality reduction via Principal Component Analysis (PCA). Three discrimination models-PLS, PCA-PLS, and PCA-LS-SVM-were constructed based on full features and optimized principal components. Results showed that the PCA-LS-SVM model achieved an overall discrimination accuracy of 100% for immature, semi-mature, and fully mature muskmelons in the prediction set, outperforming the other models. The PCA-PLS model maintained an accuracy of 97.96% while significantly improving discrimination speed. This study validates the feasibility of image-based maturity recognition in muskmelons and provides a theoretical foundation and methodological support for developing efficient and intelligent melon sorting systems (Xu *et al.*, 2020).

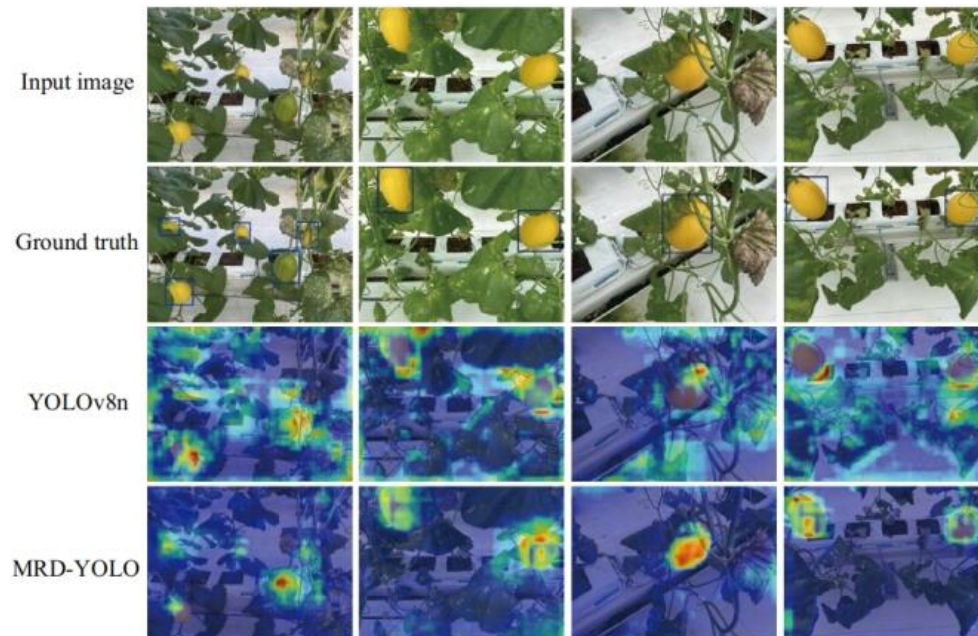
Ong *et al.* proposed a non-destructive method for detecting muskmelon sugar content by integrating machine vision with deep learning. The study employed a convolutional neural network (CNN) based on the AlexNet architecture with transfer learning, capturing melon images under both controlled conditions using a laboratory imaging system and uncontrolled environments via smartphones. Appearance features were extracted to predict soluble solids content (SSC) levels, and the CNN's performance was compared with traditional machine learning classifiers such as C4.5, Naïve Bayes, Random Forest, and Support Vector Machine. Results demonstrated that the CNN model achieved classification accuracies of 95.22% for laboratory-captured images (D1) and 83.44% for smartphone-captured images (D2) on balanced datasets. Notably, accuracy further improved to 97.69% (D1) and 89.28% (D2) on imbalanced datasets, significantly outperforming other classifiers while maintaining strong robustness under varying lighting conditions (Ong *et al.*, 2022).

Zhao *et al.* proposed an improved YOLO-ResNet70 detection model based on the YOLOv3 framework. By incorporating ResNet70 as the backbone network and integrating multi-component optimizations—including a spatial pyramid pooling (SPP) module, feature pyramid network (FPN) structure, complete intersection over union (IoU) loss function, and Leaky ReLU activation—the method constructs a detection network suitable for heavily occluded scenarios. The approach further combines an Intel RealSense D435i depth camera to achieve the transformation from pixel coordinates to 3D spatial coordinates. Experimental results show that YOLO-ResNet70 achieved a mean average precision (AP) of 89.4% on the test set with a detection speed of 61.8 frames per second (FPS), outperforming YOLOv3 and YOLOv5. The model also maintained high robustness under varying exposure conditions, with F1 scores consistently above 94%. Together with the depth sensor, the model enables precise muskmelon localization with minimal spatial error, providing a viable visual perception solution for automated harvesting systems (Zhao *et al.*, 2022).

Li *et al.* conducted a comparative study using the single-stage object detection algorithms YOLOv5 and YOLOv7 to identify "Boya No. 9" muskmelons in complex field environments. Under controlled experimental settings with consistent input size, batch size, and training epochs, YOLOv7 achieved a mean average precision (mAP) of 92.5%, surpassing YOLOv5's 90.2%, while also demonstrating a higher recall rate and greater robustness in multi-scale and occluded scenarios. The method achieved a detection speed of 83.33

FPS, confirming its real-time capability. This approach provides a practical technical foundation for developing visual perception systems in melon-harvesting robots (Li et al., 2023).

Jing et al. proposed a lightweight object detection algorithm (Figure 4) based on an improved YOLOv8n architecture. The method employs MobileNetV3 as the backbone network to reduce model complexity and introduces a Slim-neck structure-comprising GSConv and VoV-GSCSP modules-to further decrease parameter count and computational cost (Jing et al., 2024).



**Fig. 4 - Lightweight Object Detection Algorithm**

A Coordinate Attention mechanism is embedded to enhance feature extraction capability in complex scenarios. Experimental results demonstrate that the algorithm achieved a mean average precision (mAP) of 97.4% on a large-scale self-built muskmelon dataset, with only 4.8 G FLOPs and 2.06 M parameters, corresponding to 58.5% and 68.4% of the baseline model, respectively. This indicates a significant improvement in computational efficiency while maintaining high accuracy. Furthermore, the model attained 85.9% mAP on the external Roboflow dataset, showcasing strong generalization ability. The approach is suitable for real-time deployment on edge devices such as harvesting robots, providing an effective lightweight solution for fruit maturity detection.

Gómez et al. proposed a multimodal IoT architecture named MeloDI, which integrates a cloud-edge collaborative computing framework. At the physical layer, traditional sensors and drones equipped with RGB and multispectral cameras are deployed. Data undergo preliminary processing at the edge layer, while the cloud layer incorporates machine learning models to enable comprehensive analysis of multi-source information—including sensor data and vegetation indices extracted from drone imagery. Experimental results demonstrated that the configuration fusing dual data sources significantly outperformed setups using a single source. Among the models tested, the Random Forest algorithm achieved the best performance on the test set (MSE=1.6111, error rate 7.99%), validating the effectiveness of multimodal data in predicting muskmelon quality (Gómez et al., 2024).

Umar et al. developed an improved YOLOv8 model integrated with an attention mechanism for real-time muskmelon maturity detection. The model was trained on a dataset of over a thousand images collected from Indonesian orchards, with data augmentation applied to enhance robustness. Validation results showed that the model achieved a precision of 0.979 and an mAP@50 of 0.981, with a total processing time of approximately 1.9 milliseconds per image, meeting real-time requirements. Compared to recent methods, the proposed model demonstrated superior performance in detection accuracy, environmental adaptability, and efficiency, offering an accurate and efficient maturity detection solution for the agricultural industry (Umar et al., 2025).

In addition to the above detection technologies, electromagnetic technology, laser scattering imaging, thermal imaging, and other technologies have also been gradually applied to the internal quality detection of large-sized and thick-skinned fruits such as muskmelon and watermelon, and have shown certain potential.

## COMPREHENSIVE COMPARATIVE ANALYSIS OF DIFFERENT DETECTION TECHNOLOGIES

The three traditional detection techniques mentioned above, together with machine vision technology, each have their own characteristics in terms of detection principles, performance, application scenarios, and other aspects. To facilitate systematic comparison, Table 1 provides a horizontal summary of spectroscopic methods, aroma-based methods, acoustic methods, and machine vision applications across six dimensions, including detection principles, advantages, limitations, and others.

Table 1

Comparison of Different Detection Techniques for Melon

Comparative dimension	Spectral technology	Fruit aroma technology	Acoustic technology	Machine vision technology
<b>Detection Principle</b>	Measures the absorption/reflection of light by internal chemical components	Detects volatile gases	Analyzes vibration/acoustic wave response under mechanical excitation	Analyzes the color, texture, shape, and other features of fruit appearance images
<b>Advantage</b>	It can quantify internal quality (SSC, hardness) with high accuracy	Fast, non-contact, directly related to flavor	Simple equipment, low cost, and portability	It can simultaneously achieve target recognition, localization, and maturity assessment, making it easy to integrate with robots
<b>Limitation</b>	Expensive equipment, poor model generalization, and interference from lighting	The sensor has limited selectivity and poor cross-variety universality	It is susceptible to environmental noise interference, resulting in relatively low accuracy	It can only evaluate the appearance and cannot detect the internal quality; it is greatly affected by occlusion and changes in lighting
<b>Detection accuracy</b>	The SSC prediction has an $R^2$ of up to 0.95, with a maturity discrimination of $\geq 95\%$	The accuracy rate of the electronic nose is about 80%, while GC-MS has high precision but is slow	The accuracy of grade discrimination is about 90%, with poor prediction for continuous indicators	The mAP of target detection can reach over 90%, and the accuracy of maturity assessment is 85%-99%
<b>Cost and portability</b>	High cost, fixed installation in laboratory/production line	Electronic noses are low-cost and portable, while GC-MS is expensive	Low cost, extremely portable (mobile app already implemented)	Medium cost (camera + embedded platform), portable
<b>Applicable scenarios</b>	Post-harvest grading and quality inspection line	Post-harvest quality assessment, flavor analysis	Field rapid screening, for farmers' personal use	Field robot harvesting and post-harvest grading

As shown in Table 1, it is difficult for any single technology to simultaneously meet the comprehensive requirements of "high accuracy, low cost, strong robustness, and easy deployment". The fusion of spectroscopy and machine vision can acquire both internal and external information simultaneously, but at a high cost. The fusion of acoustics and machine vision offers the potential for low-cost portability. The fusion of aroma-based techniques and machine vision can be used for comprehensive evaluation of flavor and appearance. In recent years, multimodal fusion and lightweight deep learning have become important directions for breaking through bottlenecks, providing new directions for the research of muskmelon harvesting equipment.

## MUSKMELON HARVESTING MACHINERY

### *Foreign muskmelon harvesting machinery*

The United States pioneered the development and practical application of melon harvesting machinery. As early as the 1960s, melon growers in California began experimenting with mechanized harvesting techniques. In 1963, the University of California developed the world's first melon harvesting machine and conducted field performance tests. Early models were primarily designed for selective harvesting. Although their operational efficiency reached 72% of manual harvesting, they required specific cultivation planning

during the planting stage, which not only increased economic costs but also necessitated additional investment in worker training. Consequently, this model failed to achieve widespread adoption (O'Brien *et al.*, 1966).

To address these issues, researchers from academic institutions and corporate engineers subsequently carried out a series of follow-up studies.

During the 1970s, the University of California conducted research on a single-pass harvesting machine for muskmelons and continued to optimize its mechanical structure. The harvester achieved an operational speed of 1.5 miles per hour. At this speed, the manually coordinated pickup attachment demonstrated high operational efficiency. Meanwhile, an optimized vine conveyor mechanism expanded the separation area, and a debris removal device was added to the conveyor belt (Figure 5). Despite these improvements, harvesters from this period still fell short of commercial application requirements in terms of cost-effectiveness (O'Brien and Zahara, 1971; O'Brien and Harriott, 1975).



Fig. 5 - Single-operation muskmelon harvester from the University of California

Edan designed a muskmelon harvesting machine employing a robotic grasping mechanism, whose structure is illustrated in Figure 6. The tractor-pulled device was equipped with a bottom-mounted blower to clear surrounding leaves and vines, thereby exposing melons obscured by foliage. The system incorporated both proximal and distal visual sensors: the distal sensor scanned the ground to identify ripe melons and perform initial localization, while a Cartesian robotic arm, aided by the proximal sensor mounted on the chassis, precisely acquired target positions and executed grasping. Field tests demonstrated that the system achieved a recognition accuracy of 80%-85% for different melon varieties, with grasping time positively correlated to the distance between adjacent fruits. Through this dual-sensor architecture, the device realized coordinated operation between melon monitoring, identification, and robotic arm positioning for grasping (Edan *et al.*, 1995).

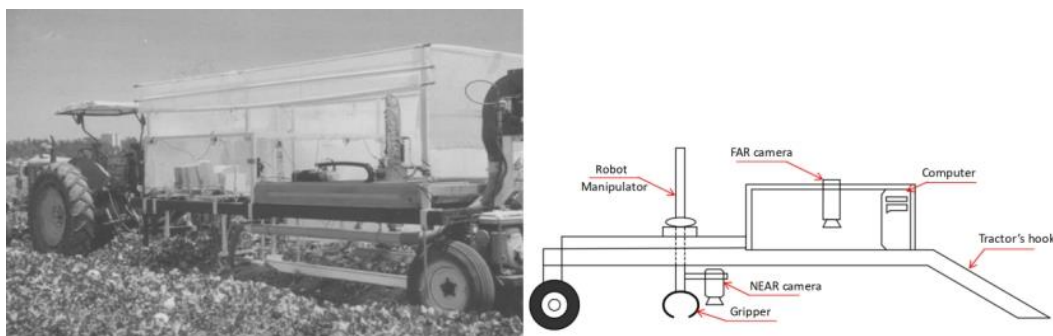


Fig. 6 - Muskmelon harvester using a robotic arm for grasping

Since the beginning of the 21st century, the United States and Spain-key melon-producing regions-have successively introduced commercially available melon harvesting machines. The economic value of melons is closely linked to fruit integrity, yet fully automated mechanical systems capable of achieving high rates of damage-free harvesting remain undeveloped. As a result, the current harvesters predominantly operate in a semi-automated mode, relying on human collaboration to ensure undamaged fruit picking. Presently, few companies possess the capability to develop and manufacture melon harvesting machinery, with major players including Argiles in Spain, and Pik Rite and Berstrom in the United States.

The FH T1 melon harvester developed by the Spanish company Argiles operates in a tractor-pulled manner, with its overall structure shown in Figure 7. The machine is equipped with hydraulically controlled foldable conveyor belts on both sides, with a total length of 13 m and a width of 0.6 m.

An additional foldable conveyor belt, 4.5 m in length, is installed at the rear and connected to the trailer via a central linking box. During operation, workers place ripe melons onto the lateral conveyor belts. The fruits are then conveyed to the rear belt, pass through the linking box into the trailer, and are finally arranged into containers by workers inside the trailer (Argiles et al., 2026).



Fig. 7 - FH-T1 type muskmelon harvester

The FH T4 muskmelon harvester developed by Argiles features a more optimized structural design, as shown in Figure 8. This model is self-propelled and capable of operating independently. The total length of its lateral conveyor belt has been increased to 17.8 m, and the belt surface is evenly equipped with numerous semi-circular soft rubber pads, significantly reducing fruit damage during transportation. In addition, the machine adopts a side-offloading system, which simplifies the conveying mechanism and offers a higher degree of automation. Compared to the FH T1 model, the FH T4 improves harvesting efficiency by approximately 30%, while reducing the required labor force by a corresponding 30% (Argiles et al., 2026).



Fig. 8 - FH-T4 type muskmelon harvester

The Model 9000 muskmelon harvester developed by the American company Pik Rite operates using a right-side oblique towing configuration, as illustrated in Figure 9. During operation, an orientation mechanism at the front guides melons onto the conveyor belt. As the melons are transported upward, the vines are subjected to significant tension, facilitating separation: the muskmelons roll off onto a lower platform, while the vines are carried to the underside of the conveyor and discharged onto the ground. The separated melons are then conveyed to a side-mounted trailer to complete the harvesting process. This model reaches a maximum harvesting rate of 20 tons per hour (Pikrite et al., 2026).



Fig. 9 - 9000-type muskmelon harvester

The muskmelon harvester developed by the American company Berstron utilizes solar power as its primary energy source (Figure 10). Equipped with 24 solar panels on the top, the machine can generate up to 10.8 kW of power under ideal light conditions and is also fitted with a backup gasoline generator. Below the solar panels, a conveyor belt featuring flexible separation ridges has an effective conveying length of 16 m, and its speed can be continuously adjusted via an electronic control system. During operation, melons are fed onto the horizontal conveyor and then transferred to an inclined lifting conveyor, which carries them forward into a trailer. The entire system can be configured and monitored through a touchscreen interface in the central control room, offering notable energy efficiency and user-friendly operation (Berstron et al., 2026).



Fig. 10 - Solar-powered muskmelon harvester

### Chinese melon harvesting machinery

At present, muskmelon harvesting in China still relies primarily on manual picking and handling, with no commercially available melon harvesting machinery yet deployed. Related research by domestic researchers and engineers in this field remains largely in the stages of prototype design and testing.

Lei et al. designed a melon picking and transport vehicle (Figure 11). The device is powered by a rechargeable lithium battery and features a three-wheel chassis with single-wheel drive, enabling operation by a single person. A detachable transport crate is mounted above the frame, capable of receiving and storing melons picked from both sides of the machine simultaneously. The crate employs a modular honeycomb design and is suspended from a lifting frame. The operator can adjust its height by stepping on a lifting pedal, thus adapting to different user statures and reducing fatigue caused by repeated bending and standing. The machine is equipped with a handheld electronic scale for weighing melons and assists in maturity assessment based on external color and texture. Furthermore, a weighing system controlled by a microcontroller automatically records the weight of harvested melons, enabling electronic documentation of each picking operation (Lei et al., 2021).

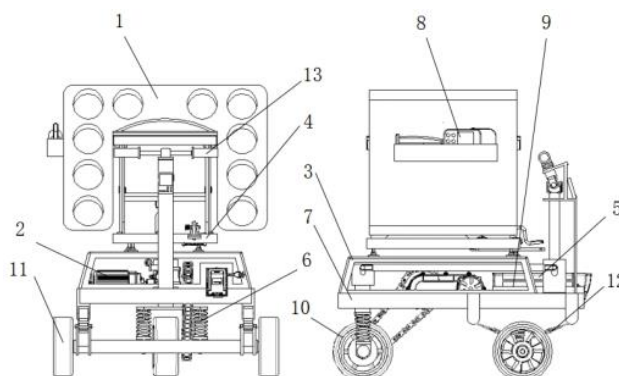
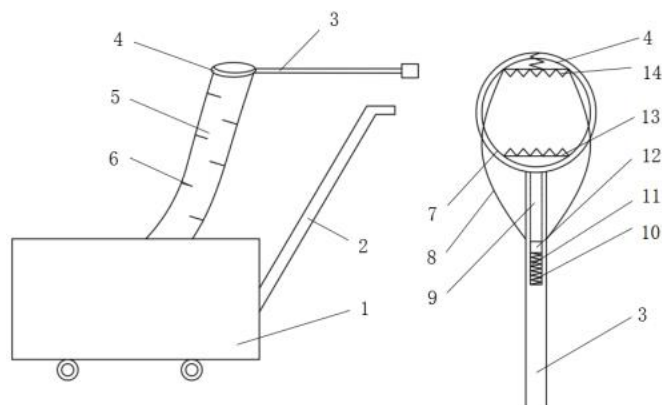


Fig. 11 - Muskmelon Picking and Transportation Machine

1. Transport nest, 2. Motor, 3. Support frame, 4. Lifting frame, 5. Storage battery, 6. Shock absorber, 7. Vehicle frame, 8. Handheld electronic scale, 9. Controller, 10. Front wheel, 11. Rear wheel

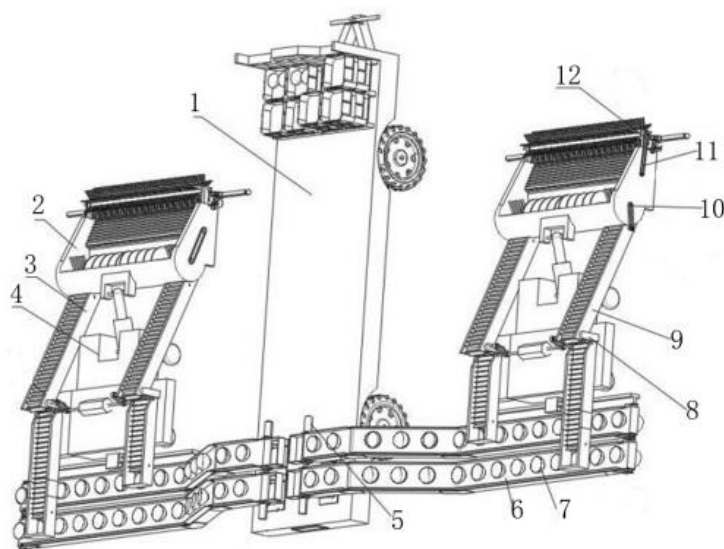
Chen et al. designed a hand-powered muskmelon harvesting device (Figure 12). The lower section of the device is equipped with a collection unit for temporary storage of harvested fruits. The inner wall of the unit is lined with sponge padding to prevent damage caused by impact during movement. A picking mechanism is attached to the side of the device and connects to the collection unit. This mechanism primarily consists of a mesh chute and a ring-shaped connector. The inner wall of the mesh chute is fitted with deceleration flaps arranged in an alternating pattern, which effectively limit the descent speed of melons entering the chute, thereby preventing impact damage due to excessive velocity (Chen et al., 2021).



**Fig. 12 - Hand-pushed cantaloupe harvesting device**

1. Collection part, 2. Handrail, 3. Handheld rod, 4. Connector, 5. Mesh slide, 6. Deceleration plate, 7. Fixed pulley, 8. Steel wire, 9. Moving rod, 10. Active cavity, 11. Spring, 12. Push block, 13. Second blade, 14. First blade

Chen et al. invented a harvesting device for muskmelons (Figure 13). The chassis frame is equipped with symmetrical conveying mechanisms. Under the action of the feed-in mounting plate, melons are fed into the device for harvesting. During this process, flexible materials are used to prevent fruit damage. The feeding mechanism can also push melons located at the edges toward the center, facilitating orderly intake. Simultaneously, the header unit severs the vines to prevent tangling during feeding, thereby maintaining harvesting efficiency. After intake, a flow-dividing mechanism distributes the melons to avoid congestion caused by excessive input. The divided melons are then conveyed onto a rear belt equipped with rubber cups. Finally, the output is handled by personnel for boxing, achieving an automated melon harvesting process (Chen et al., 2025).



**Fig. 13 - Watermelon and muskmelon harvesting device**

1. Conveyor frame, 2. Harvesting platform, 3. Conveyor frame, 4. Vehicle body, 5. Conveyor motor, 6. Conveyor belt, 7. Rubber bowl, 8. Support frame, 9. Conveyor frame, 10. Diverging mechanism, 11. Feeding mechanism, 12. Feeding mounting plate

## PROBLEMS IN MUSKMELON HARVESTING TECHNOLOGY

(1) Muskmelon maturity assessment technology has not yet reached the level of commercial application. Although spectral analysis technology can achieve up to 95% accuracy in judging the maturity of specific varieties, the accuracy rate fluctuates significantly across different varieties due to factors such as the diversity of muskmelon cultivars, the complexity of internal tissues, compositional differences, and susceptibility to external light interference. The muskmelon maturation period is relatively long, during which volatile compounds change significantly. Relying solely on aroma for maturity assessment has limited accuracy and usually requires cutting open samples for secondary validation, which increases operational complexity and cost. Furthermore, maturity assessment technology based on acoustic characteristics still needs to overcome several key challenges, including establishing and optimizing the correlation model between acoustic parameters and maturity, as well as developing suitable acoustic detection equipment.

(2) The variety of mechanized muskmelon harvesting equipment is limited, and the overall level of automation remains constrained. Research in the field of mechanized muskmelon harvesting began earlier abroad and has achieved certain results. However, due to the random distribution of melons in the field and their inconsistent fruit morphology, harvesting machinery developed based on traditional structural design methods struggles to achieve a high damage-free picking rate. Even currently commercialized muskmelon harvesters still require significant manual intervention during the picking process. This not only increases operational costs but also makes it difficult for their working efficiency to meet the practical demands of large-scale farms. In contrast, a significant gap exists in China regarding the research, development, and application of muskmelon harvesting machinery. Most related studies remain at the level of academic literature and patents, with no systematic solutions or prototypes demonstrating potential for commercial application having been reported. In actual production, muskmelon harvesting still relies entirely on manual labor, resulting in high costs and low efficiency.

(3) Artificial intelligence technology has demonstrated significant potential in key aspects such as fruit maturity recognition and localization. However, current research primarily focuses on the verification and optimization of the visual algorithms themselves. There is still a notable lack of systematic studies on the collaborative hardware-software integration of these AI technologies with actuator controllers, robotic grasping devices, logistics sorting units, and remote cloud control platforms. Although high recognition accuracy and localization precision can be achieved in laboratory settings, the insufficient integration across different modules and the lack of field-adaptive design hinder the transformation of these technologies into mature, practical solutions for integrated harvesting equipment.

### **SUGGESTIONS ON THE DEVELOPMENT OF MUSKMELON HARVESTING TECHNOLOGY**

(1) Promote research on multi-sensor fusion and lightweight intelligent detection technology. In the short term, efforts should focus on breakthroughs in multi-sensor fusion technology, deeply integrating traditional detection methods such as spectroscopy, acoustics, and machine vision with artificial intelligence algorithms, and developing miniaturized, low-power hardware platforms suitable for field environments. Specific directions include: fusion criteria combining visible-near infrared spectroscopy with deep learning, synergistic recognition using electronic nose and image features, and joint analysis of acoustic responses with visual information. By constructing a multi-modal perception system, the robustness of muskmelon maturity discrimination under varietal diversity and illumination variations can be improved, with the goal of achieving a commercial application prototype for specific varieties within 2–3 years.

(2) Strengthen research on key technologies of harvesting robots and field-adaptive system integration. To address the current bottlenecks of low automation level and limited damage-free harvesting rate in muskmelon harvesting machinery, the mid-term focus should be on the development of core components and system integration of harvesting robots. Specific technical directions include: bionic flexible end-effectors (adaptable to different fruit shapes and spatial poses), real-time recognition and localization systems based on depth vision (integrating RGB-D cameras with inertial measurement units), autonomous chassis suitable for soft soil surfaces, and low-impact fruit storage and transport platforms. Meanwhile, field adaptability validation should be carried out to address practical issues such as illumination variations, leaf occlusion, and fruits touching the ground, ultimately forming semi-automated or fully automated harvesting solutions for typical varieties (e.g., Hami melon, netted muskmelon).

(3) Develop specialized equipment for precision cultivation models such as "trellis-cultivated muskmelon fields". With increasing demands for muskmelon quality, three-dimensional cultivation models such as trellis cultivation are becoming increasingly popular, and their operating environment differs significantly from traditional flat-land cultivation. In the long term, small to medium-sized specialized harvesting equipment suitable for small-scale, three-dimensional spaces should be developed. Specific technical directions include: lightweight multi-degree-of-freedom robotic arms, climbing or lifting platforms adapted to vertical vines, and vision-based fruit localization and obstacle avoidance strategies in three-dimensional spaces. It is recommended to prioritize technical validation in facility agriculture or standardized trellis-cultivated fields, gradually forming a harvesting equipment system tailored to precision cultivation models to meet the demands of diverse future planting patterns.

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