AI Based Fruit Quality Detection Using Image Analysis

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Abstract. The increasing export market demand for good quality fruits has led to develop new techniques for quality assessment. Classical evaluation techniques of fruit quality are very laborious, time consuming and sensitive to human interpretation. In this work, an AI enabled system for analyzing the quality of the fruit based on image processing approaches is proposed to automate the process of fruit inspection. These systems use deep learning methodologies such as Convolutional Neural Networks (CNNs) to analyze fruit images and measure characteristics of fruit, such as color, texture, size, or defects. Comprehensive fruit photography (e.g., clustered or single fruit) can enable AI systems to effectively inspect fruit errors (including discoloration, bruising, deformation etc.) shape-wise in terms of freshness and ripening degree. Even more, the system can predict the quality of a generic fruit through visual properties related to the customer demand. The applied approach enables noninvasive and real-time measurements toward high efficiency and consistency and low human error. This AI-based approach offers successful solutions for automatic fruit-cultivation, sorting and packaging-quality checking, that in the end can result in improved supply chain management, and happy customers.

Keywords: AI-based Fruit Quality Inspection, Deep Learning, Convolutional Neural Networks (CNNs), Image Analysis, Fruit Defect Detection.

1 Introduction

Fruit quality significantly determines consumer satisfaction, market demand, and overall agricultural production. Fruit sorting and classification according to quality is important in the modern fruit industry to deliver the best products to consumers. In the past, this activity was performed manually using a human inspector to identify defects to determine the maturity and fruit after visual appearance. However, visual inspections are not only time- and labor-intensive, but are also erroneous, inconsistent and subjective, especially for large amounts of fruit. As the demand for fresh fruits is growing worldwide, a more efficient, accurate and scalable way of recognizing fruit quality is needed. inspection. With the help of extended algorithms and image processing methods, AI systems are trained to reflect complex visual patterns that reflect the quality of fruit, including the occurrence of defects such as color, texture, shape, bruises, cracks, and misbehaviors. can be identified. This method promotes faster, more accurate quality decisions and improves the efficiency of sorting, valuation and packaging. As a result, this technology is an automated, scalable quality control solution. could change the fruit industry through. This not only increases efficiency for businesses, but also for consumers. The quality of fruits in deep learning models, especially the folding network (CNNS), is integrated to classify and evaluate fruit quality. The proposed system aims to contribute to efficient supply chains based on visual features and provide a stable,

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automated mechanism to minimize waste in the agriculture industry in the long term. Fig 1 shows the existing model of fixed quality detection system.

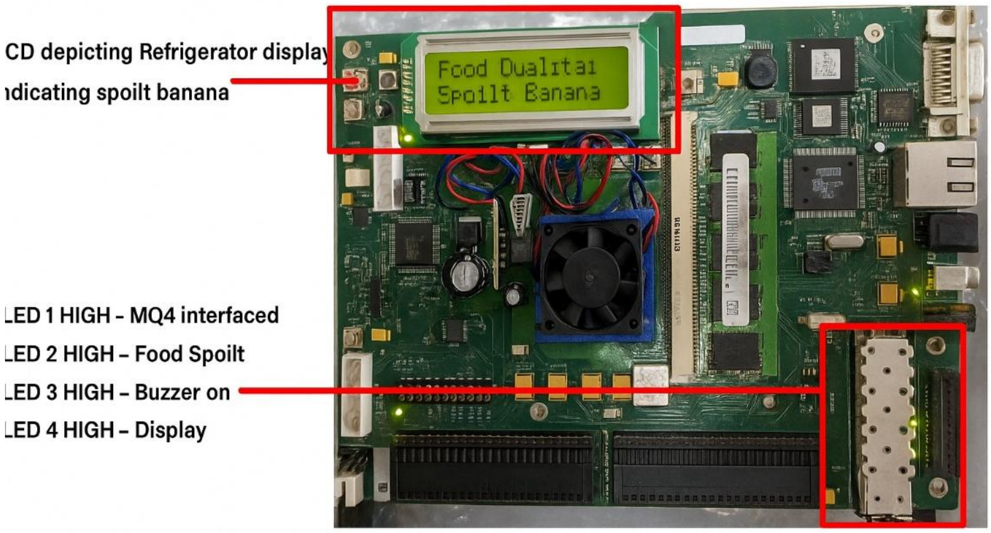

Fig. 1. Existing Model of Fixed Quality Detection System.

2 Literature Review

The fast development of artificial intelligence (AI) and machine learning has revolutionized many sectors, including agriculture, and AI systems are also more frequently used to fruit quality inspection. Existing fruit quality inspection techniques, such as manual sorting and visual inspection, are not only time consuming but also subjective and dependent on human supervision. Consequently, AI-based methods, especially convolutional neural networks (CNNs), have been leveraged to automatic fruit quality assessment with higher accuracy.

The following are few models that demonstrated the extent to which CNNs could be applied in fruit classification and quality determination, and deep learning could be used in the classification of fruits based on their quality, such as colour, texture, and shape and also it helped in reducing human errors to a large extent as well [1]. -Mahajan and Dey (2018) Xu et al. (2020) used CNNs to detect defects in citrus fruits and observed that it led to faster and more accurate defect detection in contrast to manual inspection methods. Their work also illustrates the capability of CNN for identifying different types of defects such as bruise and discoloration, which is frequently found in fruit quality inspection [2].

In recent years, apart from the CNN-based approaches, the fusion solutions of HS and DL methods have also exhibited the potentials of improving the fruit maturity detection. Ou et al. (2024) apply hyperspectral imaging with deep learning algorithms for early disease detection, like strawberry leaf gray mold, a frequent issue in fruit growing. This method not only increased disease detection but whole non-degrading survey, so it could be applied for food safety and quality control [3]. Furthermore, Gao et al. (2024) researched developing the deep learning-based models for grading apples and that their system quickly classified one apple as different quality ranks which improved the sorting and packaging process [4].

In addition, the use of AI to predict fruit ripening has also been investigated. Ghosh and Singh (2021) predicted the ripeness of fresh fruits using image processing to assist farmers in harvesting time and delivering fresh fruits to consumers [5]. Additionally, Li et al. (2022) investigated how deep learning techniques can be used for detecting defects in agricultural products, illustrating how AI can facilitate quality control process and minimize supply chain losses [6].

Gonźalez-Díaz and García (2020) have done a thorough review on AI applications for assessing fruit quality specifically by considering the potential of deep learning for analysing intricate features such as size, color, texture of fruit. They further talked about obstacles of utilizing AI in agriculture including the requirement of big data and the problem of learning labelled data to train AI models [7]. Also, Patel and Singh (2021) reviewed the potential of hyperspectral imaging for fruit quality analysis and highlighted the useful contribution of AI and hyperspectral in quality control [8].

Application of AI in the assessment of fruit quality includes processing of sorting in addition to providing defect markets. Zhang and Li (2020) surveyed the applications of AI to the sorting of various types of fruit, highlighting how AI-enabled systems might be used to inspect fruit based on certain features (e.g. shape and superficial defects) for better sorting and waste reduction. Their study recommended the use of AI in automated sorting machines for competent and extendible operation of fruit inspection [9].

Finally, Anjali et al. (2021) is dedicated in review trend about defects detection from fruits and vegetables. In their review, the authors described the increasing role of AI in enhancing the quality of fruits and minimizing post-harvest losses and stressed that progress in image analysis and deep learning would further support the evolution of increasingly accurate and fast quality sensing systems in agronomic applications [10].

3 Technological Achievement

One of the most important technical breakthroughs in the inspection of the quality of AI-equipped fruits through image analysis is the creation of folding networks (CNNs), particularly to ensure that the quality of fruits can be correctly identified. Defines identification of bruising, refinement, and form defects. These models are calibrated by fruits using large sentences from different image data records, allowing you to learn high ranking visual features related to other quality features such as maturation, texture, and surface defects. . Furthermore, using actual time processing of images makes it easier to quickly and automatically check the production line, improving efficiency and throughput. AI technology also uses multi-class classification. This recognizes several quality factors in one GO and eliminates distortions and human error. This technology can be scalable across different types of fruits and conditions, providing high accuracy and uniform inspections, and therefore an innovative solution for sorting, evaluating and packaging ancient industries.

4 Proposed System Methodology

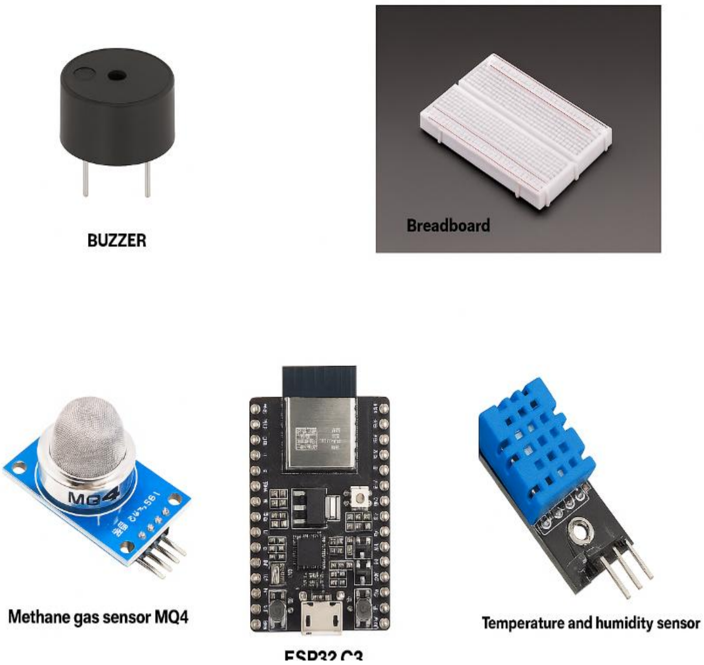

Fig.2. Hardware Components Used in IoT-Based Monitoring System.

The proposed process of AI-driven fruit quality recognition system begins to collect high-resolution images of fruits with different categories of defects at different maturation stages. Images are recorded via a high-resolution camera or a specific imaging machine mounted along the sort line for actual recording of the image, while fruit is processed through the system. Recorded images are prepared to improve important features such as brightness adaptation, noise removal, and normalization, allowing the model to interpret images under different lighting and environmental conditions. Pre-processed images use related quality features (maturity, size, surface accidents, etc.). quality. The CNN model learns to recognize a variety of defects such as bruising, stains, and color variations, and evaluate the properties that correspond to maturity and general appearance. During training, the model is adjusted to reduce classification errors through methods such as baking propagation and gradient descent. After training, the model is validated and tested with invisible images to confirm its accuracy and generalization capabilities. The trained model is implemented in a sorting system, analyzing incoming fruit photos in real time, defining the quality of each fruit, and sending feedback to an automated sorting device. Fig 2 shows the hardware components used in IoT based monitoring system.

5 System Design and Simulation

The design of AI-based fruit quality inspections includes many key components integrated to support real-time quality assessment and selection. High-resolution imaging stations, which usually include several cameras, are central to the system to take clear images of fruit along the production line. These images are derived by the preprocessing modules used to normalize the input to a deep learning model using methods such as contrast reinforcement, noise removal, and normalization. Next, the pre-processed image is a foldable folding network trained to identify and classify various quality features such as maturation, color uniformity, texture, bruises, cracks, and stains (is led by CNN). CNN models are used to generate quality values or classifications and proceed with an automated sorting process. The sorting process is integrated into sponsor or robotic arms that sort fruits according to proven quality levels. B. High, Medium, or Low Quality. Fig 3 shows the circuit diagram of proposed system.

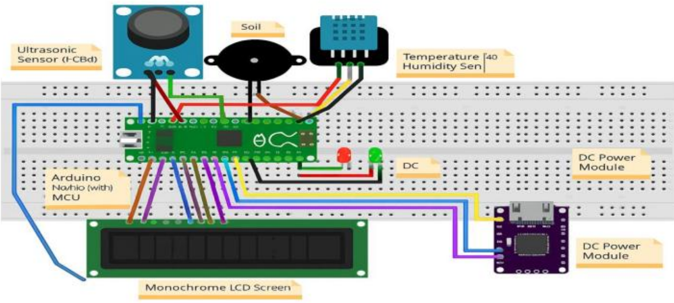

Fig. 3. circuit diagram of proposed system.

System simulation is to run several test cases to test performance under different conditions, including different lighting, fruit varieties, and defect types. Simulation allows you to complete the model. B. Variation in environmental conditions and fruit appearance. This simulation evaluates the performance of the system with accurate fruit classification and feedback to sort real- time feedback with minimal false alarms and high throughput. Use the output from the simulation to adapt both hardware and deep learning models and fine-tuning to ensure efficient integration and optimization of real applications. A successful system simulation checks its ability to improve the efficiency, consistency and scalability of fruit sorting and classification.

6 Hardware Development and Testing

The aim is to present an affordable and efficient early septic system of food to identify the lifespan of fruits and vegetables when maintaining fresh products for consumers. Table 1 and Table 2 shows all the parameters of the system components and all the components linked to the PIN number of ESP32 C3.

Table 1. Table of Specifications.

Serial No.	Component Used	Quantity
1	Raspberry Pi Pico (RP 2040)	1
2	MQ4 - Methane Gas Sensor	1

3	DHT11 - Temperature and Humidity Sensor	1
4	Breadboard	1
5	NodeMCU ESP8266	1
6	Power Supply (5V, 2A)	1
7	LCD 16*2 display	1
8	LED Lights	2
9	Buzzer	1
10	Connecting Wires	1

Table 2. Pin Numbers Connected with Raspberry Pi Pico.

Name of Component	Component Pin Number	Raspberry Pi Pico Pin Number
LCD display (16*2)	RS	GP2
LCD display (16*2)	E	GP3
LCD display (16*2)	D4	GP4
LCD display (16*2)	D5	GP5
LCD display (16*2)	D6	GP6
LCD display (16*2)	D7	GP7
NodeMCU ESP8266	Vin	VBUS
NodeMCU ESP8266	GND	GND
NodeMCU ESP8266	GPIO5	GP5
NodeMCU ESP8266	GPIO4	GP4
LED Red		GP14
LED Green		GP15
DHT11 - Temperature and Humidity Sensor	VCC	3V3(OUT)
DHT11 - Temperature and Humidity Sensor	DATA	GP16
DHT11 - Temperature and Humidity Sensor	GND	GND
Buzzer/ Alarm	VCC	GP17
Buzzer/ Alarm	GND	GND
MQ4 - Methane Gas Sensor	VCC	3V3(OUT)
MQ4 - Methane Gas Sensor	GND	GND
MQ4 - Methane Gas Sensor	A0	GP26

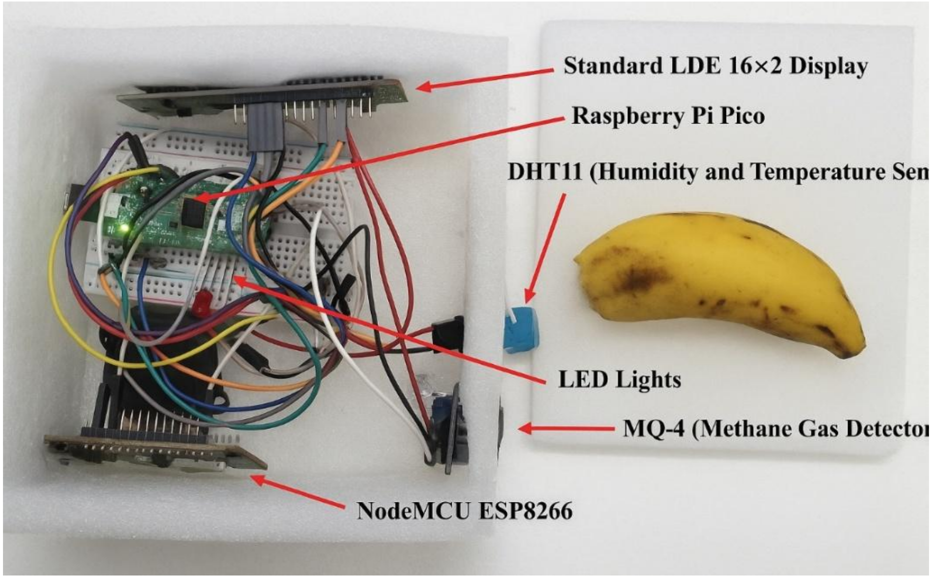

Fig.4. Lifespan detection of banana using proposed system.

The DHT-11 (temperature and atmospheric humidity sensor) and MQ-4 (Methanegassensor) are connected to the ESP32 C3 Picoto to measure temperature, atmospheric humidity and methane release data. Both the DHT-11 and MQ-4 sensors include four pens. These two sensors can measure fruit data. The ESP32 C3 is a SOC microchip with a TCP/IP protocol stack on the board for IoT-based embedded application development. The VIN is attached to the raspberry PI pico on the pin VBU. GPIO5 and GPIO4 are attached to pins GP8 and GP9, while GND pens are attached to GND Raspberry Pi Pico. The LCD 16*2 display is used to display the status of the fruit. The ESP32 C3 is used to install LED lights and summer. The system comes with 5-V and 2A supplies. The model of the proposed system to capture the lifespan of the DHT-11 (temperature and humidity sensor) and the MQ-4 (Methangassessor) are connected to the ESP32 C3 Picoto to record temperature, humidity and methane mask. The DHT-11 and MQ-4 are made up of four pens. These two sensors can collect data about fruits. ESP32 C3 is a chip microchip system with an integrated TCP/IP protocol stack for developing embedded IoT-based applications. The VIN is connected to the PIN VBUS, GPIO5, and GPIO4 PIN GP8 and GP9 Raspberry Pi Pi Pi Pim, while GND -Pin is connected to the GND Raspberry Pi Pico. The LCD 16*2 screen is used to display the fruit status. The ESP32 C3 is used to make lighting fixtures for summer lighting and LED lights. The system provides 5-V and 2A power. The proposed model of the system for recognizing fruit lifespan is fig 4.

Using a variety of sensors and connections, we can determine IoT- based systems to determine fruit quality and recognize lifespans to monitor and determine fruit quality and freshness. It helps consumers access to freshness and healthy fruits by minimizing food spoilage. It prevents people from consuming lazy fruit. It is dangerous to their health.

7 Performance Analysis and Discussion

Quality detection of KI fruits by imaging tests shows high performance in several measurements, including accuracy, accuracy, recall and processing speed. Deep learning models such as B. folding network (CNNS), allowing accurate recognition of external and internal fruit quality features such as aging, surface defects, and color equality. Overall, CNN-based systems and sophisticated imaging methods such as multispectral and hyperspectral imaging can capture more subtle aspects of fruit quality than those based on traditional models of machine learning. It's excellent. The important performance indicator is accuracy, usually 85% to 98% in fruit type and defect complexity. Accuracy is important for classifying false positive aspects (defect classification, defect classification, if there is no defect), and is important and important when storing false negatives (without classification, (If there is, no classification of defects). Typically, the accuracy is greater than the recall. This means that the model is conservative when marking defects, but the callback guarantees that most defects are included. The balance between accuracy and recall is also a good measure of model output, usually above 0.9 on a well-tuned system. - Scale production settings. A system that processes fruits with 1-2 fruits per second using feedback from the local transport time of the sorting system is ideal for commercial applications. In contrast, traditional machine vision systems with much lower speeds without AI fruit can be processed and may reduce the accuracy of recognition of subtle defects.

Table 3. Hypothetical Performance Comparison.

Method	Accuracy	Prec ision	Recall	F1 Sco re	Processing Speed	Real- Time Capability
CNN (RGB Images)	90%	88%	85 %	0.8 6	1-2 fruits/second	High
CNN (Multis pectral Images)	95%	92%	90 %	0.9 1	1-2 fruits/second	High
Traditio nal ML (RGB Images)	80%	78%	75 %	0.7 6	0.5 fruits/second	Moderate

This table 3 highlights that CNN-based systems, in particular multispectral imaging-based, can provide better real-time skills than traditional models of machine learning. Continuing advances in AI and image processing technologies may improve the efficiency and effectiveness of detecting fruit quality.

8 Conclusion

Evaluating fruit quality using artificial intelligence (AI)-based image analysis is an innovative development in the agriculture and food processing sectors. Use deep learning, especially folding networks (CNNS) and imaging techniques. B. Provides multispectral and hyperspectral imaging, and methods for determining non-destructive fruit quality in reliable real-time, for these systems. The ability to automatically identify fruit defects, assess maturation, and visual classification significantly improves the speed and reliability of fruit sorting, while at the same time minimizing human interference and labor costs. Problems such as environmental variation, discrepancies in the appearance of fruits, and handling of different types of defects continue to exist. Continuously updated KI and computer vision technologies reduce these issues using approaches such as data scaling, transmission learning, and improved hardware integration. These technologies change the quality control process, minimize food waste, improve supply chain management, and provide the highest quality product to consumers, and provide AI-powered fruit quality detection. The future is bright. Further research and development will further improve these systems, making them more scalable and flexible to consider the various agricultural environments around the world.

9 Resulting Configuration and Outcome

The resulting configuration of the AI-based fruit quality detection system integrates high-resolution cameras or multispectral sensors to capture detailed images of fruits as they move along the sorting line. These cameras are paired with an image preprocessing module that enhances the quality of the captured images through techniques like noise reduction, contrast adjustment, and normalization, ensuring that the relevant features are highlighted for analysis. The processed images are then fed into a deep learning model, typically a Convolutional Neural Network (CNN), trained to recognize and classify fruit quality based on various attributes such as ripeness, color, shape, and surface defects like bruises or cracks. The AI system classifies the fruits into different quality grades (e.g., high, medium, low) and provides real-time feedback to an automated sorting mechanism, such as robotic arms or conveyor systems, that physically sorts the fruits based on their quality. The outcome of this configuration is a highly efficient, automated system that improves the accuracy, speed, and consistency of fruit quality detection while reducing labor costs, minimizing waste, and ensuring high-quality produce reaches consumers. Additionally, the system's scalability and adaptability allow it to be used across various types of fruits and production environments, further enhancing its practical value in the agricultural sector.

10 Applications

Image analysis AI fruit quality testing has many uses in food processing and agriculture. Perhaps the most important application is the automatic evaluation and sorting of AI system rate characteristics such as color, maturation, texture, and surface errors (e.g., discolouration, cracks, bruises, etc.). This technology minimizes human workers' use and allows for effective sorting of bulk goods fruits on production lines with guaranteed uniform quality control. Furthermore, AI-driven recognition systems are used in packaging quality security where fruits are classified for various market segments. Depending on the quality. This not only maximizes the supply chain, but also reduces food waste by properly separating them. This is not only not suitable for direct sales, but also for processing and other purposes. Additionally, these systems reduce post-harvest losses with proper handling and fruit storage depending on the quality, resulting in longer durability and improved marketability. In the course of the technology, detection of the quality of fruits of AI-based fruits for use in precision agriculture is also considered. This helps to monitor fruit growth and harvest time forecasts. This allows for improved plant management and predicted yields. It will become.

11 Challenges and Future Directions

Despite significant advances in detecting fruit quality through AI and image analysis, some challenges have yet to be met. Dealing with appearance variability caused by attributes such as fruit size, shape, color, and surface structure, and caused by different attributes between different fruits and different tire stadiums of the same fruit type is one of the most important challenges. That's it. Ambient conditions, including lighting, shadows and ambient noise, can also affect image quality and inconsistency in identification accuracy. Furthermore, these defects are not always visible in regular RGB images, so detection of weak defects, such as internal bruises and initiation of decay, remains a challenging task, although it is still highly accurate. Another challenge is that large labeled data records are required for training deep learning models that are acquired and expensive, especially rare or seasonal fruits. However, the future of recognizing fruit quality in AI-based fruit quality is promising in many ways to improve.

This range is a combination of polyvision and more accurate measurements of hyperspectral properties such as sugar, texture, and internal defects. Another area is the development of transfer learning and domain coordination, allowing the model to be transferred more through various fruit types and environmental conditions. The development of more powerful and energy- efficient hardware, such as AI-specific chips and edge computing hardware, also improves real-time performance of these systems. This means it is even more suitable for applications in the field of industrial standards. Finally, with improved data availability and cloud computing, AI-driven fruit quality detection is increasingly intelligent, scalable, and precise to better optimize plant management and food distribution. The Aglar platform will further improve, making it even more intelligent and scalable.

References

[1] Mahajan, P. M., & Dey, S. (2018). Fruit quality classification using convolutional neural networks. Journal of Food Engineering, 243, 68–75. https://doi.org/10.1016/j.jfoodeng.2018.06.004

[2] Xu, X., Li, Y., & Wang, W. (2020). Detection of citrus fruit defects using convolutional neural networks and computer vision. Computers and Electronics in Agriculture, 174, 105467. https://doi.org/10.1016/j.compag.2020.105467

[3] Ou, Y., Yan, J., Liang, Z., & Zhang, B. (2024). Hyperspectral imaging combined with deep learning for the early detection of strawberry leaf gray mold disease. Agronomy, 14(11), 2694. https://doi.org/10.3390/agronomy14112694

[4] Gao, X., Li, S., Su, X., Li, Y., Huang, L., Tang, W., Zhang, Y., & Dong, M. (2024). Application of advanced deep learning models for efficient apple defect detection and quality grading in agricultural production. Agriculture, 14(7), 1098. https://doi.org/10.3390/agriculture14071098

[5] Ghosh, P., & Singh, R. (2021). Artificial intelligence-based prediction of fresh fruit ripeness using image processing techniques. Information Processing in Agriculture, 8(1), 21-34. https://doi.org/10.1016/j.inpa.2021.01.005

[6] Li, J., Zhang, H., & Liu, Z. (2022). A deep learning-based approach for fruit defect detection in agricultural products. Advances in Agriculture, 2022(2), 8521236. https://doi.org/10.1155/2022/8521236

[7] González-Díaz, C., & García, C. (2020). A review of deep learning applications in fruit quality assessment. Sensors, 20(10), 2974. https://doi.org/10.3390/s20102974

[8] Patel, D., & Singh, A. (2021). Challenges in fruit quality detection with AI and the role of hyperspectral imaging. Food Quality and Safety, 6(2), 105–112. https://doi.org/10.1093/fqsafe/fyab012

[9] Zhang, Y., & Li, L. (2020). Artificial intelligence for fruit quality inspection: A comprehensive review. Computers and Electronics in Agriculture, 178, 105759. https://doi.org/10.1016/j.compag.2020.105759

[10] Anjali, N., Kannan, R., Andres, F., & Ghinea, G. (2021). Trend review related to defects detection from fruits and vegetables. Preprints. https://doi.org/10.20944/preprints202111.0035.v1