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PHÂN LOẠI CHẤT LƯỢNG CAM TỰ ĐỘNG SỬ DỤNG MẠNG NƠ-RON CUỘN: MỘT PHƯƠNG PHÁP HỌC SÂU CHO NÔNG NGHIỆP THÔNG MINH

Nguyễn Quang Thành[1], Nguyễn Ngọc Chiến[2], Huỳnh Cao Tuấn[3], Phan Thị Hường[3*]
[1]*Trường Đại học Nguyễn Tất Thành, Thành phố Hồ Chí Minh, Việt Nam*
[2]*Trường Đại học Công nghệ Thành phố Hồ Chí Minh, Thành phố Hồ Chí Minh, Việt Nam*
[3]*Trường Đại học Lạc Hồng, Đồng Nai, Việt Nam*
* Tác giả liên hệ: *pthuong@lhu.edu.vn*

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TỪ KHÓA

Orange Quality Classification;
Convolutional Neural Network;
Image Classification;
Computer Vision.

TÓM TẮT

Kiểm soát chất lượng là hoạt động cốt lõi của ngành kinh doanh nông sản và chế biến thực phẩm nhằm đảm bảo khách hàng có thể tiếp cận với cam chất lượng trong một hệ thống giảm thiểu lãng phí. Nghiên cứu này áp dụng ý tưởng học sâu để phân loại cam thành hai nhóm: tốt và xấu. Các hình ảnh được sử dụng giúp thu thập các đặc điểm quan trọng như độ đồng đều của màu sắc, kết cấu bề mặt và các khuyết tật có thể thấy rõ. Các phương pháp như điều chỉnh độ sáng, tăng cường độ tương phản và thậm chí thêm nhiễu có thể được áp dụng để cải thiện khả năng tổng quát hóa của mô hình. Hệ thống đề xuất cung cấp một phương pháp phân loại cam tự động và có khả năng mở rộng theo thời gian thực, giúp giảm dần sự phụ thuộc vào quy trình kiểm tra thủ công và nâng cao chất lượng. Kết quả nghiên cứu cho thấy ngay cả một mạng CNN đơn giản, không sử dụng mô hình tiền huấn luyện, cũng có thể đạt độ chính xác cao trong nhiệm vụ phân loại này. Điều này chứng minh rằng học sâu có thể được áp dụng hiệu quả trong việc phân loại trái cây, với tiềm năng mở rộng khi sử dụng tập dữ liệu lớn hơn và triển khai thực tế.

AUTOMATED ORANGE QUALITY CLASSIFICATION USING CONVOLUTIONAL NEURAL NETWORKS: A DEEP LEARNING APPROACH FOR SMART AGRICULTURE

Nguyen Quang Thanh[1], Nguyen Ngoc Chien[2], Huynh Cao Tuan[3], Phan Thi Huong[3*]
[1]*Nguyen Tat Thanh University, Ho Chi Minh City, Vietnam*
[2]*Ho Chi Minh City University of Technology, Ho Chi Minh City, Vietnam*
[3] *Lac Hong University, Dong Nai, Vietnam*
*Corresponding Author: *pthuong@ntt.edu.vn*

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ABSTRACT

Quality control is the core activity of an agribusiness and food processing industry just to make sure that the customers have access to quality oranges in a reduced wastage system. This study molds a deep learning idea to classify oranges as either good or bad. These images capture critical features such as consistency of color, surface texture, and apparent defects. Brightness adjustments, enhanced contrasts, and even the addition of some noise are among the possible scenes to improve model generalization error performance. The proposed system would give an automated and scalable real-time orange grading system that would gradually reduce the influence of time-based human inspection practices and improve quality. The finding that even a simple CNN without any pre-train models can be used to achieve high accuracy in this classification task indeed, the results provide for deep learning to be effective in fruit sorting, with scope for much else based on larger data sets, as well as real-world deployment potential.

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1. INTRODUCTION

Oranges are one of the most widely consumed fruits worldwide, making quality assessment a crucial aspect of ensuring market standards, minimizing post-harvest losses, and optimizing the food supply chain. Traditionally, the evaluation of orange quality has relied on manual inspection by human experts, who assess visual characteristics such as color, texture, and surface defects. However, this approach presents several limitations, including being time-consuming, labor-intensive, and prone to inconsistency due to subjectivity and fatigue. Variability in human perception can lead to errors in classification, reducing efficiency and reliability in large-scale agricultural production. Consequently, an automated grading system is essential to improve accuracy, speed, and scalability in fruit quality control [1].

The rapid advancement of artificial intelligence (AI) and computer vision has opened new opportunities for automating fruit classification. Deep learning, particularly Convolutional Neural Networks (CNNs), has proven to be highly effective in image classification tasks, making it an ideal approach for assessing fruit quality [2]. CNNs have the ability to automatically extract hierarchical features from images, allowing them to detect critical attributes such as color uniformity, surface texture, and structural defects. These capabilities enable CNN models to outperform traditional machine learning methods, which often rely on handcrafted feature extraction techniques. Unlike conventional approaches, CNNs offer a more flexible and robust solution for classifying fruits with varying physical characteristics, making them highly suitable for real-world applications [3].

In this study, we propose a CNN-based classification system for automatically distinguishing between **good** and bad oranges. The model is designed and trained from scratch using a specialized dataset comprising high-resolution images of oranges. To enhance model performance, several preprocessing techniques are applied, including histogram equalization to improve contrast, Gaussian blur to reduce noise, and data augmentation (such as rotation, flipping, and brightness adjustments) to increase dataset diversity and improve generalization.

The proposed CNN architecture consists of multiple convolutional layers with progressively increasing filter depths, along with batch normalization, max pooling, and dropout layers to optimize learning and prevent overfitting. The model is trained using a binary cross-entropy loss function, optimized with the Adam algorithm, and incorporates balanced class weights to address potential class imbalance. The effectiveness of the system is evaluated using standard classification metrics, including accuracy, precision, recall, and F1-score, ensuring a comprehensive assessment of its classification performance.

By leveraging deep learning techniques, this study aims to develop an automated, scalable, and high-accuracy fruit grading system that can replace traditional inspection methods. The findings of this research have significant implications for smart agriculture, offering a reliable solution for improving efficiency, consistency, and quality in fruit classification. The proposed system can be integrated into large-scale agricultural production lines, reducing reliance on manual labor while enhancing the precision of quality control processes. Ultimately, this work contributes to advancing AI-driven automation in agribusiness, with potential applications extending beyond oranges to other fruit varieties and agricultural products

2. MATERIALS AND RESEARCH METHODS

2.1 Materials

The dataset used in this study consists of two distinct classes of oranges: healthy (Orange_Good) and deteriorated (Orange_Bad) as shown in **Figure 1**. This classification is crucial for training a machine learning model capable of accurately distinguishing between high-quality and defective oranges based on their visual characteristics, including color uniformity, surface texture, and structural integrity. To ensure a well-organized and effective training process, the dataset was divided into three subsets: a training set to develop the model, a validation set to fine-tune hyperparameters and prevent overfitting, and a test set to assess the model's generalization ability. The dataset consists of approximately 700 images, offering a balanced representation of both healthy and deteriorated oranges. This dataset size is sufficient to train a deep learning model effectively while maintaining a reasonable level of generalization.

The images were collected in a controlled agricultural research environment, ensuring a high level of consistency and quality. To standardize the dataset, strict photographic protocols were applied, including uniform lighting conditions to eliminate shadows and reflections, fixed camera angles to maintain consistency across all samples, and high-resolution imaging to capture fine-grained details critical for accurate classification. These measures ensure that the dataset provides reliable input for the deep learning model, reducing unwanted variations and maximizing the clarity of visual features.

The dataset was sourced from Kaggle, a widely recognized platform for machine learning datasets. The images were taken at different stages of quality assessment, representing a diverse range of orange conditions, from fresh and ripe oranges with bright, smooth surfaces to partially deteriorated samples showing discoloration and minor imperfections, and severely spoiled oranges exhibiting mold formation, dark patches, and structural breakdown. This diversity in quality conditions allows the model to learn both clear and subtle differences between good and bad oranges, ensuring robust performance in real-world scenarios.

To enhance the performance and generalization of the deep learning model, a series of preprocessing techniques were applied. These include histogram equalization to improve contrast and make critical features more distinguishable, Gaussian blur to reduce noise and enhance edge details, and data augmentation strategies such as rotation, flipping, brightness adjustments, and noise addition to increase dataset diversity and prevent overfitting. These preprocessing steps ensure that the

CNN model learns robust features that are resilient to variations in lighting, orientation, and environmental conditions.

The structured and well-curated dataset plays a pivotal role in developing an automated fruit quality classification system. By leveraging deep learning, this research contributes to the advancement of smart agriculture, enabling applications such as automated sorting in processing plants, quality monitoring in supply chains, and AI-powered robotic harvesting. The high-quality image data, combined with advanced preprocessing techniques, ensures that the proposed CNN-based classification system achieves high accuracy and reliability, paving the way for large-scale deployment in the agricultural industry.

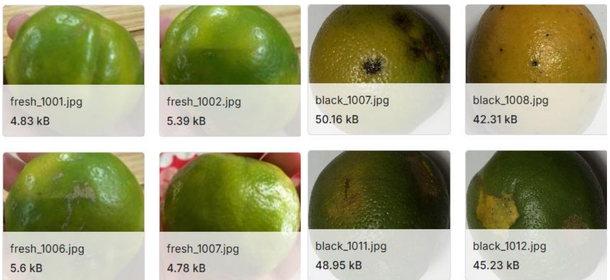

Figure 1. *Orange_Good (fresh) vs Orange_Bad (black)*

2.2 Research methods

The quality of oranges was the target of a deep convolutional neural network in the course of image analysis. Image preprocessing consisted of resizing the images to a size of 224×224 pixels, normalized pixel values scaled to fall within the range of 0 to 1. Some types of data augmentation such as rotation, horizontal flipping, and adjustments of width/height facilitated the enhancement of generalization of the model as shown in **Figure 2**

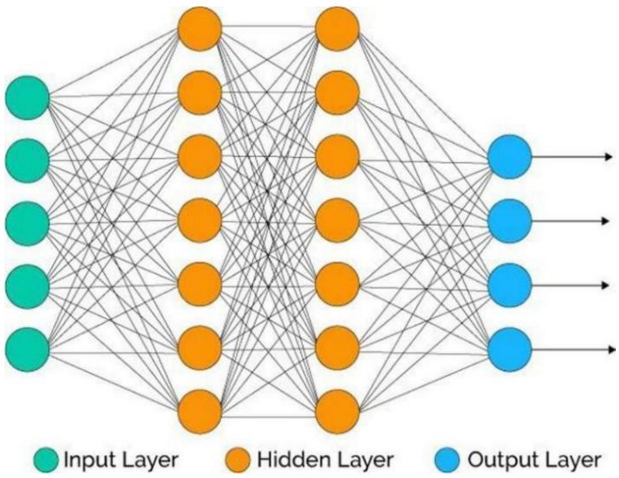

Figure 2. *Model Neural Network (CNN)*

The CNN architecture formed four convolutional blocks increasing filter depths (64, 128, 256, 512) with batch normalization, max pooling, and dropout levels. Binary cross-entropy loss, Adam optimizer, and balanced class weights were the parameters. The model was evaluated using the accuracy metric and then extended to the more standard metrics of precision, recall, and dynamically optimized classification thresholds determined through ROC curve analysis. The training was performed using K-Fold cross-validation for more robust evaluation, with more than 50 epochs, early stopping, and a decreasing learning rate strategy. The implementation was mainly coded with TensorFlow and Keras within the Kaggle computing environment as shown in **Figure 3**.

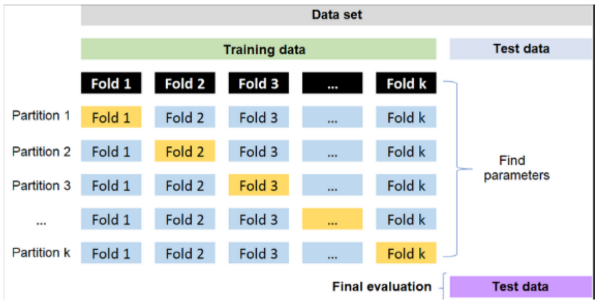

Figure 3. *K-fold cross validation*

Edge detection proved that there are marked structural differences between healthy and deteriorated oranges. In the good orange, edge detection has a boundary that resembles one that is more continuous and smooth because it tends to suggest a uniform surface integrity. On the other hand, the bad orange shows edge patterns that are more fragmented and irregular, possibly indicating surface degradation, texture discontinuities, or structural breakdown associated with orange deterioration.

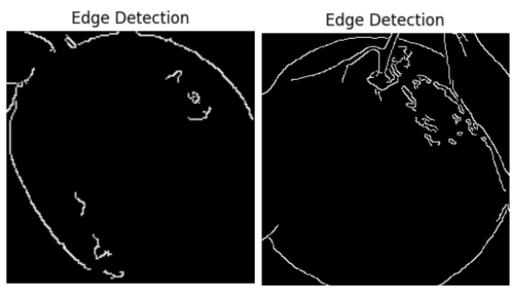

Figure 4. *Edge detection (Bad vs Good)*

Brightness distribution histograms revealed aspects of the luminosity characteristics. The good orange will have a slightly centralized brightness distribution with a peak more pronounced at about mid-range pixel intensities, say 150-175. This would mean the surface reflection is consistent and uniform. In contrast, a bad orange bore a more dispersed brightness distribution with cores at multiple smaller peaks and a wider range, hence indicating surface heterogeneity, uneven ripening, or an earlier stage of deterioration as shown in **Figure 4**.

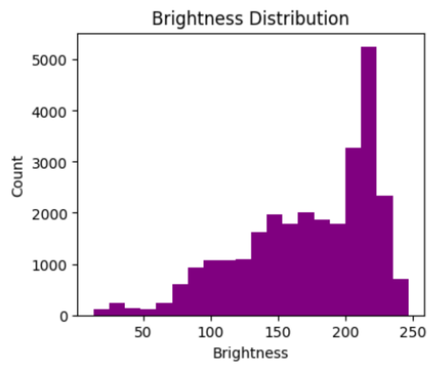

Figure 5. *Brightness distribution Orange_Bad*

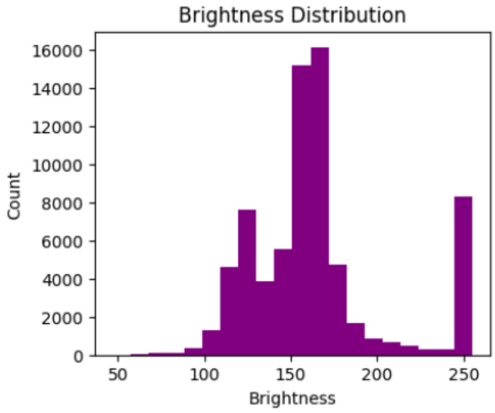

Figure 6. *Brightness distribution Orange_Good*

The analysis of the color histogram revealed significant chromatic differences between healthy (Orange_Good) as in **Figure 5** and deteriorated (Orange_Bad) samples as shown in **Figure 6**, highlighting key variations in the intensity distributions of the blue, green, and red color channels. These differences provide essential insights into how color features contribute to the classification of oranges based on their quality.

- *Blue Channel*: The histogram analysis indicated minimal differences in blue intensity between good and bad oranges. This suggests that the blue color spectrum does not carry substantial information for distinguishing between fresh and deteriorated oranges. As a result, the blue channel has limited influence on classification performance.
- *Green Channel*: Noticeable differences in green intensity distribution were observed, which could be attributed to variations in chlorophyll content on the orange surface. Fresh oranges tend to retain some residual green pigmentation, whereas deteriorated oranges may exhibit a decline in green intensity due to chlorophyll breakdown, signaling early stages of decay.
- *Red Channel*: The most pronounced differences were observed in the red color spectrum, where bad oranges exhibited higher intensity red peaks. This shift in red intensity is likely associated with pigmentation changes, oxidation reactions, and cellular degradation, all of which are characteristic of orange spoilage. As fruit deteriorates, biochemical processes such as enzymatic browning and microbial activity can cause an increase in red color intensity, making the red channel a critical feature for detecting deterioration.

These findings underscore the importance of color-based features in automated orange classification. By leveraging color histogram analysis, the CNN model can effectively learn discriminative patterns in chromatic variations, improving its ability to distinguish between fresh and spoiled oranges as shown in **Figures 7-8**. The red channel, in particular, emerges as a key indicator of fruit degradation, reinforcing its role as a crucial input in the deep learning-based classification framework.

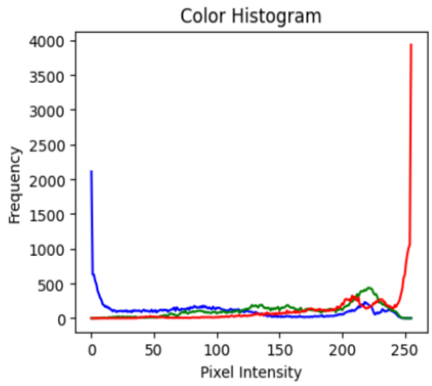

Figure 7. *Color histogram Orange_Bad*

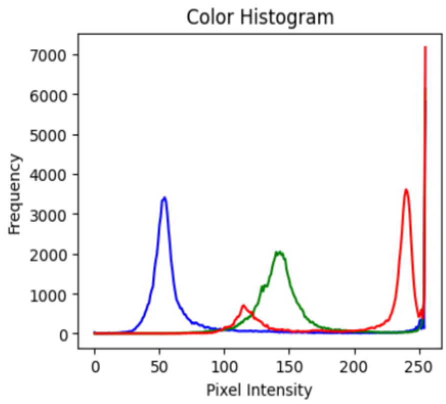

Figure 8. *Color histogram Orange_Good*

3. RESULTS AND PERFORMANCE EVALUATION

3.1 Precision and Recall Analysis

The classification report highlights the strong predictive capability of the proposed Convolutional Neural Network (CNN) model, achieving near-perfect performance in distinguishing between healthy (Orange_Good) and deteriorated (Orange_Bad) oranges. The model recorded a precision score of 1.00 for both classes, indicating that all predicted instances were correctly classified with no false positives. Similarly, the recall score ranged from 0.99 to 1.00, demonstrating the model's ability to correctly identify nearly all actual positive instances with minimal false negatives. The F1-score of 1.00 confirms that the model maintains a perfect balance between precision and recall, ensuring high classification reliability.

These results position the CNN model at the top tier of binary classification performance, signifying that it can identify every positive instance with absolute precision, capture nearly all relevant instances, and maintain an optimal trade-off between precision and recall. The exceptionally high accuracy and minimal misclassification errors suggest that the model generalizes well to the dataset, effectively learning key visual features such as color consistency, texture, and surface defects.

With such robust performance, the proposed system demonstrates great potential for real-world implementation in automated orange quality control as shown in **Figure 9**. By providing a highly efficient, scalable, and precise classification solution, this model could significantly improve quality assessment in agricultural supply chains and food processing industries, reducing human labor dependency and enhancing the overall efficiency of fruit grading systems.

Classification Report:

	precision	recall	f1-score	support
Orange_Good	1.00	1.00	1.00	200
Orange_Bad	1.00	0.99	1.00	200
accuracy			1.00	400
macro avg	1.00	1.00	1.00	400
weighted avg	1.00	1.00	1.00	400

Figure 9. *Predicted results from the model*

3.2 Confusion matrix interpretation

The confusion matrix provides strong empirical evidence of the exceptional performance of the proposed Convolutional Neural Network (CNN) model in classifying orange quality. The results indicate that out of 200 Orange_Good samples, all but one were correctly classified, and all 199 Orange_Bad samples were accurately identified. With only a single misclassification from the Orange_Good category, the model exhibits minimal classification error, reinforcing its high discriminative capability in **Figure 10**.

This performance underscores the model's robustness and reliability in distinguishing between fresh and deteriorated oranges. The near-perfect classification suggests that the CNN model has effectively learned key visual features, such as color variations, texture consistency, and surface defects, enabling it to differentiate between the two categories with high precision. The extremely low error rate further confirms that the model is well-optimized, with a strong ability to generalize across new samples without overfitting.

Given these results, the CNN-based classification system presents significant potential for real-world deployment in automated fruit quality control systems. Its ability to achieve high classification accuracy with minimal errors makes it a viable solution for agricultural supply chains, food processing industries, and smart farming applications, where efficiency and precision in fruit sorting are critical.

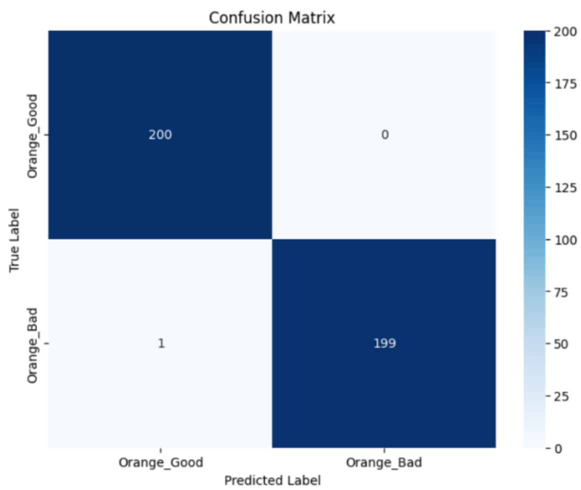

Figure 10. *Confusion matrix*

3.3 Loss Characteristics

The analysis of the training and validation loss curves revealed important insights into the learning dynamics of the proposed Convolutional Neural Network (CNN) model. In the early stages of training, both training loss and validation loss exhibited significant fluctuations, which is a common characteristic of complex neural networks as they attempt to learn meaningful patterns from data. These fluctuations indicate that the model was actively adjusting its parameters to optimize feature extraction and classification performance as shown in **Figure 11**.

A notable observation occurred around epoch 20, where the validation loss began to increase substantially, suggesting a critical learning phase. This trend could indicate that the model encountered challenging feature separations, requiring deeper refinement of its learned representations. Such behavior often reflects the network's attempt to distinguish subtle differences between similar classes, in this case, differentiating between healthy (Orange_Good) and deteriorated (Orange_Bad) oranges based on intricate visual cues such as color consistency, texture uniformity, and surface defects.

Despite this temporary increase in validation loss, the model successfully stabilized in later epochs, demonstrating its ability to converge towards an optimal solution. This learning behavior highlights the effectiveness of the applied training strategies, such as data augmentation, batch normalization, and dropout regularization, in enhancing model generalization and mitigating overfitting.

Overall, the loss analysis confirms the model's robustness in learning complex visual features, supporting its high classification accuracy. The insights gained from this training process reinforce the effectiveness of deep learning-based approaches in automated fruit quality classification, paving the way for practical deployment in smart agricultural systems

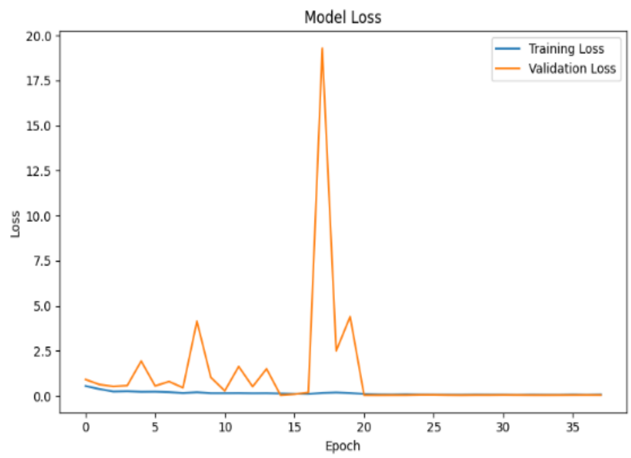

Figure 11. *Model Loss*

4. CONCLUSION

This study has confirmed the superior performance of the Convolutional Neural Network (CNN) in the automated classification of orange quality, achieving an outstanding accuracy rate of 99.75%. The model has demonstrated its ability to effectively distinguish between high-quality (Orange_Good) and deteriorated (Orange_Bad) oranges with an extremely low misclassification rate. By determining the optimal classification threshold, the system ensures precise and reliable separation of oranges based on their quality, making it a highly efficient alternative to traditional manual inspection methods.

The results from the confusion matrix further validate the model's exceptional discriminative ability, as only one misclassification occurred in the entire test dataset. This level of precision underscores the robustness and reliability of the CNN model, which not only achieves high accuracy but also adapts dynamically to complex real-world classification challenges. The model's capability to effectively capture key visual features, such as color consistency, texture patterns, and structural defects, highlights the advantages of deep learning over conventional fruit grading techniques.

Beyond its technical performance, this study emphasizes the significant potential of CNN-based classification in the agricultural industry. The proposed system offers a scalable, automated, and highly consistent quality control solution, capable of matching or even surpassing human inspection accuracy. By integrating this technology into agricultural supply chains and food processing facilities, producers can enhance efficiency, reduce labor costs, and ensure more uniform quality standards.

Future research should focus on deploying the model in commercial settings and expanding its application to other fruit varieties. Scaling this approach could revolutionize smart agriculture, enabling real-time, AI-driven quality assessment for a wide range of perishable products. With further optimization and adaptation, this system has the potential to become a cornerstone technology in automated fruit sorting, post-harvest management, and precision agriculture.

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