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Khamees and Abdusalam

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Optimizing Quality Control: A Comprehensive Analysis of Computer Vision Methods for Assessing Vegetables and Fruits

Zahow Muftah Khamees [1 *] - Abdusalam Aboubaker Abdusalam [2]

1 Department of Information Technology, Faculty of Computers and Information Technology, University of Ajdabyia, Libya.

2 Therapeutic Nutrition, University of Ajdabyia, Ajdabyia, Libya.

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ABSTRACT

Efficient quality control in the agriculture sector, particularly regarding the inspection of vegetables and fruits, stands as a critical necessity in today's health-focused industry. Conventional fruit grading methods, ill-suited for large-scale production, demand an automated, non-invasive, and economically feasible substitute. Computer vision emerges as a promising avenue, leveraging image analysis and machine learning algorithms to evaluate the quality of produce. The convergence of computer vision and image processing technologies in contemporary agriculture has brought about a substantial transformation in quality assessment methodologies. This paper conducts an in-depth exploration of the amalgamation of computer vision and image processing techniques for the evaluation of agricultural produce quality. Through a comprehensive review, this scientific analysis investigates the integration of computer vision and image processing techniques in agricultural quality assessment. It scrutinizes key studies, their practical implementations, outcomes, and the research voids they reveal. Technological progressions within the agricultural domain have the potential to amplify productivity and curtail the circulation of flawed or substandard products. Moreover, this study deliberates on the forthcoming trends in computer vision technology applications, accentuating their prospective influence on the vegetables and fruits industry.

KEYWORDS: Computer Vision, Classification Mechanisms, Fruits; Image Processing, Quality Assessment, Vegetables.

1. INTRODUCTION

In recent years, there has been a growing interest in the application of computer vision techniques for the quality and safety inspection of vegetables and fruits. This is driven by the increasing demand for high-quality produce and the need to ensure food safety for consumers. Researchers have explored various methodologies to evaluate the quality attributes of vegetables and fruits using computer vision, making it a promising field of study.

One area of research focuses on the evaluation of vegetable and fruit quality using computer vision. Conventional imaging techniques have been utilized for non-destructive evaluation of quality attributes in both fresh and packaged vegetables and fruits. These techniques enable accurate assessment of the quality of produce, helping to ensure consumer satisfaction and reduce post-harvest losses [1, 2]. Another area of interest is the sorting and grading of vegetables and fruits using computer vision and image processing techniques [3, 4].

***Correspondence**: Zahow Muftah Khamees

zhow1979@gmail.com

By automating the sorting and grading processes, computer vision systems can improve efficiency and productivity in the agricultural industry. For example, shape-based vegetable and fruit recognition and classification systems have been developed to streamline the sorting and grading of vegetables and fruits [4].

Classification of vegetables and fruits based on image processing techniques has also been explored [5]. By analyzing the visual features of produce, CV can accurately classify fruits and vegetables, aiding in inventory management and marketing decisions [5].

Additionally, fractal analysis has been proposed as an approach for fruit and vegetable classification, further enhancing the accuracy of classification systems [6].

CV techniques have also been employed for volume and mass estimation of fruits and vegetables. These methods enable automated and accurate estimation of yield and quality control, providing valuable information for farmers and producers [7].

In recent years, the use of conditional Generative Adversarial Network (GAN) data augmentation has been investigated for fruit quality and defect image classification. This technique enhances the accuracy of classification systems by generating synthetic data to augment the training set, improving the capability to detect defects in fruits [8]. Using image processing techniques and machine learning algorithms to classify fruits and vegetables. By analyzing different visual attributes such as size, shape, color and texture, the authors aim to develop a comprehensive classification system that can accurately distinguish between different product types.

Transfer learning has also been applied to vegetable and fruit quality assessment, leveraging pre-trained models to achieve accurate classification and quality assessment. This approach allows for the utilization of existing knowledge and models, reducing the need for extensive training and enhancing the efficiency of the assessment process [10]. The vegetables and fruits industry plays a pivotal role in providing nutritious and fresh produce to meet the growing demand for healthy food. Ensuring the quality and safety of vegetables and fruits is of utmost importance to protect consumer health and maintain customer satisfaction. Quality inspection involves evaluating various attributes such as size, shape, color, texture, and the presence of defects, while safety inspection focuses on identifying contaminants, pesticide residues, and other potential hazards.

In recent years, CV techniques have emerged as powerful tools for quality and safety inspection in the fruits and vegetables industry. CV utilizes digital image processing, pattern recognition, and machine learning algorithms to analyze and interpret visual information. By harnessing computer vision, researchers and industry professionals can automate inspection processes, enhance accuracy, and improve efficiency.

The objective of this review is to provide a comprehensive overview of the application of computer vision techniques for quality and safety inspection of fruits and vegetables. This review aims to highlight the potential benefits and advancements in this field. The review will cover several key topics:

2. RELATED WORK

2.1. Traditional Image Processing Techniques

Several research studies have explored the application of traditional image processing techniques in the assessment of fruit and vegetable quality, as evidenced in previous works (e.g., [4, 5, 6]). These techniques typically involve the extraction of features from images, such as color histograms, texture descriptors, and geometric shapes. For example, Jana et al. [4]. focused on shape-based features for fruit recognition and classification, whereas Chithra and Henila [5]. employed image processing techniques for fruit classification purposes. While these methods provide a straightforward and computationally efficient approach, their efficacy often depends on manually engineered features and may fall short in capturing the intricate variations in the appearance of fruits and vegetables.

In the realm of fruit and vegetable quality assessment, various studies have explored the utilization of traditional image processing methods. For instance, Jana et al. [7]. introduced a new method employing the de novo process to automatically estimate the volume and mass of produce, yielding reliable and efficient results as per the presented data. Another study concentrated on improving fruit quality assessment and defect classification by employing conditional GAN data augmentation techniques, leading to notable advancements in accurately identifying and categorizing defects across a spectrum of fruits and vegetables. However, there exists a significant research gap regarding the adaptability and generalizability of the developed classification model to a diverse array of fruit and vegetable varieties. Further investigations are necessary to ascertain the model's efficacy across different produce types.

In the study conducted by Bird et al. [8], the assessment of fruit quality and defect classification in fruits and vegetables was performed through the implementation of conditional GAN data augmentation techniques. The study presented concrete and precise outcomes within this domain. Their research focused on leveraging conditional GAN data augmentation methods for the evaluation of fruit quality and defect classification, resulting in improved accuracy in identifying defects across diverse fruits and vegetables. Looking ahead, it is crucial for future research initiatives to explore the adaptability of the classification model to various fruit and vegetable types to effectively gauge its generalizability.

Wedha et al. [9]. delved into a thorough examination of the classification system pertaining to fruits and vegetables, showcasing a commitment to understanding and improving this domain. Their study extensively delved into the classification system of fruits and vegetables with an emphasis on enhancing comprehension and refining these systems. To propel progress in this area, forthcoming research should delve into the practical implications of the proposed classification system in real-world agricultural contexts to evaluate its efficacy and relevance.

In their study, Turaev et al. [10]. utilized transfer learning methods to analyze the quality of fruits and vegetables, illustrating how transferring knowledge across various domains can improve evaluation procedures. Their research involved the application of

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transfer learning techniques to assess fruit and vegetable quality, highlighting the advantages of knowledge transfer from diverse domains in enhancing evaluation processes. To advance in this field, forthcoming research should explore the robustness of transfer learning models under varying environmental conditions and across different crop types to ensure their efficacy and adaptability.

In their book "Algorithms in Machine Learning Paradigms," Mandal et al. [11]. evaluated a variety of machine learning algorithms, highlighting their roles in evaluating the quality of fruits and vegetables in agricultural settings. The book provides a comprehensive collection of algorithms leveraging machine learning for quality assessment. Future research directions could involve comparative studies to pinpoint the most effective machine learning algorithms suited to distinct types of fruits and vegetables.

2.2. Comparing Traditional Methods to Computer Vision and Deep Learning Techniques

When comparing traditional manual inspection with computer vision methods in the fruit and vegetable inspection industry, there has been a notable shift towards utilizing computer vision techniques for evaluating ripeness and categorizing agricultural produce. While conventional manual inspection relied heavily on human expertise, it was time-consuming and lacked efficiency. In contrast, computer vision approaches have emerged as a precise and effective solution for this sector.

The innovative fusion of deep learning and computer vision techniques to classify and assess the ripeness of fruits and vegetables provides substantial benefits over manual methods. Through the utilization of automated algorithms, this approach facilitates quicker and more consistent evaluations, thereby minimizing errors and subjective interpretations. Deep learning models efficiently process large datasets, leading to improved accuracy and scalability compared to manual approaches. This advanced computational technique not only enhances classification tasks but also allows for real-time implementation in agricultural settings, enhancing productivity and quality control. Tapia-Mendez et al. proposed a deep learning method for fruit and vegetable classification and ripeness assessment, demonstrating its effectiveness in identifying produce types and ripeness levels accurately and highlighting its potential for automating quality evaluation processes [12].

By leveraging deep learning and artificial intelligence, computer vision systems can automatically and accurately analyze and categorize fruits and vegetables, leading to enhanced production speed and reduced human errors. These methods can harness diverse data like color, texture, and size to ensure precise assessments of ripeness and quality.

Manual inspection, on the other hand, involves subjective and nonstandardized assessments, making it susceptible to human error and inefficiencies. With the technological advancements and the progress of artificial intelligence, the adoption of computer vision techniques for fruit and vegetable inspection is viewed as a sustainable and efficient alternative that boosts the effectiveness of classification and evaluation processes within this critical industry.

In the study by Elhariri and colleagues [13], a random forests-based approach was employed for the classification of crop ripeness stages. Additionally, Bhargava and Bansal [14]. conducted a review focusing on the evaluation of fruits and vegetables quality using computer vision techniques. On the other hand, Jana and Parekh [15]. introduced an intra-class recognition method for fruits using color and texture features along with neural classifiers.

These studies collectively highlight diverse methodologies in the domain of fruit and vegetable analysis. Future research endeavors could potentially amalgamate these approaches to enhance the overall accuracy and efficiency in the classification and assessment of fruits and vegetables.

2.3. Key Quality Attributes and Performance Evaluation

The studies reviewed highlight the ability of CV techniques to evaluate various quality attributes of fruits and vegetables. Common attributes assessed include size, shape, color, surface defects, and ripeness. The performance of these techniques is typically evaluated using metrics like accuracy, precision, recall, and F1-score. While studies report encouraging results, there is still room for improvement in terms of generalizability and robustness to variations in lighting, image quality, and fruit/vegetable varieties.

Key quality attributes play a critical role in the evaluation of fruits and vegetables, impacting their market value, consumer acceptance, and overall utility. Various studies have focused on different aspects of quality assessment using advanced technological approaches. [2]. utilized a computer vision system for quality evaluation in fresh and packaged fruits and vegetables, emphasizing visual appearance as a key attribute. [3]. employed sorting and grading techniques based on computer vision and image processing to assess key attributes related to arecanut quality. Additionally, [4]. work on shape-based recognition and fractal analysis contributed to understanding the intricate details of fruit and vegetable characteristics.

Performance evaluation in these research endeavors often incorporated algorithms like deep learning, random forests, and support vector machines, underscoring the efficacy of machine learning in assessing quality metrics. Transfer learning, as outlined in recent studies, has demonstrated potential in refining the precision of fruit and vegetable quality appraisal.[10] These varied methodologies collectively enrich our comprehension of critical quality attributes and deliver actionable insights to enhance the overall assessment of fruits and vegetables across diverse applications. Table (1) encapsulates a synopsis of these methodologies for quality criteria.

Table (1): Synopsis of Methodologies for Quality Criteria Evaluation.

Quality Criteria	Techniques Used	Year	Ref.
Visual appearance	Computer vision systems	2020	[2]
Fruit and vegetable classification	Image processing techniques	2018	[3]
Shape recognition	Shape-based analysis	2019	[4]
Ripeness assessment of fruits and vegetables	Transfer learning techniques	2021	[10]

2.3.1. Evaluation of Vegetable and Fruit Quality using Computer Vision

The evaluation of vegetables and fruits quality is crucial in ensuring consumer satisfaction and maintaining product standards. In recent years, CV techniques have emerged as a promising tool for assessing the quality of vegetables and fruits. This paragraph will discuss the research conducted in this field, with a focus on the utilization of CV for quality evaluation.

Bhargava and Bansal conducted a comprehensive review of the use of computer vision in evaluating the quality of fruits and vegetables. They highlighted the potential of computer vision techniques in assessing various quality attributes such as color, shape, size, texture, and defects. The authors discussed the advantages of using CV, including its non-destructive nature, fast processing capabilities, and objective analysis. Examples of images in the preprocessed dataset are displayed in Figure 1 [8]. Healthy lemons are grouped into the healthy class, while moldy, gangrenous, and those with a dark style remaining are grouped to constitute the unhealthy class.

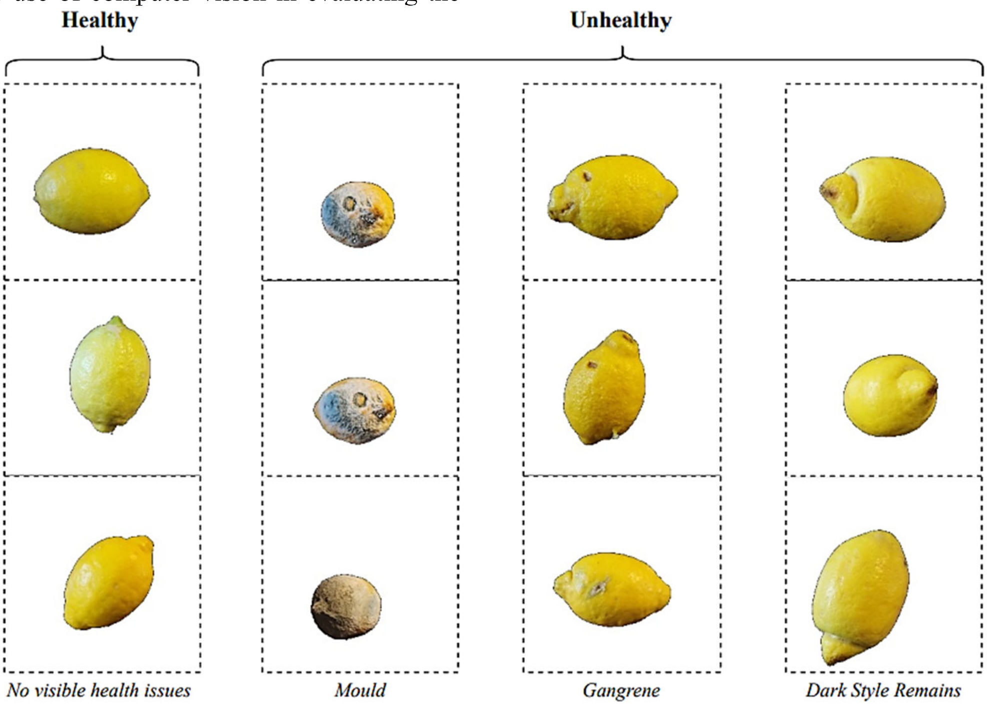

Figure 1: Visualizing healthy and unhealthy lemons within the dataset. Mold, gangrene, and dark spots.

All remaining types are considered unhealthy. The research conducted by these authors demonstrates the potential of computer vision techniques in evaluating the quality of vegetables and fruits. The use of computer vision allows for objective and efficient assessment, enabling producers and retailers to ensure consistent quality standards. Furthermore, the non-destructive nature of CV techniques minimizes product waste and reduces manual labor. Overall, the evaluation of fruit and vegetable quality using CV holds great promise for the industry, leading to improved customer satisfaction and increased efficiency in the supply chain.

2.3.1.1 Methods used in previous studies in the techniques of assessing and classifying the quality of vegetables and fruits:

CV techniques involve extracting meaningful information from digital images or videos. This method is extensively used for tasks like fruit quality evaluation, defect detection, and classification based on visual attributes.

Image processing encompasses operations on images to enhance them for analysis. This includes preprocessing steps like noise reduction, segmentation, feature extraction, and classification using algorithms tailored for image data.

Fractal analysis involves measuring the complexity of shapes in images. It is used for characterizing irregular and complex geometries, such as those found in fruits and vegetables, to aid in their classification based on structural features.

Machine learning algorithms are used for pattern recognition, classification, and prediction tasks based on input data. Techniques like k-Nearest Neighbors (k-NN), Support Vector Machines (SVM), and Deep Learning are commonly employed for fruit and vegetable classification.

Transfer learning involves leveraging pre-trained models on large datasets to improve learning on smaller, specific datasets. This method is beneficial when limited annotated data is available for training new classification models.

Deep learning utilizes neural networks with multiple layers to automatically learn features from data. Convolutional Neural Networks (CNNs) are popular in fruit and vegetable classification tasks due to their ability to extract hierarchical features from images.

2.3.1.2 Data Acquisition

Advancements in computer vision have revolutionized the way we perceive and interact with the world around us. In the agricultural sector, the integration of computer vision techniques holds immense potential for optimizing processes like fruit and vegetable grading and sorting. This section delves into the pivotal role of data acquisition in enabling the successful application of computer vision technologies in this domain.

In the realm of computer vision applications, the acquisition of data is a fundamental aspect that underpins the efficacy of subsequent analysis and decision-making processes. The process of data acquisition typically unfolds through a series of structured steps:

- **Data Collection:** The initial phase of data acquisition involves the systematic gathering of a diverse and representative dataset that correlates with the specific objectives of the computer vision application at hand. This dataset serves as the foundation upon which the algorithms will be trained and validated.

Data can be sourced through various channels and methods, encompassing a spectrum of techniques such as:

- **Raw Data Collection:** This step involves gathering images or videos that will be analyzed, which can be captured from mounted cameras or specialized sensors.
- **Data Labeling:** Images are annotated with labels assigning a category or description to each image for training computer vision models.
- **Data Cleaning:** Data may require cleaning to remove unwanted or corrupted data.
- **Data Splitting:** Data is divided into training, validation, and testing sets to measure the performance of computer vision models.
- **Data Augmentation:** Data augmentation involves applying simple transformations like image rotations or changes in lighting to provide models with more diversity.
- **Selecting Relevant Data:** It is crucial to choose data that effectively represents the problem the computer vision system is trying to solve [7].

These steps are essential in preparing data appropriately for use in computer vision applications. Each step contributes to the quality and effectiveness of the computer vision models developed for various tasks. There are two ways to get data that we can use in CV techniques.

- **Using ready-made datasets**

Utilize online databases like CUI, Roboflow, Kaggle, etc., which offer pre-collected datasets with labeled images for various computer vision tasks such as object detection, classification, or segmentation. These datasets are professionally organized, saving time and providing a diverse range of images. However, they may not always align perfectly with specific requirements, so reviewing licensing terms is crucial.

The data preparation process for computer vision involves several key steps to ensure effective model training and accurate real-world execution:

- Normalization Standardize data to have a mean of 0 and a standard deviation of 1.
- Noise Removal Eliminate unwanted noise or artifacts from the data.
- Annotation Annotate data by labeling images with the correct classes or attributes for the model to learn. Annotations can involve:
- Bounding Boxes Drawing boxes around objects in images.
- Segmentation Masks Labeling each pixel with the corresponding object class.
- Key Points Identifying specific points of interest in images.
- Augmentation Increase the training dataset size artificially through transformations to enhance model generalization. Techniques include:
- Rotation: Rotate images by a specified angle.

Flip mirror images horizontally or vertically.

- Noise Addition Introduce random noise to images.
- Data Splitting Divide the dataset into training, validation, and testing sets. Training data is used for model training, the validation set tunes hyperparameters, and the testing set evaluates model performance on unseen data.

➢ **Setting up your dataset**

This section provides instructions on preparing the data set that researchers prepare, i.e., taking pictures and not ready-made data. Before diving into data analysis, it is important to properly prepare the dataset being captured by the camera. Ensuring that data is well organized and captured under ideal conditions is essential for accurate analysis and model performance. Following these guidelines will help create a solid foundation for your data preparation process. The following points need basic requirements to obtain high-quality images.

Manual data collection is physically taking pictures or videos of objects of interest using cameras or sensors. Here are several points to consider:

- Camera specifications include high resolution (e.g., 4K or higher) for clarity, good low-light performance, fast autofocus, and the ability to manually control settings such as aperture, shutter speed, and ISO. An example of a camera meeting these criteria is some other cameras that meet these specifications include:
- Sony Alpha a7S III: Offers high resolution, good low-light performance, fast autofocus, and manual control over settings.
- Canon EOS R5: Known for high resolution and excellent low-light performance, featuring a fast and accurate autofocus system along with manual control capabilities.
- Nikon Z7 II: Provides high resolution, good low-light performance, fast autofocus, and manual control over settings.
- Hyperspectral Image Data:

Spectral data were obtained through a custom push-broom Hyperspectral Imaging (HSI) system, comprising a monochrome camera, imaging spectrograph, halogen lamps, a computer setup with specific hardware, and a motorized sample table. Acquisition involved a LabVIEW software GUI program and calibration using black-and-white references for relative reflectance determination [3].

2. Lighting Requirements:

- Consistent lighting to reduce shadows and ensure even illumination
- Use of soft boxes or diffusers to create soft, even light - Consider using multiple light sources to eliminate shadows. - Color temperature consistency for accurate color representation.

3. Distance Considerations:

- Maintain a consistent distance between the camera and the subject.
- Use markers or a fixed setup to ensure repeatability - Consider using a tripod for stability and consistency.

4. Shooting Setup:

- A dedicated area with controlled lighting - Backdrop or consistent background - Camera mounted on a tripod - Lighting equipment positioned strategically - Subject placement area clearly marked

5. Additional Considerations:

- Capture images from multiple angles if required - Include various environmental conditions if relevant to your project - Ensure proper focus and exposure for each shot - Consider capturing metadata (e.g., camera settings, time, date) for each image.

6. Post-Processing:

- Organize and label the images systematically - Perform any necessary cropping, resizing, or color correction - Ensure consistent file formats and naming conventions.

The photo is taken using a smartphone camera without a flashlight to reduce shadows or a digital camera. Pictures of the samples are shown in Figure 3[7].

Figure. 3: Images from the created dataset.

2.4. Utilizing Computer Vision for Enhanced Efficiency in Fruit and Vegetable Sorting:

In the realm of agricultural processing, the utilization of computer vision technologies has emerged as a transformative tool for enhancing efficiency in the sorting of fruits and vegetables. By harnessing the power of machine learning algorithms and advanced image processing techniques, computer vision systems can automate the sorting process with unprecedented accuracy and speed. This innovative approach not only streamlines operations but also minimizes human error, reduces waste, and improves overall productivity in the agricultural sector. In this context, the integration of computer vision holds the promise of revolutionizing traditional sorting methods, paving the way for enhanced quality control and increased efficiency in fruit and vegetable processing industries.

A survey of the research on classifying and grading fruits and vegetables using computer vision techniques [3].

Talk about the significance of automating grading and sorting procedures to increase productivity and efficiency.

Analyzing fruit detection and classification systems based on shape as an illustration of computer vision application [4].

Vegetables and fruits can be sorted and graded using a variety of CV and image processing techniques. To increase efficiency and accuracy, researchers have created a variety of algorithms and techniques to automate the sorting and grading process.

For example, Chithra et al. suggested a fruit classification system based on image processing methods. They distinguished between various fruit varieties using characteristics including color, shape, and texture. The results of the study showed how well computer vision could classify fruits.

presented a method for categorizing vegetables and fruits using fractal analysis. In order to categorize the photos of vegetables and fruits, the researchers examined their fractal dimensions. This technique offered a dependable and effective approach to tell fruits from veggies [5].

In another study, Bird et al. utilized conditional GAN (Generative Adversarial Networks) data augmentation for fruit quality and defect image classification. The researchers used deep learning techniques to enhance the accuracy of fruit quality assessment [8].

These studies highlight the potential of CV and image processing techniques in sorting and grading vegetables and fruits. By automating the classification process, these methods can save time and resources while ensuring accurate sorting and grading results.

3. ADVANTAGES OF COMPUTER VISION

1. Automation CV enables automation in various industries, including agriculture, food production, and quality control. It allows for the development of systems that can perform tasks such as fruit classification, maturity assessment, and quality inspection without human intervention. [23], [24], [25], and [26].

2. Speed and Efficiency CV algorithms can process large amounts of visual data quickly and efficiently. This speed enables real-time or near-real-time analysis and decision-making, leading to improved productivity and operational efficiency [23], [28].

Accuracy and Consistency CV systems can achieve high levels of accuracy and consistency in their classifications and assessments. They are not prone to human errors and biases, resulting in reliable and objective results [23], [26].

Non-Destructive Testing: CV techniques are non-destructive, meaning they can assess the quality, ripeness, or maturity of vegetables and fruits without causing any physical damage. This is particularly important in industries where the produce needs to remain intact for further processing or sale [24].

Scalability: CV systems can be easily scaled up or down to handle different volumes and types of vegetables and fruits. They can adapt to changing production demands and accommodate variations in size, shape, and appearance [23], [25].

4. DISADVANTAGES OF COMPUTER VISION

1. Complexity and variability vegetables and fruits naturally vary in size, shape, color, and texture, which makes classifying them difficult. Produce that deviates from the usual range or has complex traits may be difficult for CV systems to classify correctly [23, 26, 29].

2. Sensitivity to environmental elements such as reflections, shadows, and illumination can affect computer vision systems. Changes in these variables may have an effect on how reliable and accurate the classification findings are [23, 27].

3. Training Data Requirements: a sizable and varied dataset is frequently needed for training in order to develop accurate computer vision models. Such datasets can require a lot of work and effort to gather and annotate [23, 29].

4. Algorithm Development and Selection: Selecting the best CV algorithm and creating unique solutions applications can be difficult tasks that call for knowledge of machine learning and computer vision methods.

5. Maintenance and System Integration: to guarantee precise and reliable operation, computer vision systems need to undergo routine maintenance, which includes calibration. There may be difficulties integrating these systems into the manufacturing or processing workflows that are currently in place [23].

5. RESULTS

In terms of application, technology, and data, the additional research papers can be summarized as follows:

The study by Mandal et al. covers algorithms in machine learning models, potentially including techniques for categorizing vegetables and fruits. Various machine learning methods and datasets related to fruit and vegetable quality are likely utilized in this research [11].

It was suggested by Tapia Méndez et al. A deep learning-based method to classify and evaluate the ripeness of vegetables and fruits [12]. The research will likely include the use of deep learning models and image data for classification and maturity assessment purposes.

present Elhariri et al. a random forests-based classification technique for crop ripening stages. For classifying ripeness, the research may employ random forest algorithms and visual data [13].

The study by Jana and Parekh focuses on intra-class fruit recognition using neural classifiers and color and texture features. It is expected that color and texture features from fruit photos will be extracted for recognition purposes using neural classifiers [15].

Discussing the key issues and countermeasures of machine vision for vegetable and fruit-picking robots by Xin et al. likely involves exploring the application of machine vision techniques in the context of harvesting produce. The study probably addresses challenges and solutions pertaining to the use of machine vision in automating the picking process for fruits and vegetables [16].

A support vector machine-based technique for classifying the maturity of bell peppers is presented by Elhariri et al. In order to classify ripeness, support vector machine techniques and visual data may be applied in this study [17].

Tao et al. discuss the utilization of text mining as a big data analysis tool in food science and nutrition. Although not directly related to computer vision, this research underscores the use of data analysis techniques in the fields of food science and nutrition.

An Android app for automatically identifying fruits and vegetables using computer vision and machine learning is presented by Appadoo et al. The research probably entails creating an app that identifies fruits and vegetables using machine learning algorithms and computer vision techniques [19].

In their work, Zhou et al. explore the examination of fruit fly regurgitation through the application of deep learning and computer vision techniques. While distinct from fruit and vegetable grading, this research underscores the utilization of computer vision methods in studying biological processes [20]. Gom-os proposes the utilization of colorized depth images for fruit classification. This study likely employs image processing techniques and depth imaging to categorize fruit [21].

Asadi et al. forecast quality characteristics linked to distinct geographic cultivation areas in red-fleshed kiwifruit by combining data from electronic noses and computer vision systems. This study probably integrates information from both electronic nose and computer vision systems to predict quality attributes [22].

Wang et al. introduce a cross-domain fruit classification approach founded on lightweight attention networks and unsupervised domain adaptation. This study probably employs deep learning models and techniques for cross-domain fruit classification [23].

Anjali et al. explore non-destructive methods for determining the maturity index in fruits and vegetables. The study is expected to encompass a range of non-invasive techniques and data pertinent to assessing the maturity of fruits and vegetables [24].

In this study, Elhariri et al. introduced a random forests-based classification method for determining the ripeness stages of crops. This research, akin to paper 13, likely involved utilizing image data and applying random forests algorithms for ripeness classification. [26].

These additional research papers cover a wide range of topics related to fruit and vegetable grading, classification, ripeness assessment, and maturity index determination. They utilize various CV techniques, machine learning algorithms, and data types such as image data, depth data, and data fusion from different sensing systems.

The research review by Balderas-Silva et al. provides a comprehensive overview of using computer vision and machine learning for plant disease detection in agricultural monitoring. The authors discuss current methods and highlight the benefits of these techniques for accurate disease identification. However, the review would have been more valuable with specific examples and case studies demonstrating the practical application of these methods in real agricultural settings [27].

The research paper by Ni et al. focuses on monitoring the change process of banana freshness using GoogLeNet, a deep convolutional neural network. The authors propose a method based on image analysis to track the freshness level of bananas. The paper demonstrates the effectiveness of their approach in accurately determining the freshness level. However, it would have been beneficial if the authors had provided more details on the dataset used and the performance metrics of their proposed method. Additionally, exploring the applicability of their approach to other fruits or perishable items would have added further value to the research [28].

Hameed et al.'s comprehensive review discusses various techniques for fruit and vegetable classification. The paper covers a wide range of classification methods, including traditional image processing algorithms and machine learning approaches. The authors highlight the challenges and limitations of existing methods and provide insights into the latest advancements in this field. The review serves as a valuable resource for researchers and practitioners in fruit and vegetable classification. However, it would have been advantageous if the paper had discussed the limitations and potential biases of the selected techniques, as well as suggestions for future research directions [29]. The results summary of computer vision techniques on fruits and vegetables was shown in Table (2).

Table (2): Summary of computer vision techniques on fruits and vegetables.

Ref	Target	data	technology	Accuracy
[11]	classification	1656 images of fruits and vegetable	Naive Bayes	98.33%
[12]	classification and ripeness	32 classes of fruits and vegetable	MobileNet V2	100%
[13]	classification and ripeness	tomato and bell pepper 250 and 175 images	random forests& SVM	-
[15]	recognition of fruits by combining color and texture features	270 fruit images	Neural Network (NN)	-
[17]	Ripeness Classification	bell pepper 175 images	Support Vector Machine	93.89%
[19]	automatically identify fruits and vegetables	1600 images from fruits and vegetables	machine learning classifies	90.6%
[20]	fruit fly detection and tracking	100 video clips 200 images	Yolov5 and Deep Sort	99.8%
[21]	classification	apples and oranges mangoes and bananas	CNN models(AlexNet, GoogleNet, ResNet101, and VGG16)	96%
[22]	classification the quality	kiwifruits	SVM algorithm& SVR	100% 90.17%
[23]	classification	Grape	deep learning-based	95.0% and 93.2%
[26]	classification and ripeness	Tomato 175 images and 55 images	Support Vector Machine (SVM)	92.72%
[28]	classification fruit quality	Banana	transfer learning and established	98.92%
[31]	Evaluated ripeness stages of achacha fruits using spectral data; investigated the impact of fruit surface curvature.	the wavelength range of 400–780 nm for evaluating the ripeness stages of achacha fruits.	Used both classification models (SVM, PLS-DA, ANN, KNN) and regression models (PLSR, SVR) for ripeness stage prediction.	Ranged from 52.25% to 79.75% with the SVM model achieving the highest accuracy at 79.75%.

Summary of various CV techniques used in vegetable and fruit analysis. These techniques include classification, ripeness detection, and quality assessment. The accuracy of these methods ranges from 90.6% to 100%, depending on the specific algorithm or model used and the target fruit or vegetable. One common approach in these studies is the use of machine learning algorithms such as Naive Bayes, random forests, SVM, and neural networks. These algorithms leverage features extracted from images, such as color, texture, and shape, to classify fruits and vegetables accurately. Transfer learning, where pre-trained models are fine-tuned on specific datasets, is also employed in some studies, demonstrating its effectiveness in achieving high accuracy.

The influence of fruit and vegetable morphology, dimensions, orientations, and positioning on image clarity and classification precision has been a focal point in recent research. Findings from these investigations suggest that the shape of the fruit significantly impacts the precision and quality of image categorization. For example, the spherical nature of fruits like apples, oranges, and tomatoes facilitates clear image capture, thereby enhancing accuracy. In contrast, the curved structure of bananas and the small sizes of olives, dates, and leafy vegetables can pose challenges for achieving clear images, consequently impacting classification accuracy [30].

The review also highlights the use of deep learning models, such as CNNs, in fruit and vegetable analysis. These models have shown promising results in classification tasks, achieving accuracies ranging from 96% to 100%. The use of CNNs allows for the extraction of hierarchical features, enabling more robust and accurate classification.

Additionally, the review discusses the application of CV techniques in detecting fruit fly infestation, which is crucial for ensuring the safety and quality of fruits. The use of object detection models, such as Yolov5, combined with tracking algorithms like Deep Sort, has proven effective in fruit fly detection and tracking, achieving an accuracy of 99.8%.

It's crucial to take into account these CV techniques' limitations, even with the encouraging outcomes. Occlusions, changes in fruit and vegetable look, and lighting conditions are a few examples of factors that can affect how accurate the models are. To overcome these obstacles and create more durable and dependable computer vision systems for fruit and vegetable inspection, more research is required. Notably, many of these constraints are still being addressed by developments in machine learning methods, hardware technologies, and computer vision algorithms. The goal of ongoing research and development is to increase computer vision systems' robustness, accuracy, and usefulness for classification of fruits and vegetables, among other applications.

Research Gaps in Computer Vision for Fruit and Vegetable Quality Assessment While the reviewed studies provide valuable insights into the potential of computer vision (CV) for assessing fruit and vegetable quality, several significant research gaps require attention. Addressing these gaps can lead to the development of more robust, generalizable, and practical CV systems for fruit and vegetable quality assessment, ultimately enhancing efficiency, food safety, and sustainability in the agricultural sector. Below is a summarized table outlining these research gaps:

Table (3): Research Gaps in Computer Vision for Fruit and Vegetable Quality Assessment.

Research Gap	Description
Data Variability	Studies often focus on a limited range of fruits and vegetables, lacking diversity in types, shapes, sizes, and colors. Developing robust models capable of handling a broader variety of produce is essential.
Model Generalizability	Models trained on specific datasets may struggle to generalize to new data, highlighting the need for techniques to prevent overfitting and improve model interpretability.
Integration with Applications	Many studies concentrate on offline analysis, calling for the development of real-time computer vision systems for seamless integration into sorting and grading lines. Considerations such as hardware deployment in agricultural settings and integration with existing infrastructure in packing houses and farms need to be addressed.
Additional Exploration Areas	Further exploration opportunities include combining computer vision with other sensing technologies for a comprehensive quality assessment, developing non-destructive techniques for evaluating internal quality attributes, enhancing defect detection for improved quality control, and establishing standardized protocols and evaluation metrics to facilitate comparison and advancement in computer vision applications within the agricultural sector.

6. CONCLUSION

In conclusion, the application of CV techniques for the quality and safety inspection of vegetables and fruits holds great potential. Through the evaluation of vegetable and fruit quality, sorting and grading, classification, and volume estimation, CV systems can enhance the efficiency and accuracy of inspection processes in the agricultural industry. The findings from these studies contribute to the development of more efficient and automated systems for ensuring the quality and safety of vegetables and fruits. Finally, the review demonstrates the potential of computer vision technologies in enhancing the quality and safety inspection of vegetables and fruits. These techniques provide accurate and objective assessment, improved efficiency and cost savings. However, more research is needed to address the limitations and challenges associated with these technologies to ensure their widespread practical application in industry.

6.1. Challenges and Future Directions

As the research delves into optimizing quality control through a thorough examination of computer vision methods for assessing vegetables and fruits, several challenges and future directions emerge. The implementation of computer vision techniques for quality assessment in agricultural produce faces hurdles such as scalability, adaptability to diverse produce types, and real-time processing requirements. Additionally, ensuring the robustness and reliability of these systems across varying environmental conditions poses a significant challenge.

Looking ahead, future directions in this field involve enhancing the interpretability of computer vision models, integrating multi-sensor data fusion for improved accuracy, and developing more sophisticated algorithms for anomaly detection and quality prediction. Addressing these challenges and exploring these promising directions will be crucial for advancing the application of computer vision in optimizing quality control processes for vegetables and fruits, ultimately contributing to more efficient and reliable food inspection systems.

7. CONTRIBUTIONS

This paper provides an extensive review of the application of CV techniques for quality and safety inspection of vegetables and fruits. It consolidates the existing literature, emphasizing advancements, challenges, and prospective solutions in this domain. The evaluation encompasses various CV techniques, including image processing, deep learning, and machine learning algorithms assessing their efficacy in detecting defects, classifying produce, and identifying contaminants. Performance analysis delves into the accuracy, speed, and scalability of different CV systems, considering factors like lighting conditions, image acquisition, and feature extraction. Novel approaches and emerging trends in CV for fruit and vegetable inspection are presented, exploring hyperspectral imaging, 3D reconstruction, and multisensor fusion techniques to enhance inspection accuracy and reliability. Challenges in implementing computer vision systems for quality and safety inspection are identified, with discussions on solutions such as data augmentation, transfer learning, and domain adaptation to bolster algorithm robustness. The practical applications of computer vision techniques in the fruit and vegetable industry are underscored, illustrating their role in sorting, grading, and packaging processes to ensure elevated quality and safety standards across the supply chain. Future research directions are outlined, pointing towards the integration of Internet of Things (IoT), robotics, and automation technologies to forge intelligent and efficient inspection systems.

This paragraph can be summarized into points explaining strategies for enhancing agricultural quality assessment using computer vision techniques to address the limitations identified in the reviewed studies in the field of agricultural quality assessment using computer vision and image processing techniques. Several strategies can be considered:

- Enhanced Data Collection: Gather comprehensive datasets reflecting various fruit and vegetable characteristics like shapes, sizes, colors, and defects to enhance model robustness and generalizability.
- Algorithm Optimization: Continuously refine algorithms for improved accuracy and efficiency by adjusting parameters, exploring diverse model architectures, and incorporating advanced machine learning techniques.
- Feature Engineering: Develop new features or enhance existing ones to better represent the unique attributes of different produce types, crucial for enhancing classification accuracy and quality assessment.
- Cross-Validation and Validation Techniques: Implement rigorous cross-validation methods to ensure model reliability and prevent overfitting, with separate test datasets validating model generalizability.
- Integration of Sensor Technologies: Explore integrating additional sensor technologies like hyperspectral imaging to gather more information on produce quality, enhancing classification accuracy through data fusion.

- Error Analysis and Feedback Loop: Conduct thorough error analysis to pinpoint common misclassifications and model shortcomings, utilizing feedback to iteratively enhance algorithms and tackle specific challenges.
- Interdisciplinary Collaboration: Foster collaboration among agriculture, computer vision, machine learning, and domain-specific experts to leverage diverse perspectives for innovative solutions.
- Real-Time Monitoring and Adaptive Systems: Develop adaptive real-time monitoring systems to adjust to changing environmental conditions and produce quality variations, facilitating continuous learning and performance improvement.

This review has served to highlight the latest developments in CV quality assessment of fruits and vegetables. By understanding current capabilities and limitations, we can pave the way for developing more effective and practical quality control systems. Ultimately, this progress can contribute to the creation of a more sustainable and efficient agricultural sector, ensuring a safe and healthy food supply for future generations and development in the field of agriculture in Libya to increase the economy and maintain food security.

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ABBREVIATIONS AND ACRONYMS

Here are the abbreviations and acronyms used in the provided references:

SVM: Support Vector Machine

CV: Computer Vision

IPA: Information Processing in Agriculture

CNN: Convolutional Neural Network

NN: Neural Network

GAN: Generative Adversarial Networks

PLS-DA: Partial Least Squares Discriminant Analysis

ANN: Artificial Neural Network

KNN: K-Nearest Neighbors

PLSR: Partial Least Squares Regression

SVR: Support Vector Regression

YOLOv5: You Only Look Once version 5

Deep SORT: Deep Simple Online and Realtime Tracking

AlexNet: Alex Krizhevsky Network

GoogleNet: Google Network

ResNet101: Residual Network with 101 Layers

VGG16: Visual Geometry Group 16 Layers

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