Role of Computer Vision Technologies in Food Industries: Food Quality Solution

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Abstract

Computer Vision technology is being increasingly embraced in the food sector to enhance product quality, safety, and efficiency. In this systematic review, the pros and cons of its use are examined. Benefits include improved quality control, increased productivity, standardization, enhanced food safety, and valuable data collection for traceability. Nonetheless, the implementation of Computer Vision also comes with some major challenges like high capital expenditure, technical complexity, integration problems, and the requirement for qualified staff. It is vital to understand these benefits and challenges for food industry stakeholders who wish to utilize Computer Vision technologies successfully. This analysis underscores the call for further cross-disciplinary study, adaptive algorithm development, and academia-industry collaborations to help overcome present-day obstacles. All in all, Computer Vision carries a lot of promise to contribute to efficiency, safety, and sustainability in food manufacturing if technical and practical obstacles are approached deliberately.

Keywords: Computer Vision, Food sector, Product quality, Food safety, Productivity, Traceability.

1. INTRODUCTION

The food sector is subject to continuous pressure to provide high-quality, safe, and consistent products while maintaining efficient operations. Computer Vision (CV) has been one of the strong means available at this point, providing automation and intelligence to activities like inspection, sorting, grading, and packaging [1][2]. Through objective and high-speed inspection, Computer Vision technology can surpass manual inspection techniques, improving both product quality as well as process efficiency [3]. CV technologies are being utilized in a broad spectrum of food industry processes. These include fruit and vegetable surface defect detection, meat product fat content estimation, foreign object detection in packaging, ripeness and colour grading, and labelling and product integrity verification [4]. Compared to traditional manual inspection, computer vision provides a non-invasive, reliable, and quick alternative that can greatly improve operational efficiency while lowering labour costs [1]. This technology is particularly valuable for maintaining consistent, real-time quality control, as it allows inspections to be carried out directly on production lines without causing any interruptions. In the food industry, computer vision has become an essential tool, helping manufacturers spot defects early, sort and grade products accurately, verify packaging integrity, and uphold strict hygiene and safety standards. By enabling quick detection and correction of issues, it not only improves efficiency but also ensures that consumers receive safe, high-quality products. [4].

While computer vision technology offers clear benefits like boosting production efficiency, cutting down human errors, and improving quality control, its use in actual food processing environments remains uneven, mostly favouring large-scale operations [5]. This gap exists because small and medium-sized companies face a variety of hurdles. These include the technical complexities of working with unpredictable and varied food items, difficulties integrating new systems into existing workflows, and significant costs—not only for initial setup but also for ongoing maintenance. Moreover, managing these advanced technologies demands skilled personnel, which smaller businesses often lack. All these factors combine to slow down the broader adoption of computer vision in the food industry, despite its obvious advantages [6].

The majority of the current research on applications or machine learning techniques gives the impression that the literature is dispersed. Although separate studies show the promise of computer vision in discrete situations, there isn't a thorough integration of information that would offer researchers and industry stakeholders alike a clear direction [7]. In addition, few studies discuss the trade-off between technological complexity and real-world usability, particularly in resource-poor settings. The present systematic review has the objective of critically exploring the benefits and pitfalls of Computer Vision adoption in food manufacturing industries. In providing a balanced analysis, it looks to assist industry professionals, researchers, and decision-makers in making decisions for effective implementation and optimization of Computer Vision technologies in food manufacturing systems.

2. Literature Review

Sl. No.	Authors (Year)	Technology/Method Used	Findings	Conclusion
1	Khuram Shehzad, et al. (2025)	Hyperspectral imaging, CNNs, GANs	Enhanced food inspection accuracy, real-time defect detection, ripeness estimation, contamination detection	Integration of IoT and edge computing is crucial for real-time monitoring and developing sustainable, low-cost solutions
2	Zhiyao Zhao et al. (2025)	Machine vision-based image recognition	Applications in food safety, nutrition analysis, and process monitoring; improved production efficiency and product quality.	Machine vision is pivotal for intelligent transformation in the food industry.
3	Leonardo Arrighi et al. (2025)	Explainable AI (SHAP, Grad-CAM)	Enhanced transparency in AI decision-making for food quality control.	Adoption of XAI techniques improves model reliability and trust in food engineering.
4	Zhang B, et al. (2025)	Computer Vision for external quality inspection	Improved quality inspection of fruits and vegetables.	Computer Vision is effective for external quality assessment in the food industry.
5	Vikas Goyal, et al. (2024)	IoT, Computer Vision, sound analysis	Early disease detection, weight estimation, feeding behavior monitoring in poultry farms.	Digital technologies automate poultry farm management, increasing income and product quality.
6	Shayan Rokhva et al. (2024)	Pretrained MobileNetV2, transfer learning	Accurate, real-time food recognition with low computational cost.	Lightweight models like MobileNetV2 are effective for practical food recognition applications.
7	Papathanail I. et al. (2023)	Mobile Computer Vision applications	Food recognition, volume estimation, dietary assessment.	Mobile applications assist users in monitoring dietary intake effectively.
8	Mavani, N.R., Ali, J.M., Othman, S. et al. (2022)	AI, NIR, food sensors	Guidelines for AI model development in the food industry.	AI integration is essential for modernizing food industry practices.
9	Lili Zhu et al. (2021)	Deep learning, machine vision	Improved efficiency in food processing; applications in food	Machine vision significantly assists in

			grading, defect detection, and impurity removal.	enhancing food processing efficiency.
10	Lili Zhu et al. (2021)	Deep learning, machine vision	Applications in food grading, defect detection, and impurity removal.	Machine vision enhances food processing efficiency and product quality.

The authors showed the efficacy of hyperspectral imaging integrated with convolutional neural networks (CNNs) and generative adversarial networks (GANs) in food inspection [8]. They showcased real-time application potential for defect detection, ripeness quantification, and contamination evaluation. Researchers have emphasized the role of the Internet of Things (IoT) and edge computing in delivering cost-effective and sustainable food monitoring solutions [9]. One study reviewed the use of machine vision-based image recognition to improve food safety, conduct nutritional analysis, and monitor processing, finding that these technologies not only boost efficiency but also improve product quality, placing machine vision at the core of intelligent food systems. Another investigation explored the integration of machine vision and deep learning in food processing, highlighting its applications in grading, defect detection, and impurity removal, and confirming its ability to significantly increase processing speed and product quality [10]. In poultry farming, IoT, computer vision, and audio analysis have been combined to monitor animal health and activity, enabling early disease detection, weight estimation, and feeding pattern tracking—demonstrating how digital tools can automate farm management and enhance productivity [11]. To make AI-based food quality monitoring systems more transparent and easier to understand, the researchers applied Explainable AI (XAI) methods, including Grad-CAM and SHAP. These techniques help show how and why AI models make certain decisions, which in turn boosts their reliability and earns the trust of users in the food engineering field [12]. The team also demonstrated that even lightweight models with relatively low computing requirements can deliver accurate and practical results. Using a pretrained MobileNetV2 model combined with transfer learning, they successfully performed real-time food recognition tasks, proving that powerful AI solutions don't always require heavy, resource-intensive systems [13]. Their study supports earlier research showing that machine vision and deep learning technologies are highly effective for accurately detecting defects and evaluating food quality across different processing environments [14]. In addition, the authors have provided clear, step-by-step guidance for developing AI models tailored to the food industry. They emphasize that integrating AI with food sensors and near-infrared (NIR) technology could open the door to significant innovations, paving the way for more advanced, precise, and efficient food quality assessment systems [15]. In addition, they explored the growing significance of mobile computer vision applications in promoting consumer health and well-being. These applications are being used for tasks such as recognizing different foods, estimating portion sizes, and tracking dietary habits — helping individuals make more informed choices about what they eat [16].

3. Problem Statement

The global demand for safe, high-quality, and efficiently processed food is driving the need for transformation in the food industry through smart technological solutions. Among these, computer vision (CV) stands out as a promising technology that can automate labour-intensive tasks such as grading, sorting, defect detection, and ensuring safety compliance [17][18]. While CV systems have demonstrated success in controlled laboratory or pilot settings, deploying them effectively in real-world food processing environments faces several significant challenges [19]. These include variations in lighting conditions, changes in the appearance of products, limited robustness of algorithms, and difficulties integrating with existing infrastructure [20]. Moreover, the food industry spans many diverse sub-sectors, yet standardized models and frameworks for implementing computer vision across these varied contexts are still largely missing. Without understanding these obstacles and key factors for success, the widespread adoption of CV technology remains slow and inconsistent [21]. Therefore, there is a clear need for a thorough and systematic review that not only highlights the benefits and barriers but also offers practical, technology-driven solutions to accelerate the adoption and integration of computer vision in the food industry [22].

4. Proposed Solution

To address the challenges, the food industry faces in adopting computer vision technology, a well-planned, multi-layered approach is essential. One key step is developing a computer vision framework that is both

adaptable and scalable [23]. Such a framework should include modular components designed to handle everyday tasks such as sorting and grading products, detecting defects, and ensuring compliance with safety standards. For broader applicability, these modules need to be designed with enough flexibility to work effectively across different types of foods and product variations, making the system easy to customize for diverse processing environments [24].

An important part of this system is incorporating edge computing capabilities. By processing data locally, right where it's generated, edge computing reduces dependence on cloud-based systems. This approach lowers latency and enables real-time decision-making, making it possible to respond instantly to changing conditions on the production floor. Moreover, it simplifies the integration of computer vision technologies with existing food processing equipment, which can help more businesses in the food sector adopt these innovations with greater ease [25].

Another crucial factor is the development of reliable and widely applicable algorithms. To achieve this, deep learning models should be trained on large and diverse datasets that capture the many variations found in real-world food processing environments including changes in lighting, appearance, and other conditions. This training approach ensures that the algorithms maintain high accuracy and dependability even when used outside the controlled settings of a lab [26]. Together, these elements edge computing and robust algorithm design help create flexible, efficient, and trustworthy computer vision systems that can truly advance food quality monitoring and processing.

The food sector may expedite the practical implementation of computer vision technologies by integrating three components—modular architecture, edge computing, and robust algorithm development—which will eventually improve automation, quality control, and operational efficiency in food processing. The models must be able to handle challenges that are commonly encountered in real-world settings, such as fluctuating illumination or background noise [18]. Moreover, with methods such as data augmentation and synthetic data, one can simulate various real-world scenarios, improving model robustness [25]. Active learning can also be integrated, enabling the system to learn and improve continuously after deployment through human-in-the-loop feedback [26].

The element includes the development of a standardized implementation plan for the food sector. With the many sub-sectors in the sector, industry guidelines on how to implement CV systems for activities such as grading and defect detection are necessary [20. Open benchmarking and test protocols published would give companies an effective means to compare various CV tools and check if they adhere to performance benchmarks [23]. In addition to that, there should be a strategy for a digital infrastructure in support of the installation of CV technology. That requires promoting Industry 4.0 principles like applying IoT sensors and data platforms with interoperability into CV systems [27]. Also, promoting the use of vendor-neutral platforms should be done to ensure that firms are not tied to proprietary systems and can integrate CV technology on a wide range of food processing equipment [17].

One of the keys to successful CV technology deployment is cross-disciplinary collaboration. By bringing together AI developers, food technologists, and regulatory bodies, solutions can be co-designed to be effective and food safety compliant [21]. Building consortiums or innovation centres can also act as a platform where companies can share best practices, data sets, and pilot studies, facilitating quicker implementation [28]. Concurrently, upskilling and training of the workforce will be critical in ensuring the technology is implemented successfully. Building training programs for employees will enable them to use and maintain CV systems [29]. In addition, firms begin with small-scale pilot projects, which can prove the worth of CV technology and increase employees' confidence [30]. Lastly, to bridge financial and regulatory hurdles, policy and incentive backing will be important. Subsidies, grants, and tax benefits can be provided by governments to stimulate the implementation of CV technology among food producers [22]. Regulators can also make efforts to revise food safety standards, formally approving validated CV systems as safe and compliant aids for quality control and assurance [31].
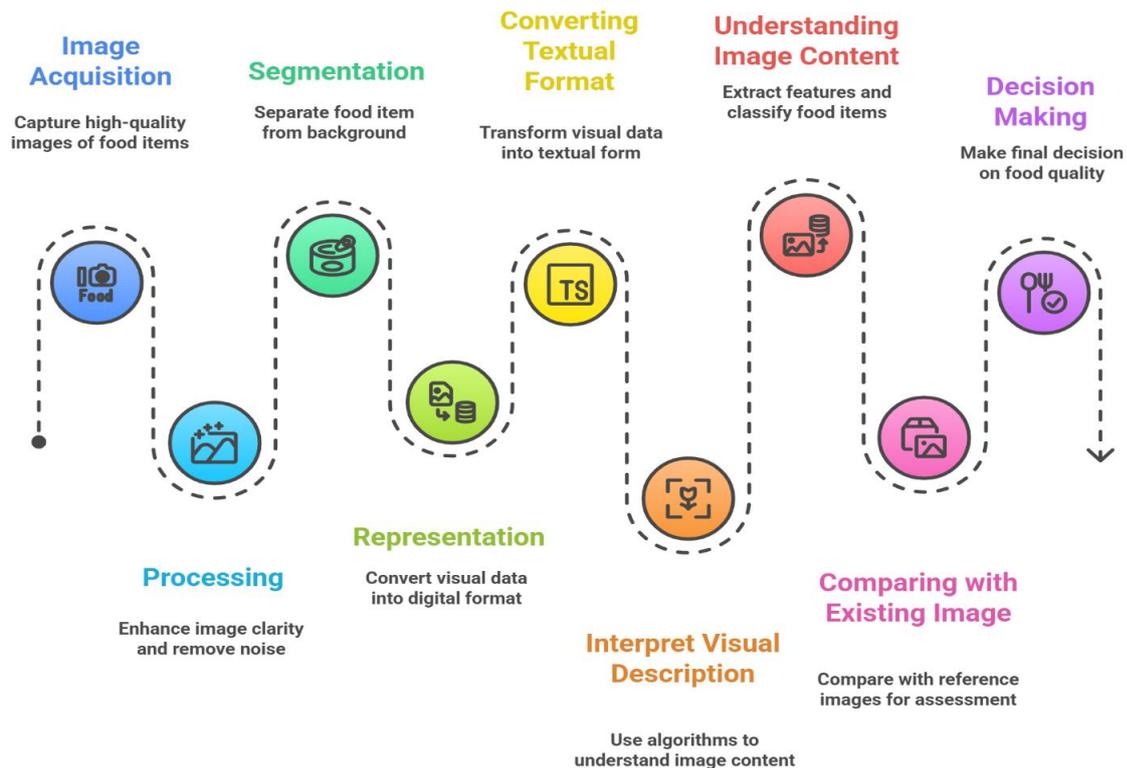
Figure 1: Steps involved in Computer Vision for food technology

With the help of the application of CV techniques to food quality assurance follows a structured workflow—from image acquisition and preprocessing to segmentation, interpretation, comparison with reference standards, and final decision-making (see Figure 1). Implementing the above strategies can transform CV from a promising research concept into a reliable, industry-wide standard for food quality and safety.

Addressing the challenges hindering the adoption of Computer Vision (CV) in the food industry requires a comprehensive, multi-layered strategy that integrates technological innovation, industry standardization, and cross-sector collaboration.
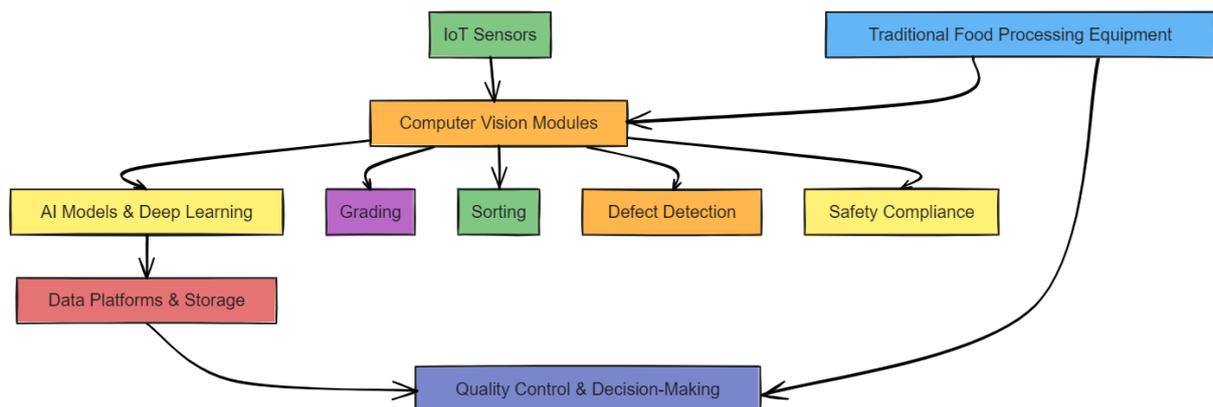
Figure 2: Integration of Computer Vision with Industry 4.0 Ecosystem for Food Quality and Safety

Figure 2. illustrates how Computer Vision (CV) integrates into an "Industry 4.0-enabled food processing ecosystem", as described in the proposed solution above. It begins with "IoT sensors" capturing real-time data from production lines, which feed into "Computer Vision modules" designed for core tasks such as grading, sorting, defect detection, and safety compliance. These modules work in tandem with "AI models and deep learning" to interpret visual inputs, storing processed results in "data platforms" for further analysis. The CV system is interconnected with "traditional food processing equipment", enabling seamless integration into existing operations. Finally, outputs from both automated inspection modules and legacy systems converge in "quality control and decision-making", ensuring products meet safety and quality standards while enhancing efficiency and adaptability.

5. Future Research

Future studies in the application of Computer Vision technology in the field of food sector must target the creation of more flexible and intelligent systems that are capable of operating stably in a wide range of processing conditions. Existing hurdles, including limitations in lighting conditions, occlusion, and irregular positioning of products, most times undermine the robustness and accuracy of vision inspection systems. Next-generation systems need to include sophisticated machine learning algorithms, especially deep learning models, which are able to learn invariant features from complex data and generalize more across different conditions [2][32].

Another major area of focus is in combining Computer Vision with auxiliary technologies such as hyperspectral imaging, robotics, and the Internet of Things (IoT). This combination is likely to yield intelligent food processing environments where there is real-time data acquisition, analysis, and decision-making enhancing both efficiency and safety [33]. Publicly available, high-quality image datasets related to food processing are still the limiting factor for training and validating Computer Vision models [34].

Low-cost, modular platforms that involve low infrastructure modifications and training would bring the advantages of automation to the entire food industry [35]. Product-specific system tailoring is another critical domain. Various food products present unique inspection challenges—e.g., finding bruises on fruits versus assessing marbling in meat—that demand customized imaging and algorithmic approaches [30]. Creating flexible architectures that can be optimized to the properties of individual food products will improve system precision and dependability. Research needs to focus on maximizing computational efficiency and incorporating edge computing technologies to provide real-time feedback and corrective actions [36]. This will be essential for minimizing downtime, reducing waste, and maintaining product consistency. Another potential future development is the fusion of vision systems with traceability and supply chain management software [37]. Connecting inspection data to Blockchain or ERP systems would improve transparency, facilitate recall efforts, and reinforce consumer confidence through recording product quality during its lifecycle [38]. User-friendly dashboards, easy-to-visualize defect detection, and smooth integration with current workflows can promote more adoption throughout the industry [39]. Lastly, there is a requirement for thorough, long-term effect studies that assess the cost-effectiveness, environmental footprint, and operational gains gained through Computer Vision implementation. These studies would give tangible evidence to inform industry investment and shape regulatory frameworks encouraging sustainable and smart automation [40].

6. CONCLUSION

The use of Computer Vision in the food sector is a paradigm shift in managing quality control, process automation, and safety assurance. Computer Vision has several benefits, such as improved accuracy in defect detection, consistency in grading and classification, less reliance on human labour, enhanced operational speed, and increased traceability throughout the food supply chain. Environmental conditions imperfect shapes and colours to texture and surface condition variations and the existence of occlusions add to the difficulty in precise detection and classification. Furthermore, the high initial costs of implementation, low availability of annotated datasets with domain-specific knowledge, and the technological disadvantage encountered by small and medium-sized enterprises (SMEs) also hinder mass adoption. Progress in the future relies on overcoming these constraints through several strategic research directions. Computer Vision is not just a technological advancement—it is a driver for the redefinition of quality, safety, and efficiency standards in the food sector. Through strategic investment in research, infrastructure, and human resources, stakeholders can maximize its revolutionary potential while building a robust, transparent, and sustainable food system for the future.

Conflict
The authors declare no conflict of interest.

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