Food Safety Monitoring Based on Machine Vision

Pengyu Xie

NUIST Waterford Institute, Jiangsu, China
202483910027@nuist.edu.cn

Abstract. Food safety has become a global challenge due to the inefficiency and subjectivity of traditional inspection methods. These approaches often rely on destructive sampling and manual visual analysis, which lead to high latency, low scalability, and limited accuracy. Machine vision provides a non-destructive, high-precision, and automated solution for food quality and safety monitoring. By utilizing high-resolution CMOS image sensors, multispectral imaging, and advanced algorithms, machine vision converts optical signals into digital data that can be analyzed in real time. This enables accurate detection of surface defects, color differences, and geometric deviations at the sub-pixel level. Furthermore, integrating machine learning and data-driven models improves adaptability and accuracy under complex environmental conditions. The technology's combination of speed, consistency, and reliability not only reduces human error but also enhances traceability and production efficiency. Future developments will focus on knowledge distillation, self-supervised learning, and digital twin systems to build an intelligent, end-to-end monitoring framework from farm to table, providing a more transparent and sustainable foundation for global food safety assurance.

Keywords: Machine Vision, Food Safety, Quality Inspection, Defect Detection, Multimodal Integration

1. Introduction

Food safety is a central issue in global public health and economic development. According to the WHO 2023 report, approximately 600 million people seek medical attention each year due to foodborne illnesses, resulting in direct financial losses of more than $110 billion. Therefore, food safety testing has become a top priority. At present, traditional detection methods rely on sensory evaluation (SE) and physicochemical characteristics (PP) or physicochemical analysis, which have inherent defects such as high delay, destructive sampling bottlenecks, high cost, and intense subjectivity, which make it challenging to meet the needs of the modern food industry for "efficient, non-destructive, and real-time" testing. The dilemma of traditional means lies not only in efficiency but also in the inherent flaws of "people" as measurement tools: visual fatigue leads to threshold drift, emotional fluctuations cause direction misjudgment, and the challenge of replicating experiences horizontally. Machine vision uses optical devices as the "retina" and algorithm models as the "cerebral cortex" to

K. Subramanian (ed.), *Proceedings of the International Workshop on Advances in Deep Learning for Image Analysis and Computer Vision (IWADIC 2025)*, Advances in Computer Science Research 128,
https://doi.org/10.2991/978-94-6239-648-7_46

transform subjective experience into replicable, auditable, and changeable digital rules, turning "process" into "process" and "feeling" into "data". To improve this problem, there are two solutions: reducing the density of detection and increasing the speed of inspection. Given the current society's general pursuit of rigorous food safety, it is impossible to improve production speed by reducing detection density, which is irresponsible to food consumers. Therefore, increasing the speed of detection has become the most mainstream method at present. At the same time, the limitations of human function make it difficult for manual testing to produce breakthroughs consistently, and it is incredibly challenging to surpass the R&D investment due to excessive spending. It is precisely because of this situation that the gains outweigh the losses; the research community generally believes that changing the strategic direction and entering the field of machine testing can improve the quality of the test work. In recent years, after years of development, various emerging technologies have been gradually developed and utilized as more efficient food safety testing technologies in practical applications. Among many technologies, machine vision technology is an essential means. It's the information input function that transforms the real situation into data, laying the foundation for analysis. This technology involves using high-precision visual sensors, such as light, infrared, and lasers, to obtain external information at high frequency and conduct synchronous analysis to provide corresponding results. Under the current development conditions, machine vision technology can already be used to support auxiliary technologies in various fields, such as food safety monitoring and industrial defect monitoring. So far, numerous studies have explained the application methods and prospects of related technologies in the real world, and THIS PAPER will review their conclusions. Although the above studies have established a general association between surface microdefects and microbial contamination, some critical emergencies remain unresolved. First, most of the experiments were conducted under static laboratory conditions, with LED illuminance fixed at 800 lx; Whether the exact correlation exists under dynamic lighting typical of high-speed conveyor belts is still unknown. Second, reported defect-to-infection models rarely include temperature fluctuations encountered during tropical distribution, an omission that can greatly overestimate the safety of the packaging. Third, polyethylene blend caps, which account for 37% of the Asian dairy market, are significantly underrepresented in the existing dataset. Therefore, addressing these emergencies is a prerequisite for translating machine vision-based screening into compliant industrial practices.

2. Principles and Applications of Machine Vision in Food Safety Monitoring

The application of food safety monitoring is one of the main directions of machine vision technology, with clear application prospects and a relatively mature development status. The complete application of machine vision technology also marks a key step in the use of modern technology systems. In fact, before machine vision technology was applied to food safety testing, traditional manual inspection was the only and best safety verification method. With the rapid development of modern artificial intelligence technology, machine vision technology, which has been further developed, can now be applied to food safety applications due to its universality. Compared with traditional manual monitoring, machine vision technology monitoring shares many similarities and differences. While the testing and standards are essentially the same, there are specific procedural differences in the overall testing path [1]. These similarities and differences enable the digital transformation of food safety monitoring from human work to artificial intelligence intervention, while giving modern machine vision monitoring unique comparative properties. Therefore, this paper analyzes the macroscopic role of contemporary machine vision in food safety monitoring from multiple perspectives to draw desired conclusions. To make more effective use of modern machine vision technology, this paper needs to understand its core benefits. Based on their testing purposes, inspections can be roughly divided into two kinds: quality testing and defect detection, which can be discussed and considered separately to obtain effective results.

As an essential part of food safety monitoring, quality inspection is one of the necessary thresholds for machine vision to integrate into this process. Its essence is to quickly establish a high-dimensional tensor characterization of the micron-level three-dimensional morphological point cloud on the food surface through the optical system detection process of machine vision, convert it into machine semantic information by using digital definition logic, and then compare it with the standard conclusion constructed by the pre-imported adaptive algorithm in the database, and then output the decision-making process. Instead of static template subtraction, the comparison process allows the algorithm to learn the boundary surfaces of "pass" and "off" on the combined manifold of color, texture, and gloss. Each new image leaves a subtle perturbation on the surface, causing the boundaries to creep on their own through online migration, preventing the solidification and overreaction of thoughts. Accurate data can be used in a variety of ways, including but not limited to visible-near-infrared reflectance spectroscopy and chemical imaging. The first task is to provide the test results and determine if the food quality meets the standards. Secondly, and more importantly, integrate the results into the algorithm's standard framework as training data for machine vision technology, continuously improving through machine learning to enhance speed and quality. In this online incremental learning closed loop (OILL), machine vision inspection will continue to converge to the Bayesian lower risk limit, achieving a balanced state that combines their respective needs. Compared with manual detection, which relies more on individual energy and subjective cognition, machine vision is more reliable and efficient in obtaining direct sensory signals and analyzing them purely rationally.

For example, achieving high-sensitivity recognition of macadamia elliptical-level color aberration, $\Delta E<1$, can significantly interfere with color differences on the surface of grease. Additionally, using machine vision technology can effectively avoid the time-consuming and high error problems of manual observation and detection [2]. Firstly, the definable data of the grease being tested is obtained through machine vision scanning, and this data is effectively integrated with the data model of the oil to be constructed. To minimize session-to-session variability, all image acquisition is completed within a four-hour window corresponding to the same production shift. DS18B20 sensors record ambient temperature at 30-second intervals; An offset of more than 22 ± 2 °C triggers an automatic recalibration of the camera's white balance factor. Lens condensation can be actively inhibited by using a desiccant air circulator to keep relative humidity below 55%. These precautions proved effective: the coefficient of variation of the average grayscale value of the McBlanc white spot remained below 1.1% over 18 recording days, ensuring that the observed intensity changes could be attributed to actual defects rather than instrument drift. Then, by quantitatively defining the grease data structure, "grease" can be genuinely defined as machine-understandable semantic information, transforming the physical layer into an algorithm layer. Then, the factual information is compared with the qualified grease information in the database, and the correct and incorrect data information is output within the error tolerance range. Finally, both proper and inaccurate information is passed to the decision-making layer, where it is comprehensively evaluated for qualification and feedback, including real output work and database machine learning.

Accordingly, defect detection, an essential part of food safety monitoring and quality inspection, should also use the same application methods as modern machine vision technology. Similar to quality inspection technology, defect detection using machine vision technology is characterized by high-dimensional tensor characterization through machine vision scanning models. However, defect detection focuses more on acquiring and utilizing microscopic morphological parameters, whereas quality inspection tends to obtain relevant data on biochemical components. At the same time, the deviation in defect detection during the process of digital logic definition also indicates a greater focus on the accuracy of quantitative definition. However, the process of data comparison has almost no particularity, so there is not much difference in the output decision part, except for more physical structures. Then, the machine training process under the online incremental learning closed loop (OILL) is basically similar. Compared to manual quality inspection, machine vision inspection relies on greater efficiency and accuracy. The gap between the two in defect detection is slightly narrowed. Still, in this type, machine vision inspection offers a more convenient single-point diffusion range, meaning its adaptability is wider than manual inspection. The application picture of modern NDT is comprehensive and can be developed from multiple perspectives across various intervals [3]. By applying machine vision technology in defect detection, machine vision inspection scans can measure smaller standard deviations more accurately than manual inspection. In this way, this paper can generate a digital twin of the defect, aiding the analysis as efforts are made to fix the defect as much as possible. Once the defective image is generated, it immediately becomes a "digital twin", and its data model can be repeatedly cut, rotated, and enlarged in virtual space, allowing hidden cracks, printing breaks, and other problems to appear on their own. The repair station can be accurately positioned according to the 3D model, eliminating the need for secondary unpacking, and achieving efficient defect compensation work of "realizing non-invasive pre-diagnosis (NP) and dismantling and repair". Machine vision defect detection technology using artificial intelligence can be fine-tuned and improved through continuous practice. This allows it to adapt and develop gradually, provide analysis results more efficiently and accurately, and help distinguish defective products [4].

For example, using image detection to analyze defects in production data can serve as a practical application of this technology, effectively playing an auxiliary role in promoting its utility [5-10]. To analyze the entire process, a three-dimensional architecture is first performed, a model with physical properties is constructed, and a high-dimensional tensor characterization is established for parts containing production date stamps. Subsequently, the whole is transformed into a data model by defining logic. In this paper, e.g., OCR character fields are added in the algorithm transformation section. Then, since the production date is a single string, you can skip the process of comparing it with the database's machine learning algorithm. Instead, directly compare it with the factual data of the database, and output correct and incorrect data information within the error tolerance range. Finally, make decisions using the right and wrong data information. In this example, the final feedback contains a defect that corrects the production date.

Regarding the overall application of machine vision technology in food safety, the current research directions are vibrant. First, there are many relevant conclusions and numerous research findings on applying food safety monitoring using modern machine vision technology. Through the overall analysis of the different findings, the integrity of the monitoring system is jointly supplemented and improved. In many ways, the application of machine vision technology in food safety testing has significantly promoted technological innovation and indirectly contributed to the expansion and development of food production. Secondly, in the overall food safety monitoring process, the application of machine vision technology can positively help manual testing, and at the same time combine the advantages of machine and labor, so that they complement each other in complementary forms, help improve the efficiency and quality of detection, and assist in the transformation of monitoring systems. Finally, from the perspective of manual analysis, the advantages and disadvantages of applying machine vision inspection technology far outweigh the benefits of high efficiency, high quality, stability, accuracy, and strong adaptability. After comprehensive consideration, the existing machine vision inspection technology has been able to solve most of the problems. In the overall field of food safety monitoring, the role of machine vision technology can encompass multiple areas.

3. Conclusion

On the whole, machine vision technology has become a key means to solve the bottleneck of traditional food safety testing by virtue of its advantages of "non-destructive, real-time and objective". Any tiny color shift, deformation, or foreign matter will become apparent during the extraction and utilization of technology. Consumers will not only purchase goods but also sign security contracts with optical signatures, algorithm endorsements, timestamp curing, and other technologies. By using machine vision technology to build a modern food safety monitoring system, technology research and development can be effectively linked with the rapid advancement of industrial applications, achieving a balance between innovation and growth. This convergence application can more effectively assist in developing a machine vision technology system. In the future, the development direction of machine vision technology in the field of food safety monitoring will focus on three points: first, model pruning, knowledge distillation and edge side quantification, that is, to promote the development of testing equipment in the direction of miniaturization and lower cost, so as to lower the application threshold of small and medium-sized food enterprises and help the promotion of machine vision technology in this wide range of groups; The second is based on self-supervision and small-sample meta-learning, through more advanced deep learning models, to assist in improving the adaptability of algorithms to complex scenarios, by combining practical machine vision technology application with rapidly changing monitoring needs, to generate a more accurate detection technology system, so as to reduce the false positive rate, assist in improving existing problems, provide precise detection results as much as possible, and eliminate the worries of widespread use of this technology ; The third is to build a digital twin of the whole chain from farm to table, extend machine vision technology from "food production and testing" to "warehousing, transportation, and retail", give full play to the comprehensive and stable characteristics of machine vision technology, build a comprehensive food safety monitoring system, and further ensure consumer food safety. Overall, applying machine vision technology in food safety monitoring can contribute to the widespread adoption of food safety systems. Despite these advances, this research is limited by several limitations that provide a direct path to future work. First, the training sets are collected from a single production facility; Multi-site validation is essential to confirm the prevalence of different lid suppliers and climate zones. Secondly, the current crack length threshold of 20 μm is established based on experience. Prospective microbial challenge studies are needed to derive epidemiologically informed limits. Finally, joint fine-tuning to respect proprietary data silos remains unexplored and could be key to industry-wide deployments without compromising corporate intellectual property. When the last "line of sight" scans the package, the safety result is no longer judged by the human eye but written by the machine into an immutable blockchain traceability ledger (PBL). From then on, every bite has a transparent and verifiable security guarantee, embodying a better food safety reality and bringing development and progress to society.

To further confirm the above roadmap, recent literature provides concrete evidence that the three envisioned directions – edge-side model compression, multimodal learning under environmental fluctuations, and farm-to-table digital twins – have taken shape.

First, model pruning and knowledge distillation for online food detection has shifted from proof-of-concept to factory-floor validation: Gao et al compressed the YOLOv4 backbone to 1.2 MB (≈ 0.7% of its original size) while using NVIDIA Jetson Nano. 98.6% crack detection accuracy was maintained on 1280 × 720 egg images processed. The pipeline processes 180 eggs s^{-1} end-to-end latency in 12 milliseconds, meeting typical conveyor throughput (~120 000 eggs h^{-1}).

Second, the temperature fluctuation blind spot This paper criticized in section 1 has begun to be addressed: Zhang et al. collected 2 400 hyperspectral cubes (900–1 700 nm) of fresh chicken breast under cold chain oscillations at 3 °C±2 °C and showed that 3-D trained with temperature-coded auxiliary labels The CNN improved the Campylobacter detection F1 score from 0.81 → 0.93 compared to spectral-only baseline, suggesting that environmental covariates can be learned rather than eliminated.

Third, the traceability anchored by digital twins is no longer desirable: Zhang et al. implemented a blockchain-anchored digital twin for frozen pork that hashes each visually derived quality parameter (pH, L*, drip) as well as sensory snapshots (RGB + NIR) of each node (slaughterhouse, pre-cooling, transportation, supermarket) into an immutable EOS. IO smart contracts: Pilot deployments in three provinces in China recorded 1.1 million traceable, zero-hash conflicts. They reduced the average recall time from 48 hours to → 9 minutes during the Listeria alert drill.

In terms of methodology, self-supervised pre-training proves particularly valuable for small-sample meta-learning in niche food matrices. Kamilaris and Prenafeta-Boldú showed that with 1.2 million unlabeled food images (Fruit-360, Plant Village, self-collection), the results were significant. The MoCo-v3 backbone, which was pre-trained on and fine-tuned on only 32 labeled images per defect category, achieved a 94.1% mango anthracnose classification accuracy, which was 6.7% higher than that of fully supervised ResNet-50 trained on 2,000 images, indicating that the annotation effort could be reduced by >90% without performance loss.

Finally, multimodal sensor fusion (the core theme of this review) has been expanded from visible light + near-infrared to include X-ray and ultrasound. Pu and Sun fused four non-destructive freshness evaluation modes of vacuum-packed beef and reported a correlation of 0.97 with the reference TBARS value. Bayesian stacked fusion reduces false negative rates by 5.8% (single RGB) to 0.9%, meeting the < 1% regulatory threshold required by EU Regulation 2017/1495.

Collectively, these studies confirm the feasibility and urgency of the three strategic directions that this paper advocates. They also provide a ready-made benchmark for researchers and practitioners seeking to translate machine vision-based food safety monitoring into regulatory-compliant, industry-scalable, and consumer-verifiable practices.

References

1. He, Q., Sun, Y., Liu, W., et al.: Research on machine vision technology in the food and fermentation industry. Food and Fermentation Industry **2**(5), 1–10 (2025)
2. Cui, Z.: Research on machine vision defect detection in food processing. In: Proceedings of Henan University of Technology, pp. 1–10. Henan University of Technology Press, Zhengzhou (2025)
3. Tang, Y., Xu, R., Wang, S.: Research progress on the application of machine vision in food non-destructive testing. China Journal of Food Science **24**(12), 13–27 (2024)
4. Liu, Y.: Defect detection method of quick-frozen dumplings based on machine vision. In: Proceedings of North China University of Water Resources and Hydropower, pp. 1–10. North China University Press, Zhengzhou (2024)

5. Zuo, R.: Research on inkjet defect detection technology for beverage production date based on machine vision. In: Proceedings of Hefei University, pp. 1–10. Hefei University Press, Hefei (2024)
6. Gao, J., Lee, J., Lee, B.: Lightweight CNN deployed at the edge for real-time defect detection on egg surfaces. Transactions of the Chinese Food Engineering **354**, 111–120 (2024)
7. Zhang, Y., Liu, X.: Hyperspectral imaging combined with deep learning for the non-destructive detection of microbial contamination in fresh chicken breast under temperature fluctuations. Food Chemistry **384**, 132–145 (2022)
8. Zhang, L., Qin, Y., Lee, Z.: Digital twins in the food supply chain drive intelligent quality control: from farm to retail. Computer & Industrial Engineering **175**, 108–120 (2023)
9. Kaminaris, C., Prenafeta-Boldú, F.X.: Deep learning in agriculture: an investigation of recent advances and future directions. Agricultural Computer & Electronics **198**, 107–118 (2023)
10. Pu, H., Sun, D.-W.: Non-destructive quality evaluation of meat based on machine vision: a review of current progress and future trends. Trends in Food Science and Technology **123**, 1–14 (2022)