Nutrition Meets Tech: An Automated Food Analysis Cameras

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Abstract
A healthy and balanced diet plays a crucial role in preventing chronic diseases such as obesity, cardiovascular disorders, and cancer. However, conventional dietary assessment methods rely on self-reporting techniques that are time-consuming, inaccurate, and often associated with underreporting and low user adherence. Recent advances in artificial intelligence (AI), computer vision, and wearable sensing technologies have enabled automated and passive dietary monitoring solutions, addressing these limitations. This study integrates AI-based food detection, mobile health (mHealth) applications, automated quality control, and artificial vision systems for dietary assessment and food-related analysis. Egocentric image datasets acquired using a wearable camera device were analysed using convolutional neural network-based algorithms to automatically detect food-related activities in real-world environments. The datasets included images of free-living daily activities such as dining, cooking, shopping, and physical exercise. Cross-dataset evaluations demonstrated high accuracy, sensitivity, and specificity in classifying food and non-food images, even from low-quality wearable camera data, thereby reducing manual processing burden and privacy concerns. In addition, automated quality control frameworks using data-centric AI paradigms were explored to evaluate multiple quality factors of packaged food products. These frameworks integrated deep learning and traditional computer vision approaches, achieving rapid prediction speeds and high classification accuracy. Artificial vision systems, including hyperspectral imaging, further enhanced food quality assessment by detecting defects and internal features beyond human visual capabilities. Overall, AI-driven dietary monitoring and food quality assessment systems show strong potential to improve nutritional data accuracy, support effective mHealth interventions, reduce food waste, and enable scalable industrial applications. Continued advancements in AI and vision technologies are expected to significantly impact personalised nutrition, public health, and food system sustainability.

Keywords: Food Image Recognition; Wearable Cameras; Automated Quality Control; Health; Egocentric Imaging

Introduction

Food is a vital component of our daily lives. Not only does food provide nutrition for survival, but it is also a cultural and health aspect. Society is becoming more conscious of health, which has led to an increase in interest in creating personalised and balanced diets. As a result of this awareness, researchers have begun to study food from an interdisciplinary perspective that incorporates computer vision, nutrition science, and industrial automation. One of the most exciting aspects of these efforts is the use of food image recognition as a subfield of fine-grained image analysis. Food image recognition has enormous potential to enhance the way we assess our diets, manage our healthcare, and develop smart retailing (Jiang, S. et al., 2025).

Self-reported data, manual food logging, and laboratory-based analysis are the mainstays of traditional dietary assessment and nutrient evaluation techniques. These methods are frequently laborious, prone to errors, and unsuitable for real-time applications. Due to these constraints, there is an increasing need for intelligent, automated, and scalable solutions that can provide accurate food identification and nutritional insights in routine settings. The use of traditional methods for analysing foodstuff often involves laboratory techniques that are very slow, which might result in a hazard not being detected in time, thus exposing consumers to harmful substances (Hassoun, A. et al., 1976).

In the past few years, biosensing devices have been gaining acceptance in the food quality monitoring process as efficient and reliable analytical methods. The combination of biological recognition elements and transducer components creates analytical instruments that are able to recognise and quantify particular analytes present in food samples (Naresh, V. et al., 2021). The biological interactions provide the biosensor with highly sensitive and very fast detection capabilities that can compete with lab methods (Srinivasan, B. et al., 2015).

While traditional methods require complicated sample pretreatment and expensive equipment, biosensors offer simple, portable, and real-time monitoring features, allowing for the quick screening of a large number of food samples, which reduces the time and cost of analysis (J. Lab. Autom. et al., 2015). Besides that, they can detect target analytes even at very low concentrations, thus giving early warning signals about possible food safety hazards (Zhang, J. et al., 2022).

Through complex data processing, quantitative analysis, and real-time decision-making, artificial intelligence (AI) is transforming biosensing platforms for the identification of foodborne pathogens (Reshadsedghi, M. et al., 2025). In certain cases, machine learning models have been successfully applied to biosensor outputs to achieve accurate pathogen classification and quantification across different food matrices, with accuracies exceeding 95% (Zhang, R. et al., 2025). AI-driven techniques improve signal processing, reduce noise, and increase the sensitivity, selectivity, and stability of mass-based, optical, and electrochemical biosensors, making accurate detection possible even in complex food matrices (Gupta, C. et al., 2024). Convolutional neural networks (CNNs) and deep learning have shown great promise in applications like pathogen identification using surface-enhanced Raman spectroscopy (SERS) (Wilson, D.I. et al., 2025).

Principles and Mechanisms of Biosensor Operation

The functioning principle of a biosensor is centred on the selective identification of a target analyte by a biological receptor, which triggers a measurable signal that reflects the concentration or presence of the analyte. The bioreceptor, referred to as the recognition element, consists of biomolecules or biological entities specifically engineered to engage with the target analyte (Prasad, M. et al., 2022). This engagement results in a biochemical or biophysical alteration, which forms the foundation for detection. The bioreceptor is linked to a transducer that transforms the interaction between the bioreceptor and the analyte into a measurable signal (Kaushik, S. et al., 2022).

Subsequently, the signal is amplified by an amplifier, which enhances its detectability and improves the signal-to-noise ratio (Manasa, G. et al., 2023). The processed signal is then examined and interpreted by a processor, with the results presented in a format comprehensible to humans. Thus, the combination of the bioreceptor, transducer, amplifier, processor, and display constitutes the core of a biosensor system, facilitating precise and effective detection of target analytes (Lee, N. et al., 2021).

The inaugural biosensor was created by Leland C. Clark, Jr. in 1956 for the detection of oxygen, earning him the designation of the "father of biosensors." In 1962, Clark showcased an amperometric enzyme electrode for glucose detection (Arya, R. et al., 2013). This was succeeded in 1969 by the introduction of the first potentiometric biosensor for urea detection by Guilbault and Montalvo Jr. (Guilbault, G. et al., 1969).

Components of a Biosensor for Food Quality Monitoring

Biosensors are only one of the tools used to monitor food quality and safety. A biosensor generally comprises biological recognition elements and transducers. The biological elements selectively recognise the target biological entities, e.g., pathogens, and the transducers convert the recognition event into a measurable signal. The biosensor components are illustrated by a schematic diagram showing the principles, applications, and limitations of each (Teodoro, L. M. P. et al., 2025).

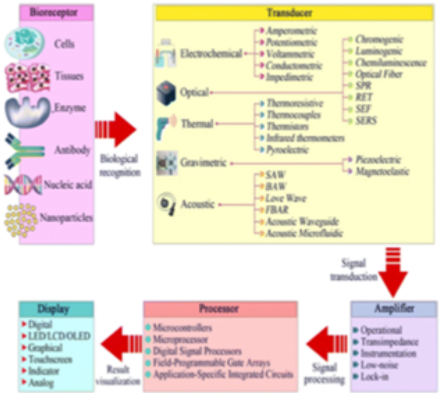

Figure 1 Schematic Diagram of Biosensor Components, Principles, Applications, and Limitations.

Recognition Element or Bioreceptor

Recognition elements are basically biomolecules that interact specifically with the target analyte and cause a biological response that is then detected as a signal. Some of the most widely used recognition components in biosensors are enzymes, antibodies, nucleic acids (DNA or RNA), cells, and MIPs (molecularly imprinted polymers) (Kumar, D. et al., 2022).

These biomolecules are highly specific to their target analytes, which makes them useful in the selective detection of compounds of interest. In order for them to be stable and active and thus give accurate and reproducible results, it is important that recognition elements be immobilised onto the biosensor surface (Olaifa, K. et al., 2025).

Applications of Biosensors in the Detection of Food Contaminants

Biosensors play an important role in the detection and determination of the levels of various contaminants in food samples. They give the analyst the advantage of rapid, highly sensitive, and selective detection. The technology of biosensors maintains the safety and quality of the supply chain.

Table 1 Detection of Food Contaminants

Biosensor Type	Application	Analyte	Biological Element
Enzyme-based biosensor	Pesticide residues; Mycotoxins in grains; Glucose levels in beverages; Lactose in dairy products; Alcohol content in beverages	Pesticides; Mycotoxins; Glucose; Lactose; Ethanol	Enzymes (acetylcholine); Enzymes (Peroxidase); Glucose Oxidase; Galactosidase; Alcohol Dehydrogenase
Antibody-based biosensor	Allergen in food products; Pathogenic bacteria in meat; Gluten in food products; Aflatoxins in spices; Foodborne viruses in water	Allergen; Bacteria; Gluten; Aflatoxin; Viruses	Monoclonal antibodies; Polyclonal antibodies; Monoclonal antibodies; —; —

Source: The table shows how enzyme-based biosensors are used to detect specific contaminants present in food.

Allergens

Biosensors allow rapid and accurate detection of allergens and allergenic components, which ultimately leads to ensuring the safety of food for people with allergenic conditions. These biosensors can use different recognition elements such as antibodies or aptamers that specifically target the allergenic proteins derived from common allergens like nuts and gluten. For example, immunosensors may employ antibodies against particular allergenic proteins, enabling rapid and sensitive detection. Moreover, DNA-based biosensors are able to investigate the presence of allergenic ingredients through genetic sequences, thus providing an accurate and reliable method of allergen detection (Mishra, R. K. et al., 2018; Reshadsedghi, M. et al., 2025).

Food Adulterants

Biosensors are very handy tools for detecting food adulterants such as contaminated raw material, fake products, or dilution with cheaper substitutes. Electrochemical biosensors have been used for the detection of melamine in dairy products (Basu, T. et al., 2024), while optical biosensors have been used for the detection of synthetic colours and dyes in food and beverages (Yang, Y. et al., 2024). Following that, these biosensors helped to comply with regulatory requirements and protect the health of consumers.

Food Quality Parameters

Biosensors also aid in assessing the different quality parameters of food products such as freshness, ripeness, and nutritional content. Biosensors containing enzymatic recognition elements are capable of identifying specific biomarkers associated with freshness and spoilage (Mishra, R. K. et al., 2018). DNA-based biosensors can target specific genetic sequences associated with allergenic ingredients (Reshadsedghi, M. et al., 2025) and have been used to detect synthetic colours and dyes in beverages and food products (Yang, Y. et al., 2024), ensuring compliance with regulatory standards. Enzymes biosensors targeting key ripening indicators, such as ethylene or specific enzymes involved in fruit softening, can accurately monitor ripeness levels (Quan, H. et al., 2024). In addition, whole cell-based biosensors allow the quantification of proteins, fats, carbohydrates, vitamins, and minerals, providing nutritional profiles of food samples (Liu, Y. et al., 2018).

Challenges and Limitations in Biosensor Implementation

Despite their promising capabilities, the widespread adoption of biosensors in food quality monitoring encounters several challenges and limitations. A significant challenge is the need for biosensors to maintain high sensitivity and specificity in diverse food matrices, which can vary widely in composition and complexity (Ruan, S. et al., 2024). Furthermore, ensuring the stability and shelf life of biosensor components, particularly biological recognition elements, presents another challenge. Environmental conditions such as temperature and pH can impact the performance and longevity of biosensors, requiring careful storage and handling protocols (Bechtsis, D. et al., 2024). In addition, standardisation and regulatory considerations pose challenges in ensuring the consistency and reliability of biosensor measurements for regulatory compliance and widespread acceptance in the food industry.

Figure 2 Biosensor Challenges And Limitations Diagram.

Shelf-Life and Stability Concerns

Concerns regarding shelf-life and stability represent significant hurdles in the development of biosensors, particularly in the realm of food quality monitoring, where long-term performance and reliability are essential. The enzyme-based biosensor created for detecting various compounds in food samples faces stability issues with the immobilised enzyme, which experiences reduced activity over time due to enzyme denaturation. To tackle this problem, numerous studies have explored various enzyme immobilisation methods, such as cross-linking and encapsulation, to shield the enzyme from degradation and preserve its activity during storage (Bhunia, A.K. et al., 2021).

Additionally, researchers have developed a DNA-based biosensor aimed at detecting genetically modified organisms (GMOs) in food products. This biosensor employed DNA probes immobilised on gold nanoparticle-modified electrodes to capture target DNA sequences from GMO samples. However, concerns emerged regarding the stability of the immobilised DNA probes, which may undergo degradation or structural alterations over time, leading to a decrease in sensitivity and detection efficiency (Kanthenga, H.T. et al., 2025).

Foodborne Pathogens and Challenges in Their Detection

Foodborne pathogens, including bacteria, viruses, and parasites, can contaminate food at multiple stages of the supply chain, threatening public health and resulting in numerous diseases and deaths worldwide (Kabiraz, M.P. et al., 2023). Norovirus, Campylobacter, Salmonella, L. monocytogenes, and E. coli are the main pathogens of concern due to their heavy occurrence, seriousness of the induced diseases, and continuous participation in foodborne outbreaks. Besides being present in food, these pathogens also secrete toxins and other harmful compounds, some of which are resistant to inactivation during food processing (Martinović, T. et al., 2016). Their survival in food environments is further assisted by the ability to create biofilms on processing surfaces, making them even more resistant to cleaning, disinfection, and antimicrobial treatments (Bhunia, A.K. et al., 2021). Notably, L. monocytogenes is extremely hardy, capable of surviving at refrigeration, acidic, and high salt conditions.

A variety of detection methods are currently used, including traditional culture-based methods, immunological assays, nucleic acid-based approaches, and next-generation sequencing (NGS) (Premarathne, J. et al., 2017). Although culture-based methods are still the main regulatory standard due to their low cost and ability to isolate live microorganisms, they are usually slow and lack sensitivity, especially for pathogens in a viable but non-culturable state. Immunological assays such as ELISA, lateral flow devices (LFDs), serotyping, and immunofluorescence are quick methods that detect foodborne microbes or their toxins through the specific binding of microbial antigens to antibodies (Premarathne, J. et al., 2018). While relatively specific, their reliability can be compromised by matrix contamination, which may result in false positives (Dwarakanath, S. et al., 2018).

Nucleic acid-based techniques, e.g., polymerase chain reaction (PCR), detect pathogens by amplifying specific DNA or RNA sequences using designed primers. They provide high sensitivity, reproducibility, and versatility; however, high cost, the requirement for specialised equipment, and the presence of inhibitors in complex food components limit their use. Next-generation sequencing technologies offer comprehensive insights into pathogen genomes, virulence factors, and the dynamics of microbial communities (Delgado, S. et al., 2014), but their routine use is limited due to high costs, intricate workflows, and the necessity for advanced bioinformatics expertise (Sirangelo, T.M. et al., 2020).

These matrix effects diminish specificity, sensitivity, and reproducibility, presenting significant obstacles to accurate detection. In response to these challenges, there has been a push towards the development of advanced, field-deployable diagnostic tools, with biosensors emerging as a particularly promising solution for the rapid, sensitive, and portable detection of foodborne pathogens. Each detection method has its own unique trade-offs, with culture-based methods preferred for regulatory compliance, molecular assays valued for their sensitivity, and biosensors recognised for their portability. These comparisons underscore the increasing pursuit of AI integration to address the limitations of traditional approaches (Sanlibaba, P. et al., 2018).

Biosensor-Based Foodborne Pathogen Detection

Biosensors have emerged as sophisticated analytical tools that address the limitations of traditional and molecular diagnostic techniques by facilitating rapid, sensitive, and portable detection of foodborne pathogens (Bozal, A. et al., 2018). A biosensor typically consists of a biorecognition element that selectively interacts with the target analyte, a transducer that converts this recognition event into a measurable physicochemical signal, and a signal processor that amplifies and interprets the output for qualitative or quantitative evaluation.

In the realm of food safety, biosensors utilise highly specific interactions between pathogens or their molecular markers and immobilised recognition elements, enabling real-time monitoring even within complex food matrices. Their benefits include rapid response times, generally within minutes to hours, on-site applicability, reduced reliance on centralised laboratories, and compatibility with point-of-care or miniaturised devices, making them particularly appealing for enhancing food safety surveillance (Yuan, Z. et al., 2025).

Antibodies are extensively utilised due to their specificity, as demonstrated in innovative impedance immunosensors for the swift and sensitive detection of L. monocytogenes in milk. However, their instability under varying temperature or pH conditions remains a concern (Zhang, D. et al., 2025). Smartphone-integrated optical biosensors have also shown portable and cost-effective detection of E. coli in milk and water, highlighting their practical applicability in the field. Furthermore, biosensors have been effectively employed for the determination of L. monocytogenes in chicken meat and milk (Acikgoz-Erkaya et al., 2024).

With significant advancements in nanomaterials, surface chemistry, and microfluidics, biosensors are swiftly transitioning from experimental prototypes to practical instruments for ensuring food safety. Their capacity to combine highly selective recognition with rapid and sensitive transduction paves the way for reliable, field-deployable diagnostics (Guo, J. et al., 2018).

Artificial Intelligence in Biosensing Platforms

The growing complexity of food matrices poses considerable challenges for traditional biosensors, making it essential to implement advanced detection technologies. Food samples typically comprise proteins, lipids, and carbohydrates that can compete with target analytes for binding sites on the surfaces of biosensors, consequently diminishing assay specificity and sensitivity. Furthermore, biosensors often produce intricate datasets characterised by signal variability, background noise, and matrix interferences, complicating data interpretation and limiting reliability in practical applications (Cui, F. et al., 2020).

To address these issues, artificial intelligence, which includes machine learning (ML) and deep learning (DL), offers robust solutions by facilitating automated data analysis, pattern recognition, and predictive modelling. Specifically, ML algorithms can efficiently handle smaller and noisier datasets that are prevalent in continuous monitoring applications, while also addressing challenges such as electrode fouling, interference from non-target analytes, and inconsistencies in samples (Siavash Moakhar, R. et al., 2025).

Machine learning is a primary branch of AI that enables computational systems to learn from data without explicit programming. It encompasses three main approaches: supervised, unsupervised, and reinforcement learning. Supervised learning relies on labelled datasets, where input-output pairs guide model training with human oversight. Unsupervised learning identifies hidden structures within unlabelled data, autonomously uncovering patterns and groupings. Reinforcement learning operates through trial-and-error interactions with an environment to optimise decision-making in pursuit of defined objectives. Unlike conventional ML methods that rely significantly on manual feature extraction, DL models autonomously identify the pertinent features necessary for detection and classification (Mishra, R.K. et al., 2021).

Artificial intelligence possesses the capability to impact every phase of biosensor development. It can assist in the selection of analytes by identifying biomarkers that exhibit the greatest discriminatory power, facilitate the design of recognition elements through in silico modelling of binding interactions, enhance signal transduction by refining sensor calibration, and simplify data analysis through comprehensive classification and predictive algorithms (Flynn, C.D. et al., 2024).

AI-Assisted Selection and Multi-Analyte Analysis

Selecting the right analytes is crucial for the development of biosensors capable of reliably detecting foodborne pathogens. However, traditional methods typically rely on trial-and-error experimentation, which is time-consuming and may miss subtle yet significant biomarkers.

Artificial intelligence has revolutionised this process by analysing extensive omics datasets, including genomics, proteomics, and metabolomics, to identify candidate biomarkers with enhanced precision and efficiency. Machine learning algorithms can reveal hidden patterns, forecast molecular interactions, and prioritise analytes with substantial diagnostic potential while reducing cross-reactivity. Moreover, artificial intelligence facilitates multi-analyte profiling, allowing for the simultaneous evaluation of multiple indicators to enhance diagnostic sensitivity and specificity. When diverse fluorescence responses were aggregated and analysed using machine learning algorithms, the system achieved swift, accurate, and highly sensitive identification of foodborne pathogens (Wang, F. et al., 2024).

Colorimetric Biosensor

Colorimetric biosensors rely on visible changes resulting from nanoparticle aggregation or enzymatic reactions, often allowing detection by the naked eye without the need for advanced instrumentation. Artificial intelligence tackles these challenges by automating the processing and interpretation of colorimetric signals, thereby reducing subjectivity and improving precision in complex, multivariate sample environments. Pattern recognition and sophisticated data analytics empower AI-driven colorimetric biosensors to achieve greater accuracy, while integration with portable platforms such as smartphones enhances real-time applicability (Yang et al., 2025).

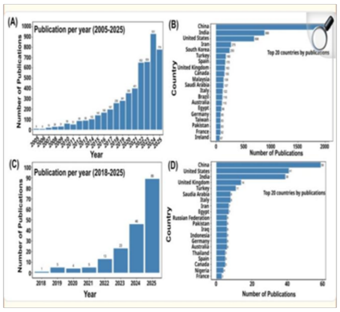

Figure 3 Colorimetric Biosensor Application Example

Emerging Technologies

A. AI Revolution

Over the course of a few decades, the manufacturing sector and contemporary industry have reached unprecedented levels of productivity due to the advent of automation. In the early 1900s, the concept of machines performing tasks with greater precision, thereby replacing human efforts across various fields, was always envisioned as a future possibility. In recent years, Artificial Intelligence has set remarkable records by taking over tasks such as object recognition and computer vision (Feigenbaum, E. et al., 1982).

Artificial Intelligence encompasses a multitude of methods and phenomena, with two principal concepts, Neural Networks (NN) and Deep Learning (DL), being pivotal for AI's remarkable progress (Norvig, P.R. et al., 2002). This advancement is now achievable thanks to the modern high computing power of Graphics Processing Units (GPU), which has enabled neural networks to replicate the functions of the human brain. Through extensive data, neural networks have begun to perform extraordinary feats, and leading technology companies such as Google, Microsoft, Amazon, Facebook, and Apple have initiated their research in AI by gathering substantial amounts of data (Pan, Y. et al., 2016).

In just a few years, DeepMind's technology has advanced from performing simple tasks like document review and spam email categorisation to tackling complex challenges such as object recognition, context building, and scene understanding (Markoff, J. et al., 2016). Even intricate domains like medicine and pharmaceuticals have benefited, as evidenced by AI's ability to predict eye diseases solely by analysing retinal scans (Narayanaswamy, A. et al., 2016).

B. Computer Vision and Its Sub-Concepts

Technologies including computer vision and AI are becoming increasingly prominent across various sectors such as medicine, automotive, smart robotics, and vision-based AI systems, as well as virtual agents (Ponsa, D. et al., 2012). This surge has led to a significant influx of investments in AI-driven industries and services. On a global scale, increased population has significant influence on aspects such as government policies and services. The major concern regarding this issue is balancing the demand and supply of food in developing countries with increasing population. The relative increase in technological progress paves a way for better economic status of the country, and governments and private investors are working on inducing AI and computer vision technologies into sectors such as the food industry and agriculture for solving specific problems and increasing productivity (Bryant, J. et al., 2015). Tech giants such as Microsoft and Google are providing their technology to these countries and supporting global economic stability. For example, with the collaboration of Microsoft and India's International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) in adopting Microsoft Cortana Intelligent Suite for collection of agricultural data and analysing it through machine learning algorithms, the Indian Government established pilot sites in 13 districts with soil analysis laboratories, smart irrigation schemes, and Inclusive Market Oriented Development (IMOD) strategies to benefit farmers through public-private investments (Singh et al., 2018).

Figure 4 Ai And Computer Vision In Agricultural And Food Industry Applications.

C. AI-Based Food Processing Strategies

The availability of data concerning food and edible products has prompted researchers to investigate the food industry through the lens of AI. By 2015, computers had become sufficiently advanced to identify food items. Deep learning advancements have progressed from simple document review and categorisation to complex object recognition, context building, and scene understanding, with applications now extending into medicine, pharmaceuticals, and agricultural data analysis.

Conclusion

Ensuring food safety within an increasingly globalised supply chain requires the implementation of rapid, precise, and scalable pathogen detection strategies. While traditional culture-based methods are dependable, they are insufficiently swift to satisfy contemporary demands. In contrast, advanced molecular and immunological techniques face several challenges related to sensitivity, reproducibility, and applicability in the field.

Biosensors have surfaced as promising solutions to address these challenges by offering portability, quick response times, and the ability to integrate into real-time monitoring systems. However, issues such as matrix interference, limited sensitivity across various food types, high production costs, and regulatory obstacles still hinder their broader acceptance.

Artificial intelligence presents a significant opportunity to mitigate many of these challenges, as it facilitates advanced signal processing, enhances sensitivity and specificity, and enables reliable pathogen classification across diverse food matrices. Machine learning models, including support vector machines and convolutional neural networks, have been effectively utilised to interpret complex biosensor outputs, thus enabling rapid and highly accurate pathogen identification in food samples. AI-driven multimodal data fusion, along with integration with IoT and edge computing, is transforming the capabilities of biosensors from mere proof-of-concept prototypes to scalable diagnostic solutions.

This review also offers a thorough understanding of computer vision and intelligence methodologies that address numerous agricultural applications, including food processing, agriculture-related applications, farming, plant data analysis, smart irrigation, and next-generation farming. The importance of the AgriTech industry and investments in AI and vision technologies has been examined with pertinent sources and use cases. This review acts as a comprehensive resource for multidisciplinary information related to AI and vision techniques in the food and agricultural sectors.

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