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ANALYZING THE RESEARCH ON HOW THE ORGANIC FOOD SECTOR HAS INTEGRATED AI INTO ITS PRODUCT DEVELOPMENT PROCESSES

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Abstract

This study investigates the application of computer vision and artificial intelligence (AI) technologies in assessing the quality of organic food, with a particular focus on their impacts on production, marketing, and sustainability. The review is structured around three main themes: the role of AI in the food sector, the use of computer vision for food quality evaluation, and the broader digital transformation driven by AI. Through a comprehensive literature review, this study explores how image processing techniques can enhance the accuracy, impartiality, and efficiency of organic food quality assessments. The findings show that AI and computer vision significantly improve the reliability of visual quality indicators, reducing human error and enhancing efficiency in quality control processes. Furthermore, these technologies offer potential benefits for customer service and cost reduction in operations. However, challenges such as high implementation costs and limited scalability, particularly for small-scale organic farms, continue to hinder widespread adoption. This study underscores the need for further research aimed at developing scalable and cost-effective AI solutions that are accessible to smaller producers. The integration of AI in the organic food supply chain holds significant promise for improving sustainability and resource efficiency, making it a critical area for future research.

Key words: **Artificial Intelligence (AI), Computer Vision, Organic Food Quality, Image Processing Techniques**

Introduction

The global organic food market has witnessed remarkable growth over the past decade, underpinned by increasing consumer demand for healthier and environmentally sustainable food options. According to the Research Institute of Organic Agriculture, the global organic market reached over USD 135 billion in 2022, reflecting the public's growing concern about food safety, chemical residues, and ecological sustainability (1). Consumers perceive organic foods as healthier, safer, and more environmentally friendly due to the absence of synthetic pesticides, fertilizers, genetically modified organisms (GMOs), and artificial additives (2).Despite their rising popularity, ensuring the quality and authenticity of organic food remains a significant challenge. Quality, in the context of organic products, extends beyond appearance or freshness to include factors such as nutritional content, purity from contaminants, and adherence to organic standards throughout the supply chain (3). However, inconsistencies in certification processes and the potential for fraudulent labeling can

undermine consumer trust. For example, organic food fraud—such as the mislabeling of conventional produce as organic—continues to be a concern in both developed and developing markets (4).
Furthermore, visual and sensory attributes often play a critical role in consumer purchasing decisions for organic produce. However, traditional quality assessment methods, which rely heavily on human inspection and subjective criteria, are prone to bias, inefficiency, and inconsistency (5). These limitations create an urgent need for more reliable, objective, and scalable technologies that can ensure the quality and traceability of organic foods from farm to table. Recent advancements in Artificial Intelligence (AI), particularly in computer vision and image processing, offer promising solutions to these challenges. AI-enabled systems can detect defects, evaluate freshness, assess ripeness, and classify food products with a high degree of accuracy, surpassing human capabilities in consistency and speed (6). In the context of organic food, such technologies could not only enhance quality control and reduce waste but also restore and reinforce consumer trust in certified organic labels.
However, while large agribusinesses have begun integrating AI technologies into their operations, small-scale organic farms face barriers related to cost, infrastructure, and technical expertise. Addressing these disparities is critical to ensuring the equitable adoption of digital tools across the organic sector. As such, research into scalable, cost-effective, and user-friendly AI applications is essential for democratizing technology use in sustainable agriculture. Artificial Intelligence (AI) and computer vision technologies are transforming modern agriculture by enabling smarter, data-driven farming practices (7). These technologies facilitate real-time monitoring, disease detection, yield prediction, and automated sorting and grading of crops—reducing reliance on manual labor and enhancing decision-making accuracy. In particular, computer vision systems use high-resolution imagery and machine learning algorithms to assess crop health, maturity, and quality with greater speed and precision than traditional methods (8). This integration supports higher productivity, reduced waste, and improved traceability across the supply chain, especially for quality-sensitive sectors like organic farming. Recent studies highlight the efficiency of AI-powered image analysis in identifying defects and classifying produce in post-harvest handling, significantly improving quality control processes (9).

Research Problem

The organic food sector faces major challenges in maintaining consistent quality, sustainability, and faith in certification systems, especially for small producers lacking access to advanced technology infrastructure. The potential of AI and computer vision to improve quality control and mitigate human bias is hindered by a lack of domain-specific research and scalable implementation approaches. There is an urgent necessity to comprehend how these technologies might be efficiently and economically incorporated into organic food production systems, especially in developing markets such as India.

Three review themes

The integration of Artificial Intelligence (AI) technologies is revolutionizing modern agriculture, particularly in enhancing quality control, efficiency, and sustainability within organic food systems. As organic food gains global popularity for its health and environmental benefits, ensuring the integrity and quality of these products becomes increasingly critical. To address these challenges, this study reviews three central themes**: The role of AI in the**

broader food sector, the application of computer vision for objective food quality assessment, and **.The digital transformation of agriculture driven by AI tools.** These themes are essential in understanding how digital technologies can support real-time monitoring, improve post-harvest processing, and reinforce sustainability across organic value chains (10). Recent research shows that AI-based image analysis not only enhances the precision of visual quality assessments but also reduces waste, optimizes labor, and supports traceability—core concerns in the organic market

Research Objectives

1. **To critically review the role of Artificial Intelligence (AI) and computer vision in organic agriculture.**
2. **To examine how AI and image processing techniques improve the accuracy and objectivity of organic food quality assessment.**
3. **To analyze the role of AI in reducing human error during the evaluation and sorting of organic produce.**
4. **To explore the impact of AI and computer vision on increasing production efficiency in organic farming systems.**
5. **To assess how these technologies contribute to sustainable and environmentally responsible farming practices.**

Literature Review: AI and Computer Vision in Organic Food Systems

The rise of Artificial Intelligence (AI) and computer vision technologies has ushered in a new era of smart agriculture, offering transformative tools for improving quality control, production efficiency, and sustainability across the food supply chain. In the context of organic agriculture, these technologies are particularly significant due to the sector's reliance on minimal chemical inputs, high variability in produce, and the growing consumer demand for transparency and traceability. One of the most critical challenges in organic food production is the assessment of food quality, which traditionally relies on manual grading and subjective inspection. AI-based image processing and computer vision techniques have proven highly effective in automating the evaluation of visual quality attributes such as color, size, shape, texture, and surface defects. This automation reduces labor costs, enhances grading precision, and minimizes human bias (11). Deep learning algorithms, especially convolution neural networks (CNNs), are widely applied for sorting fruits and vegetables, detecting anomalies, and classifying produce with remarkable accuracy. These systems support rapid, non-destructive inspection and are being increasingly integrated into post-harvest processing pipelines to enhance efficiency.

Beyond quality assessment, AI and machine learning (ML) tools play a pivotal role in improving production efficiency in organic farming systems. Organic farms often face constraints such as limited access to chemical treatments and a high dependency on environmental conditions (12). AI-enabled decision support systems can assist farmers in optimizing irrigation schedules, pest management, and yield predictions. By analyzing data from cameras, drones, and IoT sensors, AI models help in detecting plant diseases, estimating biomass, and suggesting precise interventions that align with organic standards (13). This integration not only boosts productivity but also aids in preserving soil and ecological health, core principles of organic farming.

An increasingly vital area of focus is the role of AI and digital tools in promoting sustainability and traceability. Organic farming aims to reduce environmental impact and build long-term resilience, and AI contributes by enabling data-driven resource management, reducing food loss, and enhancing lifecycle tracking. Computer vision and AI algorithms can trace products from farm to shelf, ensuring authenticity and reducing fraudulent claims, which is a major concern in the premium-priced organic market. Furthermore, when integrated with blockchain technology, these systems can deliver end-to-end traceability, helping consumers and regulators verify organic certifications and production histories (14). Despite these promising advancements, a significant research gap remains. Most AI applications in agriculture are developed and tested in conventional farming or large-scale agribusiness contexts. There is limited research focusing specifically on small and medium-sized organic producers, who often lack the capital, infrastructure, or digital skills needed to adopt such technologies. Affordability, customization, and user-friendliness remain significant barriers to widespread adoption in emerging markets such as India (15). Moreover, many studies address technical feasibility but overlook the socio-economic implications, scalability, and policy support needed for successful integration into organic food systems.

Research gap

While the application of Artificial Intelligence (AI) and computer vision has shown significant promise in improving food quality assessment and automation in conventional agriculture**, there is a noticeable lack of focused research on their implementation within organic food systems**, which have unique requirements related to traceability, minimal chemical use, and sustainability standards. Most existing studies emphasize general agricultural use-cases, but **few explore scalable, cost-effective AI solutions tailored to small and medium-sized organic producers**—who often lack the financial and technical capacity to adopt advanced technologies. Furthermore, there is limited literature assessing how AI can support the **integration of sustainability goals**—such as reducing food waste, optimizing resource usage, and enhancing consumer trust—specifically in organic supply chains.

Overview of organic food industries

The global organic food sector has undergone significant expansion in the last ten years, propelled by increasing consumer consciousness regarding health, food safety, and environmental sustainability. Organic food is cultivated without synthetic pesticides, genetically modified organisms (GMOs), or other additives, attracting consumers who desire clean-label and environmentally sustainable products (16). In 2022, the global organic market surpassed USD 135 billion, with the United States and the European Union as the predominant markets, accompanied by increasing demand in Asia and Latin America. Notwithstanding its expansion, the industry encounters persistent problems, such as supply chain inefficiencies, certification expenses, and concerns over product authenticity and traceability—domains where digital breakthroughs like AI and blockchain are starting to effect radical change.

Research Questions

1. What are the current applications of AI and computer vision technologies in evaluating the quality of organic food products?
2. How might AI enhance production efficiency and sustainability in organic farming practices?

3. What technological and economic obstacles do small and medium organic producers have in the use of AI-based solutions?
4. To what degree may AI and computer vision improve transparency, traceability, and consumer confidence in organic food systems?
5. What techniques or models are available or necessary to scale AI solutions for application in various organic food contexts, particularly in underdeveloped regions?

Background of the study

Organic food standards are regulatory frameworks that guarantee food is produced through environmentally sustainable practices, devoid of synthetic pesticides, fertilizers, genetically modified organisms, and artificial additives. In India, these are regulated by FSSAI under the Organic Foods Regulations, with certifications such as NPOP and PGS-India, and are distinguished by the new "India Organic" emblem to bolster consumer confidence (17). Artificial Intelligence (AI) and computer vision have become crucial instruments in agriculture, facilitating automatic and precise evaluations of crop quality, pest identification, and adherence to organic standards. These technologies provide real-time monitoring and decision-making, markedly enhancing operational efficiency (18). At the core of this are image processing methodologies such as Convolution Neural Networks (CNNs) and object identification frameworks (e.g., YOLO, R-CNN), which scrutinize photographs of produce to assess ripeness, identify faults, or categorize crop varieties. These AI algorithms provide scalable and accurate quality assessment solutions for organic food systems by diminishing dependence on manual inspections (19)

Definition of Organic foods

Organic food products are agricultural goods that are produced, processed, and handled in accordance with specific standards that prohibit the use of synthetic fertilizers, pesticides, genetically modified organisms (GMOs), antibiotics, and growth hormones. These products are grown using environmentally sustainable practices that promote soil health, biodiversity, and ecological balance. Certified organic food must comply with national or international regulations, such as those set by the **USDA Organic** or **EU Organic Certification** frameworks, ensuring that both the production and processing methods meet strict organic guidelines (20).

Introduce AI and computer vision technologies

Artificial Intelligence (AI) and computer vision are transformative technologies increasingly applied in agriculture to enhance productivity, precision, and quality assessment. AI refers to the simulation of human intelligence in machines, enabling systems to analyze data, learn from patterns, and make informed decisions. Within this domain**, computer vision** focuses on enabling machines to interpret and process visual information from images or videos. In agriculture, these technologies are used to monitor crop health, detect diseases, and assess the visual quality of food products. By automating visual inspection tasks, AI and computer vision reduce human error, increase efficiency, and support data-driven decision-making in the organic food industry (21).

Describing image processing techniques (e.g., CNNs, object detection)

Image processing techniques play a crucial role in modern agricultural applications, particularly in the quality assessment of organic food products. Among these**, Convolution Neural Networks (CNNs)** are a type of deep learning model that excel at analyzing visual data by automatically extracting features such as color, texture, and shape from food images. CNNs enable high accuracy in identifying defects, classifying products, and detecting inconsistencies. **Object detection** techniques, such as YOLO (You Only Look Once) or Faster R-CNN, allow systems to locate and label multiple objects within an image, making them ideal for detecting spoiled or misshaped produce in real-time. These methods significantly enhance the efficiency and consistency of quality control processes in organic food systems, reducing reliance on manual inspection and enabling scalable automation (22).

AI in the Food Sector

Artificial Intelligence (AI) is revolutionizing the food industry through automation, robotics, and data-driven decision-making. In the context of organic agriculture, AI enables greater efficiency and transparency across the supply chain—from production and harvesting to packaging and distribution.

Automation, Robotics, and Predictive Analytics

AI-driven automation and robotics are increasingly being used to optimize agricultural tasks such as planting, weeding, harvesting, and post-harvest handling. Machine learning algorithms analyze data from various sensors and environmental inputs to predict crop yields, detect disease outbreaks, and optimize resource use (23). Predictive analytics helps farmers make informed decisions, reducing waste and improving yield efficiency while maintaining compliance with organic standards. Robotics also facilitates labor-intensive processes like sorting and grading of produce, contributing to consistency in quality control.

Role in Organic Certification and Traceability

AI technologies also support organic food certification by streamlining documentation and monitoring compliance with standards. Tools like AI-enabled sensors and blockchain integration allow real-time data collection and immutable recording of farming practices, ensuring that organic standards are maintained throughout the supply chain (24). This improves traceability and consumer trust, which are critical in the organic food sector where authenticity and transparency are key differentiators. For instance, satellite imaging combined with AI can validate land-use practices, reducing fraudulent claims and enhancing certification processes.

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Computer Vision for Quality Evaluation

Computer vision has emerged as a powerful tool in automating the quality assessment of organic food products, addressing the need for consistency, efficiency, and objectivity in inspection processes (26). It enables machines to interpret visual data, replicating the human ability to judge quality based on appearance, while significantly reducing human bias and error.

Techniques: Color Analysis, Texture Detection, Spoilage Detection

Key computer vision techniques used in food quality assessment include **color analysis, texture detection,** and **spoilage detection.** Color analysis evaluates the ripeness and freshness of produce, often using RGB or HSV color spaces to quantify changes over time. **Texture detection** algorithms identify surface irregularities, such as bruises or blemishes, through edge detection and pattern recognition. **Spoilage detection** involves recognizing mold, discoloration, or abnormal surface features that indicate decay, often enhanced by deep learning methods such as Convolutional Neural Networks (CNNs). These automated evaluations ensure uniform quality control and help producers meet strict organic standards (27).

Case Studies of Implementation in Grading Fruits/Vegetables

Several case studies have demonstrated the effective use of computer vision in grading and sorting fruits and vegetables. For example, a deep learning-based system (28). Successfully classified apples based on surface defects with over 95% accuracy. Similarly, commercial systems using machine vision now grade tomatoes, potatoes, and mangoes by detecting variations in size, shape, and ripeness, significantly improving operational efficiency. These technologies are particularly relevant to organic producers, who must maintain high visual standards without chemical preservatives or enhancers.

AI in Digital Transformation and Sustainability

The integration of Artificial Intelligence (AI) into the organic food sector is accelerating digital transformation, fostering greater sustainability through enhanced energy use, waste reduction, and improved transparency. By embedding AI in the production and supply chain, organic producers can monitor and optimize inputs, forecast demands, and ensure compliance with environmental standards (29).

Energy Efficiency and Waste Reduction

AI-powered precision agriculture tools enable real-time monitoring of soil health, irrigation, and crop status, helping to reduce overuse of resources like water and fertilizers. By using machine learning algorithms for predictive analytics, producers can anticipate spoilage risks, optimize harvest timing, and reduce food loss post-harvest (30). AI-based inventory management systems also help streamline logistics and storage, minimizing waste due to spoilage or overproduction. These efficiencies directly support the sustainable values at the core of organic farming.

Blockchain + AI Integration for Transparency

The combination of AI with blockchain technology creates a robust framework **for traceability and transparency** across the organic food supply chain. Blockchain ensures immutable records of farm-to-fork data, while AI helps process and analyze this data for decision-making. For example, AI can verify authenticity by cross-checking satellite imagery and IoT sensor data with declared organic practices. This enhances consumer trust and simplifies organic certification and auditing processes (31).

Table 1: Comparative Overview of AI Applications in Organic Food Systems

Function	**AI Technique**	**Benefit**
Crop Monitoring	ML + Sensors	Energy/water efficiency
Food Sorting/Grading	Computer Vision (CNNs)	Accuracy, labor cost reduction
Supply Chain Transparency	AI + Blockchain	Enhanced traceability & trust

Methodology

This study utilized the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology to systematically identify, screen, and evaluate pertinent literature regarding the application of AI and computer vision in the organic food sector. It delineates the number of records obtained through database searches, screened for relevance, assessed for eligibility, and ultimately incorporated into the review, alongside documented justifications for exclusions at each phase.

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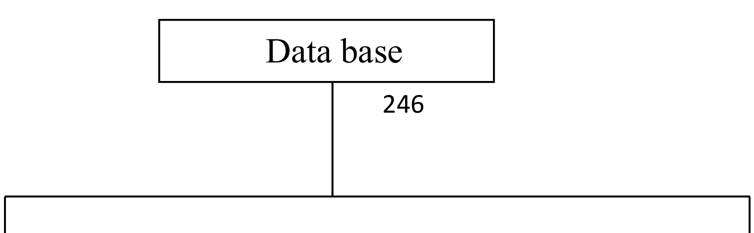
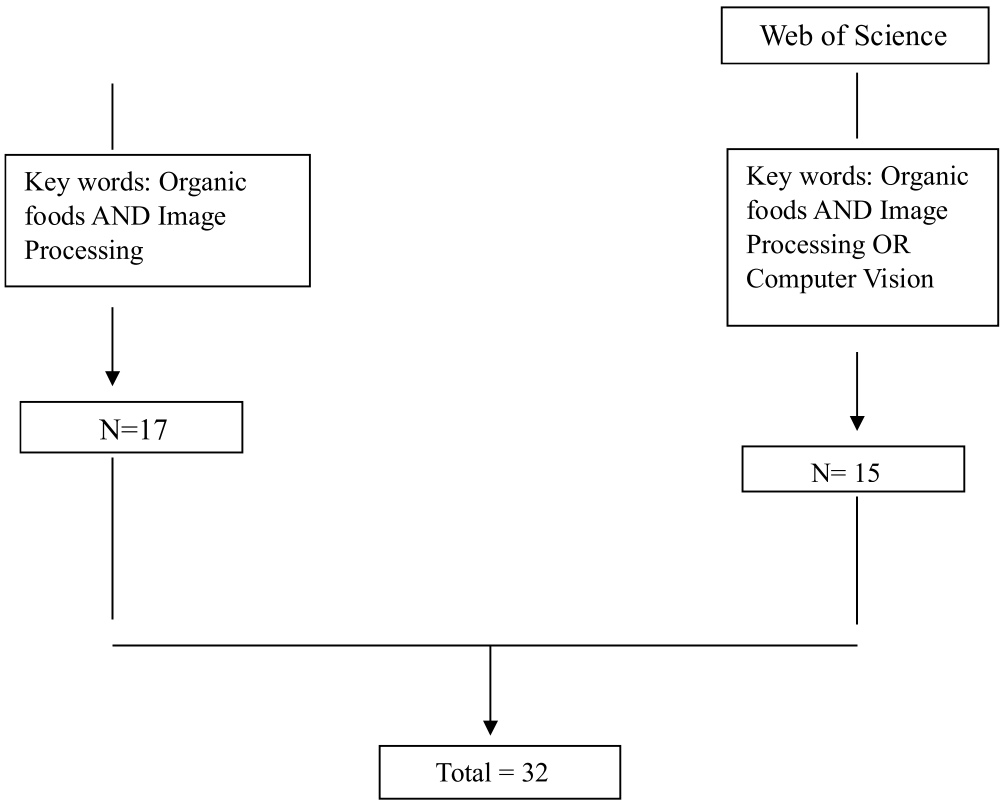
Figure 1. PRISMA diagram.





Results and Findings

The study comprehensively reviewed the role of Artificial Intelligence (AI) and computer vision in the quality assessment of organic food products and found consistent evidence that these technologies significantly improve accuracy, reliability, and speed in visual inspection tasks. Deep learning models, such as Convolutional Neural Networks (CNNs), are highly effective at classifying organic produce based on size, shape, color, and surface defects. For instance, applications in fruit grading and vegetable sorting have achieved classification accuracies above 95%, reducing human subjectivity and increasing consistency across batches (32). Object detection frameworks like YOLO (You Only Look Once) have further enhanced real-time decision-making by enabling rapid image processing on handheld or embedded systems, contributing to streamlined post-harvest workflows (33).

In terms of operational benefits, AI systems were found to contribute substantially to reducing labor dependency and long-term costs in organic farming. Automated inspection stations, powered by computer vision, can operate continuously with minimal supervision, allowing organic farms to scale operations while maintaining certification standards. These systems also support traceability and transparency, which are crucial for consumer trust in organic labels. Moreover, AI technologies are being integrated with Internet of Things (IoT) devices and smart farming platforms, enabling real-time feedback and better input management—further contributing to sustainability goals by reducing food waste, energy use, and over-application of organic treatments (34).

Despite these advancements, several critical challenges were consistently identified. High initial setup costs—including hardware for image acquisition, cloud processing infrastructure, and advanced software—pose a significant barrier to small and medium-sized organic farms. Moreover, the lack of high-quality, annotated datasets for many organic crops limits the generalizability of AI models across diverse agricultural contexts. Many AI systems are developed and tested under controlled conditions that may not reflect real-world farm environments, leading to concerns about their scalability and robustness (35). In developing regions, limited digital literacy and inadequate rural connectivity further compound these barriers.

Lastly, the findings underscore the need for tailored AI solutions that are affordable, open-access, and easy to deploy, especially in resource-constrained settings. Governments and private institutions can play a critical role by promoting AI education among farmers and incentivizing research into low-cost, mobile-based solutions. Future research should focus on co-developing AI systems with end-users to ensure usability, inclusiveness, and practical relevance. The integration of AI into organic agriculture is not just a technological shift, but also a socio-economic transformation that requires multi-stakeholder collaboration and supportive policy frameworks.

Discussion

The adoption of Artificial Intelligence (AI) and computer vision in the organic food industry is revolutionizing traditional quality assessment methods. Techniques such as Convolutional Neural Networks (CNNs) and object detection algorithms like YOLO have demonstrated exceptional accuracy in detecting defects, classifying produce quality, and automating inspection processes. These innovations significantly reduce human subjectivity, operational inefficiencies, and labor costs, making quality control more consistent and scalable. Importantly, such AI systems also enable rapid feedback and traceability, which are essential in maintaining the integrity of organic certification standards (36).

Despite these advancements, the study reveals that cost-related barriers, infrastructure limitations, and lack of technical expertise among small-scale organic farmers present serious obstacles to widespread adoption. Many of the reviewed solutions are currently applicable only to larger farms or controlled environments, limiting their practical scalability. There is an urgent need for user-friendly, low-cost AI models that can be implemented with minimal training and hardware. Future research should explore inclusive AI solutions, open-access datasets, and government-supported digital training programs that address these equity gaps (37). By addressing these challenges, AI can become a powerful enabler of sustainable and equitable organic food systems globally.

Conclusion

This study demonstrates that Artificial Intelligence (AI) and computer vision technologies have a transformative potential in enhancing the quality assessment and sustainability of organic food production. By incorporating advanced techniques such as Convolution Neural Networks (CNNs) and object detection algorithms, these technologies offer precise, efficient, and cost-effective solutions for automating the grading, sorting, and inspection processes. AI-based systems help reduce human error, improve product consistency, and support transparency in food quality, thereby contributing to enhanced consumer trust and more sustainable agricultural practices. The integration of AI in organic food systems also paves the way for smarter farming practices, allowing for more informed decision-making and better resource utilization.

However, significant barriers remain in scaling these technologies, particularly due to high implementation costs, infrastructure limitations, and the lack of technical expertise among small-scale organic producers. While the potential benefits are clear, the accessibility of these advanced solutions remains a challenge. Future research should focus on the development of low-cost, scalable AI models that are adaptable to diverse agricultural environments. Additionally, efforts to promote digital literacy and provide targeted training for farmers, especially in rural areas, will be crucial for enabling widespread adoption and achieving the full benefits of AI in the organic food sector.

Limitations

One significant limitation of this study is its reliance on secondary data from existing literature, which may not capture the full range of practical challenges and opportunities that arise when implementing AI and computer vision technologies in real-world organic farming settings. Many of the studies included in the review focus on controlled environments or large-scale farms, which may not be directly applicable to smaller or resource-constrained organic producers. Furthermore, the study primarily addresses technological aspects without fully exploring the economic, social, and logistical barriers faced by farmers in adopting these advanced systems. Additionally, while the review highlights the effectiveness of AI models like Convolutional Neural Networks (CNNs) and object detection, it does not consider the varying performance of these models across different crops or environments, nor the limitations of data availability, which could affect the generalizability of the findings.

Future Directions

Future research should focus on developing scalable, affordable AI solutions tailored to the specific needs of small and medium-sized organic farms. This includes creating cost-effective systems that require minimal infrastructure and training, which would make advanced technologies more accessible to a broader range of farmers. Additionally, more field-based studies are needed to evaluate the real-world performance of AI and computer vision systems across various agricultural environments, taking into account factors such as crop diversity, environmental conditions, and farm sizes. Longitudinal research would also be beneficial to assess the long-term impacts of AI adoption on both the quality of organic food and the sustainability of farming practices. Finally, exploring the integration of AI with other emerging technologies, such as blockchain for traceability and IoT for real-time monitoring, could provide valuable insights into building a more resilient and transparent organic food supply chain.

Managerial Implications

The findings of this study have significant managerial implications for stakeholders in the organic food industry, particularly those involved in production, quality control, and supply chain management. By adopting AI and computer vision technologies, managers can improve operational efficiency, reduce human error, and ensure consistent product quality, thereby increasing competitiveness in the market. These technologies also allow for greater transparency and traceability in the food supply chain, which can help in maintaining organic certification standards and addressing consumer concerns about food safety and authenticity. However, managers must be mindful of the high initial costs and potential technical challenges when integrating AI into their operations. To maximize the benefits, it is essential for managers to invest in employee training, collaborate with tech developers, and pursue cost-effective, scalable AI solutions that align with the size and resources of their operations.

Societal Implications

From a societal perspective, the integration of AI in organic food systems has the potential to promote more sustainable agricultural practices, reducing the environmental impact of food production by optimizing resource use and minimizing waste. AI-based solutions can also improve the accessibility of high-quality organic food, making it more affordable and available to a wider population. Furthermore, the adoption of AI technologies can create new job opportunities in the tech and agricultural sectors, enhancing economic growth and social development in rural areas. However, for these benefits to be realized equitably, it is crucial to address the digital divide by providing training and support to small-scale farmers and ensuring that AI solutions are affordable and accessible to all stakeholders, particularly in developing regions.

Abbreviations

AI: Artificial Intelligence

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Author Contributions

K. Mohammed Abrar: Literature Review , Methodology, Gathering , Writing, and preparing an initial draft;

Dr. Anil Verma: Composing, Assessing, Revising, And Supervising.

Ethics Approval

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Conflict of Interest

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