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Multimodal Deep Learning – IoT Systems for Tomato Crops: A Systematic Review

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ABSTRACT

The paper aims to provide a systematic synthesis of recent literature on multimodal deep learning–IoT systems applied to tomato crops, placing them in the broader context of precision agriculture and rural development. The digital transformation of agriculture, marked by the intensive use of sensors, IoT platforms and deep learning models, creates important premises for improving productivity, risk management and economic sustainability of farms, but, at the same time, generates a fragmented and heterogeneous solution landscape. Against this background, the study pursues three main objectives: (O1) identifying and classifying the main multimodal deep learning–IoT systems for tomato crops, based on the types of data used (images, environmental sensors, agronomic data), the proposed architectures and the implementation contexts; (O2) to critically review the technical approaches and reported performances, by comparing deep learning solutions and multimodal fusion strategies from the perspective of robustness, scalability and feasibility in real farm conditions; (O3) to identify research gaps and formulate future directions, with a focus on the potential of these systems to support technical and economic decisions in agriculture and to contribute to rural development. Methodologically, the paper follows a systematic review approach, based on the query of the main international scientific databases and the application of explicit study inclusion criteria. The results show the existence of significant progress in the detection of foliar diseases and microclimate monitoring, but also important limitations related to the size and quality of the datasets, the lack of economic evaluations and long-term studies in commercial farms. The main conclusion is that multimodal deep learning–IoT systems for tomatoes represent a promising but insufficiently integrated field, and this paper provides a useful reference framework for both researchers and decision-makers interested in the digitalization of agriculture and strengthening the resilience of rural farms.

1. Introduction

According to specialized studies, tomatoes are one of the most important horticultural crops globally, playing a major role both in terms of food security and in terms of rural household income. However, tomato production is strongly affected by diseases, especially fungal diseases, as well as by the variability of environmental conditions and the inefficient use of resources. Thus, the digitalization of agriculture, using advanced monitoring and analysis technologies, becomes essentially both for increasing yields, reducing losses, and supporting sustainable rural development.

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In recent years, deep learning applications in plant disease detection have experienced accelerated development. A recent review of deep learning techniques for plant disease detection shows significant progress in the accuracy of early identification of symptoms on leaves, including in tomatoes (Pacal et al., 2024). Moreover, there is already an analysis dedicated exclusively to tomato crops, which synthesizes deep learning models applied for disease and pest detection in real field and greenhouse scenarios (Jelali, 2024). Applied studies propose robust architectures for the classification and segmentation of tomato leaf diseases, demonstrating high accuracy and laying the foundations for automated diagnostic systems (Nawaz et al., 2022; Sun et al., 2025).

In parallel, the Internet of Things (IoT) field has generated increasingly advanced solutions for monitoring environmental parameters in greenhouses and fields. Integrated IoT systems for tomato cultivation and pest management demonstrate that real-time monitoring of temperature, humidity, soil moisture and other factors allows for the optimization of irrigation and phytosanitary interventions, with a direct impact on productivity (Ariss et al., 2024; Hasan et al., 2024; Thillai Rani et al., 2024). Other works propose hybrid IoT–machine learning platforms for soil monitoring and supporting decisions regarding fertilization and irrigation in tomato crops (Babu et al., 2024).

An emerging trend, particularly relevant to this article, is multimodal systems, which combine data from different sources: images, environmental sensors, spectroscopic or tactile sensors. An example of this is deep learning-assisted data fusion techniques, which have been used to simultaneously assess the ripeness of tomatoes by integrating information from colour images, near-infrared spectra, and haptic sensors (Liu et al., 2024). In parallel to this example, a series of recent reviews on sensor technologies for greenhouse tomato production highlight the potential of multimodal fusion to improve monitoring and management decisions (Yu et al., 2025). However, approaches that explicitly integrate multimodal deep learning with IoT infrastructures in a unified framework for intelligent monitoring for tomatoes, are still fragmented, and a systematic synthesis is lacking. In this context, the present systematic review study aims to provide a solid scientific reference on recent developments in the field of multimodal systems based on deep learning and IoT applied to tomato crops, with a focus on their relevance for agriculture and rural development.

Such a synthesis is of direct interest for research in agriculture and rural development, at national and international levels. By centralizing and critically evaluating recent literature, the study provides not only a technical analysis of the current state of knowledge, but also a conceptual framework for identifying future research directions, with significant implications for both technological innovation and for substantiating policies and improving practices in rural areas. In this context, the study proposes the following analysis objectives:

(O1) identify and classify the main multimodal deep learning–IoT systems applied to tomato crops, based on the types of data used, the proposed architectures and the implementation contexts relevant to commercial farms and rural farms;

(O2) carry out a critical analysis of the technical approaches and reported performances, by comparing different deep learning solutions and multimodal fusion strategies from the perspective of robustness, scalability and feasibility of their implementation in real farm conditions;

(O3) identify research gaps and formulate future development directions, with a focus on the potential of these systems to support technical and economic decisions in agriculture, to contribute to increasing the resilience of rural farms and to underpin public policies oriented towards innovation and sustainability.

2. Literature review

The digital transformation of agriculture, often referred to as Agriculture 4.0, but also as precision agriculture, has led in recent years to a growing interest in integrating artificial intelligence (AI) and Internet of Things (IoT) technologies into all agricultural production systems. A series of recent studies highlight the fact that machine learning and deep learning techniques have become key tools for monitoring crops in general, for detecting crop diseases, but also for optimizing resource use, thus contributing to increasing productivity and reducing environmental impact (Islam, 2025; Waqas et al., 2025). Another series of review articles highlights the fact that the integration of AI with sensor technologies and robotics represents one of the central directions of smart agriculture, with major potential for small and medium-sized farms, including those in rural areas of developing countries (Micle et al., 2024; Miller et al., 2025).

2.1. Deep learning and multimodal fusion in agriculture

At the methodological level, recent literature highlights the shift from classical computer vision models to deep learning architectures for object detection, disease classification and agronomic parameter estimation. A systematic review dedicated to object detection in agriculture, based on PRISMA, highlights the rapid evolution of CNN architectures and their modern variants (YOLO, RetinaNet, Faster R-CNN), as well as the trend of integration with real-time data streams for field applications (Dalal & Mittal, 2025). Another review focuses on deep learning-based multimodal fusion for plant monitoring and resource conservation, showing that combining images with sensor data (climatic, soil, spectroscopic, etc.) allows for a more complete characterization of crop health and better support for management decisions (Yang et al., 2025). The integration of AI with smart sensor technologies in arable and pasture agriculture is also analysed in a recent systematic review, which shows that the use of deep neural networks, combined with IoT infrastructures, allows for both early detection of biotic and abiotic stress and input optimization, with direct implications for economic and environmental sustainability (Miller et al., 2025; Waqas et al., 2025). These works clearly position deep learning-based multimodal fusion as a central pillar of digital agriculture.

These contributions show that multimodal fusion based on deep learning is no longer just an isolated experiment, but tends to become a dominant methodological framework in digital agriculture: models no longer operate only on images or only on time series, but on combinations of visual, sensory and agronomic data, with the potential to transform the way crops are monitored and decisions are made at the farm level. However, most of these studies maintain a general character, focused on diverse crops or demonstration systems, and pay limited attention to the particularities of crops with high economic importance, such as tomatoes, respectively the specific context of small and medium-sized farms in rural areas.

Furthermore, the existing synthesis literature focuses almost exclusively on the technical performance of the models (accuracy, precision, inference time), dealing less with aspects related to integration into real IoT infrastructures, implementation costs or the impact on risk management and economic sustainability of farms. From this perspective, the need for focused analyses that address multimodal deep learning–IoT systems in a well-defined, applied framework and explicitly link them to precision agriculture and rural development objectives becomes evident. The present paper responds to this need through a systematic review dedicated to tomato crops, placing the discussion at the intersection of technological innovation, agricultural productivity and rural farm resilience.

2.2. Deep learning approaches for tomato disease detection

In the case of tomato crops, the recent literature shows an explosion of deep learning applications for foliar disease and pest detection. A series of recent comprehensive reviews synthesize the main deep learning approaches for tomato disease and pest detection, using both laboratory and field datasets, and highlight high classification accuracies, often above 95%, under controlled conditions (Jelali, 2024). A more recent analysis, focused on the classification, detection and segmentation of tomato leaf diseases, emphasizes the transition to more advanced architectures (ResNet, EfficientNet, transformer models) and the use of data augmentation techniques to increase the robustness of models under real conditions (Das et al., 2025; Sun et al., 2025).

Numerous applied studies propose specialized models for tomatoes. For example, efficient disease detection networks (E-TomatoDet) are being developed, which explicitly target challenges such as small disease areas and leaf occlusion in complex environments, achieving superior performance to baseline models (Sun et al., 2025). Other works propose ensemble models (e.g. combining MobileNetV2 and ResNet50) or lightweight architectures for disease classification, designed to be implemented on resource-limited devices while maintaining high accuracy (Batool et al., 2024; Jelali, 2024; Sharma et al., 2025). A transition towards models based on Vision Transformers (ViT) and attention mechanisms is also observed, which allow for better spatial context capture and reduce sensitivity to variations in illumination and leaf positioning (Ananthi et al., 2024; Karimanzira, 2025). Overall, these contributions confirm the rapid maturation of the field, but also the fact that most experiments are performed on isolated images, often without the integration of environmental data or operational constraints from real farms. To better understand how these works fit into the broader landscape of precision agriculture and digital agriculture, a bibliometric analysis was conducted based on articles indexed on the Web of Science Core Collection, using VOSviewer (Figures 1–3) (Clarivate, 2025).

Figure 1 illustrates the keyword co-occurrence network and highlights four major thematic clusters: “tomato”, “growth/yield”, “precision agriculture” and “deep learning/computer vision”. This structure shows that tomato crop research is at the intersection of classical agronomic studies (physiology, diseases, productivity) and new approaches to precision agriculture and automated image analysis. Nodes associated with sensors, internet of things and smart agriculture appear in the proximity of the “precision agriculture” cluster but are still weakly connected simultaneously with “tomato” and “deep learning”, suggesting the existence of partially integrated initiatives rather than consolidated multimodal systems.

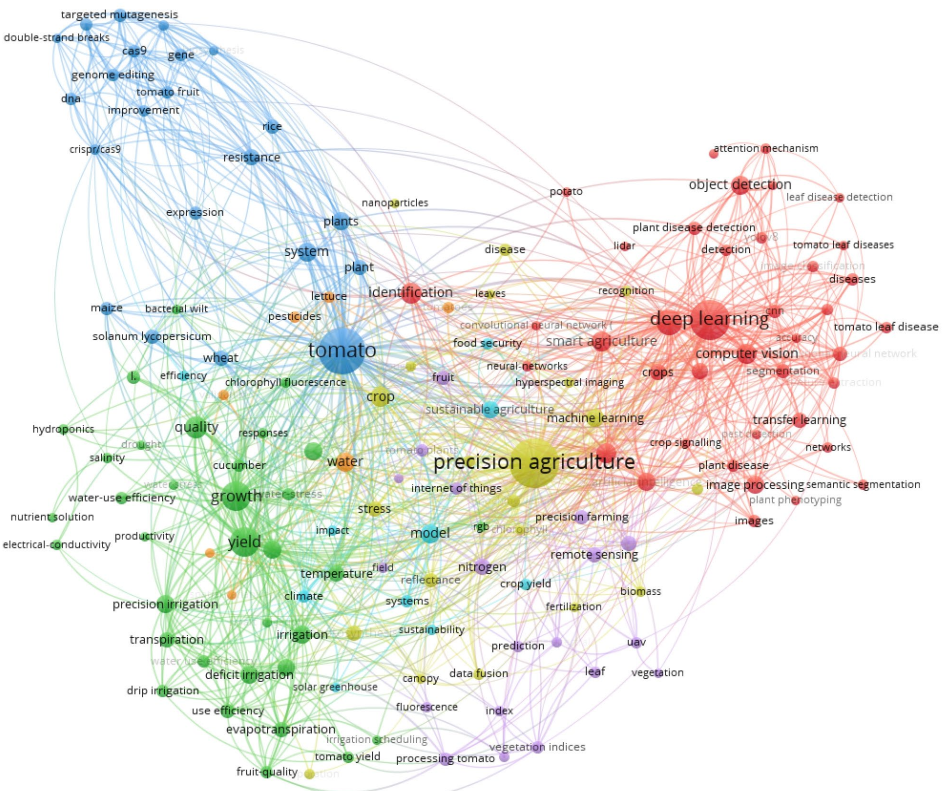

Figure 1. Tomato–precision agriculture–deep learning thematic network

Source: created by the authors with VOSviewer, based on Web of Science Core Collection data (2025)

This image supports, from a bibliometric perspective, the need to achieve objective O1, through rigorous identification and classification of deep learning–IoT systems reported in the literature.

Figure 2 adds a dense perspective on the same relationships, highlighting the thematic “hotspots” around the term’s “tomato”, “precision agriculture”, “yield/growth” and “deep learning.” The high intensity of the yellow areas confirms that these topics have generated a considerable volume of publications in recent years, while the low-density areas between the clusters indicate that the full fusion of deep learning-based analytics, IoT infrastructures and tomato cultivation is still incomplete. From the perspective of the O2 objective, this distribution suggests that while there are numerous cutting-edge technical approaches in each cluster (e.g. disease detection, irrigation optimization, microclimate monitoring), comparative assessments and unified frameworks that analyse the performance of integrated systems and their feasibility in real farm conditions are lacking.

Figure 3 details the thematic clustering structure, clearly showing the links between “tomato”, “precision agriculture” and “deep learning”. The agronomic cluster (“tomato”) contains terms such as plants, resistance, diseases, pesticides; the production cluster (“growth/yield”) is related to water use efficiency and input management; and the technological cluster (“deep learning/computer vision”) brings together concepts such as plant disease detection, object detection, image segmentation, transfer learning.

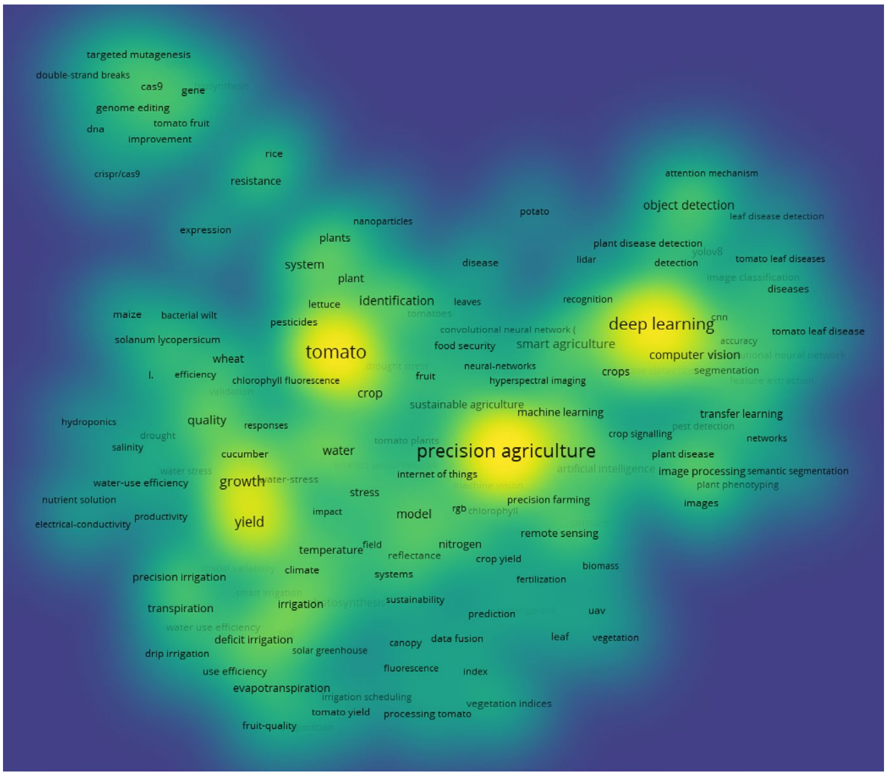

Figure 2. Thematic hotspots in tomato crop research

Source: created by the authors with VOSviewer, based on Web of Science Core Collection data (2025)

The positioning of the terms "internet of things", "smart agriculture" and "sensors" at the interface between agronomy and technology confirms the direction of convergence, but also the fact that multimodal deep learning–IoT systems for tomatoes are still dispersed and insufficiently mapped. This finding is directly relevant to objective O3, indicating a conceptual and methodological gap in the current literature and justifying the approach to formulating future research directions, with a focus on relevance for rural farms and rural development.

The specialized literature analysed in this study constituted the foundation both for the construction of the theoretical framework and for the creation of the three bibliometric figures, which visually synthesize the evolution and structure of the field. By querying and selecting articles indexed on the Web of Science and mapping them with the help of VOSviewer, the main thematic cores were identified: tomatoes, precision agriculture, deep learning, IoT, but also the links between them. The co-occurrence network, density maps and thematic clusters captured in Figures 1–3 clearly show that the international literature has developed, in parallel, consistent lines of research on tomato disease detection, microclimate monitoring and the digitalization of agricultural processes, but that multimodal deep learning–IoT approaches still appear fragmented and dispersed. This bibliometric evidence explicitly supports the need and relevance of a dedicated systematic review, capable of integrating existing contributions into a unitary perspective.

In this context, this article positions itself as a natural continuation of the specialized literature, providing a coherent framework for understanding, classifying and critically evaluating these systems, with direct implications for technological innovation, agricultural productivity and rural development.

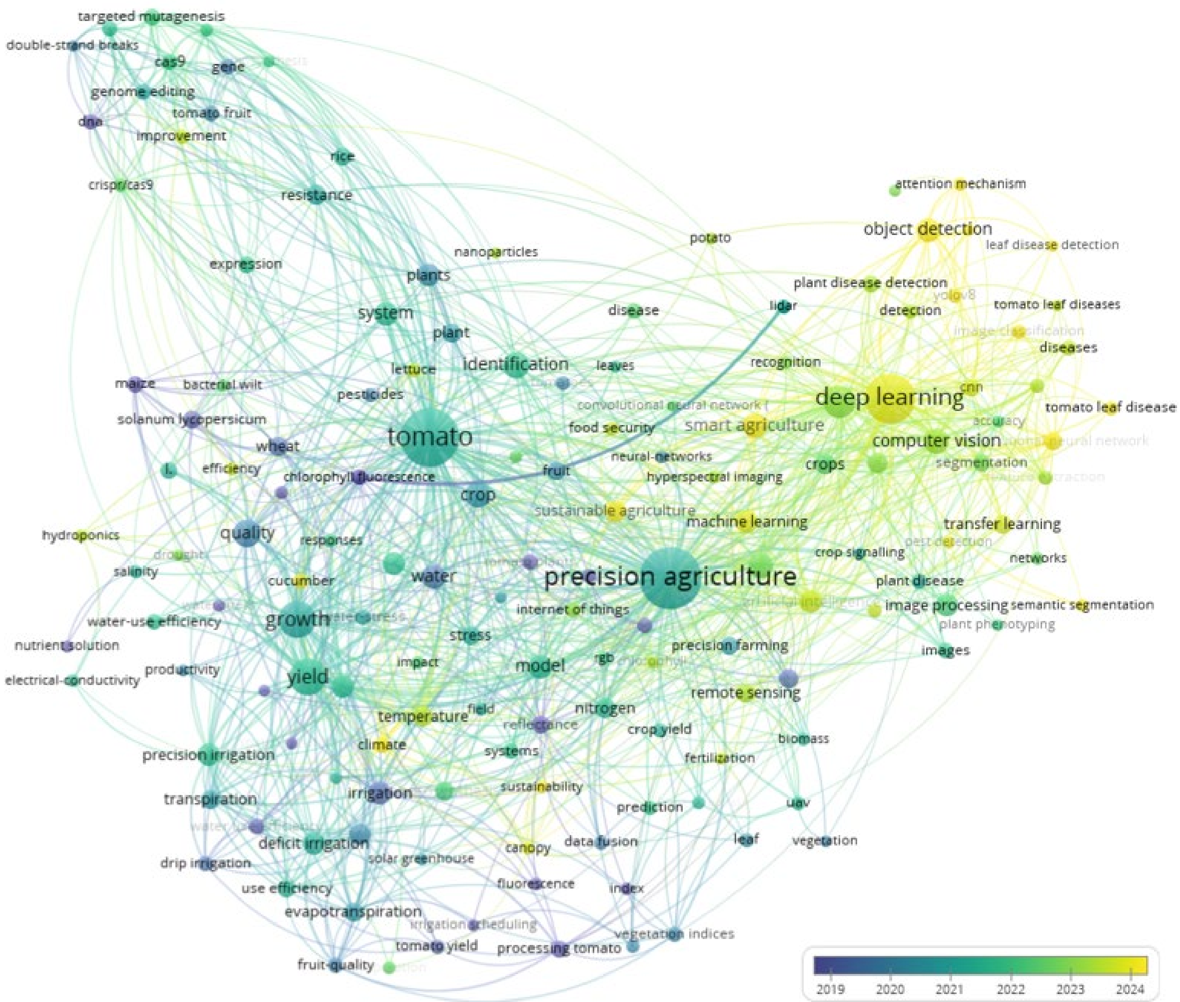

Figure 3. Thematic clusters in tomato research related to precision agriculture and deep learning

Source: created by the authors with VOSviewer, based on Web of Science Core Collection data (2025)

By combining content analysis (models, architectures, results) with bibliometric analysis (keyword networks, density and thematic clusters), this chapter clearly positions the topic of multimodal deep learning–IoT systems for tomato crops within the broader framework of international research and substantiates, in a coherent way, the need to achieve objectives O1–O3.

2.3. IoT systems for monitoring and managing tomato crops

On the IoT side, the literature of recent years highlights the accelerated development of monitoring systems for greenhouses and tomato crops in both commercial and experimental contexts. IoT platforms for monitoring microclimate in commercial tomato greenhouses have demonstrated, for example, the existence of significant spatial gradients of temperature and vapor pressure deficit, which justifies the use of distributed sensor networks and sophisticated control algorithms for uniform growing conditions. However, a significant part of these new solutions remains at the prototype or case study level under controlled conditions. This is because long-term evaluations of commercial farms and small rural holdings are still limited, and this aspect is emphasized by several authors in the recent literature (Šalagovič et al., 2024).

The proposal of cloud-enabled IoT systems for the management of indoor tomato crops as low-cost solutions has proven to offer advantages in real-time monitoring of parameters, but also of soil moisture, temperature and light, to automate operations such as irrigation, thus demonstrating both technical reliability and the potential to increase productivity in the field. Other works have highlighted the combination of IoT and wireless sensor networks (WSN) for greenhouse tomato cultivation. These studies have highlighted the importance of scalable and energy-efficient infrastructures in spatial monitoring of the growing environment. In terms of social and technological adoption, there are also studies that analyse urban tomato gardening experiences supported by IoT systems and mobile applications, highlighting how such technologies can facilitate the adoption of digitally assisted agricultural practices even in family households and contribute to digital literacy in vulnerable environments. In recent years, research in the field is very much oriented towards the use of IoT in combination with explainable AI methods. This aspect highlights the interpretation of the relationship between microclimate and key physiological processes, such as fruit expansion in tomatoes, and this provides a promising framework for fine-tuning the cultivation conditions in smart greenhouses (Ibarra-Cabrera et al., 2024; Juneidi, 2022).

However, despite all these advances, the existing literature often treats separately the IoT components for environmental monitoring and the artificial intelligence modules for analysis and detection. Moreover, the assessments regarding the economic impact and relevance for small and medium-sized farms in rural areas are fragmented. This context justifies the need for a systematic, long-term analysis that would critically classify and compare multimodal deep learning–IoT systems for tomato crops (O1, O2), but also highlight research gaps and development directions with potential for agriculture and rural development (O3).

2.4. Deep learning–IoT integration in multimodal tomato systems

A growing number of papers aim to explicitly integrate deep learning and IoT into complete “smart farming” systems for tomatoes. For example, IoT platforms dedicated to tomato greenhouses are proposed, which collect data from sensors (temperature, humidity, soil moisture) and images from cameras, using deep learning models to detect the ripening stage or to identify diseases, and then provide farmers with management recommendations through cloud dashboards or mobile applications (Mac et al., 2024). Integration on edge devices (e.g. Raspberry Pi + camera) is also found in the specialized literature, with an emphasis on the feasibility of implementation in farms with limited resources.

Also, a series of more advanced systems highlight the use of IoT networks together with robotic elements (e.g. soil robots or drones) that aim at real-time detection of tomato diseases and targeted interventions. All these analyses come and highlight, on the one hand, the opportunity to reduce pesticide consumption in the case of tomatoes, but also to increase operational efficiency, on the other hand (Abhinaya, 2025; Saxena et al., 2025). However, articles in the specialized literature in recent years highlight the fact that many of these implementations are still at the prototype or case study level. Moreover, evaluations, especially long-term ones in commercial farms, remain largely limited. In most of the researched works, deep learning–IoT integration is achieved through multimodal data fusion, either at the input level, i.e. the direct combination of images with time series from sensors, or at the decision level, meaning the aggregation of results obtained separately from computer vision models and environmental data analysis models. The approaches typically propose CNN-type architectures or attention-based models for image analysis, combined with dense neural networks or sequential models (LSTM, GRU) for sensor data, which allows for a more complete characterization of crop condition and disease risk.

However, we note that the literature indicates several common limitations, namely the use of small and inhomogeneous data sets, the lack of standardized testing procedures under variable field conditions, as well as the absence of rigorous assessments of the economic impact and benefits for small and medium-sized farms. Also, the user interaction component is often treated superficially, with systems being designed from a technical perspective rather than from the real needs of farmers and the specific context of rural farms.

This context highlights the need for a systematic synthesis that would inventory and classify the types of multimodal systems proposed to date (O1), critically compare the multimodal fusion architectures and strategies reported in the literature (O2), and identify both methodological gaps and research and implementation opportunities with direct relevance for agriculture and rural development (O3).

3. The economic and rural development dimension of digital agriculture

From an economic perspective, recent research on precision agriculture technologies shows that the use of sensors, GPS guidance systems, satellite imagery and data-driven methodologies contributes to increasing yields, reducing costs and improving the financial sustainability of farms, including small ones (Sanyaolu & Sadowski, 2024). A series of studies, carried out at European level, underline the fact that these technologies can increase the profitability and efficiency of investments, but at the same time highlight a series of important barriers, such as high initial costs, small farm sizes and limited access to finance. All of this makes it necessary to have public policies and support models adapted to the context of family farms (Geng et al., 2024; Sanyaolu & Sadowski, 2024).

Other recent analyses, on the impact of digital technologies in agriculture, show that they can generate considerable economic benefits at a global level. However, their adoption is uneven, especially among smallholder farmers, as digital skills, communication infrastructure and financial accessibility remain major challenges for them (Mgendi, 2024). In the case of tomato crops, case studies on commercial greenhouses and demonstration projects suggest that the use of IoT systems and artificial intelligence techniques can simultaneously improve the quality and quantity of production, while reducing water and chemical input consumption, with direct implications for farmers' incomes and the economic resilience of rural farms (Kramarz & Runowski, 2025).

In this context, a knowledge gap is emerging: although there are numerous works that separately treat deep learning for tomato disease detection and IoT systems for monitoring the growing environment, systematic syntheses that analyse multimodal deep learning–IoT systems in an integrated manner, both from a technical perspective and from the perspective of their potential to support rural development and farmers' economic decisions, are still limited (Choruma et al., 2024; Saxena et al., 2025; Smidt & Jokonya, 2022). It is precisely this gap that justifies the need for a systematic review dedicated to this topic, capable of providing a reference framework for research, public policy and agricultural practice in rural areas.

4. Conclusions

The systematic analysis carried out in this paper has highlighted that the topic of multimodal deep learning–IoT systems for tomato crops is at the intersection of major development directions in the specialized literature: the digitalization of agriculture, intelligent detection of plant diseases, precision agriculture and, increasingly, the concern for economic sustainability and rural development. The results obtained confirm, on the one hand, the rapid maturation of the technological components (deep learning models, IoT platforms, sensor infrastructures), and on the other hand, the still fragmentary nature of their integration into a unitary, scalable and relevant framework for real farms.

In relation to O1, the identification and classification of the main multimodal deep learning–IoT systems, the study showed that the literature includes a variety of approaches, which can be organized into several major categories: systems oriented towards the detection of foliar diseases (based predominantly on images), systems for monitoring and controlling microclimate in greenhouses (focused on sensor data), and hybrid solutions, in which images, environmental data and agronomic information are combined in multimodal architectures. The proposed typology contributes to the ordering of a dispersed field and provides a clear benchmark for future comparisons between solutions, facilitating both the understanding of the current landscape and the identification of insufficiently covered niches (e.g., the systematic integration of economic or farm management data).

Regarding O2, the critical analysis of technical approaches and performances, the review highlighted that although the deep learning models used (CNN, advanced architectures, attention-based models) frequently achieve very high performances on controlled datasets, their robustness under real farm conditions is less documented. Similarly, the proposed IoT infrastructures demonstrate technical feasibility and significant potential for optimizing irrigation, microclimate and inputs, but their long-term evaluations, on commercial farms or in small and medium-sized farms, remain limited. The analysis in this article highlighted the lack of standardized testing protocols, the reliance on small and often heterogeneous data sets, and the insufficient attention paid to rural constraints (connectivity, costs, digital skills). These findings highlight the need for somewhat more rigorous comparative studies and pilot projects carried out in real production contexts.

Regarding O3, identifying research gaps and formulating future directions, the results clearly show that the current literature only sporadically addresses the economic and rural development dimension of these technologies. Few papers analyse the impact on farmer incomes, economic risk or farm resilience, and discussions on public policies, financing models and support mechanisms for adoption are rare. In this context, this paper proposes several major directions for future research: the development of larger and more diverse multimodal datasets, including economic variables; the design of robust edge–cloud systems adapted to small farms; cost–benefit assessments and impact studies in rural areas; and the exploration of the policy framework that can facilitate the adoption of these technologies in an equitable and sustainable manner.

From the perspective of its place in the specialized literature, the study positions itself as a reference work for the field of multimodal deep learning–IoT systems applied to tomato crops, by bringing together, in a unified framework, the technical, agronomic and economic dimensions. While a significant part of the literature focuses on improving the performance of algorithms or on the description of IoT prototypes, this review shifts the emphasis towards an integrated understanding, oriented towards practical relevance and contribution to rural development. Thus, the paper not only synthesizes the current state of knowledge but also provides a clear research agenda for the scientific community interested in the digital transformation of agriculture and its role in strengthening the sustainability of farms and rural communities.

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