White paper N1 -2024-2025

Acknowledgements

This white paper, as well as the associated research work, was carried out with the financial support of the European PRIMA Med programme (Partnership for Research and Innovation in the Mediterranean Area).

This document is published as open access. It may be used as a teaching resource in university education, as training material for professionals, as well as a reference document and state-of-the-art overview for Master's and PhD students.

The authors acknowledge and thank the PRIMA Med programme for its support, which enabled the conduct of this research and the open dissemination of its results for the benefit of the scientific, academic, and professional communities

----

Whitepaper article

Digital Twin-Enabled Precision Management for Mediterranean Cereal Crops: *

CERERE Project — PRIMA Med Partnership

HIGHLIGHTS

- Agricultural digital twins replicate real farms to enhance decision-making.
- Digital twin advance farm automation using IoT, AI, AR/XR and related technologies.
- Multiple application areas of digital twin in agriculture is explored.
- Multiple application areas of digital twin in Mediterranean cereal agriculture are explored, from soil-irrigation management to post-harvest quality preservation.
- Potential applications and challenges specific to rain-fed and supplementary-irrigated cereal systems are discussed.

ARTICLE INFO

Keywords:
Agriculture
Cyber physical systems
Federated learning
Digital twin
Smart agriculture

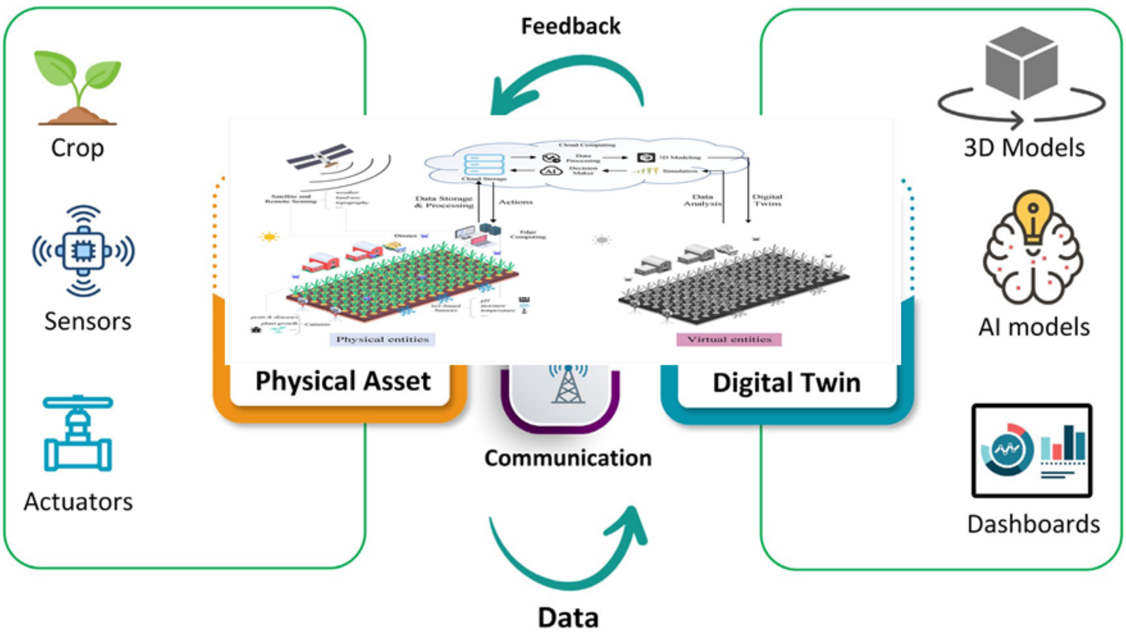
ABSTRACT

Smart farming has introduced agricultural systems that are increasingly autonomous and highly interconnected, yet their application to Mediterranean cereal production remains underdeveloped. The Agricultural Digital Twin (ADT) represents an innovative breakthrough for smart farming in the Mediterranean basin, with the potential to greatly improve productivity and sustainability in cereal systems exposed to terminal drought, high inter-annual rainfall variability, and soil spatial heterogeneity. Simulation using theoretical and static models has long been a conventional tool for verifying, validating, and optimizing agricultural tasks. With the emergence of next-generation information technologies, data availability has increased manifold. Digital twin (DT) modeling is essential for accurately representing the physical entity, providing functional services and meeting the requirements of modern Mediterranean cereal farms. This study provides a detailed analysis of the key aspects of ADTs in Mediterranean cereal contexts, offering deeper insights into potential application areas and discussing major implementation challenges. The CERERE project, funded under the PRIMA Mediterranean Partnership for Research and Innovation, specifically addresses the crop-modeling and socio-technical challenges of deploying DT technology in Mediterranean cereal systems. This study explores applications of ADT in controlled environment pre-breeding, soil and irrigation management under water scarcity, crop monitoring and cultivation support for durum wheat and barley, post-harvest activities, and agricultural machinery optimization. Given that DT technology is relatively nascent in Mediterranean cereal agriculture, this study provides valuable research direction to stakeholders involved in integrating digital twins into cereal production processes through research and development.

1. Introduction

By 2050, the global population is projected to exceed 9.7 billion, demanding a 60% increase in cereal production compared to 2005–2007 baselines [1,2], it is essential that we accelerate food production. This is particularly crucial given the increasing scarcity of resources on our planet [3]. From the early days of mechanization, where tractors and simple machinery began to replace manual labor, to the current era of data- driven technologies, agriculture has constantly adjusted to support the growing demands of the global population [4]. Digital agriculture refers to the utilization of communication, information, and spatial analytics technology by end users to effectively plan, track, and control the operational and strategic decisions of their agricultural system [5].

Smart farming, a subset of digital agriculture involves monitoring multiple parameters to enhance crop productivity and optimize variables such as the prevailing environmental conditions, irrigation methods, pest and fertilizer management, weed control, soil quality, greenhouse conditions, and cost reduction of process inputs [6–9]. Data-driven decision-making has become more feasible as computers are now capable of performing tasks that were once exclusive to humans, such as complex communication and advanced pattern recognition [10,11]. Modern smart farms utilize the cutting edge technologies such as Internet of Things (IoT), big data, artificial intelligence (AI), and automation throughout every stage of producing, harvesting, packing, transporting, and consuming agricultural commodities [12–14]. The combination



/ig. 1. Overview of digital twin technology.

of above-mentioned technologies improves the effectiveness of agricultural management by offering a plethora of benefits [15,16]. IoT devices including sensors, gather massive amounts of data related to soil properties, crop parameters, weather conditions, and different equipment performance for efficient farm management [17,18].

The above-mentioned cutting edge technologies extend capabilities beyond the physical system, offering enriched information and deeper insights into physical structures. Digital Twins (DTs) are central to this advancement, delivering detailed and accurate information on physical systems, far exceeding the capabilities of conventional modeling and simulation approaches [19–21]. By utilizing real-time data acquisition, organization, processing, and analysis, DTs provide a digital representation of physical systems, enabling accurate monitoring and forecasting of both present and future states, as well as the reconstruction and redesign of existing models, systems, and procedures [22]. Both the IoT and DT revolve around the utilization of resources. In the field of IoT, resources refer to devices that are linked to the internet, enabling interaction between individuals and their devices either directly or through a software system [23,24]. Within the framework of DT, resources are described in a more flexible manner, encompassing assets, devices, and both physical and virtual entities. Both notions adhere to the belief that communication between resources should primarily occur through machine-to-machine (M2M) contact, minimizing human involvement [25,26]. Furthermore, the creation of an intelligent DT system necessitates the use of sophisticated AI algorithms on the gathered data [27]. In order to achieve this goal, intelligence is attained by enabling the DT to identify, optimize, and make dynamic decisions based on data from physical sensors and/or virtual twin models [28].

The utilization of DTs in agriculture has the potential to revolutionize agricultural methods by generating a virtual model of actual objects and operations [29–31]. This allows for continuous monitoring, simulation, and optimization in real-time. These systems have the capability to simulate whole farms, including crops and livestock, accurately predict outcomes, and simulate different scenarios using real-time data [32,33]. When applied to agriculture, DTs enable a seamless flow of information between farm assets, biological processes, and computational models, thereby empowering stakeholders with data-driven insights, predictive intelligence, and real-time control. This capability marks a shift from traditional, reactive farming practices to proactive, adaptive, and optimized decision-making [34,35]. Unlike static digital models, DTs enable continuous monitoring, feedback-driven learning, and simulation of future scenarios [36,37]. This makes them especially valuable in applications in smart agriculture. Furthermore, as agriculture increasingly incorporates IoT sensors [38], drones [39], edge computing [40], and AI algorithms [41], the digital infrastructure necessary for implementing DTs is rapidly taking shape. From the standpoint of research and development, understanding why DT integration is vital in agriculture means recognizing its unique potential to optimize input use, enhance system robustness, ensure traceability, and reduce environmental impact. DTs offer a solution to the long-standing limitations in agricultural monitoring and forecasting by creating virtual testbeds where management strategies can be safely evaluated before real-world deployment [42–44]. Fig. 1 shows the overview of DT technology. Although DTs in agriculture provide significant perks, their adoption is currently at an infancy stage [45,46]. The gradual adoption of these practices may be attributed mostly to the sophisticated nature of agricultural operations, which are subject to a multitude of random variables like weather, soil conditions, and crop growth patterns. These factors are frequently stochastic and beyond human control, introducing additional levels of complexity that are not commonly seen in industrial operations [47]. Moreover, the extensive and varied characteristics of agricultural fields require detailed and accurate spatial and temporal data, which makes the process of collecting data technically expensive and challenging. However, continuous progress in data analytics, IoT, and AI is slowly resolving these difficulties, opening up opportunities for the wider use of digital twins in precision agriculture [48,49].

2. Related works and contributions

The concept of DT has gained significant attention in agriculture, with numerous studies reviewing its potential to enhance decision-making, resource optimization, and system monitoring (Table 2). Nasirahmadi and Hensel [45] provided an overview of the role of DTs in advancing digitalization within the agricultural sector, focusing on application areas such as soil and irrigation management, crop production, and post-harvest processing. While the study outlined key challenges and highlighted future research needs within these domains, it did not offer a comprehensive exploration of the broader technological landscape supporting DT development. Similarly, Purcell and Neubauer [50] conducted a comprehensive Systematic Literature Review (SLR) to identify state-of-the-art research on the application of DT technologies in agriculture. Their review curated 31 papers, thematically clustered into six key application domains: urban and controlled environment farming, livestock farming, product design, supply and value chains, and policy, environment, and infrastructure. The studies were further categorized by the level of DT integration including model-level, partially integrated, and fully integrated, where partially integrated DTs formed the largest group. These intermediate-stage implementations, however, provide valuable insights into the design and deployment processes of DTs across novel applications. The review also documented 10 studies featuring fully integrated DTs meeting essential criteria such as real-time data acquisition, dynamic modeling of entity behavior, and feedback mechanisms. Pylianidis et al. [51] also conducted a literature review on DTs in agriculture, identifying 28 use cases between 2017 and 2020 and comparing these with DT applications in other domains. Purcell et al. [52] presented an exploratory review emphasizing the alignment of DT technology with sustainable agriculture. They proposed a high-level roadmap outlining milestones for enabling open, scalable, and sustainable DT development in agriculture, noting the potential of DTs to support greenhouse gas reduction, efficient resource use, and optimized production, while mentioning the need to consider potential negative impacts early in the design process. Additionally, based on this emphasis on sustainability, Cesco et al. [53] proposed a conceptual framework for integrating DT technology into smart agriculture. Their study demonstrated its application through a case study on nitrogen fertilization management. While many studies have examined DT applications from a general agricultural perspective, some have focused on specific domains within agriculture, such as greenhouse horticulture, hydroponics, and livestock systems, to explore the unique opportunities and challenges of DT implementation in these contexts. Ariesen-Verschuur et al. [54] conducted a systematic review of DT technology in greenhouse horticulture, positioning it as an emerging advancement for smart, data-driven cultivation. They identified eight articles explicitly addressing DTs, alongside 115 studies indirectly related through IoT-based systems. Their review highlighted that while DTs in greenhouse horticulture are in their early stages, they hold potential for enhancing productivity and sustainability. Most existing applications focus on monitoring and controlling processes like climate regulation, energy use, and lighting, while more advanced uses such as predictive and prescriptive DTs remain limited. Sridevi and Kumar [55] explored the role of Digital Twin technology in hydroponics, a widely used soil-less cultivation method. Their study discusses how DTs can support the design, operation, monitoring, optimization, and maintenance phases in hydroponic systems. Eleni Symeonaki et al. [56] examined the application of DT technology in livestock systems within the framework of Agriculture 5.0, synthesizing recent research to identify opportunities and challenges in DT adoption for livestock production. The review revealed that DT adoption is in its early stages but holds promise for improving animal welfare, management, and productivity. Most of the 11 reviewed studies focused on dairy cattle and swine, with emphasis on precision livestock farming, real-time monitoring, and environmental control. The study emphasizes that although DTs can provide valuable insights into feeding behavior, stress management, and breeding strategies, challenges such as high initial implementation costs, data security concerns, lack of interoperability, and the need for farmer education remain key barriers to broader adoption.

In another study, Wang [46] reviewed recent progress and open issues of DT technology in agriculture by analyzing 70 peer-reviewed documents to map trends, focused domains, processes, reference architectures, and challenges. The review highlights that while DT adoption is expanding with increasingly comprehensive functions, significant gaps remain, particularly in accurately capturing the characteristics and behaviors of physical entities within virtual models. Multiple review studies [22,47,57] have also examined how DT technology is being applied in agriculture, emphasizing its role in improving decision-making, optimizing operations, and enabling real-time monitoring across diverse farming systems. While numerous studies have explored the integration of digital twin with agriculture, most focus primarily on application-level perspectives, with limited discussion on the detailed technological foundations that enable these systems. In particular, there is a notable gap in existing reviews concerning an in-depth examination of enabling technologies and recent advances such as federated learning, TinyML models, and edge computing, which play a vital role in the successful application of digital twins in agriculture. Although challenges and future directions have been discussed in many prior studies, this review uniquely contributes by providing a comprehensive technological perspective, key enabling technologies, challenges and recent technological trends that can drive effective implementation of digital twin systems in smart agriculture.

3. Methodology

The methodology for this study on digital twins in smart agriculture involved a systematic and comprehensive approach to literature selection and analysis. The procedure initiated with the identification of relevant scientific databases that could provide a robust collection of articles. Scopus, Web of Science, and PubMed were chosen due to their extensive coverage of high-quality, peer-reviewed literature. A carefully crafted search strategy was employed, utilizing specific keywords related to digital twins and agriculture to ensure the retrieval of relevant studies. The initial search produced a total of 294 articles, which formed the primary pool of literature for this review. These publications span from 2014 to 2024. Following the initial collection, the articles underwent a preliminary screening process to determine their relevance and alignment with the scope of this review. This screening involved evaluating each article based on several criteria, including its compatibility with the defined scope of the study, matching with the research rationales (Table 1), the alignment of its content with the objectives of the review, and the presence of conclusive results. Articles that did not match these specific criteria were eliminated from further evaluation. This phase was essential in reducing the extensive collection of articles to a more feasible quantity, ensuring that only the most relevant studies were included in the subsequent stages of the review. Once the preliminary screening was completed, a more detailed and rigorous evaluation was conducted to refine the selection further. This involved a thorough assessment of each article's methodological rigor, relevance to the topic, and the significance of its findings. Articles that were duplicates or did not meet the stringent inclusion criteria were excluded from the final selection. Additionally, the focus was on selecting studies that provided comprehensive insights and conclusive findings related to the application of DT in agriculture. This detailed evaluation ensured that the final set of articles included only those that could significantly contribute to the understanding of the topic. Through this rigorous selection process, a final set of 48 articles was chosen for inclusion in the review (Fig. 2). These selected articles form the basis of the systematic literature review, providing a thorough and in-depth understanding of the present state and future potential of digital twins in digital agriculture. This review aims to present a comprehensive overview of the advancements, challenges, and opportunities related to the integration of digital twins in agricultural processes. The selected articles collectively contribute to a meticulous and detailed exploration of how DTs can improve agricultural productivity and sustainability.

4. Digital twin technology

From the very beginning of computers, digital models of real-world systems have been integral to many software and computer applications. In agriculture systems, this digital model may be thought of as a simple CAD drawing of agricultural machinery, a virtual model

Table 1
Research questions and rationales.

Sl. No	Research question	Rationales
RQ1	Why is the integration of digital twin technology important in modern agricultural practices?	The goal is to identify the core reason for integrating digital twin technology into agriculture.
RQ2	What major transformations can digital twin technology bring to the agricultural sector?	Gain insights into potential applications of digital twin across different agriculture activities.
RQ3	What are the challenges and implementation barriers associated with digital twin solutions in agriculture?	To explore the research opportunities and potential challenges for digital twins in agriculture.

Table 2
Some of the prominent review/survey studies related to digital twin in agriculture.

Article	Year	Key focus areas	Detailed digital technological aspects	Challenges	Future scope
[45]	2022	Soil and irrigation, Crop production and Post-harvest processing	×	✓	✓
[51]	2021	Smart agriculture and other disciplines (manufacturing, construction, business, telecommunications, etc.)	×	✓	✓
[52]	2023	Land cultivation, Livestock farming and Controlled Environment Farming	×	✓	✓
[50]	2023	Crop, Livestock, Controlled environment, Aquaponics, Policy, environment, infrastructure, Product design, smart services, machinery management, Supply and value chain	×	✓	✓
[55]	2020	Hydroponics and smart farming	×	✓	×
[56]	2024	Livestock management and production	×	✓	✓
[46]	2024	Controlled Growing Setting, Horticulture, Food Supply Chain, Crop Production, Animal Husbandry, Forestry, Aquaculture	×	✓	✓
[22]	2023	Smart Agricultural Applications	✓	✓	✓
[47]	2023	Soil quality assessment	×	✓	×

and layout of a grain storage system, etc. The development of these digital representations has facilitated the creation of very advanced computer-aided systems for designing, production activities, and managing various operations. Nevertheless, the concept of a DT extends beyond a mere virtual digital representation of a system and tries to electronically depict the fundamental nature of a dynamic physical system in real-time [58]. Earlier, digital twinning was utilized as a maintenance tool for continuous tracking of the aircraft's structure. Subsequently, the object was duplicated as an exact replica to mimic its full lifecycle and assess its performance. Subsequently, the object was re-constructed as an exact digital replica to mimic its full lifecycle and assess its performance. Following that, the concept of digital twinning began to gain momentum across several industries. The core objective was to enhance their processes by making them more dynamic and optimized [28].

4.1. Digital model, digital shadow and digital twin

The concepts of digital model, shadow, and twin represent the evolution the physical world that can be mirrored digitally [31]. These terms are essential in the digital transformation. Kritzinger et al. [59] described the differentiation between the three concepts as given below.

- **Digital Model**: A Digital Model is a static digital representation of a physical object, either existing or planned. They do not have automatic data transmission between physical and digital entities. An enhanced representation of the physical object is shown through a digital model. These can be computer models of proposed resources and mathematical models of products, or other representations. Data from the physical system can be used to update the digital model, but all data transfer is manual. Any modifications performed on the physical object do not automatically reflect in the digital model, and vice versa.
- **Digital Shadow**: A Digital Shadow shows an intermediate step where there is an automatic unidirectional transfer of data from the physical object to the digital object. In this setup, changes in

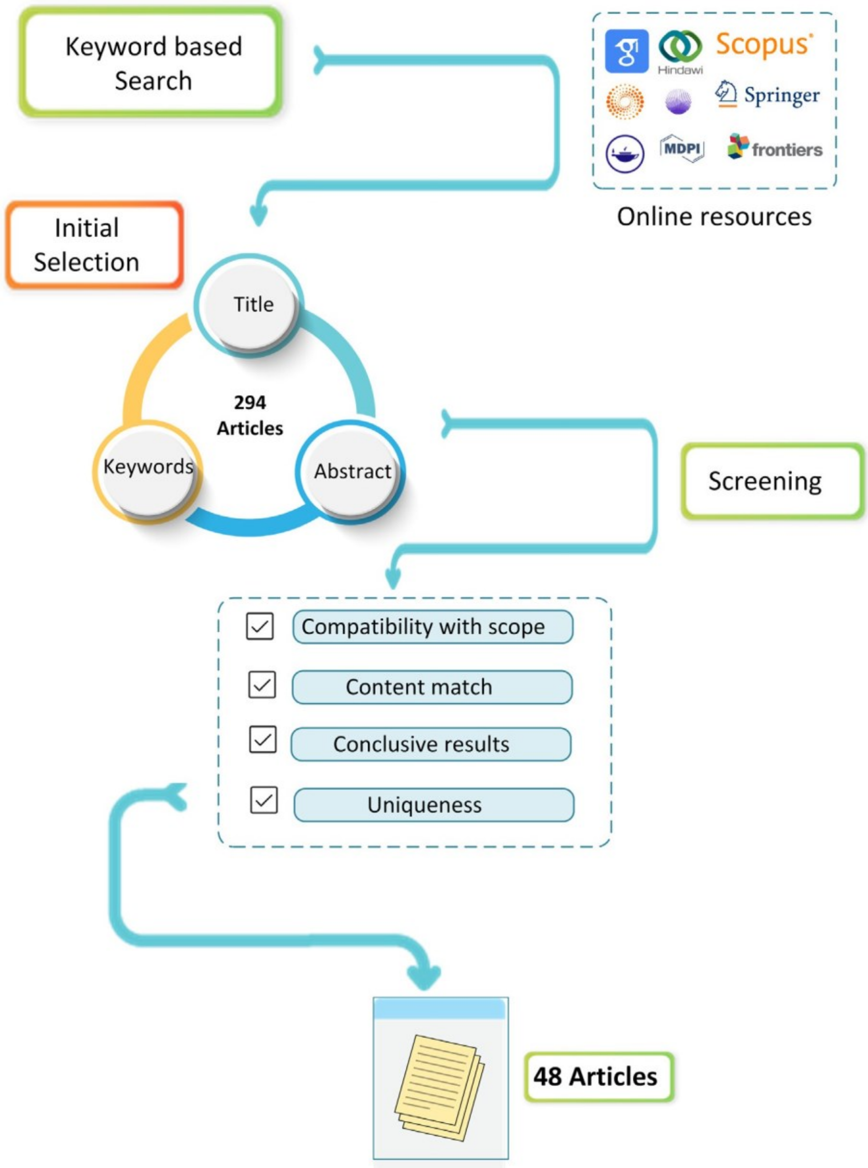
the physical object result in corresponding changes in the digital object. However, the reverse is not true. i.e., changes in the digital object do not reflect the physical object. Digital shadow allows for real-time monitoring and analysis without direct control.

- **Digital Twin**: DT is a fully integrated, bidirectional data exchange between the physical and digital objects. This relationship allows both real-time updates and monitoring for digital object to influence and control the physical object. Changes in either the physical or digital objects are directly reflected in the other. Sophisticated simulations, predictions, and optimizations can be carried out using DT.

This structured approach clarifies the progression from static models to dynamic and interactive systems (Fig. 3).

4.2. Enabling technologies

Digital Twin (DT) should not be viewed as an independent technology but rather as a system of systems that integrates a wide range of enabling technologies [60,61]. It serves as an intelligent virtual representation of a physical entity, facilitating continuous and bidirectional information exchange between the physical and digital environments [62]. The technologies involved in a DT can vary significantly depending on the specific use case. These include mechanisms for IoT-based data generation, such as sensors for real-time data capture and actuators for executing control actions, alongside connectivity technologies that ensure seamless data transmission [63]. Blockchain further enhances the system by enabling secure and tamper-proof data integrity across distributed environments [64]. Communication infrastructures, including edge, cloud, and fog computing, support reliable, low-latency, and scalable data exchange across the system components [65]. Tools for simulation and control of virtual products, such as 3D modeling, simulation environments, virtual reality (VR), and augmented reality (AR), enable detailed replication and interaction with the physical asset [66]. In addition, AI-driven intelligent processing plays a central role in enabling advanced analytics and autonomous



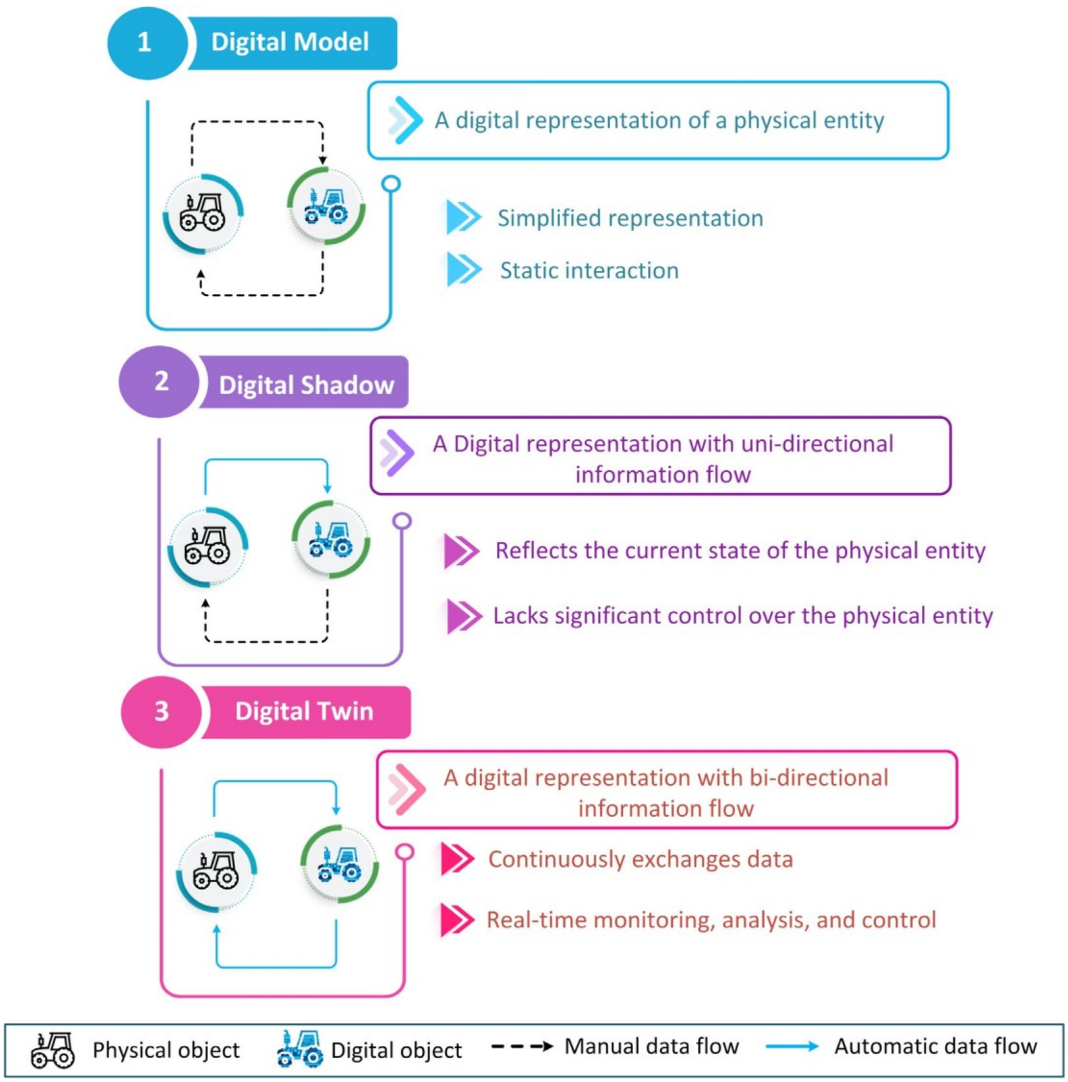
/ig. 2. Methodology employed in the study for article selection.

decision-making [67]. This includes techniques such as machine learning, deep learning, natural language processing, fuzzy logic, and computer vision [68,69]. Moreover, federated learning supports collaborative model training across decentralized devices while preserving data privacy [70], and TinyML enables lightweight AI models to oper- ate directly on resource-constrained edge devices [71–73], facilitating real-time inference. The key enabling technologies that constitute the foundation of a digital twin are summarized in Fig. 4

4.2.1. Internet of things

The IoT plays a fundamental role in the implementation and operational efficiency of DT systems, particularly in the context of smart farming [74,75]. IoT comprises a vast network of interconnected physical devices including sensors, actuators, embedded systems, and communication interfaces that collectively capture, transmit, and in some cases, act upon data from the physical environment [76,77]. Within agriculture, this interconnected infrastructure functions as the critical bridge between real-world conditions and their virtual representations. The data collected through IoT devices provides the basis for developing digital counterparts of agricultural machinery, greenhouses, fields, livestock systems, and other farm components [54,78]. These digital representations are not static snapshots but dynamic, continuously updated models that evolve in real time, reflecting changes in the physical system [79,80].

The seamless and continuous acquisition of real-time data enabled by IoT technology allows DTs to provide a comprehensive and high-fidelity view of the agricultural ecosystem [81,82]. Sensors deployed across various physical assets provide environmental, biological, and operational data that feed into the digital twin Equally important in this ecosystem are the actuators, which serve as the interface between digital decisions and physical actions. The presence of actuators in the DT-IoT loop facilitates automation, enabling intelligent systems to respond quickly and efficiently to dynamic agricultural conditions without the need for constant human intervention [38]. To support the seamless operation of this interconnected system, robust and reliable communication technologies are essential. The choice of communication protocols in agriculture depends on various factors including data bandwidth requirements, geographical coverage, power consumption, and network availability. In localized settings such as greenhouses or livestock facilities, short-range wireless protocols may be used to

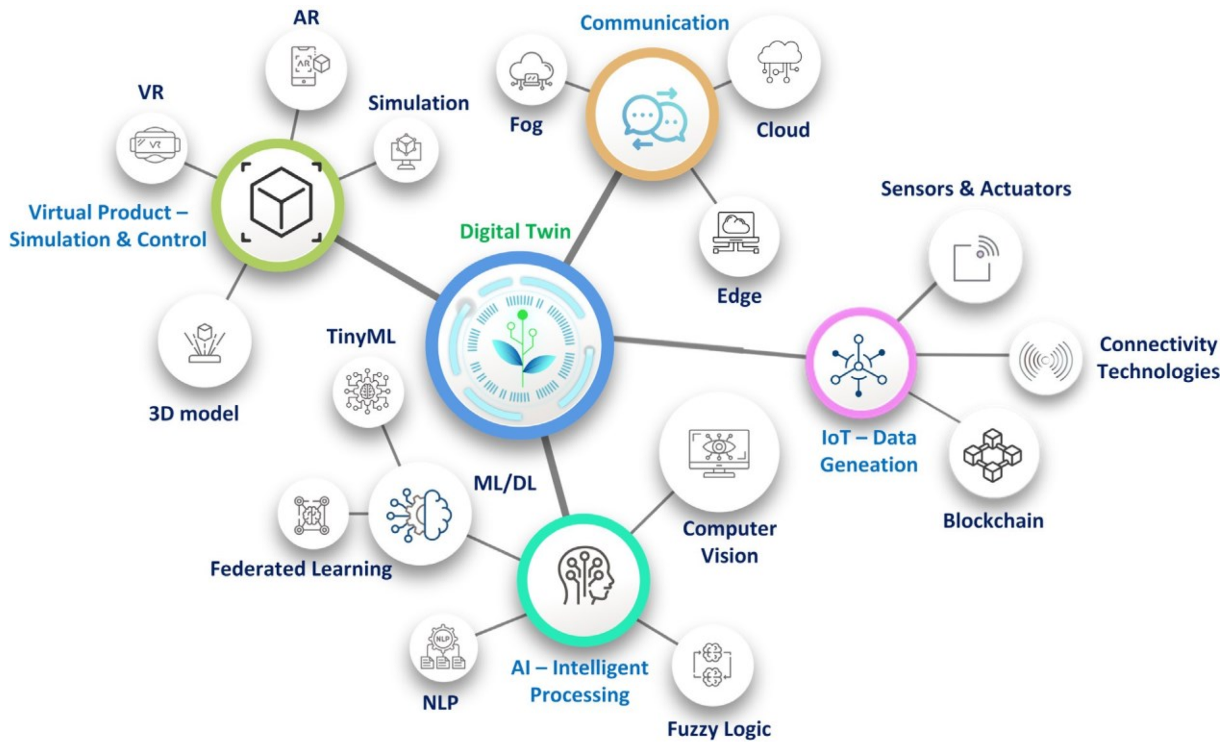


/ig. 3. Schematic of Digital model, Digital shadow and Digital twin.

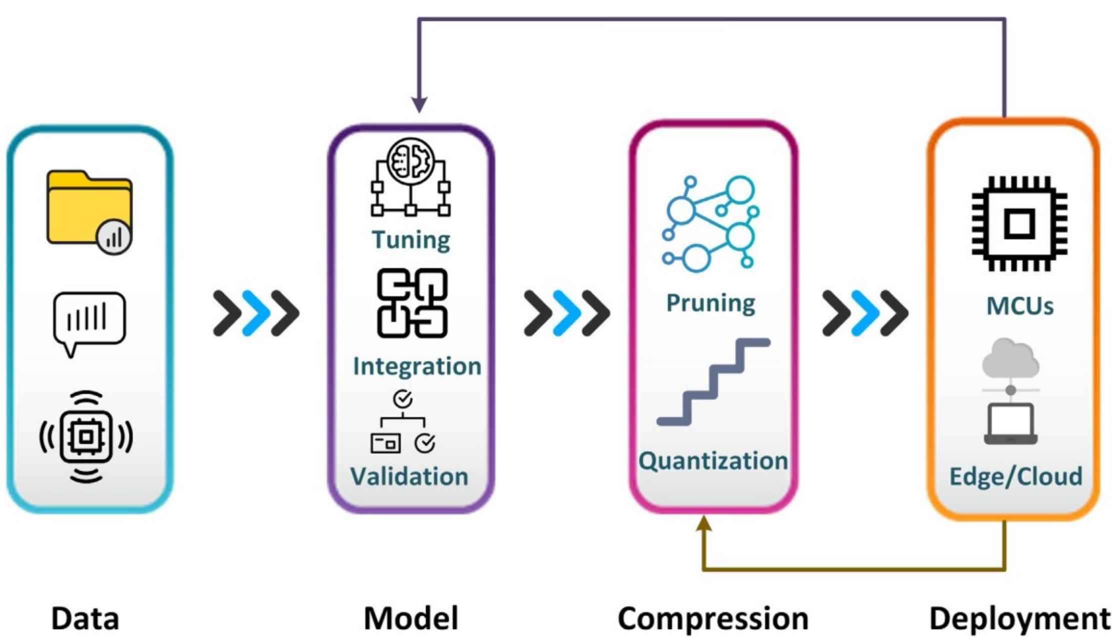
connect devices and transmit data to central gateways. For large-scale outdoor environments, low-power wide-area networks are typically preferred due to their ability to operate over long distances with minimal energy requirements [83,84]. Satellite communication also plays a vital role in remote agricultural zones where terrestrial infrastructure is lacking, providing global coverage and integration with GPS-based geospatial services [85,86]. Edge computing is increasingly integrated into these systems to allow preliminary data processing closer to the source, reducing latency, conserving bandwidth, and ensuring faster response times. The success of IoT-enabled digital twins also depends on the integrity, security, and reliability of the data being transmitted and acted upon [87]. Blockchain is increasingly being explored as a means to enhance trust, transparency, and data traceability within distributed agricultural systems [88,89]. Its decentralized and tamper-resistant architecture offers significant potential in addressing the integrity and provenance of sensor data streams.

4.2.2. Blockchain

Blockchain technology is increasingly recognized as a foundational enabler for secure, transparent, and trustworthy digital twin systems [90]. As digital twins evolve into complex, interconnected ecosystems involving data generation, model synchronization, and autonomous decision-making, the need for reliable, decentralized mechanisms to validate and govern data transactions becomes critical [91,92]. In many DT applications, especially those that involve Internet of Things (IoT) devices, a vast amount of data is continuously generated by distributed sensors and actuators. Ensuring the authenticity, traceability, and immutability of this data is vital for the fidelity and operational dependability of the DT. Blockchain offers a robust solution by providing a distributed ledger architecture in which every data transaction is cryptographically secured, time-stamped, and permanently recorded. This establishes a verifiable chain of trust, mitigating the risks of data tampering, unauthorized access, and system inconsistencies. Beyond its role in data security, blockchain contributes significantly to the governance and coordination of complex digital twin environments. In contemporary DT implementations, multiple stakeholders, ranging from equipment manufacturers and service providers to regulatory bodies and end users may interact with different components of the digital model. Blockchain enables decentralized access control, where participants are assigned specific roles and permissions through programmable logic embedded in smart contracts. Another critical dimension where blockchain reinforces digital twin technologies is in version control and lifecycle traceability [93]. Digital twins often undergo continuous updates as new data streams, simulation outputs, or control strategies are introduced. Capturing these changes in a transparent and non-repudiable manner is crucial for ensuring scientific reproducibility, regulatory auditability, and historical accountability. Blockchain can serve as a tamper-proof registry for digital twin events [94,95], recording model updates, simulation results, or even decision rationales across



/ig. 4. Prominent technologies involved in digital twin.



/ig. 5. Schematic of tinyML model deployment on micro-controllers and edge devices [98].

time. This historical traceability enhances not only trust but also the interpretability of AI-assisted recommendations or autonomous system behaviors embedded within the DT. [96,97].

4.2.3. Artificial Intelligence and emerging paradigms

Artificial Intelligence plays a pivotal role in enabling Digital Twin technology by significantly enhancing its capabilities, adaptability, and application scope [99,100]. AI encompasses a wide range of subfields, including machine learning (ML) [101], deep learning (DL) [102,103], natural language processing (NLP) [104], computer vision [105], fuzzy logic [106], and emerging paradigms like TinyML, Federated Learning, etc. These components offer the computational intelligence, analytical depth, and contextual awareness necessary for developing dynamic and self-evolving digital twins. DTs rely heavily on data-driven models to represent, monitor, and optimize physical systems. ML algorithms form the backbone of this capability by enabling automated data analysis, anomaly detection, and prediction generation based on large-scale, real-time datasets derived from their physical counterparts [48,107]. These models can learn patterns and operational dynamics, facilitating real-time decision-making and adaptive control. DL, a specialized branch of ML, augments this process by using deep neural networks to extract complex representations from high-dimensional and unstructured data sources such as images, videos, sensor fusion streams, and time-series data [108]. Computer vision, an integral part of AI, allows DTs to process and interpret visual information captured from physical environments [51,109]. It enables functionalities such as object detection, activity recognition, and surface condition assessment. In agriculture, for example, DTs equipped with vision capabilities can monitor plant health, detect pest infestations, and assess crop maturity by analyzing visual attributes from drone or satellite imagery. This facilitates precision farming, minimizes waste, and maximizes yield. Similarly, in farm machinery, computer vision enables digital twins to detect equipment faults, monitor operational efficiency, and support preventive maintenance through continuous visual inspection. Natural Language Processing (NLP) strengthens DTs by enabling them to comprehend, generate, and interact using human language [110,111]. NLP-based interfaces allow users to query the DT, issue commands, or receive explanations in natural language, thereby increasing accessibility and human interpretability. Fuzzy logic contributes by introducing human-like reasoning to DTs, especially in scenarios where data is imprecise, uncertain, or linguistically described. This is crucial for agricultural, climatic, or biological systems where variability and vagueness are inherent. Fuzzy logic-based DTs can handle subjective inputs such as "moderate humidity" or "slightly dry soil" and convert them into actionable control strategies, improving interpretability and decision robustness under uncertainty [106].

Recent advancements in machine learning have given rise to distributed, efficient, and embedded intelligence paradigms that align closely with the evolving requirements of DT systems [112,113]. As the scale and complexity of physical systems grow, there is an increasing demand for intelligent processing directly at the edge, and for collaborative intelligence that respects privacy and decentralization. These needs have driven the development of two highly relevant AI paradigms: TinyML and Federated Learning. TinyML, which focuses on deploying ML models on low-power, resource-constrained edge devices, is increasingly relevant in DT frameworks [114], particularly in sectors like agriculture, precision manufacturing, and smart infrastructure. Integrating TinyML into DTs enables real-time analytics and localized decision-making directly on embedded systems, thus reducing latency, preserving bandwidth, and increasing system reliability by minimizing dependence on centralized cloud servers [72,115]. In agricultural digital twins, model compression techniques such as quantization, pruning, and knowledge distillation are often applied to reduce the computational and memory footprint of machine learning models without significantly compromising accuracy [116,117](Fig. 5). These techniques enable efficient deployment of vision-based disease detection models [118] or sensor fusion algorithms onto microcontrollers embedded in field-deployed units. This capability becomes critical in environments with intermittent connectivity or where real-time responsiveness is necessary, such as autonomous agricultural machinery. Federated Learning, another cutting-edge advancement, facilitates collaborative model training across distributed nodes while keeping raw data localized. This decentralized learning model is vital for DT applications in privacy-sensitive domains [119]. In agricultural DTs, for instance, edge devices deployed across geographically distributed farms can collaboratively learn a unified crop disease prediction model without transmitting sensitive or proprietary data to a central server. The FL process typically begins with a centralized server initializing a global model, which is then sent to participating client devices [70, 120]. Each client trains this model locally using its private data and subsequently sends the learned model updates (such as weights or gradients) back to the server. The server then aggregates these updates, commonly using algorithms like Federated Averaging, to update the global model (Fig. 6). This updated model is redistributed to the clients for the next round of training. FL enhances the scalability, robustness, and intelligence of digital twin ecosystems without compromising data confidentiality [121,122].

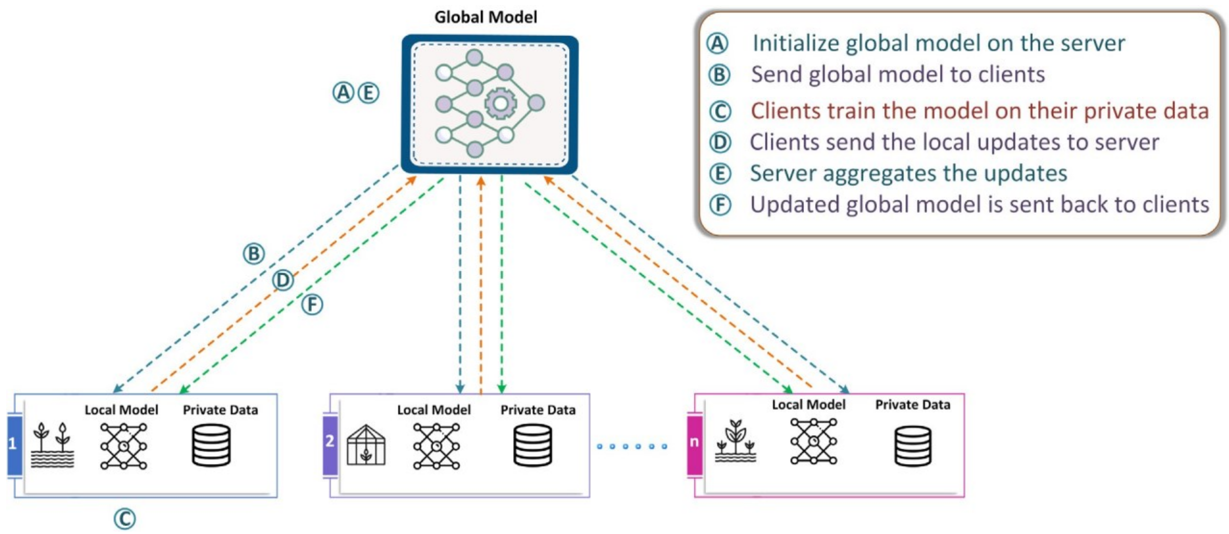
4.2.4. Cloud, fog and edge computing

In agricultural digital twins, where data is continuously generated across large and often remote spatial domains, an efficient and adaptive communication framework is essential. A layered architecture comprising cloud, edge, and fog computing forms the backbone of this infrastructure [123,124].

Cloud computing has a pivotal role in facilitating DTs by offering the essential processing capacity, storage, and scalability required to manage the immense volumes of data produced in agricultural fields [45, 79]. In order to precisely replicate physical conditions and activities, ADTs rely heavily on continuous data processing and advanced analytics, which necessitate a robust and adaptable infrastructure. Cloud systems enable these capabilities by supporting the seamless integration of IoT devices, field sensors, satellite feeds, and remote sensing tools [125,126]. The cloud facilitates cost-effective resource allocation and dynamic scalability, allowing DT systems to adjust processing capacity based on real-time demands. Furthermore, cloud computing enables the implementation of sophisticated AI and ML algorithms, enhancing the predictive and prescriptive functionalities of the digital twin models. It also allows centralized processing and real-time analysis of spatially distributed data collected from diverse agricultural assets [127,128]. Additionally, cloud platforms offer robust security mechanisms and compliance standards that ensure data privacy, integrity, and traceability. While cloud computing offers considerable advantages, it may not suffice for applications that demand ultra-low latency, high-frequency actuation, or must operate under intermittent connectivity conditions. In such cases, edge and fog computing provide essential complementary functionalities [129,130]. Edge computing involves placing computational resources closer to the data source, allowing for immediate data processing and decision-making. This is particularly useful in scenarios where real-time responsiveness is critical. By analyzing data locally, edge nodes reduce the need to transmit large volumes of raw data to centralized cloud servers, thereby conserving bandwidth and reducing response times. Moreover, edge computing ensures system continuity even in low-connectivity or bandwidth-limited environments, a common condition in rural and large-scale farm settings. Fog computing builds upon the capabilities of edge computing by introducing a distributed, intermediary layer of computing infrastructure positioned between edge devices and the cloud. It allows for local data aggregation, short-term storage, and mid-level analytics. In agricultural DTs, fog nodes may be deployed at greenhouse control systems, farm gateways, or local edge servers to coordinate data from multiple sensors and actuators across specific regions. By integrating cloud, edge, and fog computing, agricultural digital twins benefit from a hybrid communication infrastructure that is contextually adaptive.

4.2.5. Virtual product technologies for modeling, simulation, and interaction

Virtual product technologies comprising 3D modeling, simulation, and immersive interaction tools such as augmented reality (AR), virtual reality (VR), and mixed reality (MR) are integral to the functionality and effectiveness of digital twin systems in agriculture. Collectively known as extended reality (XR), these technologies provide the visual and interactive frameworks required to represent, analyze, and interact with physical systems within a digital environment. XR is increasingly recognized as a powerful component of digital twin implementations in smart farming and precision agriculture [131–133]. It enhances the interpretability of complex, multi-source datasets by allowing users to engage directly with digital replicas in a spatially meaningful and intuitive manner. By creating immersive, spatially aligned interfaces,



/ig. 6. Workflow of federated learning.

XR enables users to interact with large-scale and high-dimensional data in a human-centered way, thereby improving understanding and operational efficiency. By reducing the cognitive burden associated with interpreting abstract data charts or remote dashboards, AR enhances on-site decision-making efficiency [134,135]. AR devices allow users to interact with a digital twin while remaining aware of the surrounding physical context, making it ideal for field operations, real- time inspections, and human-in-the-loop control systems. In contrast, VR provides fully immersive, computer-generated environments that allow users to engage with digital twins in controlled and reproducible settings. This is particularly valuable for simulation, education, and remote collaboration. It supports the creation of scenario-driven virtual environments, where users can experience and interact with different conditions, system states, or intervention strategies in a risk-free manner. These experiences are particularly useful during planning, training, and strategy development, and can be extended with real- time telemetry to simulate live operational data. Mixed reality (MR) further extends the value of XR by blending the physical and digital worlds in a way that allows physical and virtual elements to coexist and interact in real time. MR systems offer persistent spatial mapping, allowing users to anchor digital twin elements in the real environment and interact with them dynamically. This enables complex workflows such as digital co-authoring, collaborative diagnostics, and synchronized monitoring of live systems. Unlike traditional 2D visualizations, MR enhances depth perception and contextual understanding, which are critical when operating in complex or multidimensional physical environments.

Beyond immersive visualization, the backbone of any DT system lies in the precision and adaptability of its 3D modeling and simulation capabilities. High-resolution 3D models serve as the structural digital counterpart to physical agricultural entities. These models are often constructed using data from LiDAR scans, photogrammetry, structured light sensors, or Computer-Aided Design (CAD) tools. The use of CAD is particularly important in modeling mechanical components, structural systems, and embedded electromechanical systems with high dimensional fidelity. These parametric models support interoperability across design, simulation, and control platforms and are well-suited for automated updates using sensor inputs. The dynamic synchronization of these models with real-time data supports the DT's role as a live, evolving system rather than a static digital replica. These 3D models provide the substrate upon which simulations are conducted, enabling the analysis of physical processes, prediction of future system states, and evaluation of control strategies. Simulation tools embedded within DT systems allow stakeholders to virtually test and optimize operations before implementation. These simulations not only improve planning accuracy but also reduce reliance on trial-and-error approaches that are time-consuming and resource-intensive. Moreover, simulation environments facilitate system optimization through iterative testing, sensitivity analysis, and reinforcement-based decision modeling. They also enable the exploration of "what-if" scenarios, supporting risk analysis, contingency planning, and continuous process improvement. As simulation engines become increasingly integrated with real-time data and feedback loops, digital twins evolve into closed-loop control systems capable of autonomous adaptation and optimization over time.

4.3. Interplay of technologies in digital twin

In the context of digital twin implementations in agriculture, the interplay among enabling technologies becomes practically evident. The IoT framework serves to capture essential parameters such as environmental, soil, and crop physiological data. These sensor readings are interpreted and used to actuate systems like irrigation pumps, cooling systems in greenhouses, or robotic arms in harvesting. These actions occur in near real-time, enabled by reliable connectivity solutions and localized edge or fog computing, which reduce latency and offload processing from centralized cloud servers. Blockchain plays a foundational role in ensuring that interactions are stored securely and transparently. This becomes essential in agricultural systems involving multiple stakeholders or compliance-sensitive environments. For instance, in smart food supply chains, blockchain ensures that environmental data logged during storage and transport is immutable and auditable. Smart contracts can automate tasks such as verifying whether perishable goods were maintained within safe temperature and humidity ranges. The digital twin's intelligence is driven by AI technologies that enable predictive and adaptive functionalities. Machine learning models can forecast irrigation requirements, detect pest outbreaks, or predict yield based on weather and growth conditions. In plant phenotyping systems, for instance, computer vision detects early signs of disease or nutrient deficiency by analyzing high-resolution imagery. Fuzzy logic enables flexible decision-making when sensor values are borderline, such as determining optimal irrigation timing under fluctuating microclimates. Federated learning supports collaborative model development across different farms or agricultural facilities while preserving data privacy. For example, multiple greenhouses can contribute to improving crop growth prediction models without exchanging raw data. TinyML ensures that intelligence is distributed to even the most constrained edge devices, enabling real-time local responses like activating misting systems or nutrient dispensers in response to stress indicators. Human interaction with agricultural digital twins is enhanced through natural language processing, allowing operators to query the system intuitively—asking questions like "Why did the greenhouse temperature drop overnight?" or "What is the projected harvest date?" This improves usability for non-technical users. Visualization and virtual product technologies, including CAD-based 3D modeling, advanced simulation platforms, and immersive environments, represent field, greenhouse, or supply chain processes with high fidelity. Simulations allow farmers to experiment with planting densities, irrigation strategies, or climate scenarios before real-world implementation, reducing trial-and-error in physical operations. Augmented reality (AR) overlays real-time data such as crop health metrics, equipment diagnostics, or task guidance directly onto the physical environment, enhancing field-level situational awareness. Virtual reality (VR) environments can be used for remote monitoring, operational training, or scenario-based planning. Mixed reality (MR) further allows seamless interaction between digital and physical elements, enabling operators to manipulate holographic crop data or receive adaptive system recommendations in an intuitive format.

4.4. Interactions among DT components

The interaction between different components is a seamless flow of data and decisions that enable real-time monitoring, analysis, and control of physical objects in digital twin [22]. A physical object (PO) refers to an actual element existing in the real world, such as a machine, a farm field, or any observable system. This component is equipped with sensors that are enabled by IoT technology. These sensors continually collect data about the object's state and performance. The information acquired by these sensors is transferred to the digital twin. The DT functions as a comprehensive digital representation, whereby all data is consolidated, analyzed, and recorded. This synchronization between the PO and its DT ensures that the virtual model accurately represents the current state of the physical object at any given time, facilitated by cloud computing that provides scalable storage and computational resources. After the data is acquired and combined in the DT system, it is then sent to the Analysis Engine for further analysis and processing. The Analysis Engine is equipped with sophisticated algorithms and computational tools powered by AI that analyze the incoming data to derive significant insights. This study may involve identifying anomalies, predicting future states, or optimizing operational parameters. The AI-powered Analysis Engine generates results, which are subsequently transmitted back to the DT, serving as the intermediate. The DT incorporates these analytical observations into its digital model, continuously revising the representation of the PO according to the most recent findings. The Decision Module benefits from the updated information in the DT, which provides predictive and prescriptive insights gained by AI, hence improving the decision-making process. The interaction among different components of DT is shown in Fig. 7.

The Decision Module relies on the insights provided by the DT to make informed decisions. These decisions are made on the basis of thorough analysis and real-time data presented by the DT, ensuring that actions are data-driven and optimized for the best possible outcomes. Advanced visualization techniques, such as XR, including AR and VR, can be employed to present the data and analytical results in an immersive and interactive manner. This allows the Decision Module to better understand the context and implications of the data, facilitating more effective and accurate decision-making processes. After a choice has been made, the DT conveys the required steps to the Execution Module. This module is tasked with executing these operations on the actual object. The Execution Module guarantees the precise implementation of optimized choices in the PO, whether it includes modifying operational settings, starting maintenance actions, or any other type of intervention. The dynamic and linked character of digital twins is shown by the closed-loop interaction between the Physical Object (PO), Digital Twin, Analysis Engine, Decision Module, and Execution Module.

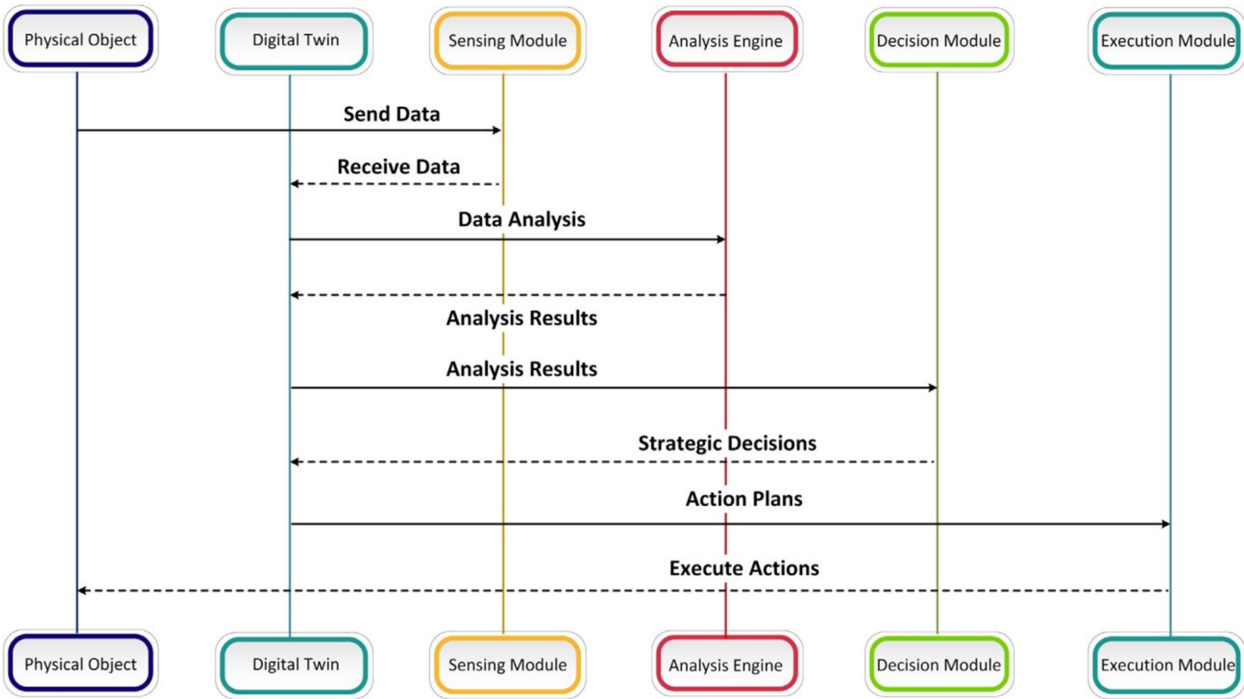
5. Digital twin in agricultural applications

Digital Twin and allied technologies like IoT-AI-XR are at the forefront of transforming agriculture, enabling precise and data-driven decision-making. Table 3 shows the prominent studies related to digital twins integrated with AI (DL/ML) models for intelligent solutions. The following sub-sections will explore these major areas and highlight how DT is driving advancements and efficiency in existing agriculture practices.

5.1. Digital twin in controlled environment agriculture

Integrating Digital Twin (DT) technology into Controlled Environment Agriculture (CEA) systems significantly advances sustainable and efficient agricultural practices. CEA refers to the cultivation of crops within enclosed and technologically regulated environments such as greenhouses, vertical farms, and indoor growing facilities, where environmental parameters like temperature, humidity, light intensity, and carbon dioxide (CO_2) concentration are meticulously controlled to optimize plant growth and resource utilization. Digital Twins serve as dynamic, real-time virtual counterparts of physical CEA systems, enabling continuous monitoring, simulation, and optimization of agricultural processes [54,140]. DTs allow for real-time tracking of environmental variables and plant health indicators. This facilitates a deeper understanding of crop responses to changing conditions, helping operators make informed, data-driven decisions. The ability to run predictive simulations within the virtual twin allows stakeholders to assess the potential outcomes of various interventions such as altering lighting schedules, irrigation levels, or nutrient formulations without disrupting the physical system. This predictive capability is especially critical in minimizing risks, reducing crop failure, and enhancing yield consistency. A key strength of DTs in CEA lies in their ability to aggregate and synthesize heterogeneous data streams from a variety of sources, including IoT-based sensors, weather and climate models, historical growth data, and AI-driven crop phenotyping tools. By integrating these diverse inputs, the digital twin constructs a comprehensive, context-aware model of the cultivation environment. This comprehensive representation enables advanced analytics, such as root cause analysis, anomaly detection, and adaptive control strategies, thus improving system responsiveness and stability. Moreover, Digital Twin technology enhances resource efficiency by enabling precision control of inputs such as water, nutrients, and energy. Similarly, feedback from the virtual model can guide adaptive irrigation practices to conserve water and prevent nutrient leaching. By promoting data-informed decision-making and system transparency, they support eco-friendly cultivation practices and help reduce the environmental footprint of agricultural production in controlled settings.

Several recent studies explored the application of digital twin in CEA. Chaux et al. [141] introduced a DT architecture designed for CEA systems, aiming to improve productivity and minimize resource consumption. The study used simulation software for controlling the climate. The architecture was implemented in a case study as a fully integrated Digital Twin system for greenhouse automation. The physical system, the greenhouse was equipped with two DHT11 sensors for measuring both indoor as well as outdoor temperature and relative humidity, a 12V fan, and a 12V compact submersible pump. The Arduino Uno was used as the controller and Raspberry Pi 4 was the Gateway, which establishes a connection with the storage layer via wireless communication, and interfaces with the Arduino. phpMyAdmin, an



/ig. 7. Interaction among different components of Digital Twin.

Table 3
Summary of prominent studies related to digital twin integrated with AI (DL/ML) models for intelligent solutions.

Reference	Application Area	Objective	Dataset	DL Model	Findings
[79]	Crop Monitoring	Detection of plant diseases and nutrient deficiencies	Image dataset - plant village dataset for disease identification	MobileNet and UNet model	LoRaWAN based solution provided robust solution for communication and the Mobile Net model achieved an accuracy of 95% in disease identification
[136]	Controlled environment agriculture	Development of decision support system for Aquaponics using DT	Sensor data (pH, EC, Water level, light intensity, temperature, humidity, etc.) and simulation data	State of the art ML models - LR, SVR, DT, Ensemble Model	DT and SVR performed well in predicting the fish growth rate and for plant growth LR model was most suited
[137]	Post-harvest engineering	Fruit quality monitoring during storage	Thermal dataset of banana images consisting of fresh, good, bad, rotten class of bananas	Convolutional Neural Network model	DL model exhibited 99% accuracy
[32]	Livestock management	Monitoring physiological cycle of cattle	Sensor data of 98 cattle indicating 8 activities (Resting, Rumination, Activity (High, Medium), Panting, Grazing and Walking	LSTM model	Model was successful in predicting the state change of cattle in the upcoming cycle. Model loss error on prediction set: 5.197
[138]	Livestock management	Development DT for entire lifecycle of cow	Data from indoor positioning and inertial measurement unit (IMU)	SVM, KNN and LSTM Models	LSTM model outperformed other models. LSTM Model accuracy on data from indoor position detection and IMU devices: 94.97%
[139]	Controlled environment agriculture	Real-time remote monitoring and process management in greenhouse (lighting, water level, heating and cooling)	Real time database data and data from sensors (Climate data, temperature, soil type, plant type, species type,etc.)	State of the art ML models - LR, RF, KNN, DT, ANN, etc	ANN model showed 98% accuracy for process management.
[75]	Irrigation management	Smart irrigation management using digital twin	Dataset includes soil and meteorological parameters	Adaptive Neuro-Fuzzy Inference System (ANFIS) coupled with Genetic algorithm model	The system was able to accurately predict soil moisture levels for upcoming days. ANFIS-GA model predicted the soil condition with an accuracy of 95.85%

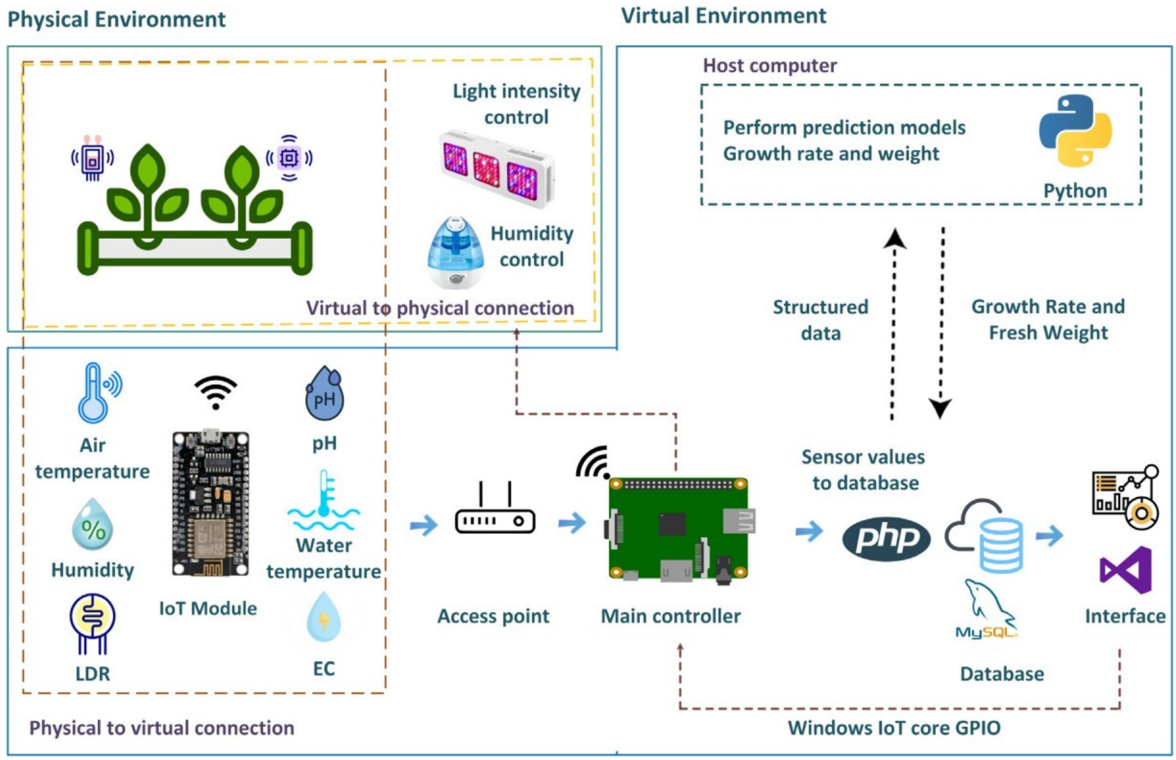
administrative tool for handling a MySQL server, is responsible for managing the data in cloud storage. The intelligence layer, created in Visual Studio and coded in Python, facilitates communication with the cloud using MySQL and with the gateway using the MQTT protocol. The simulation tools EnergyPlus and DSSAT were selected to optimize productivity in the DTs. EnergyPlus prioritizes the optimization of techniques for controlling the microclimate of crops, whereas DSSAT primarily focuses on the management of treatments for crops. In another study about controlled environments and digital twins, González et al. [142] created a monitoring DT (mDT) for improving CEA services. The mDT uses open-source software tools to collect data from CEA facilities for storage, computation and evaluation of data in local as well as remote ways. mDT operate with an objective of establish- ing extensive database of CEA and further using them for predictive modelling. As the current implementation focuses on data acquisition, processing, and visualization without automated actuation, it represents a partially integrated digital twin – or digital shadow – within the CEA context. In another study, Hull et al. [143] presented a foundational approach by employing a data-driven thermal model using Support Vector Regression to predict internal greenhouse temperatures. Their work emphasizes the capability of DTs to simulate and forecast environmental conditions, enabling proactive climate control and operational efficiency. This approach effectively predicted temperatures inside the tunnel and regulated the operation of the cooling fan and wet wall. Building on such predictive capabilities, Qu [144] introduced a comprehensive DT framework for greenhouse climate control, which combines multi-objective optimization and evolutionary algorithms to refine actuator operations. This modular framework showcases the potential of DTs not just for simulation, but for integrated decision support aimed at reducing energy use and production costs. Expanding the functional scope of DTs beyond climate management, Dai et al. [145] proposed a pest management-oriented DT system that integrates machine learning models optimized via genetic algorithms. This system demonstrates how virtual and real-time feedback loops can enhance integrated pest management, supporting timely interventions and economic gains. Their approach reflects a shift toward data fusion and decision intelligence within CEA-focused DT applications. Further diversifying the landscape, Spyrou et al. [146] explored the integration of extended reality (XR) with DTs in the context of pharmaceutical cannabis production. By merging DTs with XR technologies, their study addresses the complexities of regulatory compliance, quality assurance, and user engagement in a highly specialized sector. The positive reception from stakeholders suggests that XR-enhanced DTs hold promise for intuitive interaction and training within complex agricultural environments.

Monteiro et al. [148] carried out an investigation to achieve industrial-scale readiness (TRL7) for digital twins in vertical farms. Trial prototypes and industrial-scale prototypes were developed in the investigation. Laboratory-scale demonstration prototype was developed by interfacing multiple sensors (temperature, relative humidity, light intensity, and concentration of CO_2) and actuators with Raspberry Pi. Further, a web interface was used for tracking the parameter values. In the following phases, the size and complexity were gradually increased. In the industrial scale prototype, the number of sensors was increased to ninety-four and this showed an increase in complexity of the physical layer. This necessitated a robust approach to hardware design using RPi's GPIO multiplexing for sensor data acquisition. This was coupled with a fault-tolerant system to minimize the impact of any sensor malfunctions. The development included a 3D representation crucial for accommodating scalability demands both at design time and runtime. In a similar, aquaponic environment, Reyes et al. [147] investigated and developed a framework of DT specifically for hydroponic grow beds within the aquaponic system. The DT was successful in monitoring the real-time parameters like pH, electroconductivity, water and air temperatures, humidity, and light intensity, utilizing AI techniques to predict crop growth rates and weights (Fig. 8). For aquaponic system, Ghandar et al. [136] employed a cyber–physical implementation with adaptive features using a DT and ML. Several ML models such as LR, SVR, DT, and XGB were evaluated in the study to identify the optimal model for integrating into the decision support system. Ubina et al. [49] developed a DT infrastructure tailored for intelligent fish farming, leveraging AIoT principles. Their system combines real-time data collection from smart devices with cloud-based processing to deliver four major DT services: automated feeding, fish metric estimation, environmental monitoring, and health diagnostics. Each service is supported by AI-driven modules that perform predictive and analytical tasks, enhancing decision-making and enabling remote, web-based farm management. This approach exemplifies the power of data-centric automation in optimizing aquaculture production and sustainability. Similarly, Asfarian and Wulandari [149] proposed a DT platform architecture for smart aeroponic potato cultivation in Indonesia. Their design encompasses a sensor-enabled smart farm, a secure cloud-based backend for data storage and processing, and a user-centric front-end for visualization and control. The architecture is designed with scalability and security in mind, using REST APIs and transport layer encryption to ensure safe communication between system components. The platform's data analytics module employs machine learning and simulation techniques, transforming raw sensor data into actionable insights for farmers and stakeholders. This study highlights the role of DTs in bridging data acquisition with intelligent farm management, particularly in resource-efficient farming systems like aeroponics. Samikannu et al. [150] further demonstrated DT implementation in an aquaponics setting, focusing on real-time monitoring and control of physical processes. By incorporating image segmentation techniques to estimate crop growth and integrating various IoT sensors, their system enables continuous observation and model-driven decision-making. In general, recent studies indicate that the integration of Digital Twin (DT) technology in Controlled Environment Agriculture (CEA) holds significant potential for enhancing agricultural yield and improving resource efficiency [139,151–154].

5.2. Digital twin in soil and irrigation management

DT technology redefines soil and irrigation management by providing real-time monitoring, modeling, and optimization abilities. This technique utilizes data from several sources, such as sensors, remote sensing, and weather stations, to build a virtual replication of the real soil and irrigation systems. Within the field of soil management, digital twins make use of data pertaining to soil characteristics, including texture, structure, moisture content, and nutrient levels [47,155]. This continually updated data enables accurate and location-specific treatments. AI algorithms analyze this data, making predictions about the results of various soil management practices and providing guidance for making the best decisions. By replicating the behavior of the physical environment, DTs support proactive decision-making, enabling farmers and agronomists to fine-tune irrigation strategies, optimize water usage, and maintain soil health under varying climatic and field conditions [156,157]. Moreover, these systems facilitate early detection of issues such as over-irrigation, leaching, or drought stress, allowing timely interventions that can prevent yield loss. The adoption of DTs in this context also supports long-term sustainability goals by enhancing water-use efficiency, preserving soil quality, and reducing the ecological footprint of agricultural operations. As the pressure to produce more with fewer resources intensifies, DTs offer an adaptive framework for managing soil and irrigation systems with greater precision and reliability.

Within the field of irrigation management, digital twins encom- pass detailed representations of water sources, distribution networks, moisture levels in soil, and water requirements of the crop. Real-time data integration enables accurate irrigation scheduling, ensuring crops receive the ideal water quantity, thereby reducing waste and improving crop output. DTs are employed to enhance the efficacy of advanced irrigation technologies, including drip and variable-rate irrigation systems. These digital twins simulate different irrigation scenarios to determine the most effective patterns for water usage. Issues in the irrigation approaches are improved by DT using the prediction made. This proactive strategy helps in reducing the amount of water wasted and the stress on crops. DT technologies are utilized to address irrigation challenges.



/ig. 8. Integration of digital twin for hydroponic grow beds within an aquaponic system employed by Reyes et al. [147].

Manocha et al. [75] developed a smart irrigation system using DT for estimating the daily irrigation requirements. The solution has been developed as a fully integrated Digital Twin framework. The real-time transmission of commands is enabled to the IoT system. The study employed soil moisture, temperature, and humidity data to calculate the water needs and provide irrigation suggestions to the farmers. The collected attributes are simulated by the digital twin and analyzed using ANFIS-GA model for estimating the soil moisture. In another study, Brocca et al. [158] introduced a Digital Twin Earth (DTE) model for hydrology. High-resolution Earth observation data with advanced modeling were used to simulate key hydrological processes such as soil moisture, precipitation, and river discharge. The model demonstrated success in forecasting floods and optimizing irrigation in the Mediterranean Basin. Complementing this, Rodríguez-Alonso [159] proposed a DT platform for wastewater treatment plants using a microservices architecture optimized for edge computing. By integrating LSTM-based predictive maintenance, active sludge modeling, and real-time data with BIM, the platform improved operational efficiency and resource use. Meanwhile, Cho et al. [160] developed a GIS-BIM integrated DT for agricultural infrastructure, enabling detailed visualization and real-time analysis of irrigation and drainage systems. Through UAV surveys and flow sensor data, the system allows farmers to adjust irrigation practices based on real-time crop health indicators, potentially improving yield outcomes. Alves et al. [161] investigated the integration of an IoT platform equipped with simulation software to create a digital twin for managing irrigation. The primary objective was to create an automated pipeline for control and oversight of irrigation systems, taking into account the local variations in order to enable independent watering of separate management zones. The solution comprises an IoT platform based on FIWARE and a discrete event simulation model created using Siemens Plant Simulation software. The simulation model accurately reproduces the actions and functions of an irrigation system as described in a particular application context. The platform and the simulation model communicate in real time utilizing an OPC UA server. This technology has the potential to enhance farming operations and decrease water use by permitting farmers to acquire data on soil, weather, and crops, and to assess various irrigation methods. In another study, Bellvert et al. [162] investigated to determine if it is possible to automatically schedule irrigation for a commercial vineyard by using regulated deficit irrigation (RDI) strategies and incorporating near real-time data on the fraction of absorbed photosynthetically active radiation (fAPAR) obtained from Sentinel-2 images. In the study, the crop evapotranspiration simulations produced by the digital twin were compared to remote sensing estimations utilizing surface energy balance models and Copernicus-based inputs. The capability of DT approaches in soil and water management practices has been pointed out in numerous other recent studies [163,164] also, indicating the pivotal role in future irrigation system. Li et al. [165] addressed the technical challenge of modeling dynamically changing soil conditions during subsoiling by proposing a DT framework based on line structured light. Through field and indoor experiments, they compared three laser centerline extraction methods: extreme value, grayscale centroid, and the Steger algorithm. The grayscale centroid method demonstrated optimal performance, balancing low processing time (16 ms) with consistent memory usage and environmental stability. Additionally, their analysis revealed that image capture frequency positively influences 3D reconstruction quality, while platform movement speed has a negative impact, affirming the feasibility of real-time DT-based soil modeling. In contrast, Tsakiridis et al. [155] introduced a conceptual and architectural framework for a cognitive soil DT system capable of integrating diverse datasets to simulate ecosystem services. The study emphasized challenges such as data integration, model accu- racy, and privacy, while also highlighting opportunities for policy evaluation, sensor innovation, and enhanced soil monitoring. The call for an open-source, collaborative infrastructure reinforces the impor- tance of transparency and cross-disciplinary engagement. From the reviewed studies, it is evident that the majority of smart irrigation systems adopt a fully integrated Digital Twin architecture, enabling real-time sensing, data-driven decision-making, and automated actua- tion. However, a considerable number of implementations in irrigation and soil management are based on digital shadow, which focus primar- ily on data acquisition and monitoring, lacking closed-loop control and bidirectional communication.

5.3. Digital twin in crop monitoring and cultivation support

Within the context of crop health monitoring, DTs enable the timely identification of stress factors, such as insufficient intake of nutrients, lack of water, or the presence of pathogens, by means of continual analysis of sensor data. This allows for prompt responses that can reduce any reductions in yield. In addition, digital twins enhance accurate pest and disease management by combining data on pest populations, environmental conditions, and crop susceptibility [109,166]. This integration aids in the creation of focused and efficient control strategies. Estimating yields is another crucial issue in which digital twins provide significant advantages. Digital twins have the capability of accurately predicting possible agricultural yields by modeling the growing pattern of crops under different situations. The predictive capability is improved by the continuous feedback loop between the real and virtual worlds, enabling the calibration and validation of models using real-world data. However, DT applications in crop monitoring predominantly adopt a digital shadow approach, focusing on data collection and analysis for environmental and crop health parameters, with limited integration of real-time control or closed-loop feedback.

Madeira et al. [166] utilized DT technology to efficiently monitor the land and plants of small and medium scale farms. Through DT environment, effective plant disease prediction was carried out with the help of multi-sensor data. The study introduces the TWINSOR concept with mixed reality that utilizes a range of sensors, including satellite images. An ML-based data analysis service was employed to analyze and make strategic decisions. The system is collaboratively created with stakeholders to guarantee its benefits to farmers. Us- ing technologies such as TWINSOR, small-scale agricultural operations have opportunity to enhance performance and minimizing the use of pesticides. In another promising study, Mummaneni et al. [167] employed digital twins for the paddy field to assess the health and nutrient requirements. An extensive 3D model was created in the study that included strategically positioned sensors to collect real-time data on pH, EC, humidity, moisture, NPK levels, and visual data using cameras. A model combining CNN and EfficientNetB1, optimized with an Adam optimizer was trained to accurately identify diseases and nutrient deficiencies. The digital twin employs remote sensing, data analytics, and IoT devices for producing instantaneous monitoring and examination of crop health and nutrient concentrations. In another study, Angin et al. [79] proposed a digital twin framework, AgriLoRa, that utilizes a wireless sensor network installed on farms for crop monitoring. This WSN is combined with cloud servers that employ computer vision algorithms to identify plant diseases, weed cluster, and nutrient deficits. In order to assess the viability of precise plant disease diagnosis, the authors carried out initial tests utilizing agricultural vision datasets and computer vision modelsMobileNet and UNet. AgriLoRa demonstrates potential as an affordable and accurate smart agriculture solution, catering to the growing need for high-yield produce among farmers worldwide. Onwude et al. [168] developed a mechanistic-driven DT of the fruit growth process to identify how weather variations between growing locations affect Valencia orange quality at harvest. Daily data on temperature, humidity, rainfall, solar radiation, and wind speed is included in the digital model. The findings show that several quality parameters of oranges are significantly impacted by the local meteorological conditions. The study also brought to light how the growing process affects the temperature gradient inside the fruit.

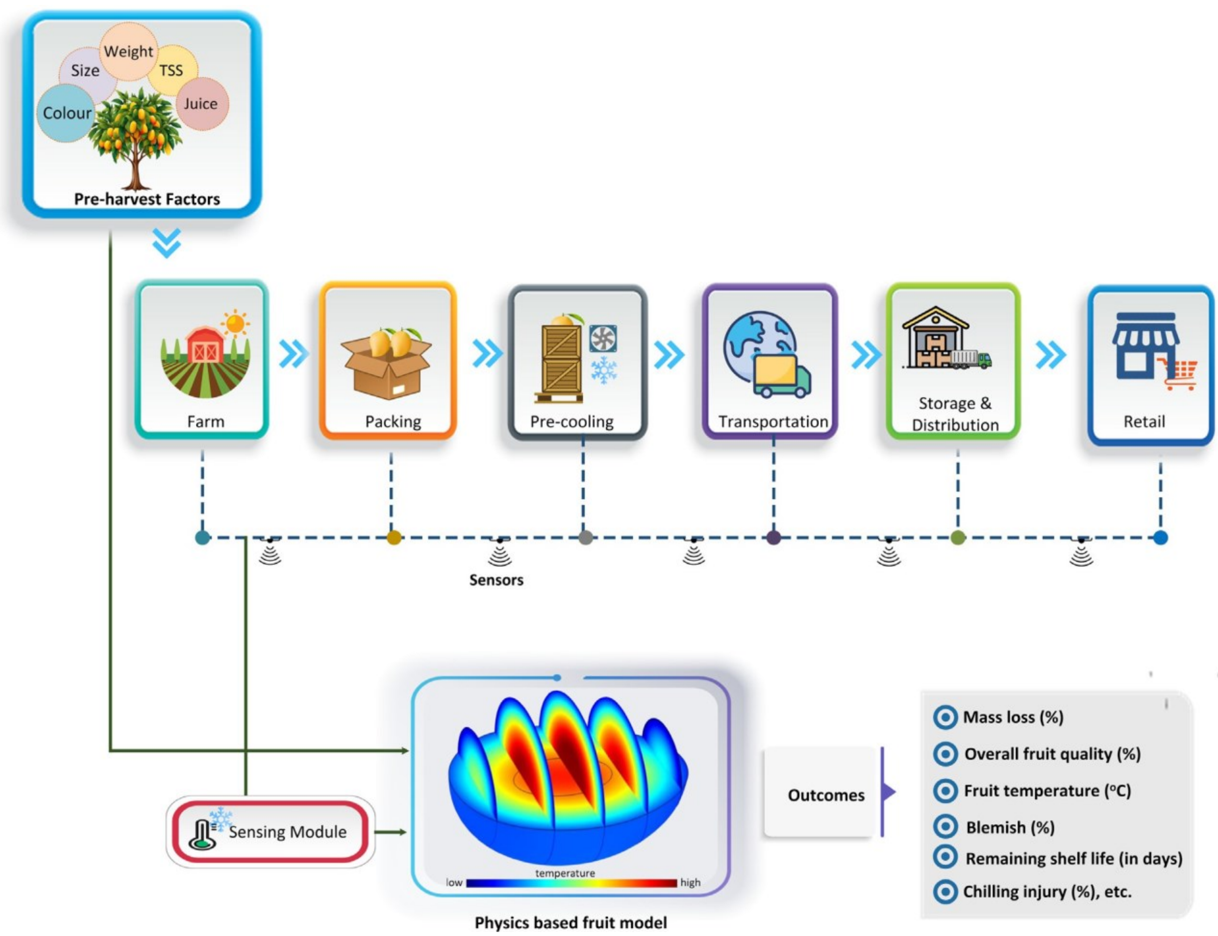
Khatraty et al. [169] proposed a DT architecture for rice field management that integrates IoT sensors, satellite data, and deep learning models to predict yield, weather, and soil conditions. Their approach enhances decision-making by providing farmers with real-time insights and future directions such as rice classification and light intensity measurement using specialized sensors. In another study Archambault et al. [170] proposed a modeling methodology to bridge the gap between agronomists and growers in controlled environment agriculture by linking crop phenology with morphology. Their approach generates 3D visualizations of crop morphology from phenological models to support prescriptive digital twin operations. Applied to vertical strawberry farming and field-grown canola, the model showed promising results for strawberries but required refinement for canola. The study highlights the need for better calibration and morphological state continuity for real-time and autonomous digital twin applications. Skobelev et al. [171] introduced an ontologically driven multi-agent digital twin of plants (DTP), designed to simulate the crop production process by considering physiological, morphological, and technological parameters. The architecture features a dynamic knowledge base and allows for real-time crop and variety changes without reprogramming. Their prototype system, validated through experimental cultivation, supports multi-crop adaptability and regional decision-making for agronomists. In another related study, they extended the DTP by incorporating environmental and resource-based models to enhance accuracy at various plant growth stages [172]. Chunjiang et al. [173] leveraged large language models (LLMs) within a DT framework to model vegetable crop growth, overcoming the limitations of traditional rule-based systems. Using high-resolution sensor data and intelligent agent ensembles, their system achieved high accuracy in predicting growth stages and conditions, demonstrating significant improvements over conventional models.

Research has demonstrated substantial progress in the field of crop development [176,177], crop monitoring [109,178–180], and cultivation support, emphasizing the possibility of enhanced productivity and environmentally friendly farming practices.

5.4. Digital twin in post-harvest operations

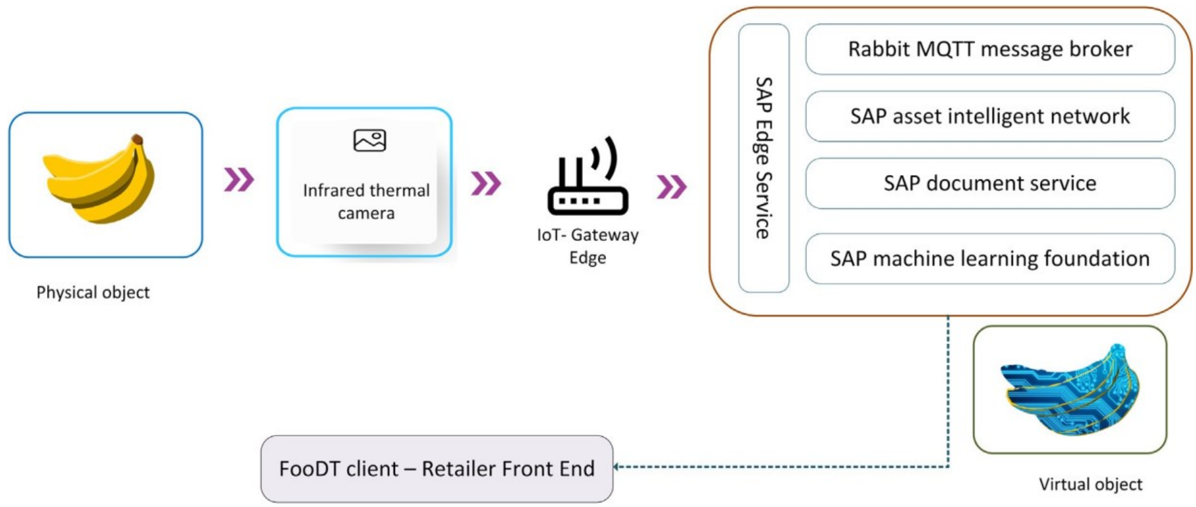
The digital twin used in post-harvest operations may combine up-to-date information, historical data, and predictive modeling to enhance the efficiency of handling, preserving, and transporting agricultural produce [181,182]. DTs allow for accurate monitoring and management of the post-harvest environment by replicating it digitally, including parameters like temperature, humidity, and storage conditions. This ensures the product's quality and safety. Additionally, DT aids in the execution of sophisticated management systems to mitigate post-harvest losses, a major issue in the agricultural industry. Through the process of simulating various situations, stakeholders can predict future problems and take proactive measures to address them. For instance, DTs can replicate the impact of different storage conditions on the shelf-life of perishable goods, enabling real-time adjustments to ensure the optimal possible conditions. Moreover, these models can aid in the efficient scheduling and routing of transportation, minimizing delays and preserving the quality of the produce during transit [183,184]. In addition, digital twins facilitate traceability and ensure compliance with food safety requirements by preserving a comprehensive, digital record of all post-harvest processes. This feature is especially vital in cases of contamination or spoiling, since it allows for quick detection and separation of impacted batches, hence reducing the impact on the supply chain.

DT technology shows great potential for optimizing and improving the efficiency of fruit and vegetable supply chain management [175, 185–187] by providing real-time monitoring, predictive analytics, and data-driven decision-making capabilities. In general, digital Twin implementations for fruit condition monitoring typically follow a partially integrated approach, often characterized as digital shadows, where unidirectional data flow enables monitoring, predictive modeling without real-time control or feedback mechanisms. Defraeye et al. [175] developed a digital fruit twin using mechanical modeling and with reference to the recorded environmental temperature, this DT mimics the thermal behavior of mango fruit across the cold chain. Understanding, recording, and this strategy greatly simplifies the prediction of temperature-dependent deterioration in fruit quality across every stage of the supply chain. In another study, Shoji et al. [188] utilized a physics-based DT to manage the hygrothermal conditions around fresh



/ig. 9. Framework of a physics driven digital twin in transport chain of fresh horticultural produce [174] (image of mango fruit digital twin adapted from Defraeye et al. [175])

fruits and vegetables in order to improve their preservation (Fig. 9). As conventional temperature monitoring in cold chains often takes place just from the supplier to the distribution center, the authors expanded the monitoring of temperature across the whole cold chain. From pre-cooling to retail, the thermal data was converted into meaningful measures using physics-based DTs. The analysis examined 331 cold-chain shipments of cucumbers, eggplants, strawberries, and raspberries. The research included thermal data into digital twins to accurately measure mass loss, fruit quality, and remaining shelf life. Similar to this study, Onwude et al. [174] also studied regarding physics-based DTs to address variability in fruit quality while arriving at retail. A Markov Chain Monte Carlo (MCMC) approach was utilized to create a virtual population of 1,000 individual orange fruits during harvest. After that, multiple orange quality parameters such as mass loss, fruit quality index, shelf life remaining, injury severity due to chilling, etc, were assessed with respect to pre-harvest conditions. Additionally, their variations in hygrothermal conditions during transportation was also studied. Zhang et al. [189] presented a physical twin model for accurately simulating and monitoring kiwifruit core temperature during postharvest pre-cooling. By analyzing six fruit characteristics across two kiwifruit cultivars, fruit weight and volume were identified as key factors influencing pre-cooling efficiency, while physiological traits had lesser impact. A physical twin, constructed using specialized clay and soil, achieved high accuracy in replicating core temperature dynamics. Integrated with real-time detection and wireless transmission, the model offers a precise and intelligent solution for core temper- ature monitoring, supporting improved pre-cooling management and long-term storage of kiwifruit. Maheshwari et al. [190] proposed a DT-based framework to integrate procurement, production, and distribution (PPD) strategies in a medium-scale food processing company. Using mixed-integer linear programming (MILP) and agent-based simulation (ABS), the study captures the interactions among suppliers, manufacturers, and customers under operational constraints. The approach enhances supply chain performance by improving scheduling, reducing lead times, and minimizing data redundancy. It also strengthens overall operational and equipment effectiveness while supporting real-time decision-making. In another study, Nair et al. [191] introduced a novel, low-cost digital twin framework for food safety using monocular depth estimation and mixed reality (MR) technologies. The system reconstructs 3D models of fresh produce from single 2D images and enables interactive visualization in the Unity MR environment, including deployment on Microsoft HoloLens 2. The approach accurately assesses surface degradation such as bruising, allowing dynamic monitoring of quality deterioration. The integration of Global-Local Path Networks (GLPN) enhances depth perception, while the mesh-overlay technique aids in visualizing structural compromise. Melesse et al. [137] performed an investigation in the field of postharvest engineering aimed at reducing fruit waste by monitoring and estimating the conditions of fresh fruits throughout their lifecycle. The study described a DT as a virtual replica of real produce. A thermal camera was employed as a data collection tool because of its capacity to detect surface and physiological changes in fruits during storage. The collection of thermal data, categorized into four distinct groups, was utilized to train the model using advanced intelligence technologies provided by SAP (Fig. 10). A deep CNN was utilized to monitor the fruit's condition using temperature data, resulting in a remarkable prediction accuracy



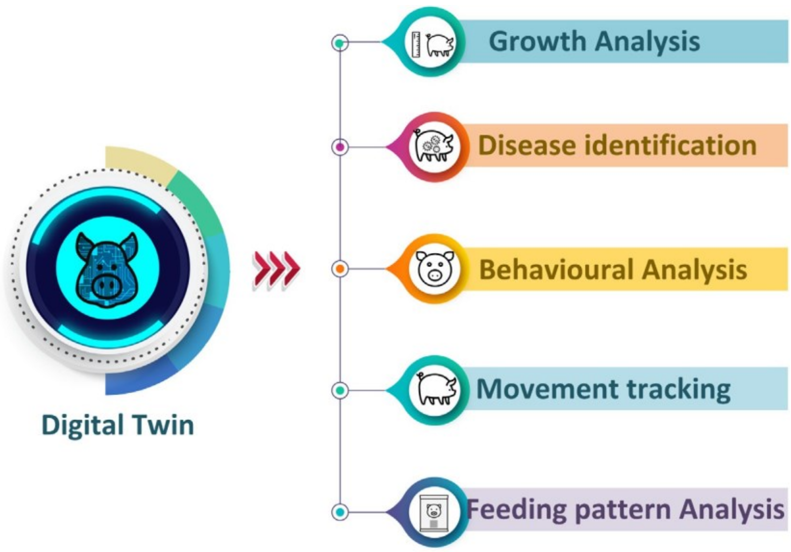
/ig. 10. Architecture for fruit based digital twin developed by Melesse et al. [137].

of 99%. This innovative method showcases the possibility of creating efficient digital replicas of fruits. From cold chain logistics to pre-cooling and food safety, DTs offer scalable, data-driven solutions suited to various types of produce and operational needs. The integration of physics-based models and real-time data enhances transparency, traceability, and operational efficiency. As adoption progresses, digital twins are expected to play a key role in strengthening post-harvest management systems.

5.5. Digital twin in livestock monitoring and management

Animal welfare, productivity, and operational efficiency are all being improved by the increasing use of DT technology in livestock monitoring and management [192,193]. DTs are capable of simulating and predicting animal health status, and interactions. Through the use of sensors to track body temperature, heart rate, activity levels, and dietary intake, the DT can offer a thorough understanding of the physiological and behavioral conditions of livestock. Through the processing of this data by advanced algorithms, diseases, stress, and other health problems may be detected early, allowing for prompt treatments and lowering morbidity and death rates. Digital twins also offer a platform for maximizing feeding schedules, housing conditions, and general farm management procedures by simulating various management techniques and climatic situations.

DTs used in livestock management also back precision farming initiatives, which improve resource usage effectiveness and efficiency through data-driven choices. Better land, water, and feed management as a result supports more sustainable methods. Additionally, the continuous feedback loop created by the digital twin allows for dynamic adjustments to management practices, ensuring optimal conditions for animal welfare and productivity. Fig. 11 shows some of the promising application areas of DT in livestock management. Several studies have explored the application of digital twin technology in livestock monitoring and management. Zhang et al. [138] presented a DT architecture for cows with the objective of enhancing animal welfare and production efficiency. The system classifies feeding and non-feeding behaviors using data from inertial measuring units (IMUs) and indoor positioning data. A custom-made collar integrated with Ultra-wideband chips and inertial measurement units (IMUs) was placed on the five healthy non-lactating Holstein cows for collecting accurate and real-time location and movement of the neck. Machine learning models SVM, KNN, and LSTM were employed for classifying cow behavior. The client interface in the system offered a user-friendly approach for the stakeholders to manage the cows, including notifications for abnormal circumstances to improve reaction times and operational effectiveness. In another study, Zhang et al. [193] developed a multimodal data fusion framework to construct a cow digital shadow. This shadow was able to understand key behaviors such as drinking, feeding, lying, standing, and walk- ing. The data from inertial measurement units (IMUs) mounted on custom-made collars and video feeds from barn cameras were utilized and through which both motion and visual modalities are captured. Deep learning models viz., EfficientNet, BiLSTM, and Transformer architectures were employed to enhance behavioral classification. The approach demonstrated substantial improvements in behavior recognition compared to single modality methods. In a similar study on cattle, Han et al. [32] utilized the DL model, LSTM to predict the physiological cycles and real-time monitoring. The work utilized a farm IoT system and sensor-generated data to remotely monitor and track cattle, generating a digital twin model based on DL. Studies show that DT Livestock farming has achieved success rates of 92%, 94%, and 94% success rate in estimating the heart rate [194]. The HVAC system in pig houses plays a crucial role in optimizing the atmosphere to promote pig growth, therefore improving production efficiency (heating, ventilation, and air conditioning). Jeong et al. [195] performed research investigating the influence of DT technology on HVAC systems in pig houses, with a special emphasis on enhancing production. In order to assess the effectiveness of the digital twin structure in the pig house, a series of simulations were performed utilizing real-world datasets. The results showed that the use of DT-based dynamic simulation analysis not only delivered energy-efficient solutions during the design phase but also offered valuable insights into optimal HVAC system control that can be applied during real-time operation. Petrov and Atanasova [196] investigated the application of augmented reality (AR) and virtual reality (VR) technologies in animal husbandry education and management. They proposed a framework that integrates the Five-Domain Model with Precision Livestock Farming (PLF), enabling the creation of 3D virtual models of barns and animals using data from IoT sensors. These immersive digital resources serve multiple purposes from providing safe and humane educational environments to enhancing the professional experience of breeders. In addition, the framework incorporates AI-driven monitoring to detect anomalies and suggest corrective measures, contributing to proactive animal welfare management. In another study, Raba et al. [197] through the IoFEED project, implemented a digital twin approach to optimize animal feed supply chains. By deploying sensors in farm bins to collect real-time inventory data, and combining this with advanced optimization techniques, the study addressed logistical challenges such as feed type compatibility, depot constraints, and biosecurity considerations. Jo et al. [198] presented a design approach for a smart pig farm that uses digital twin technology to enhance animal well-being. The proposed framework consisted of a



/ig. 11. Key application area of digital twin in livestock management.

digital farm engine and a digital farm framework layer. The purpose of the digital farm engine layer is to evaluate livestock farms based on specified criteria. This layer consists of four components: modeling and analysis, simulation, big data, and visualization. On the other hand, the primary function of the digital farm's framework layer is to regulate the communication among sensors and devices installed in physical animal farms.

Despite being in its nascent stage, DT technology for livestock management has shown promising progress, with significant work underway to improve the productivity [194,199,200]. These ongoing studies indicate a strong momentum toward the adoption and advancement of DTs in livestock management [196,201].

5.6. Digital twin in agriculture machinery

The use of digital twin technology in farm machinery signifies a notable progression in intelligent farming [78,202]. Crop production machinery, including tractors, harvesters, and robots, can employ digital twins to gather and analyze real-time data. These digital twins constantly monitor and describe the conditions of their physical counterparts [203,204]. This feature enables prediction and recommendation of solutions based on the gathered data, enhancing performance and minimizing fuel and energy usage. Through the utilization of big data analytics [205,206] and AI models, DTs have the ability to identify possible machine malfunctions before or as they happen, hence reducing downtime and minimizing expenses associated with maintenance. Furthermore, the utilization of efficient edge-computing systems in combination with digital twins minimizes delay by restricting the volume of transferred data, guaranteeing prompt and precise information flow. This technology facilitates instantaneous monitoring and decision-making and improves the efficiency of autonomous robots, harvesters, and tractors. Digital twins aid in the maintenance of equipment performance by anticipating and resolving problems before they worsen, hence minimizing waste and emissions caused by machinery malfunctions and inefficiencies. Yin et al. [207] proposed a lightweight, network-based digital twin system for combine harvesters to overcome limitations posed by traditional systems that rely on large-scale physical engines and lack the ability to model complex transmission components. Their framework integrates physical modeling, real-time data interaction, and human–computer interfaces to enable precise simulation and fuel consumption prediction, exemplified through the Lovol GM100 combine harvester.

For efficient robotic harvesting of delicate fruits like raspberry fruit, Junge et al. [208] presented an innovative approach. Soft robotic technology was used along with a sensor embedded physical twin for the harvesting purpose. This approach is an extension of digital twin to the physical domain and was utilized for training the robotic harvester in the labs. This simulator enables direct comparisons with human demonstrations and facilitates refinement of robot controls. This system showed 80% of success rate with the robot that was taught in the lab. This technique is beneficial in efficient design and optimization of harvesting robot with cost-effectiveness and improving precision. Nemtinov et al. [209] developed digital replicas of agricultural machinery, with a specific emphasis on integrated units used for seed preparation and planting. The authors provide a hierarchical framework for the DT model that consists of multiple parts. It included parametric 3D geometric models, individual units, techniques, mechanisms, and components, along with the associated attributive data. The study showed the development of a full DT architecture that precisely represents and effectively analyzes complex agricultural machinery using digital means. This strategy is helpful in improving the design, maintenance, and operating efficiency of agricultural machines. In another study, A DT based robotic system was developed by Malik et al. [210] for precision weed removal in carrot fields using laser technology. Gazebo-ROS was used for implementation and the manipulator was designed with four degrees of freedom to ensure targeted weed elimination with high spatial accuracy. Their work demonstrated the feasibility of DTs for environmentally sustainable agricultural interventions. In a similar study, Flores et al. [211] attempted to address the challenge of creating realistic digital farm environments for robotic simulation. The proposed method was semi-automated method and generated a detailed tomato farm models compatible with ROS 2 in both Gazebo and Unity. Their open-source contribution provides a parameterizable DT environment for enhanced AI-based sim-to-real transfer.

Recently, there has been an increasing interest in user-centered design methods in the creation of machines, employing immersive technologies like VR and MR. These technologies enable the development of digital prototypes that include user feedback throughout the product design phase. Moser et al. [212] developed an interactive digital twin utilizing mixed-reality technology to replicate tractor driving. This allows for the involvement of actual users in the early evaluation of user experience (UX). The purpose of this transdisciplinary approach is to verify the design of the control dashboard for the tractor. The outcome of this study is an MR simulator that integrates virtual material with physical controls, capable of accurately replicating plowing tasks. This cutting-edge simulator improves the design process by enabling designers and engineers to collect crucial user input in the early stages, therefore enhancing the overall usability and effectiveness of the agriculture machinery.

The implementation of DTs in agricultural machinery significantly contributes to sustainable farming practices by facilitating the implementation of predictive maintenance and enhancing the efficiency of machinery operations [35,45,213–215].

6. Discussions

The present study is structured around key research questions that shape the scope and depth of this review. RQ1 addresses the significance of integrating digital twin (DT) technology into modern agricultural practices, aiming to uncover the core motivations behind its adoption in this domain. This study highlights how the agricultural sector is increasingly confronted with environmental uncertainties, resource inefficiencies, and labor shortages. In response to these pressures, digital twin technology is presented as a potential approach that enables real-time, data-driven decision-making through the continuous synchronization of physical systems with their virtual counterparts. The enabling technologies defined in this study form the technological backbone of digital twin systems in agriculture. Together, they empower DTs to function as dynamic, high-fidelity virtual replicas of physical farming environments, capable of simulating, predicting, and controlling agricultural processes with remarkable precision. Beyond immediate productivity gains and resource optimization, the value of digital twins (DTs) in agriculture extends to broader objectives such as enhancing climate resilience and improving operational adaptability. In an era of increasing climatic variability, DTs provide a powerful framework for simulating diverse environmental conditions and proactively adjusting farm operations. For instance, a DT-enabled automated irrigation system can integrate real-time weather forecasts, soil moisture data, crop growth stages, and evapotranspiration rates to autonomously regulate water delivery. This ensures that crops receive precise amounts of water when and where needed, minimizing over-irrigation or water stress. Such closed-loop systems not only conserve water resources but also help stabilize yields under erratic weather conditions, demonstrating how DTs enable agriculture to shift from reactive to predictive and adaptive management practices. Looking ahead, the incorporation of emerging enabling technologies is expected to further elevate the capabilities and reach of agricultural digital twins. As discussed in the enabling technologies section, emerging tools like blockchain, federated learning, and TinyML have huge role to play in advancing the effectiveness and accessibility of agricultural digital twins. The RQ2 explores the major transformations DTs can bring to the sector by uncovering their potential applications across diverse farming activities. While RQ1 sets the rationale for why DTs matter, RQ2 shifts the focus to how they can drive change at scale. As demonstrated throughout the review, their applications span precision irrigation, crop modeling, greenhouse automation, and even livestock health monitoring, highlighting the diverse ways DTs are being utilized in agricultural systems. Another key observation from the reviewed literature is that the analytical and decision-making capabilities within most digital twin frameworks in agriculture are predominantly driven by machine learning and deep learning models. Among these, convolutional neural networks (CNNs) are the most commonly employed, particularly in applications involving image-based analysis.

As seen across application areas like soil monitoring, livestock tracking, and crop health assessment, the dominant architecture is that of digital shadows, where sensor data is collected, visualized, and sometimes analyzed, but with little or no autonomous feedback loop to influence physical systems in real time. This observation aligns with the findings of Purcell and Neubauer [50], whose study indicates that partially integrated systems – or digital shadows – constitute the majority of implementations across current agricultural research and practice. Their analysis emphasizes that while these systems do not fulfill the complete criteria of a digital twin, they nonetheless represent a critical phase in the technological adoption curve. However, rather than being viewed as limitations, these early-stage implementations offer valuable insights into the developmental pathway of digital twins. They serve as stepping stones that reveal the technical, organizational, and contextual requirements needed to evolve toward fully functional digital twins. Moreover, the dominance of digital shadows underscores the importance of incremental development and modular system design, especially when applying digital twin concepts to new and diverse agricultural applications. This limitation arises primarily because agriculture, as a domain, is still in the early stages of adopting the high levels of cyber–physical integration required for full digital twin functionality. These systems largely serve as decision-support tools for human operators rather than fully autonomous control systems. Nonetheless, these partially integrated systems still provide meaningful value. For instance, platforms that combine crop growth models with weather and phenological data help optimize yield predictions and guide decisions around irrigation and fertilizer use, demonstrating tangible benefits even without full bidirectional feedback. However, there are emerging applications that increasingly adopt true digital twin with bidirectional communication. For example, automated irrigation systems represent a notable advancement, where soil moisture data is not only monitored but also used to trigger real-time adjustments in irrigation schedules through actuators, closing the loop between sensing, decision-making, and action. Similarly, harvesting robots equipped with real-time imaging and decision systems adjust their behavior based on dynamic crop conditions, such as ripeness or spatial orientation, reflecting a true twin architecture. In precision greenhouse management, digital twins are employed to monitor parameters like temperature, humidity, and CO_2 levels, and then autonomously control heating, ventilation, and nutrient delivery systems to maintain optimal growth environments. These examples illustrate that while the majority of current systems are still operating as digital shadows due to infrastructural and contextual limitations, there is a growing body of applications moving toward the full integration required for digital twin functionality. RQ3, which explores the challenges and implementation barriers of digital twin solutions in agriculture, is also systematically addressed in this study. The discussion highlights several critical obstacles that hinder widespread adoption, including infrastructural constraints, lack of data and system interoperability, high deployment and maintenance costs, and the limited technical expertise available. Collectively, the research questions RQ1, RQ2, and RQ3 have guided a structured exploration of the importance, true potential, and implementation barriers of digital twin technology in agriculture.

7. Key performance indicators for agricultural digital twin

Key performance indicators (KPIs) are critical assessing the efficiency of DTs in the field of agriculture. This section examines five essential KPIs viz., productivity, product quality, cost savings, resource utilization, and user satisfaction (Fig. 12). Every Key Performance Indicator (KPI) provides different perspective in order to assess the influence of DT technology and are well inter connected.

- **Productivity**: The productivity KPI helps in assessing the efficiency related to maximizing agricultural output, enhancing resource utilization, and optimizing labor and machinery usage. DTs can improve overall output by offering accurate yield estimation method and suggest the best technique to achieve it. They provide better monitoring strategies which allows farmers to make effective decision making for improved crop management. For example, the soil quality and weather conditions can be monitored using DTs and the best suitable time for sowing and

/ig. 12. Key performance indicators for digital twin.

harvesting can be predicted and thus, crop can grow in ideal conditions. Further, pest outbreaks and nutrient deficiencies can be detected at the early phase for minimizing the loss.

- **Quality of Product**: The quality of a product describes the excellence of agricultural produce. Digital twins are essential for monitoring and enhancing crop quality by offering in-depth analysis of different development parameters. They monitor and evaluate data related to soil composition, water quality, weather conditions, and crop health, allowing farmers to uphold ideal growth conditions. For instance, a digital twin can assist in modifying irrigation schedules and fertilizer applications to guarantee that crops receive the appropriate quantity of water as well as nutrients when required. This precision farming method leads to the production of crops.
- **Cost Savings**: Cost saving is a crucial KPI for digital twins in agriculture, reflecting the reduction in expenses associated with farming operations. Although the implementation of DT technology in agriculture involves a significant initial setup cost, the long-term economic benefits often outweigh these upfront investments. By employing digital twins, farmers may analyze and optimize the utilization of resources, deployment of labor, and workflows, resulting in substantial cost reductions. DTs facilitate the identification of potential issues and the recommendation of cost-effective measures by offering real-time data and predictive analytics. Moreover, digital twins can contribute to the reduction of machinery downtime by accurately forecasting maintenance requirements and strategically planning repairs in advance.
- **Resource Optimization**: Resource optimization KPI quantifies the effective utilization of resources such as water, fertilizers, insecticides, and energy in farming operations. Digital twins enhance resource optimization by offering comprehensive, up-to-date knowledge regarding the requirements and state of crops. They allow the implementation of precise agricultural techniques, guaranteeing the efficient and wise use of resources. Digital twins not only optimize input utilization but also contribute to decreasing energy consumption by providing recommendations for energy-efficient agricultural techniques and machinery usage.
- **User Satisfaction**: User satisfaction KPI measures the efficiency and usability of DT solutions from the viewpoint of farmers and other stakeholders. A high level of user satisfaction signifies that the system is user-friendly, straightforward to navigate, and offers significant data that improves farming operations. In order to attain high levels of satisfaction, DTs must provide clear and practical advice, and they should be available through user-friendly interfaces. Training and support services play a vital role in assisting users to optimize the use of DT technologies. experience.

8. Challenges and future directions

The integration of DTs into agriculture presents significant challenges that must be tackled in order to achieve successful implementation. Agricultural stakeholders encounter issues that necessitate robust technology solutions and organizational preparedness, such as integrating IoT sensors in diverse farming situations and efficiently processing and modeling large-scale data. Some of the prominent challenges of agricultural digital twins are listed below.

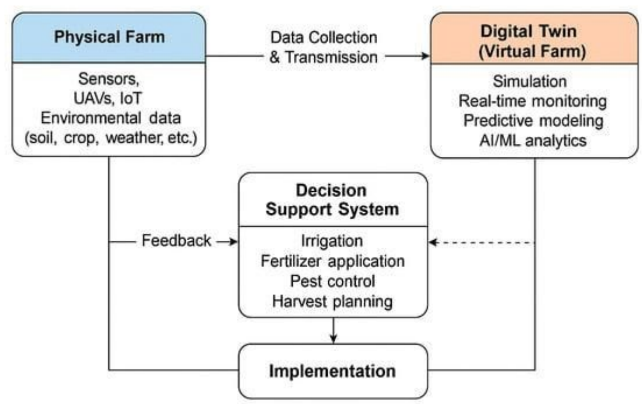
- **Interoperability of components:** The various equipment, soft- ware and hardware platforms used in agriculture are created by different vendors. For this reason, it is necessary to ensure the smooth integration for the effective implementation of the DTs. The efficiency of data collection and analysis heavily depends on the differences in data formats, protocols and standards used for data exchange, etc. Standardized protocols are hence essential. The pre-existing farm management software and databases are also a key hindrance in migration. Most of the farms already using specialized software for different activities. Interacting with these existing systems while developing DT is a challenging task. Hence, it is essential to adopt interoperability frameworks which can align with agricultural standards such as ISO 11783 (for tractor–implement communication) [216,217] and agroXML (for farm data documentation) [218,219]. Developing open source middleware solution can be beneficial. Approaches like development of plug-and-play modules that can standardize data across different components can also be effective. This can help small and mid-size farms to achieve interoperability with DT technology without sophisticated components. Development of region-specific ontologies can also potentially benefit DT platforms to understand domain-specific parameters effectively.

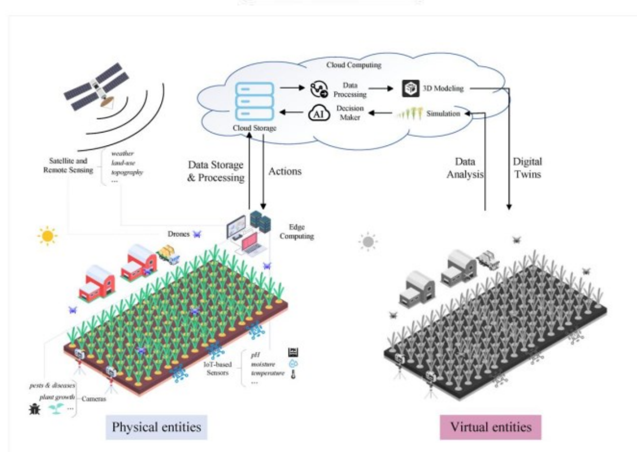
- **Synchronization of Technology and Asset Lifecycles:** Agricultural assets such as tractors and storage facilities have long life spans compared to the software and digital tools. This difference in lifecycle affects the stability of DT systems. The software used for design and simulation may become obsolete. This makes the DT system incompatible with new systems. The maintenance and upgradation of obsolete software and data formats used for the creation of digital twins are always cumbersome. Vendor lock-in is also another prominent issue where the agricultural stakeholders rely solely on one software to provide support. Additionally, when the vendor stops providing support or makes major changes to the software, it can cause issues with the performance of DT. This can also result in operational inefficiency. To tackle all these, modular DT architecture needs to be promoted, and modern data formats like JSON can be used. Establishing long-term service level agreements with software vendors can also ensure continued support. Maintaining open source DT reference models for common assets can also benefit small and medium-sized farms in faster adoption and extension.
- **Technological maturity and understanding:** There are significant gaps in understanding the potential and benefits of DT for individuals and industries [220]. The realization of Digital Twins is driven by the integration of multiple enabling technologies mentioned earlier. As these technologies continue to emerge and are still in stages of development, they affect the progress of DT. Additionally, selecting the appropriate platform from a large pool of DT implementation software requires a comprehensive knowledge of the capabilities of each choice and how they correspond to specific agricultural requirements. To address these gaps in the agricultural domain, capacity-building programs specific to different user groups should be developed. These can include region-specific digital twin demonstration pilots that allow hands-on experience and contextual learning. Moreover, development of farmer-friendly visual dashboards and local-language interfaces can help in solving this challenge.
- **Cost and infrastructure requirements:** Coupling DTs in agricultural application involves initial setup cost. This covers the expenses associated with purchasing IoT sensors, data storage and other infrastructure setup cost. Farmers often have limited resources and they operate on a small scale and this high initial cost might prevent them from adoption of new technologies. Maintaining or upgrading the existing infrastructure to accommodate drastically changing technology needs is also difficult. In order to address this, a shared service model can be developed. In this, the farmers can access the different infrastructure through collaboration between government agencies, private companies and other agencies. The adoption of low-cost, open-source hardware along with energy-efficient communication protocols like LoRaWAN can also help for cost-effectiveness. Establishing local fabrication ecosystems, supported by rural innovation hubs or agri- tech incubators is also beneficial. Additionally, integrating digital twin platforms with existing agricultural extension networks and mobile applications can extend their benefits without requiring significant new infrastructure. Policy interventions includ- ing subsidies for smart farming technologies and improved rural connectivity, can play a critical role in accelerating widespread adoption.
- **Latency:** Time latency is a crucial challenge in the deployment of agricultural digital twins. Most of the applications require real-time monitoring and rapid response. Accuracy and timeliness of decision making and the overall efficiency of digital twin are very much dependent on this. This issue is severe in traditional cloud-based architectures. The data must travel to and from centralized servers and this introduces communication delays. Edge computing is a panacea for this, where the data processing is made closer to the source, at the field level. This reduces latency and enables fast data processing and better synchronization between the physical and digital assets. Edge computing reduces the load on cloud servers by processing the critical tasks gets carried out at the edge. The system reliability is also maintained by carrying out the essential tasks even during the network failures. This Edge device, often combined with light weight AI models can help in generating intelligent decisions without relying on the cloud platforms and only the essential or high priority data will be transferred to the cloud. Handling latency is of paramount importance in the development of digital twins.
- **Privacy and Security Concerns:** Agricultural digital twins create massive volumes of data from various sources. Managing and analyzing this immense data to generate meaningful insights is difficult. Agricultural data generally includes sensitive information regarding farming approaches employed, land usage, yield information, pesticide usage, and personal data of farmers. This data must be kept private and unauthorized access to agricultural data can result in serious consequences. Since the data is stored and processed on linked networks and cloud, DTs are vulnerable to attacks such as malware, phishing and data interception. Protecting agricultural data from unauthorized access and manipulation requires strong cybersecurity measures including encryption, access limits, and security audits. To address these challenges in agriculture, approaches such as federated learning and blockchain can be leveraged to enhance data privacy, ownership, and traceability without compromising analytical capabilities. These technologies allow data to remain decentralized, reducing the risks associated with central storage and unauthorized access. Smart contracts can formalize data-sharing agreements, ensuring that stakeholders retain control over how their information is accessed and used. Agricultural data hubs managed by public institutions or cooperatives can adopt role-based access controls to protect sensitive datasets. Complementing these technical safeguards, cybersecurity awareness programs for farmers and agri-tech workers – along with simplified, user-friendly privacy dashboards – can help improve digital literacy, build trust, and enable informed decision-making.

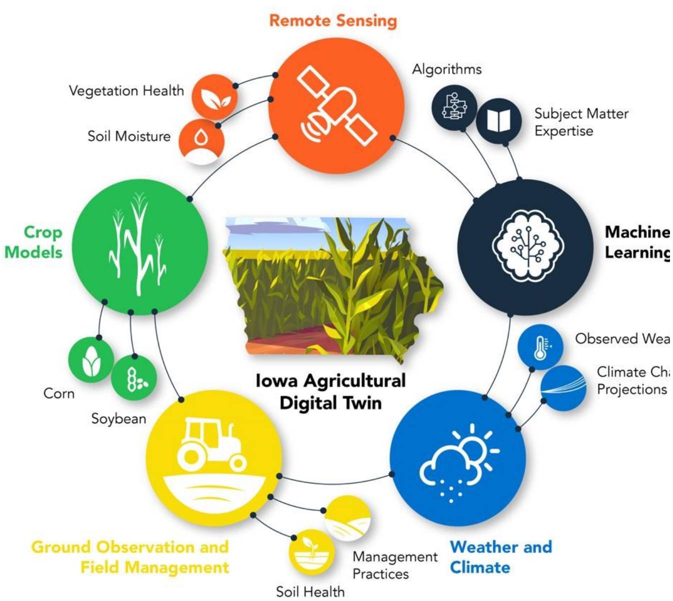
Future research in agricultural digital twins must evolve from siloed, task-specific applications toward efficient, secure, and intelligent systems that span the entire agricultural lifecycle. One foundational need is the development of advanced digital twin definition languages (DTDLs), such as Microsoft's DTDL, that go beyond static entity descriptions to include dynamic property management, service orchestration, and context-aware behavior [221]. In agriculture, these languages should be able to semantically represent complex crop types, soil variations, climatic zones, machinery usage patterns, and lifecycle processes. Such formalism would enable seamless integration of DTs with IoT-based sensor networks, actuators, and cloud–edge infrastructures. Moreover, expanding the role of digital twins across all stages from planning and infrastructure design to operation, adaptation, and decommissioning, can lead to improved lifecycle cost estimation, early risk detection, and long-term resilience of agricultural systems. Modeling is another core aspect demanding significant advancement. Current approaches predominantly rely on black-box, data-driven models such as ANN based models, which often lack transparency and are limited in generalizability. Future DT systems should emphasize hybrid modeling paradigms that combine AI with domain knowledge through physics-based simulations or process-based environmental models. These hybrid frameworks can enhance robustness in real-world agricultural settings, where conditions are dynamic. An important adjunct to these systems is the integration of explainable AI (XAI), which enables interpretability of model decisions. In critical decision areas such as irrigation timing, pest outbreak alerts, or disease classification, transparency is essen- tial for building trust and ensuring informed user engagement. Data privacy, ownership, and integrity are crucial concerns as DTs gener- ate and process vast amounts of farm-level, geospatial, and personal data. Hence maintaining transparency is crucial in digital twin. Future research must continue exploring privacy-preserving architectures, especially federated learning, which enables decentralized training of AI models without transferring raw data. Future research should explore advanced security paradigms such as quantum-resistant cryptography to ensure long-term protection against quantum-enabled attacks, and secure multi-party computation to facilitate privacy-preserving collaboration and analytics among distributed stakeholders. Additionally, the adoption of zero-trust architecture offers a forward-looking strategy to enhance system resilience by enforcing continuous verification and minimizing implicit trust across the digital twin ecosystem. Improving modeling approaches is crucial for enhancing the ability of digital twins in agriculture to make accurate predictions and adapt to changing conditions. Future research should investigate hybrid methodologies that integrate physics-based models with data-driven procedures and other promising modeling techniques such as federated or gossip learning in order to enhance dependability and performance. The research should prioritize the development of context-aware adaptive DTs that can independently adapt to changes in their environment by utilizing adaptive AI and ML methods. Moreover, it is of utmost importance to tackle the difficulties related to interoperability. Research should focus on creating standardized protocols and frameworks that make it easier to exchange data, maintain information, and communicate across different agricultural situations. This involves improving the interoperability across digital twins, IoT devices, farm management systems, and cloud platforms, while also guaranteeing strong data security and privacy safeguards. Addressing data capture, sharing, security, and ownership challenges is vital for completely leveraging the potential of digital twins in agriculture. The research should prioritize the creation of standardized and efficient approaches for integrating data from various sensors, while also assuring integrity, confidentiality, and compliance with regulations. Scalability and equitable access are equally critical. DT solutions must be designed to operate in both high-tech and resource-constrained environments. Lightweight, modular digital twins capable of running on hybrid cloud–edge infrastructures can support real-time operation in rural areas with limited connectivity. The concept of Digital Twin-as-a-Service (DTaaS), hosted via regional agri-cloud platforms and accessed through mobile applications or SMS gateways, offers a scalable model for broader outreach. Equally important is the human–DT interaction layer. As digital twins increasingly influence operational and strategic decisions in agriculture, there must be an emphasis on explainability, usability, and accessibility. Research should focus on integrating multimodal human–machine interfaces, including voice-based interactions, gesture control, and augmented reality (AR) overlays for field-level visualization. Interfaces must be designed for low-literacy, multilingual, and mobile-first user bases to ensure inclusivity.To use farm digital twins responsibly, it is essential to build them correctly from the start. This means making sure they are fair and transparent for everyone. Responsible deployment of agricul- tural digital twins requires well-defined policy, ethical, and governance frameworks. Ethical AI principles should be embedded from the design phase onward for ensuring transparency and fairness.

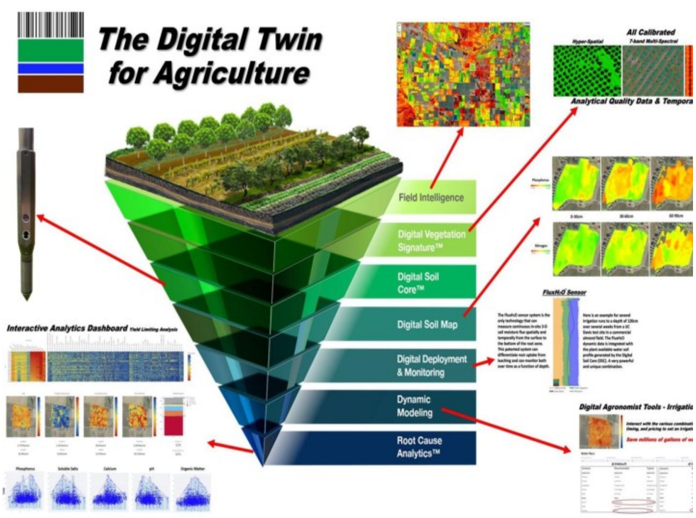
9. Conclusions

This present study emphasizes the vital role of DT technology in promoting a more effective and sustainable agriculture sector. By integrating IoT-enabled sensing, artificial intelligence, and other cutting edge technologies, digital twins offer dynamic, real-time, and interactive representations of agricultural systems. These virtual counterparts enable precise monitoring and control of on-farm processes, thereby optimizing the use of critical inputs such as water, fertilizers, and pesticides while minimizing environmental impact. Moreover, DTs empower data-driven decision-making by providing predictive insights that help farmers proactively manage risks associated with pest outbreaks, weather anomalies, equipment malfunctions, and other operational challenges. Despite these significant benefits, the widespread adoption of digital twins in agriculture faces several hurdles. Key challenges include high initial investment costs, the need for reliable and scalable digital infrastructure, limited digital literacy among end users, and concerns related to data privacy, cybersecurity, and system interoperability. Additionally, the integration of diverse technological components ranging from sensors to cloud platforms requires standardized frameworks and cross-platform compatibility. To fully realize the promise of digital twins in agriculture, future research must prioritize the development of cost-effective, modular, and scalable solutions specific to farms of varying sizes and resource capacities. Emphasis should be placed on improving interoperability through open standards, enhancing user experience through intuitive interfaces, and embedding ethical and privacy-preserving mechanisms into system design. Bridging the gap between advanced technologies and everyday farming practices will be key to enabling widespread adoption and ensuring that digital twins contribute meaningfully to global food security, environmental sustainability, and the digital empowerment of farming communities.









References

[1] I.Y. Odegard, E. van der Voet, The future of food—Scenarios and the effect on natural resource use in agriculture in 2050, Ecol. Econom. 97 (2014) 51–59.

[2] FAO, How to feed the world in 2050. Insights from an expert meet, in: Insights from an Expert Meeting At FAO, vol. 2050, FAO Rome, Italy, 2009, pp. 1–35.

[3] M. Shepherd, J.A. Turner, B. Small, D. Wheeler, Priorities for science to overcome hurdles thwarting the full promise of the 'digital agriculture'revolution, J. Sci. Food Agric. 100 (14) (2020) 5083–5092.

[4] K. Paul, S.S. Chatterjee, P. Pai, A. Varshney, S. Juikar, V. Prasad, B. Bhadra, S. Dasgupta, Viable smart sensors and their application in data driven agriculture, Comput. Electron. Agric. 198 (2022) 107096.

[5] É.L. Bolfe, L.A.d.C. Jorge, I.D. Sanches, A. Luchiari Júnior, C.C. da Costa, D.d.C. Victoria, R.Y. Inamasu, C.R. Grego, V.R. Ferreira, A.R. Ramirez, Precision and digital agriculture: Adoption of technologies and perception of Brazilian farmers, Agriculture 10 (12) (2020) 653.

[6] S. Wolfert, L. Ge, C. Verdouw, M.-J. Bogaardt, Big data in smart farming–a review, Agricult. Sys. 153 (2017) 69–80.

[7] L. Klerkx, E. Jakku, P. Labarthe, A review of social science on digital agriculture, smart farming and agriculture 4.0: New contributions and a future research agenda, NJAS 90 (2019) 100315.

[8] S. Fountas, B. Espejo-García, A. Kasimati, N. Mylonas, N. Darra, The future of digital agriculture: technologies and opportunities, IT Prof. 22 (1) (2020) 24–28.

[9] H. Tian, T. Wang, Y. Liu, X. Qiao, Y. Li, Computer vision technology in agricultural automation—A review, Inf. Process. Agric. 7 (1) (2020) 1–19.

[10] Y. Zhong, J. Gao, Q. Lei, Y. Zhou, A vision-based counting and recognition system for flying insects in intelligent agriculture, Sensors 18 (5) (2018) 1489.

[11] G. Nagasubramanian, R.K. Sakthivel, R. Patan, M. Sankayya, M. Daneshmand, A.H. Gandomi, Ensemble classification and IoT-based pattern recognition for crop disease monitoring system, IEEE Internet Things J. 8 (16) (2021) 12847–12854.

[12] S. Hackfort, Patterns of inequalities in digital agriculture: A systematic literature review, Sustainability 13 (22) (2021) 12345.

[13] K. Jha, A. Doshi, P. Patel, M. Shah, A comprehensive review on automation in agriculture using artificial intelligence, Artif. Intell. Agric. 2 (2019) 1–12.

[14] A. Subeesh, C. Mehta, Automation and digitization of agriculture using artificial intelligence and internet of things, Artif. Intell. Agric. 5 (2021) 278–291.

[15] S.S. Gill, I. Chana, R. Buyya, IoT based agriculture as a cloud and big data service: the beginning of digital India, J. Organ. End User Comput. (JOEUC) 29 (4) (2017) 1–23.

[16] J.A. Delgado, N.M. Short Jr., D.P. Roberts, B. Vandenberg, Big data analysis for sustainable agriculture on a geospatial cloud framework, Front. Sustain. Food Syst. 3 (2019) 54.

[17] E.S. Mohamed, A. Belal, S.K. Abd-Elmabod, M.A. El-Shirbeny, A. Gad, M.B. Zahran, Smart farming for improving agricultural management, Egypt. J. Remote. Sens. Space Sci. 24 (3) (2021) 971–981.

[18] A. Tzounis, N. Katsoulas, T. Bartzanas, C. Kittas, Internet of things in agri- culture, recent advances and future challenges, Biosyst. Eng. 164 (2017) 31–48.

[19] Q. Qi, F. Tao, T. Hu, N. Anwer, A. Liu, Y. Wei, L. Wang, A.Y. Nee, Enabling technologies and tools for digital twin, J. Manuf. Syst. 58 (2021) 3–21.

[20] C. Cimino, E. Negri, L. Fumagalli, Review of digital twin applications in manufacturing, Comput. Ind. 113 (2019) 103130.

[21] B.R. Barricelli, E. Casiraghi, D. Fogli, A survey on digital twin: Definitions, characteristics, applications, and design implications, IEEE Access 7 (2019) 167653–167671.

[22] N. Peladarinos, D. Piromalis, V. Cheimaras, E. Tserepas, R.A. Munteanu, P. Papageorgas, Enhancing smart agriculture by implementing digital twins: A comprehensive review, Sensors 23 (16) (2023) 7128.

[23] S. Li, L.D. Xu, S. Zhao, The internet of things: a survey, Inf. Syst. Front. 17 (2015) 243–259.

[24] L. Atzori, A. Iera, G. Morabito, The internet of things: A survey, Comput. Netw. 54 (15) (2010) 2787–2805.

[25] M. Jacoby, T. Usländer, Digital twin and internet of things—Current standards landscape, Appl. Sci. 10 (18) (2020) 6519.

[26] Y. He, J. Guo, X. Zheng, From surveillance to digital twin: Challenges and recent advances of signal processing for industrial internet of things, IEEE Signal Process. Mag. 35 (5) (2018) 120–129.

[27] M. Groshev, C. Guimarães, J. Martín-Pérez, A. de la Oliva, Toward intelligent cyber-physical systems: Digital twin meets artificial intelligence, IEEE Commun. Mag. 59 (8) (2021) 14–20.

[28] M.M. Rathore, S.A. Shah, D. Shukla, E. Bentafat, S. Bakiras, The role of ai, machine learning, and big data in digital twinning: A systematic literature review, challenges, and opportunities, IEEE Access 9 (2021) 32030–32052.

[29] M. Escribà-Gelonch, S. Liang, P. van Schalkwyk, I. Fisk, N.V.D. Long, V. Hessel, Digital twins in agriculture: Orchestration and applications, J. Agricult. Food Chem. (2024).

[30] G. Chaudhary, M. Khari, M. Elhoseny, Digital Twin Technology, CRC Press, 2021.

[31] M. Attaran, B.G. Celik, Digital twin: Benefits, use cases, challenges, and opportunities, Decis. Anal. J. 6 (2023) 100165.

[32] X. Han, Z. Lin, C. Clark, B. Vucetic, S. Lomax, AI based digital twin model for cattle caring, Sensors 22 (19) (2022) 7118.

[33] W. Li, D.-l. Zhu, Q. Wang, S.-h. Zeng, Research review on crop digital twin system for monitoring growth status and environmental response, 2022.

[34] D.S. Ametefe, N. Hussin, D. John, G. Dzorgbenya Ametefe, A. Adozuka Aliu, Z. Abdi Ali, Revolutionising agriculture for food security and environmental sustainability: A perspective on the role of digital twin technology, CABI Rev. 19 (1) (2024).

[35] C. Verdouw, B. Tekinerdogan, A. Beulens, S. Wolfert, Digital twins in smart farming, Agricult. Sys. 189 (2021) 103046.

[36] F. Ibrahimov, U. Rzayeva, R. Balayev, Opportunities and perspectives of the digital twins' conception: the case in agriculture, East.-European J. Enterp. Technol. 1 (13) (2023) 121.

[37] I.N. Krasnikova, V.L. Simonov, A.E. Petelin, Features of development of an agricultural warehouse digital twin, in: BIO Web of Conferences, vol. 83, EDP Sciences, 2024, p. 03004.

[38] W.-S. Kim, W.-S. Lee, Y.-J. Kim, A review of the applications of the internet of things (IoT) for agricultural automation, J. Biosyst. Eng. 45 (4) (2020) 385–400.

[39] G. Dutta, P. Goswami, Application of drone in agriculture: A review, Int. J. Chem. Stud. 8 (5) (2020) 181–187.

[40] X. Zhang, Z. Cao, W. Dong, Overview of edge computing in the agricultural internet of things: Key technologies, applications, challenges, IEEE Access 8 (2020) 141748–141761.

[41] R.C.d. Oliveira, R.D.d.S.e. Silva, Artificial intelligence in agriculture: benefits, challenges, and trends, Appl. Sci. 13 (13) (2023) 7405.

[42] A. Barbie, W. Hasselbring, M. Hansen, Digital twin prototypes for supporting automated integration testing of smart farming applications, Symmetry 16 (2) (2024) 221.

[43] G. Majore, I. Majors, Digital twin modelling for eco-cyber-physical systems: In the case of a smart agriculture living lab, in: PoEM (Forum), 2022, pp. 98–112.

[44] A. Barbie, W. Hasselbring, M. Hansen, Enabling automated integration testing of smart farming applications via digital twin prototypes, in: 2023 IEEE Smart World Congress, SWC, IEEE, 2023, pp. 1–8.

[45] A. Nasirahmadi, O. Hensel, Toward the next generation of digitalization in agriculture based on digital twin paradigm, Sensors 22 (2) (2022) 498.

[46] L. Wang, Digital twins in agriculture: a review of recent progress and open issues, Electronics 13 (11) (2024) 2209.

[47] L. Silva, F. Rodríguez-Sedano, P. Baptista, J.P. Coelho, The digital twin paradigm applied to soil quality assessment: a systematic literature review, Sensors 23 (2) (2023) 1007.

[48] M.J. Kaur, V.P. Mishra, P. Maheshwari, The convergence of digital twin, IoT, and machine learning: transforming data into action, Digit. Twin Technol. Smart Cities (2020) 3–17.

[49] N.A. Ubina, H.-Y. Lan, S.-C. Cheng, C.-C. Chang, S.-S. Lin, K.-X. Zhang, H.-Y. Lu, C.-Y. Cheng, Y.-Z. Hsieh, Digital twin-based intelligent fish farming with artificial intelligence internet of things (AIoT), Smart Agric. Technol. 5 (2023) 100285.

[50] W. Purcell, T. Neubauer, Digital twins in agriculture: A state-of-the-art review, Smart Agric. Technol. 3 (2023) 100094.

[51] C. Pylianidis, S. Osinga, I.N. Athanasiadis, Introducing digital twins to agriculture, Comput. Electron. Agric. 184 (2021) 105942.

[52] W. Purcell, T. Neubauer, K. Mallinger, Digital twins in agriculture: challenges and opportunities for environmental sustainability, Curr. Opin. Environ. Sustain. 61 (2023) 101252.

[53] S. Cesco, P. Sambo, M. Borin, B. Basso, G. Orzes, F. Mazzetto, Smart agriculture and digital twins: Applications and challenges in a vision of sustainability, Eur. J. Agron. 146 (2023) 126809.

[54] N. Ariesen-Verschuur, C. Verdouw, B. Tekinerdogan, Digital twins in greenhouse horticulture: A review, Comput. Electron. Agric. 199 (2022) 107183.

[55] T. Sreedevi, M.S. Kumar, Digital twin in smart farming: A categorical literature review and exploring possibilities in hydroponics, in: 2020 Advanced Com- puting and Communication Technologies for High Performance Applications, ACCTHPA, IEEE, 2020, pp. 120–124.

[56] E. Symeonaki, C. Maraveas, K.G. Arvanitis, Recent advances in digital twins for agriculture 5.0: applications and open issues in livestock production systems, Appl. Sci. 14 (2) (2024) 686.

[57] A.C. Tagarakis, L. Benos, G. Kyriakarakos, S. Pearson, C.G. Sørensen, D. Bochtis, Digital twins in agriculture and forestry: a review, Sensors 24 (10) (2024) 3117.

[58] B.L. MacCarthy, D. Ivanov, Chapter 5 - the cloud, platforms, and digital twins—Enablers of the digital supply chain, in: The Digital Supply Chain, Elsevier, 2022, pp. 77–91, http://dx.doi.org/10.1016/B978-0-323-91614-1.00005-8, URL https://www.sciencedirect.com/science/article/pii/B9780323916141000058.

[59] W. Kritzinger, M. Karner, G. Traar, J. Henjes, W. Sihn, Digital twin in manufacturing: A categorical literature review and classification, IFAC-PapersOnLine 51 (11) (2018) 1016–1022, http://dx.doi.org/10.1016/j.ifacol.2018.08.474, URL https://www.sciencedirect.com/science/article/pii/S2405896318316021. 16th IFAC Symposium on Information Control Problems in Manufacturing INCOM 2018.

[60] W. Hu, T. Zhang, X. Deng, Z. Liu, J. Tan, Digital twin: A state-of-the-art review of its enabling technologies, applications and challenges, J. Intell. Manuf. Spec. Equip. 2 (1) (2021) 1–34.

[61] A. Fuller, Z. Fan, C. Day, C. Barlow, Digital twin: enabling technologies, challenges and open research, IEEE Access 8 (2020) 108952–108971.

[62] J. Ríos, G. Staudter, M. Weber, R. Anderl, Enabling the digital twin: a review of the modelling of measurement uncertainty on data transfer standards and its relationship with data from tests, Int. J. Prod. Lifecycle Manag. 12 (3) (2020) 250–268.

[63] R. Krishnamurthi, A. Kumar, D. Gopinathan, A. Nayyar, B. Qureshi, An overview of IoT sensor data processing, fusion, and analysis techniques, Sensors 20 (21) (2020) 6076.

[64] U. Bodkhe, S. Tanwar, K. Parekh, P. Khanpara, S. Tyagi, N. Kumar, M. Alazab, Blockchain for industry 4.0: A comprehensive review, IEEE Access 8 (2020) 79764–79800.

[65] M. De Donno, K. Tange, N. Dragoni, Foundations and evolution of modern computing paradigms: Cloud, iot, edge, and fog, IEEE Access 7 (2019) 150936–150948.

[66] S. Machała, N. Chamier-Gliszczyński, T. Królikowski, Application of AR/VR technology in industry 4.0., Procedia Comput. Sci. 207 (2022) 2990–2998.
[67] K. Sharifani, M. Amini, Machine learning and deep learning: A review of methods and applications, World Inf. Technol. Eng. J. 10 (07) (2023) 3897–3904.
[68] P.P. Shinde, S. Shah, A review of machine learning and deep learning applications, in: 2018 Fourth International Conference on Computing Communication Control and Automation, ICCUBEA, IEEE, 2018, pp. 1–6.
[69] P. Pandey, R. Litoriya, A. Tiwari, A framework for fuzzy modelling in agricultural diagnostics, J. Eur. Syst. Autom. 51 (2018).
[70] L. Li, Y. Fan, M. Tse, K.-Y. Lin, A review of applications in federated learning, Comput. Ind. Eng. 149 (2020) 106854.
[71] L. Dutta, S. Bharali, Tinyml meets iot: A comprehensive survey, Internet Things 16 (2021) 100461.
[72] V. Tsoukas, A. Gkogkidis, E. Boumpa, A. Kakarountas, A review on the emerging technology of TinyML, ACM Comput. Surv. 56 (10) (2024) 1–37.
[73] V. Viswanatha, A. Ramachandra, P.T. Hegde, V. Hegde, V. Sabhahit, Tinyml- based human and animal movement detection in agriculture fields in India, in: International Conference on Emerging Research in Computing, Information, Communication and Applications, Springer, 2023, pp. 49–65.
[74] R.G. Alves, G. Souza, R.F. Maia, A.L.H. Tran, C. Kamienski, J.-P. Soininen, P.T. Aquino, F. Lima, A digital twin for smart farming, in: 2019 IEEE Global Humanitarian Technology Conference, GHTC, IEEE, 2019, pp. 1–4.
[75] A. Manocha, S.K. Sood, M. Bhatia, IoT-digital twin-inspired smart irrigation approach for optimal water utilization, Sustain. Comput.: Inform. Syst. 41 (2024) 100947.
[76] J. Xu, B. Gu, G. Tian, Review of agricultural IoT technology, Artif. Intell. Agric. 6 (2022) 10–22.
[77] K. Wang, Y. Wang, Y. Sun, S. Guo, J. Wu, Green industrial internet of things architecture: An energy-efficient perspective, IEEE Commun. Mag. 54 (12) (2016) 48–54.
[78] F.F. Foldager, C. Thule, O. Balling, P. Larsen, Towards a digital twin-modelling an agricultural vehicle, in: Leveraging Applications of Formal Methods, Ver- ification and Validation: Tools and Trends: 9th International Symposium on Leveraging Applications of Formal Methods, ISoLA 2020, Rhodes, Greece, October 20–30, 2020, Proceedings, Part IV 9, Springer, 2021, pp. 109–123.
[79] P. Angin, M.H. Anisi, F. Göksel, C. Gürsoy, A. Büyükgülcü, Agrilora: a digital twin framework for smart agriculture., J. Wirel. Mob. Netw. Ubiquitous Comput. Dependable Appl. 11 (4) (2020) 77–96.
[80] R. Minerva, G.M. Lee, N. Crespi, Digital twin in the IoT context: A survey on technical features, scenarios, and architectural models, Proc. IEEE 108 (10) (2020) 1785–1824.
[81] D.D. Eneyew, M.A. Capretz, G.T. Bitsuamlak, Toward smart-building digital twins: BIM and IoT data integration, IEEE Access 10 (2022) 130487–130506.
[82] Z. Jiang, Y. Guo, Z. Wang, Digital twin to improve the virtual-real integration of industrial IoT, J. Ind. Inf. Integr. 22 (2021) 100196.
[83] R. Herrero, Fundamentals of Iot Communication Technologies, Springer, 2022.
[84] A. Ikpehai, B. Adebisi, K.M. Rabie, K. Anoh, R.E. Ande, M. Hammoudeh, H. Gacanin, U.M. Mbanaso, Low-power wide area network technologies for internet-of-things: A comparative review, IEEE Internet Things J. 6 (2) (2018) 2225–2240.
[85] V. Bhanumathi, K. Kalaivanan, The role of geospatial technology with IoT for precision agriculture, in: Cloud Computing for Geospatial Big Data Analytics: Intelligent Edge, Fog and Mist Computing, Springer, 2018, pp. 225–250.
[86] S.L. Ullo, G.R. Sinha, Advances in IoT and smart sensors for remote sensing and agriculture applications, Remote. Sens. 13 (13) (2021) 2585.
[87] C. Alcaraz, J. Lopez, Digital twin: A comprehensive survey of security threats, IEEE Commun. Surv. Tutor. 24 (3) (2022) 1475–1503.
[88] T. Huynh-The, T.R. Gadekallu, W. Wang, G. Yenduri, P. Ranaweera, Q.-V. Pham, D.B. da Costa, M. Liyanage, Blockchain for the metaverse: A review, Future Gener. Comput. Syst. 143 (2023) 401–419.
[89] H. Xiong, T. Dalhaus, P. Wang, J. Huang, Blockchain technology for agriculture: applications and rationale, Front. Blockchain 3 (2020) 7.
[90] I. Yaqoob, K. Salah, M. Uddin, R. Jayaraman, M. Omar, M. Imran, Blockchain for digital twins: Recent advances and future research challenges, IEEE Netw. 34 (5) (2020) 290–298.
[91] O. Bermeo-Almeida, M. Cardenas-Rodriguez, T. Samaniego-Cobo, E. Ferruzola-Gómez, R. Cabezas-Cabezas, W. Bazán-Vera, Blockchain in agriculture: A systematic literature review, in: International Conference on Technologies and Innovation, Springer, 2018, pp. 44–56.
[92] K. Dey, U. Shekhawat, Blockchain for sustainable e-agriculture: Literature review, architecture for data management, and implications, J. Clean. Prod. 316 (2021) 128254.
[93] Q. Yao, H. Zhang, Improving agricultural product traceability using blockchain, Sensors 22 (9) (2022) 3388.
[94] S. Krishnapriya, G. Sarath, Securing land registration using blockchain, Procedia Comput. Sci. 171 (2020) 1708–1715.
[95] M. Shuaib, S.M. Daud, S. Alam, W.Z. Khan, Blockchain-based framework for secure and reliable land registry system, Telkomnika (Telecommun. Comput. Electron. Control) 18 (5) (2020) 2560–2571.
[96] K. Demestichas, N. Peppes, T. Alexakis, E. Adamopoulou, Blockchain in agriculture traceability systems: A review, Appl. Sci. 10 (12) (2020) 4113.
[97] S.N. Khan, F. Loukil, C. Ghedira-Guegan, E. Benkhelifa, A. Bani-Hani, Blockchain smart contracts: Applications, challenges, and future trends, Peer-to-Peer Netw. Appl. 14 (5) (2021) 2901–2925.
[98] MathWorks, Rapid deployment of deep learning on edge devices, 2024, URL https://www.mathworks.com/company/technical-articles/rapid-deployment-of-deep-learning-on-edge-devices.html. (Accessed 6 July 2025).
[99] N. Misra, Y. Dixit, A. Al-Mallahi, M.S. Bhullar, R. Upadhyay, A. Martynenko, IoT, big data, and artificial intelligence in agriculture and food industry, IEEE Internet Things J. 9 (9) (2020) 6305–6324.
[100] S.A. Oke, A literature review on artificial intelligence, Internat. J. Inform. Management Sci. 19 (4) (2008) 535–570.
[101] M.I. Jordan, T.M. Mitchell, Machine learning: Trends, perspectives, and prospects, Science 349 (6245) (2015) 255–260.
[102] Y. Guo, Y. Liu, A. Oerlemans, S. Lao, S. Wu, M.S. Lew, Deep learning for visual understanding: A review, Neurocomputing 187 (2016) 27–48.
[103] A. Subeesh, N. Chauhan, Biotic stress management in soil-less agriculture systems: A deep learning approach for identification of leaf miner pest infestation, Procedia Comput. Sci. 233 (2024) 371–380.
[104] D. Khurana, A. Koli, K. Khatter, S. Singh, Natural language processing: State of the art, current trends and challenges, Multimedia Tools Appl. 82 (3) (2023) 3713–3744.
[105] V. Dhanya, A. Subeesh, N. Kushwaha, D.K. Vishwakarma, T.N. Kumar, G. Ritika, A. Singh, Deep learning based computer vision approaches for smart agricultural applications, Artif. Intell. Agric. 6 (2022) 211–229.
[106] R. Makkar, C.R. Makkar, Application of fuzzy logic: A literature review, Int. J. Stat. Appl. Math 3 (1) (2018) 357–359.
[107] J. Lee, M. Azamfar, J. Singh, S. Siahpour, Integration of digital twin and deep learning in cyber-physical systems: towards smart manufacturing, IET Collab. Intell. Manuf. 2 (1) (2020) 34–36.
[108] Y. Xu, Y. Sun, X. Liu, Y. Zheng, A digital-twin-assisted fault diagnosis using deep transfer learning, IEEE Access 7 (2019) 19990–19999.
[109] M. Gupta, M. Kumari, C. Ved, Digital twin in agriculture sector: Detection of disease using deep learning, in: Digital Twin Technology, CRC Press, 2021, pp. 47–60.
[110] S.M.R. Naqvi, M. Ghufran, S. Meraghni, C. Varnier, J.-M. Nicod, N. Zerhouni, Human knowledge centered maintenance decision support in digital twin environment, J. Manuf. Syst. 65 (2022) 528–537.
[111] Y. Han, Y. Song, Y. Wang, C. Tao, Assessment of digital twin virtual-real connected interaction based on NLP, in: 2023 2nd International Conference on Artificial Intelligence and Intelligent Information Processing, AIIIP, IEEE, 2023, pp. 367–373.
[112] S.P. Ramu, P. Boopalan, Q.-V. Pham, P.K.R. Maddikunta, T. Huynh-The, M. Alazab, T.T. Nguyen, T.R. Gadekallu, Federated learning enabled digital twins for smart cities: Concepts, recent advances, and future directions, Sustain. Cities Soc. 79 (2022) 103663.
[113] S. AbdulRahman, S. Otoum, O. Bouachir, A. Mourad, Management of digital twin-driven IoT using federated learning, IEEE J. Sel. Areas Commun. 41 (11) (2023) 3636–3649.
[114] Y. Gao, H. Li, G. Xiong, H. Song, AIoT-informed digital twin communication for bridge maintenance, Autom. Constr. 150 (2023) 104835.
[115] Y. Abadade, A. Temouden, H. Bamoumen, N. Benamar, Y. Chtouki, A.S. Hafid, A comprehensive survey on tinyml, IEEE Access 11 (2023) 96892–96922.
[116] A. Alba, J. Villaverde, A. Lacara, J. Domingo, D. Aguirre, Optimized FLOPs- aware knowledge distillation for TinyML applications in agriculture, in: 2025 International Conference on Advancement in Data Science, E-Learning and Information System, ICADEIS, IEEE, 2025, pp. 1–6.
[117] A. Gautam, M.B. Faruqui, N. Akhtar, U.B. Rashidullah Khan, Boosting precision agriculture using deep learning models on edge devices, in: International Symposium on Intelligent Informatics, Springer, 2023, pp. 193–209.
[118] D.A.N. Gookyi, F.A. Wulnye, E.A.E. Arthur, R.K. Ahiadormey, J.O. Agyemang, K.O.-B.O. Agyekum, R. Gyaang, TinyML for smart agriculture: Comparative analysis of TinyML platforms and practical deployment for maize leaf disease identification, Smart Agric. Technol. 8 (2024) 100490.
[119] A. Rizwan, R. Ahmad, A.N. Khan, R. Xu, D.H. Kim, Intelligent digital twin for federated learning in aIoT networks, Internet Things 22 (2023) 100698.
[120] C. Zhang, Y. Xie, H. Bai, B. Yu, W. Li, Y. Gao, A survey on federated learning, Knowl.-Based Syst. 216 (2021) 106775.
[121] K.R. Žalik, M. Žalik, A review of federated learning in agriculture, Sensors 23 (23) (2023) 9566.
[122] P. Kumar, G.P. Gupta, R. Tripathi, PEFL: Deep privacy-encoding-based federated learning framework for smart agriculture, IEEE Micro 42 (1) (2021) 33–40.
[123] Y. Kalyani, L. Vorster, R. Whetton, R. Collier, Application scenarios of digital twins for smart crop farming through cloud–fog–edge infrastructure, Futur. Internet 16 (3) (2024) 100.
[124] H. Soy, Y. Dilay, Fog-connected digital twin implementation for autonomous greenhouse management, in: Digital Twin Driven Intelligent Systems and Emerging Metaverse, Springer, 2023, pp. 125–139.

[125] A.R. Biswas, R. Giaffreda, IoT and cloud convergence: Opportunities and challenges, in: 2014 IEEE World Forum on Internet of Things, WF-IoT, IEEE, 2014, pp. 375–376.

[126] M. Barcelo, A. Correa, J. Llorca, A.M. Tulino, J.L. Vicario, A. Morell, IoT-cloud service optimization in next generation smart environments, IEEE J. Sel. Areas Commun. 34 (12) (2016) 4077–4090.

[127] M. Hori, E. Kawashima, T. Yamazaki, Application of cloud computing to agriculture and prospects in other fields, Fujitsu Sci. Tech. J. 46 (4) (2010) 446–454.

[128] S. Liu, L. Guo, H. Webb, X. Ya, X. Chang, Internet of things monitoring system of modern eco-agriculture based on cloud computing, IEEE Access 7 (2019) 37050–37058.

[129] Y. Kalyani, R. Collier, A systematic survey on the role of cloud, fog, and edge computing combination in smart agriculture, Sensors 21 (17) (2021) http://dx.doi.org/10.3390/s21175922, URL https://www.mdpi.com/1424-8220/21/17/5922.

[130] M. O'Grady, D. Langton, G. O'Hare, Edge computing: A tractable model for smart agriculture? Artif. Intell. Agric. 3 (2019) 42–51, http://dx.doi.org/10.1016/j.aiia.2019.12.001, URL https://www.sciencedirect.com/science/article/pii/S2589721719300339.

[131] M. Aloqaily, O. Bouachir, F. Karray, I. Al Ridhawi, A. El Saddik, Integrating digital twin and advanced intelligent technologies to realize the metaverse, IEEE Consum. Electron. Mag. (2022).

[132] S.B. Far, A.I. Rad, Applying digital twins in metaverse: User interface, security and privacy challenges, J. Metaverse 2 (1) (2022) 8–15.

[133] D. Mourtzis, Digital twin inception in the era of industrial metaverse, Front. Manuf. Technol. 3 (2023) 1155735.

[134] E. Anastasiou, A.T. Balafoutis, S. Fountas, Applications of extended reality (XR) in agriculture, livestock farming, and aquaculture: A review, Smart Agric. Technol. 3 (2023) 100105.

[135] J. Huuskonen, T. Oksanen, Soil sampling with drones and augmented reality in precision agriculture, Comput. Electron. Agric. 154 (2018) 25–35.

[136] A. Ghandar, A. Ahmed, S. Zulfiqar, Z. Hua, M. Hanai, G. Theodoropoulos, A decision support system for urban agriculture using digital twin: A case study with aquaponics, IEEE Access 9 (2021) 35691–35708.

[137] T.Y. Melesse, M. Bollo, V. Di Pasquale, F. Centro, S. Riemma, Machine learning-based digital twin for monitoring fruit quality evolution, Procedia Comput. Sci. 200 (2022) 13–20.

[138] Y. Zhang, Y. Zhang, M. Gao, B. Dai, S. Kou, X. Wang, X. Fu, W. Shen, Digital twin perception and modeling method for feeding behavior of dairy cows, Comput. Electron. Agric. 214 (2023) 108181.

[139] H. Rahman, U.M. Shah, S.M. Riaz, K. Kifayat, S.A. Moqurrab, J. Yoo, Digital twin framework for smart greenhouse management using next-gen mobile networks and machine learning, Future Gener. Comput. Syst. 156 (2024) 285–300.

[140] A. Kantaros, D. Piromalis, Setting up a digital twin assisted greenhouse architecture, Am. J. Eng. Appl. Sci. (2022).

[141] J.D. Chaux, D. Sanchez-Londono, G. Barbieri, A digital twin architecture to optimize productivity within controlled environment agriculture, Appl. Sci. 11 (19) (2021) 8875.

[142] J.P. González, D. Sanchez-Londoño, G. Barbieri, A monitoring digital twin for services of controlled environment agriculture, IFAC-PapersOnLine 55 (19) (2022) 85–90.

[143] K. Hull, M.J. Booysen, M. Mabitsela, E. Phiri, Using a digital twin for greenhouse tunnel temperature management and prediction, in: 2023 IEEE AFRICON, IEEE, 2023, pp. 1–6.

[144] Y. Qu, A digital twin framework for commercial greenhouse climate control system, 2023.

[145] M. Dai, Y. Shen, X. Li, J. Liu, S. Zhang, H. Miao, Digital twin system of pest management driven by data and model fusion, Agriculture 14 (7) (2024) 1099.

[146] O. Spyrou, W. Hurst, C. Verdouw, Virtual reality-based digital twins: A case study on pharmaceutical cannabis, Big Data Cogn. Comput. 7 (2) (2023) 95.

[147] A. Reyes Yanes, R. Abbasi, P. Martinez, R. Ahmad, Digital twinning of hydroponic grow beds in intelligent aquaponic systems, Sensors 22 (19) (2022) 7393.

[148] J. Monteiro, J. Barata, M. Veloso, L. Veloso, J. Nunes, A scalable digital twin for vertical farming, J. Ambient. Intell. Humaniz. Comput. 14 (10) (2023) 13981–13996.

[149] A. Asfarian, W. Wulandari, Digital twin platform architecture design to support smart aeroponic potato cultivation in Indonesia, in: Business Innovation and Engineering Conference, BIEC 2022, Atlantis Press, 2023, pp. 92–99.

[150] R. Samikannu, A.K. Koshariya, E. Poornima, S. Ramesh, A. Kumar, S. Boopathi, Sustainable development in modern aquaponics cultivation systems using IoT technologies, in: Human Agro-Energy Optimization for Business and Industry, IGI global, 2023, pp. 105–127.

[151] J. Monteiro, J. Barata, M. Veloso, L. Veloso, J. Nunes, Towards sustainable digital twins for vertical farming, in: 2018 Thirteenth International Conference on Digital Information Management, ICDIM, IEEE, 2018, pp. 234–239.

[152] D.A. Howard, Z. Ma, J.M. Aaslyng, B.N. Jørgensen, Data architecture for digital twin of commercial greenhouse production, in: 2020 RIVF International Conference on Computing and Communication Technologies, RIVF, IEEE, 2020, pp. 1–7.

[153] K. Wang, W. Xie, B. Wang, J. Pei, W. Wu, M. Baker, Q. Zhou, Simulation-based digital twin development for blockchain enabled end-to-end industrial hemp supply chain risk management, in: 2020 Winter Simulation Conference, WSC, IEEE, 2020, pp. 3200–3211.

[154] M. Jans-Singh, K. Leeming, R. Choudhary, M. Girolami, Digital twin of an urban-integrated hydroponic farm, Data-Centric Eng. 1 (2020) e20.

[155] N.L. Tsakiridis, N. Samarinas, E. Kalopesa, G.C. Zalidis, Cognitive soil digital twin for monitoring the soil ecosystem: A conceptual framework, Soil Syst. 7 (4) (2023) 88.

[156] R. Parvathi, R. Jhapte, M. Sucharitha, S.M. Nair, V. Krishnaprasath, Digital twins for an irrigation system, in: Handbook of Industrial and Business Applications with Digital Twins, CRC Press, pp. 267–281.

[157] M. Awais, W. Li, H. Li, M.J.M. Cheema, S. Hussain, C. Liu, Optimization of intelligent irrigation systems for smart farming using multi-spectral unmanned aerial vehicle and digital twins modeling, Environ. Sci. Proc. 23 (1) (2022) 13.

[158] L. Brocca, S. Barbetta, S. Camici, L. Ciabatta, J. Dari, P. Filippucci, C. Massari, S. Modanesi, A. Tarpanelli, B. Bonaccorsi, et al., A digital twin of the terrestrial water cycle: a glimpse into the future through high-resolution Earth observations, Front. Sci. 1 (2024) 1190191.

[159] C. Rodríguez-Alonso, I. Pena-Regueiro, Ó. García, Digital twin platform for water treatment plants using microservices architecture, Sensors 24 (5) (2024) 1568.

[160] J. Cho, C. Kim, K.J. Lim, J. Kim, B. Ji, J. Yeon, Web-based agricultural infrastructure digital twin system integrated with GIS and BIM concepts, Comput. Electron. Agric. 215 (2023) 108441.

[161] R.G. Alves, R.F. Maia, F. Lima, Development of a digital twin for smart farming: Irrigation management system for water saving, J. Clean. Prod. 388 (2023) 135920.

[162] J. Bellvert, A. Pelechá, M. Pàmies-Sans, J. Virgili, M. Torres, J. Casadesús, Assimilation of sentinel-2 biophysical variables into a digital twin for the automated irrigation scheduling of a vineyard, Water 15 (14) (2023) 2506.

[163] H.J. Henriksen, R. Schneider, J. Koch, M. Ondracek, L. Troldborg, I.K. Seidenfaden, S.J. Kragh, E. Bøgh, S. Stisen, A new digital twin for climate change adaptation, water management, and disaster risk reduction (HIP digital twin), Water 15 (1) (2022) 25.

[164] C. Barkakoti, S. Joshi, Advancement of digital twin in irrigation and smart farming, in: 2023 International Conference on Sustainable Computing and Data Communication Systems, ICSCDS, IEEE, 2023, pp. 1245–1250.

[165] X. Li, B. You, X. Wang, Z. Zhao, T. Qi, J. Xu, A study of soil modelling methods based on line-structured light—Preparing for the subsoiling digital twin, Comput. Electron. Agric. 227 (2024) 109685.

[166] R.N. Madeira, P.A. Santos, O. Java, T. Priebe, E. Graça, E. Sárközi, B. Asprion, R.P.-B. Gómez, Towards digital twins for multi-sensor land and plant monitoring, Procedia Comput. Sci. 210 (2022) 45–52.

[167] S. Mummaneni, T.S. Sappa, V.G.D. Katakam, Enhancing crop health through digital twin for disease monitoring and nutrient balance, Inform. Autom. Pomiary W Gospod. I Ochr. Śr. 14 (1) (2024) 57–62.

[168] D. Onwude, P. Cronje, J. North, T. Defraeye, Digital replica to unveil the impact of growing conditions on orange postharvest quality, Sci. Rep. 14 (1) (2024) 14437.

[169] Y.B. Khatraty, N. Mellouli, M.T. Diallo, M.F. Nanne, Smart digital-twin hub concept for rice yield prediction and monitoring from multivariate time series data, in: 2023 24th International Conference on Control Systems and Computer Science, CSCS, IEEE, 2023, pp. 48–55.

[170] P. Archambault, H. Sahraoui, E. Syriani, A modeling methodology for crop representation in digital twins for smart farming, in: Proceedings of the ACM/IEEE 27th International Conference on Model Driven Engineering Languages and Systems, 2024, pp. 342–352.

[171] P. Skobelev, A. Tabachinskiy, A. Strizhakov, E. Kudryakov, E. Simonova, Experimental studies of the digital twin of plant based on ontologies and multi-agent technologies, WSEAS Trans. Environ. Dev. 20 (2024) 624–632.

[172] P. Skobelev, A. Tabachinskiy, E. Simonova, A. Galitskaya, A. Strizhakov, E. Kudryakov, Ontological model of wheat production process for digital twin of plant, in: International Conference on Intelligent Information Technologies for Industry, Springer, 2024, pp. 117–126.

[173] Z. Chunjiang, L. Jingchen, W. Huarui, Y. Yusen, Vegetable crop growth modeling in digital twin platform based on large language model inference, Smart Agric. 6 (6) (2024) 63.

[174] D. Onwude, F. Bahrami, C. Shrivastava, T. Berry, P. Cronje, J. North, N. Kirsten, S. Schudel, E. Crenna, K. Shoji, et al., Physics-driven digital twins to quantify the impact of pre-and postharvest variability on the end quality evolution of orange fruit, Resour. Conserv. Recycl. 186 (2022) 106585.

[175] T. Defraeye, G. Tagliavini, W. Wu, K. Prawiranto, S. Schudel, M.A. Kerisima, P. Verboven, A. Bühlmann, Digital twins probe into food cooling and biochemical quality changes for reducing losses in refrigerated supply chains, Resour. Conserv. Recycl. 149 (2019) 778–794.

[176] P. Skobelev, V. Laryukhin, E. Simonova, O. Goryanin, V. Yalovenko, O. Yalovenko, Multi-agent approach for developing a digital twin of wheat, in: 2020 IEEE International Conference on Smart Computing, SMARTCOMP, IEEE, 2020, pp. 268–273.
[177] P. Skobelev, I. Mayorov, E. Simonova, O. Goryanin, A. Zhilyaev, A. Tabachin- skiy, V. Yalovenko, Development of models and methods for creating a digital twin of plant within the cyber-physical system for precision farming management, J. Phys.: Conf. Ser. 1703 (1) (2020) 012022.
[178] S. Kim, S. Heo, An agricultural digital twin for mandarins demonstrates the potential for individualized agriculture, Nat. Commun. 15 (1) (2024) 1561.
[179] I. Zarembo, S. Kodors, I. Apeina¯ns, G. La¯cis, D. Feldmane, E. Rubauskis, Digital twin: Orchard management using UAV, in: Environment. Technologies. Resources. Proceedings of the International Scientific and Practical Conference, vol. 1, 2023, pp. 247–251.
[180] C. Mitsanis, W. Hurst, B. Tekinerdogan, A 3D functional plant modelling framework for agricultural digital twins, Comput. Electron. Agric. 218 (2024) 108733.
[181] D. Schmidt, L.F. Casagranda, M.A. Butturi, M.A. Sellitto, Digital technologies, sustainability, and efficiency in grain post-harvest activities: A bibliometric analysis, Sustainability 16 (3) (2024) 1244.
[182] D.I. Onwude, G. Chen, N. Eke-Emezie, A. Kabutey, A.Y. Khaled, B. Sturm, Recent advances in reducing food losses in the supply chain of fresh agricultural produce, Processes 8 (11) (2020) 1431.
[183] B.B. Rodolfo, O.C.P. Rodrigo, G.L.Y. Jesus, Digital twins application in the post-harvest supply chain of fruits and vegetables: A systematic review of the literature, in: IEOM Soc. Int. Proc. Int. Conf. Ind. Eng. Oper. Manag, 2022, pp. 118–130.
[184] T.Y. Melesse, V. Di Pasquale, S. Riemma, Recent advances of digital twin application in agri-food supply chain, Enterp. Interoperability X: Enterp. Interoperability Connect. Digit. Twins (2024) 147–157.
[185] T. Defraeye, C. Shrivastava, T. Berry, P. Verboven, D. Onwude, S. Schudel, A. Bühlmann, P. Cronje, R.M. Rossi, Digital twins are coming: Will we need them in supply chains of fresh horticultural produce? Trends Food Sci. Technol. 109 (2021) 245–258.
[186] G. Dyck, E. Hawley, K. Hildebrand, J. Paliwal, Digital twins: A novel traceability concept for post-harvest handling, Smart Agric. Technol. 3 (2023) 100079.
[187] C.C. Nwaizu, T.O. Olanrewaju, C. Iluno, Application of digital twin in evaluating quality changes in tomato value-chain in Nigeria, in: 2022 ASABE Annual International Meeting, American Society of Agricultural and Biological Engineers, 2022, p. 1.
[188] K. Shoji, S. Schudel, D. Onwude, C. Shrivastava, T. Defraeye, Mapping the postharvest life of imported fruits from packhouse to retail stores using physics-based digital twins, Resour. Conserv. Recycl. 176 (2022) 105914.
[189] J. Zhang, W. Zhang, J. Liang, B. He, G. Ding, Y. Cheng, X. Deng, Y. Zeng, A physical twin model for simulation of kiwifruit core temperature during pre-cooling and cold storage, Postharvest Biol. Technol. 212 (2024) 112862.
[190] P. Maheshwari, S. Kamble, A. Belhadi, M. Venkatesh, M.Z. Abedin, Digital twin-driven real-time planning, monitoring, and controlling in food supply chains, Technol. Forecast. Soc. Change 195 (2023) 122799.
[191] M. Nair, R.E. Fernandez, Advancing mixed reality digital twins through 3D reconstruction of fresh produce, IEEE Access 12 (2024) 4315–4327.
[192] S. Neethirajan, B. Kemp, Digital twins in livestock farming, Animals 11 (4) (2021) 1008.
[193] Y. Zhang, Y. Zhang, H. Jiang, H. Du, A. Xue, W. Shen, New method for modeling digital twin behavior perception of cows: Cow daily behavior recognition based on multimodal data, Comput. Electron. Agric. 226 (2024) 109426.
[194] S. Mishra, S.K. Sharma, Advanced contribution of IoT in agricultural production for the development of smart livestock environments, Internet Things 22 (2023) 100724.
[195] D.-y. Jeong, S.-K. Jo, I.-B. Lee, H. Shin, J.-g. Kim, Digital twin application: Making a virtual pig house toward digital livestock farming, IEEE Access (2023).
[196] P. Petrov, T. Atanasova, Digital twins with application of AR and VR in livestock instructions, Probl. Eng. Cybern. Robot. 77 (2021) 39–50.
[197] D. Raba, R.D. Tordecilla, P. Copado, A.A. Juan, D. Mount, A digital twin for decision making on livestock feeding, INFORMS J. Appl. Anal. 52 (3) (2022) 267–282.
[198] S.-K. Jo, D.-H. Park, H. Park, S.-H. Kim, Smart livestock farms using digital twin: Feasibility study, in: 2018 International Conference on Information and Communication Technology Convergence, ICTC, IEEE, 2018, pp. 1461–1463.
[199] V. Erdélyi, L. Jánosi, Digital twin and shadow in smart pork fetteners, Int. J. Eng. Manag. Sci. 4 (1) (2019) 515–520.
[200] M. Mu, Y. Zhou, D. Wu, Digital twins on animal husbandry: Insights and application, Procedia Comput. Sci. 214 (2022) 1182–1189.
[201] S. Neethirajan, Affective state recognition in livestock—artificial intelligence approaches, Animals 12 (6) (2022) 759.
[202] X. Zhao, W. Wang, L. Wen, Z. Chen, S. Wu, K. Zhou, M. Sun, L. Xu, B. Hu, C. Wu, Digital twins in smart farming: An autoware-based simulator for autonomous agricultural vehicles, Int. J. Agric. Biol. Eng. 16 (4) (2023) 184–189.
[203] G. Dafang, D. Yuefeng, W. Xiuheng, H. Siyu, L. Xiaoyu, Z. Yan'an, C. Du, Digital twin for agricultural machinery: from concept to application, Smart Agric. 5 (2) (2023) 149.
[204] A. Semin, D. Mironov, M. Kislitskiy, A. Zasypkin, V. Ivanov, Improving the theoretical and methodological framework for implementing digital twin technology in various sectors of agriculture, Emerg. Sci. J. 7 (4) (2023) 1100–1115.
[205] J. Wu, S. Guo, J. Li, D. Zeng, Big data meet green challenges: Big data toward green applications, IEEE Syst. J. 10 (3) (2016) 888–900.
[206] A. Kamilaris, A. Kartakoullis, F.X. Prenafeta-Boldú, A review on the practice of big data analysis in agriculture, Comput. Electron. Agric. 143 (2017) 23–37.
[207] Y. Yin, B. Ma, Z. Meng, L. Chen, M. Liu, Y. Zhang, B. Zhang, C. Wen, Construction method and case study of digital twin system for combine harvester, Comput. Electron. Agric. 226 (2024) 109395.
[208] K. Junge, C. Pires, J. Hughes, Lab2Field transfer of a robotic raspberry harvester enabled by a soft sensorized physical twin, Commun. Eng. 2 (1) (2023) 40.
[209] K. Nemtinov, M. Eruslanova, A. Zazulya, Y. Nemtinova, H.S. Salih, Creating a digital twin of an agricultural machine, in: MATEC Web of Conferences, vol. 329, EDP Sciences, 2020, p. 05002.
[210] M.E.M. Malik, M.S. Mahmud, A digital twin-enabled approach for precision weed management in specialty crops using a 4-DoF robotic system, in: 2024 ASABE Annual International Meeting, American Society of Agricultural and Biological Engineers, 2024, p. 1.
[211] J.P. Espejel Flores, A. Yilmaz, L.A. Soriano Avendaño, G. Cielniak, Comparative analysis of unity and gazebo simulators for digital twins of robotic tomato harvesting scenarios, in: Annual Conference Towards Autonomous Robotic Systems, Springer, 2024, pp. 15–27.
[212] B. Moser, et al., UX evaluation of a tractor cabin digital twin using mixed reality, July 5–July 8, 2022, Cambridge, MA, USA, in: Transdisciplinarity and the Future of Engineering: Proceedings of the 29th International Society of Transdisciplinary Engineering (ISTE) Global Conference, vol. 28, IOS Press, 2022, p. 370.
[213] A. Kampker, V. Stich, P. Jussen, B. Moser, J. Kuntz, Business models for industrial smart services–the example of a digital twin for a product-service-system for potato harvesting, Procedia Cirp 83 (2019) 534–540.
[214] N. Tsolakis, D. Bechtsis, D. Bochtis, Agros: A robot operating system based emulation tool for agricultural robotics, Agronomy 9 (7) (2019) 403.
[215] Y. Zhang, Y. Du, Z. Yang, D. Chen, Z. Song, Z. Zhu, Construction method of high-horsepower tractor digital twin, Digit. Twin 2 (2022) 12.
[216] J. Backman, T. Oksanen, A. Visala, Applicability of the ISO 11783 network in a distributed combined guidance system for agricultural machines, Biosyst. Eng. 114 (3) (2013) 306–317.
[217] D.S. Paraforos, C. Aubé, L. Athanasakos, I. Avgoustakis, S. Baron, T. Bresilla, S. Fountas, J. Hemming, P. Karagiannis, N. Mylonas, et al., Connecting agricultural robots and smart implements by using ISO 11783 communication, IFAC-PapersOnLine 55 (32) (2022) 200–205.
[218] M. Kunisch, J. Frisch, D. Martini, S. Böttinger, agroXML–a standardized language for data exchange in agriculture, in: Proceedings of 6th Biennial Conference of European Federation of IT in Agriculture Glasgow, 2007.
[219] D. Martini, M. Schmitz, E. Mietzsch, agroRDF as a semantic overlay to agroXML: a general model for enhancing interoperability in agrifood data standards, in: CIGR Conference on Sustainable Agriculture Through ICT Innovation, 2013.
[220] M. Singh, E. Fuenmayor, E.P. Hinchy, Y. Qiao, N. Murray, D. Devine, Digital twin: Origin to future, Appl. Syst. Innov. 4 (2) (2021) 36.
[221] K.K. Alnowaiser, M.A. Ahmed, Digital twin: current research trends and future directions, Arab. J. Sci. Eng. 48 (2) (2023) 1075–1095.