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REVIEW

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A Review on Digital Twin Technology: A New Frontier in Agriculture

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Abstract: Farming is crucial for various aspects of daily life, including food, the economy, environment, culture, and community. It provides employment opportunities, generates income, and increases the export of agricultural products, particularly in rural areas. Sustainable farming practices promote soil health, biodiversity, and ecosystem services and are essential in many parts of the world. Farming is deeply rooted in cultures and traditions and is a way of life for many communities, passed down from generation to generation. Without farming, we would not have the abundance and variety of food that we enjoy today. Advancements in technology, such as artificial intelligence, machine learning, and the Internet of Things, have greatly impacted agriculture by producing vast amounts of digital data on crops, soil, and weather conditions. However, managing and analyzing these data can be challenging for farmers, especially those in developing nations. To address this issue, affordable digital farming solutions, including open-source software platforms, sensor networks, and mobile apps, are being developed to help farmers optimize their resources, increase yields, and profits. Digital twin technology can play a crucial role in digital farming by providing farmers with a virtual replica of their physical farm. It is a digital depiction of a real-world asset, such a farm or a particular crop field, that gathers information from sensors, weather stations, and satellite pictures. This technology has arisen that has been hailed as revolutionary in a number of fields, including manufacturing machines, construction, agriculture, healthcare, and the automotive and aerospace industries. However, the technology is still in its early stages in agriculture, and it can be challenging to handle the interactions between different farming-related digital twin components. Additionally, digital twinning can require significant investment in technology and infrastructure, which may be a barrier for small-scale farmers.

Keywords: agriculture, artificial intelligence, digital twins, Internet of Things (IoT), Product Life Cycle

1. Introduction

Farming has been an integral part of India's cultural heritage for thousands of years. Agriculture is not just a source of livelihood for the majority of the population, but it is also deeply intertwined with their culture, traditions, and way of life. India is one of the world's largest agricultural producers, and the sector employs over 50% of the country's workforce (FAO, 2022). However, despite its importance, Indian agriculture has been facing several challenges such as low productivity, lack of access to modern technology, inadequate infrastructure, and unpredictable weather conditions. To overcome these challenges, the Indian government and private players are now turning toward digital farming (Team YS, 2020). As artificial intelligence has increasingly been incorporated into many agricultural processes, there has been significant modernization and technological advancement in the agriculture sector recently (Dawn et al., 2023; Janssen et al., 2017). Digital farming or precision farming is the use of advanced technology to monitor, measure, and manage agricultural practices in a precise and efficient manner. This includes the use of tools like sensors, drones, GPS, and other data-driven technologies to optimize crop yields, reduce wastage, and improve profitability (Wolfert et al., 2017). Artificial intelligence, machine learning, cloud computing, deep learning, the Internet of Things (IoT), robotics, big data, remote sensing, and other quick-moving technology breakthroughs are causing significant changes in agricultural productivity through the introduction of intelligent farming systems (Kamilaris & Prenafeta-Boldú, 2018; Tzounis et al., 2017; Zhai et al., 2020). In India, digital farming is gaining attraction as a way to address some of the challenges facing the agriculture sector. With the widespread availability of smartphones and Internet connectivity, farmers can now access a range of digital tools and services that can help them make

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informed decisions about crop management, pest control, irrigation, and soil health (IBEF, 2022). For example, there are now several mobile apps that provide farmers with weather forecasts, market prices, and information on crop diseases and pest management. Other technologies such as precision irrigation systems and smart tractors are also being developed to help farmers save water and energy while improving crop yields. Farmers are able to determine instantly whether there is a problem on the farm or if anything might go wrong in the future. Therefore, farmers may simulate potential preventive actions and assess their effects (Mendes et al., 2020). Digital farming is not only beneficial to farmers but it also has the potential to transform the entire agricultural value chain. By providing better data and insights, digital farming can help reduce wastage, increase efficiency and profitability, and ultimately, contribute to food security for the growing population of India. By leveraging advanced technologies, farmers can now access a range of tools and services that can help them improve crop yields, reduce wastage, and boost profitability (Javaid et al., 2022). This not only benefits farmers but also contributes to the overall development of the agricultural value chain, ultimately leading to food security and economic growth for the country.

Digital twins have the potential to revolutionize the way agriculture is managed, by providing farmers with real-time data about crops, soil conditions, weather patterns, and other important variables. However, there are several novel and new challenges that need to be addressed to fully realize the potential of digital twins in agriculture (Nasirahmadi & Hensel, 2022). Some of the key challenges are data integration, accuracy and reliability, scalability, data privacy and security, and user adoption. Agriculture involves multiple data sources, including data from sensors, satellites, weather stations, and historical records. Integrating all of these data into a single digital twin platform can be a significant challenge, especially when the data are heterogeneous and come from different sources. The accuracy and reliability of the data used to create digital twins are critical for making informed decisions. However, sensors and other data sources may have limitations in terms of accuracy, reliability, and precision, which can affect the accuracy of the digital twin model (Abbasi et al., 2022). Agriculture involves large areas of land and multiple crops, which can make it challenging to scale digital twin models. Developing scalable digital twin models that can accurately represent the variability across different fields is an important challenge. Agriculture involves sensitive data, such as crop yield data and soil data, which must be protected against unauthorized access or misuse. Ensuring data privacy and security is critical for the successful deployment of digital twins in agriculture (Botín-Sanabria et al., 2022). Finally, user adoption is a key challenge in deploying digital twins in agriculture. Farmers may be resistant to adopting new technologies or may not have the technical skills needed to operate digital twin platforms. Ensuring that digital twins are user-friendly and easy to use is important for user adoption (Purcell & Neubauer, 2023).

Overcoming these challenges will require collaboration among stakeholders, including farmers, technology providers, and policymakers, to develop and implement standardized, cost-effective, and secure digital twinning solutions that can be easily integrated into existing farming systems (Grieves & Vickers, 2017). Digital twinning has the potential to be very effective for farmers by providing real-time data on soil health, weather conditions, crop growth, and other factors that affect crop yields. This can enable farmers to make informed decisions about when to plant, irrigate, fertilize, and harvest their crops, leading to increased efficiency and productivity (Zhang et al., 2020). The concept of digital twins was developed to address these problems. By combining complex system analytic techniques, decision-making, and technological integration, digital twins are virtual reality simulations of real-world physical systems (Batty, 2018; Boschert & Rosen, 2016). The adoption of digital twinning in digital farming has the potential to revolutionize the way agriculture is practiced in India. By creating a virtual replica of the farm, farmers can now simulate and test various scenarios before implementing them in the real world. This not only helps in optimizing crop yields but also in reducing resource wastage and improving efficiency (Verdouw et al., 2015; Verdouw et al., 2016). With the advancements in technology and the increasing availability of digital tools and services, the future of digital farming in India looks promising, and it is essential for farmers to adapt to these new techniques to ensure sustainable and profitable agriculture in the years to come.

In summary, this review article aims to explore the potential of digital twins in transforming the agriculture sector in India. It delves into the applications and challenges associated with digital twins in agriculture, highlighting the need for collaboration and adoption of these transformative technologies. By providing a comprehensive review of the current state and future prospects, this article aims to contribute to the growing body of knowledge on digital twins in agriculture and its implications for the agricultural value chain in India. An extensive literature review has been done to identify the key applications and challenges associated with the adoption of digital twins in agriculture. Main aim is to provide readers with valuable insights into the various aspects of digital twins, including their impact on decision-making, resource optimization, and crop management. By analyzing and synthesizing existing literature, authors have highlighted the importance of digital twins in addressing the specific needs and challenges of the agriculture industry in India.

Moreover, this review also sheds light on the necessity of collaboration among stakeholders, including farmers, technology providers, and policymakers, to facilitate the successful integration of digital twinning solutions into existing farming systems. Authors emphasize the importance of developing standardized, cost-effective, and secure digital twin platforms to ensure widespread adoption and benefits across the agricultural value chain.

By presenting a comprehensive overview of the current state and future prospects of digital twins in agriculture, authors aim to contribute to the growing body of knowledge in this domain. Through this review, authors seek to inspire further research and innovations in the field, ultimately supporting sustainable and profitable agriculture in India while addressing food security challenges.

2. Literature Review

Digital twins refer to a digital simulation of a physical process or system that combines artificial intelligence and physical feedback data so that farmers can automatically make the necessary adjustments as needed based on the feedback from the physical data and present the simulation of physical attributes in virtual reality in real time (Liu et al., 2019; Schleich et al., 2017; Vatn, 2018). The customization of complicated systems is one of the goals of digital twins (Jones et al., 2017). Because local system idiosyncrasies are frequently too complicated to be accounted for in a general model, digital twins can be employed to do so. Customized digital twins represent the many scenarios that the system may face, such as system health, operational efficacy, and profitability (Singh et al., 2022), while simulating the distinctive characteristics of each system instance and deployment. They provide a range of automated processes, including data collecting from sensors, simulations, actuator control, and report preparation. Operations become more efficient and streamlined as a result, requiring little to no attention, time, or human knowledge. As a result, they can run constantly with the fewest possible instances of human error (Schluse et al., 2018). Data fusion is another essential component of digital twins. They can assess potential action outcomes using data generated by multiple data sources from viewing the physical twins from various perspectives, intelligently integrating and enhancing information collected from various sources and processing it, which would otherwise not be possible using human senses (e.g., data from sensors, satellites, or information provided by other proprietors). They may employ human-centric intelligence to put controls in place for factors that were previously neglected, such as human–machine interaction for safer workplaces (Ma et al., 2019). Continuous operation along with information give a complete picture of the system's past, present, and ability to forecast future states (Cai et al., 2017). They exhibit dynamic behavior, such as depiction and simulation of past, present, and future behavioral data of actual items, and go beyond the scope of static product designs (Boschert & Rosen, 2016; Grieves & Vickers, 2017; Verdouw et al., 2015). This will make it possible for farmers and other interested parties to respond quickly in the event of a departure from the norm. Since they view systems from several perspectives, they are also able to quantify the overall impact of the uncertainties involved. The stakeholders can then receive this information in a customized manner based on their level of knowledge (Lin et al., 2021). There are frequently inbuilt permission-level controls in digital twins. Different users may prefer different report formats and control mechanisms. Consequently, permitting various levels of data openness and accessibility based on the significance of the operations being carried out and the sensitivity of the data being handled (Shahat et al., 2021). At the start of the century, Michael Grieves proposed that a virtual system of digital simulation could be made of a physical system containing the information of it. It is connected through the entire lifecycle of the physical system (Grieves &Vickers, 2017). On these lines, NASA created a simulation of the spaceship which was of ultra-high fidelity to allow mirroring of the actual and accurate conditions of the original spaceship in a mission from the Earth (Glaessgen & Stargel, 2012). Grieves (2014) proposed that digital twins' system should have a framework that includes the "physical space", the "virtual space," and connection of information flow between the two spaces (Grieves, 2014). Mayani et al. (2018) felt that digital twins are a bridge between the physical and digital worlds. Poddar (2018) and Sharma et al. (2018) considered it a virtual simulated model of a physical entity. Although somewhat different from each other, none of these definitions has ever departed from the basic framework of the digital twins. A digital twin system is made up of both software and hardware parts (Figure 1), with middleware acting as the data handling component.

Digital twins are primarily enabled by IoT sensors, which begin information transmission between physical items and their digital representations. Additionally, the hardware includes routers, edge servers, IoT gateways, and other network hardware. Actuators are devices that convert digital data into mechanical motions. In fact, the analytics engine is a crucial part of digital twins because it turns straightforward observations into useful business data. It frequently draws strength from model-based machine learning (Pushpa & Kalyani, 2020). A digital twin also has to have dashboards for real-time monitoring, modeling tools, and numerical simulations. The middleware for information management is yet another crucial component. The system is built around a storage system that gathers data from many sources. In an ideal world, the middleware infrastructure would also be able to handle networking, data aggregation, processing, quality control, data visualization, data modeling and regulation, and many more tasks (Bujari et al., 2021). These solutions include universal IoT platforms and industrial platforms because they typically come with built-in support for digital twins (AltexSoft, 2021). The communication bridge between both spaces is crucial for efficient data interchange. The physical space is made up of physical items like sensors and actuators, while the virtual space is made up of "multiphysical, multi-scale, probabilistic simulation models of a complex model" (Durão et al., 2018; Van der Burg et al., 2021). Digital twins are used in a variety of industries to meet a variety of user needs (Qi et al., 2021). Researchers have enhanced the original three-part digital twin structure in order to make its uses more common in new contexts. The original three-component structure now includes "digital twins data fusion" and "service system" modules, and the connections between the

Figure 1
Components of digital twins system (adapted from Altexsoft, 2021)

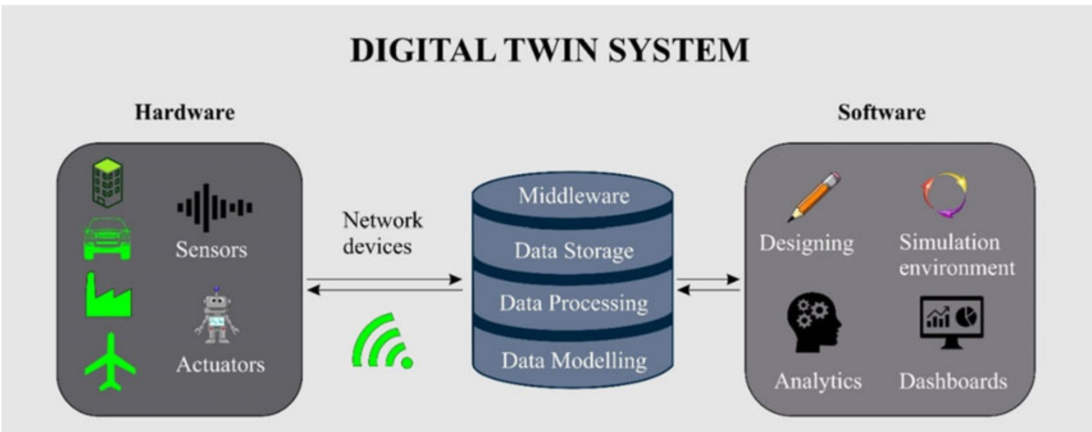
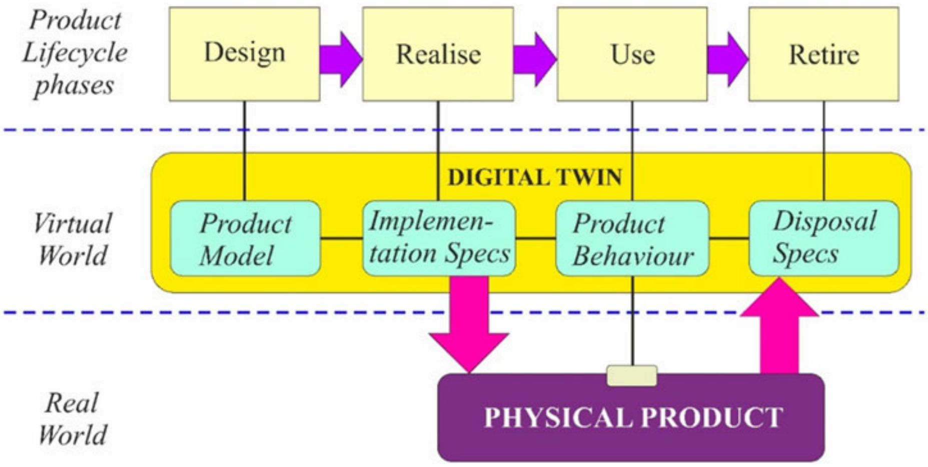


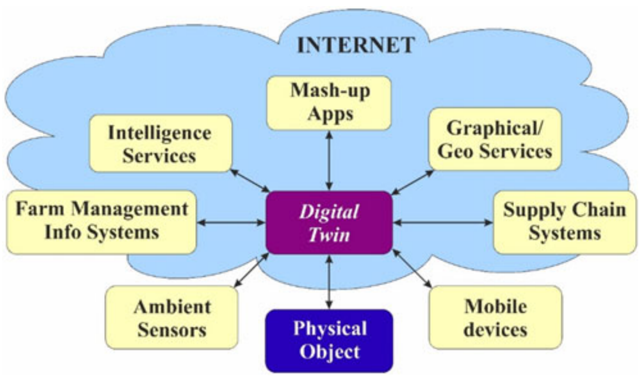
Figure 2
Role of digital twins during the Product Life Cycle (PLC) (adapted from Verdouw et al., 2021)



spaces have also been strengthened (Tao et al., 2021). Parrott and Warshaw (2017) also suggested a six-component structure with five enabling components and a six-step procedure. Here, "sensors" and "actuators" serve as enabling elements, with "act," "create," and "communicate" serving as the processes. In contrast, "data" and "analytics" serve as enabling elements, with "aggregate," "analyze," and "insight" serving as the processes in the virtual space. The term "integration" creates a link between the two spaces. The Product Life Cycle (PLC) can be designed using a digital twin, which permits fast and efficient evaluation of design decisions on the goods' function and quality without the need for costly physical prototypes (Grieves & Vickers, 2017; Schleich et al., 2017). A physical thing can be realized using the designed digital twin as a foundation. If there are deviations, it can be changed. During use, a physical object's present and past states are tracked using sensors and AutoID devices. Actuators can also be used to remotely operate an object. The physical thing is finally disposed of in the disposal stage, while the conceptual object might not be disposed of for a while due to traceability, adherence, and training reasons. In Figure 2, this procedure is depicted.

IoT is a crucial technology for enabling interaction between real-world and digital twin things. The IoT allows real items to interact, perceive, communicate, and share knowledge and information with their digital siblings, or "twins," as was previously stated (Canedo, 2016; Grieves & Vickers, 2017; Sundmaeker et al., 2010; Verdouw et al., 2015; Uckelmann et al., 2011). As seen in Figure 3, the Internet acts as a hub for digital twins that are used to store data and maintain communication. These digital twins connect relevant data that are updated regularly from various sources. Different definitions of digital twins have been made from both the PLC and IoT perspectives. The mirroring of physical items throughout their lifecycles, including the emulation of object activity, is highlighted using the PLC perspective. "A Digital Twin is a comprehensive physical and functional description of a component, product, or system, which includes more or less all information which could be useful in all—the current and subsequent—lifecycle phases," Boschert and Rosen stated in 2016 (Boschert & Rosen, 2016). A digital depiction of actual physical items employing sensors is highlighted from the IoT perspective. Using the IoT approach, Knibbe (2019) described digital twins in 2019 as "computational representations of both living and non-living things and processes." Through the use of data integration, artificial intelligence, and machine learning, they can be utilized to characterize, evaluate, and simulate the present and future states of and interventions in these objects (Knibbe, 2019). Using data integration, artificial intelligence, and machine learning, a digital twin is a dynamic representation of a real-world object that replicates its states and behavior throughout its lifecycle and can be used to monitor, analyze, and simulate the current and future states of and interventions on these objects (Garcia, 2022). Digital twins provide real-time assessment and management by reflecting the characteristics and capabilities of physical things. It presents a virtual "mirror space model" of a physical object that allows us to track deep, multiscale, and probabilistic dynamic state assessment, predict operational life, and assess task completion rate through the use of high-performance computations, sophisticated sensor feedback data, logical data analysis, and more (Githens, 2007). Digital twins can be used in a variety of fields, including agriculture, construction, healthcare, the automotive and aerospace industries, manufacturing equipment, and other areas, in addition to being integrated with artificial intelligence.

Figure 3
Digital twins in the Internet of Things (IoT) (adapted from Verdouw et al., 2021)



Digital twins can be classified into six distinct types, although during usage, these features and types can overlap and may not be independent of each other. They are as follows.

2.1. Imaginary digital twins

They are conceptual twins of objects that are non-existent in real-life and outline the data needed to form the physical twins. They might consist of functional and resource prerequisites, three-dimensional models, and discarding and recycling details (Grieves & Vickers, 2017; Verdouw et al., 2015). They can simulate the behavior of designed, non-existent objects. These digital twins are purely conceptual and are not based on any existing physical entity. They are useful for conceptualizing new designs and ideas but do not offer the benefits of data analysis that other types of digital twins can provide. It can be used for brainstorming and ideation and has no limitations based on existing physical entities. But, it does not offer the benefits of data analysis and cannot be used for predictive or prescriptive maintenance (Grieves & Vickers, 2017).

2.2. Monitoring digital twins

They are digital counterparts of the actual states and behaviors of real-life physical objects. They are connected real time (or almost real time) to their physical twins and can be used to monitor situations, actions, and external environments (Boyes & Watson, 2022).

They can be of two types:

I. Descriptive – They give an understanding of the past and present occurrences concerning the connected real-life physical object and

II. Diagnostic – They explain the reasons for the past and present occurrences by linking the real-life physical object with appropriate information.

Real-time monitoring allows for quick identification and resolution of issues, optimizing production and reducing downtime. However, its limitations lie in providing monitoring and analysis only, without the capability to offer predictive or prescriptive insights (Boyes & Watson, 2022).

2.3. Predictive digital twins

They give a digital forecast of the future states and behavior of real-life objects dynamically using real-time (or almost real-time) information about the physical twin and then employing predictive analytical methods, like statistical predictions, simulations, and machine learning methods. They are used in a variety of industries, including manufacturing and healthcare. Predictive insights allow for proactive maintenance and optimization, and this can help reduce downtime and increase efficiency. But this requires significant historical data for accurate predictions and this may not account for unforeseen events or changes in the environment (Van Dinter et al., 2022).

2.4. Prescriptive digital twins

They utilize output from monitoring and predictive digital twins as an input to intelligently suggest and prescribe remedial and precautionary measures to attain favorable results based on optimization algorithms and expert heuristics. They are commonly used in healthcare and transportation. They can provide actionable insights to improve performance. This allows for proactive maintenance and optimization. But this requires significant historical data for accurate predictions and recommendations and may not account for unforeseen events or changes in the environment (Van Dinter et al., 2022).

2.5. Autonomous digital twins

They can work autonomously without human intervention and fully control the behavior of real-life objects. They can self-learn, self-diagnose, and self-adapt to users' choices. They can operate autonomously, reducing the need for human intervention and optimize performance and reduce downtime. This requires significant historical data and complex algorithms for accurate decision-making and may not account for unforeseen events or changes in the environment (Porter & Heppelmann, 2014).

2.6. Recollection digital twins

They maintain complete historical data and form the digital memory of the real-life physical objects, which are not existent any longer in real-life. They can be significant in reducing the environmental impact of disposal, optimizing the next generation objects, and product tracing over quality and safety issues. This can capture and store data about a physical entity for future analysis and can be used to optimize performance and reduce downtime. But this is limited to historical data, cannot provide real-time insights, and also requires sensors and other technologies to capture data (Grieves & Vickers, 2017).

Overall, each type of digital twin has its own advantages and disadvantages. The choice of which type to use will depend on the specific needs and goals of the organization or industry. In general, the more advanced types of digital twins, such as prescriptive and autonomous digital twins, require more data and complex algorithms but offer greater benefits in terms of proactive maintenance and optimization.

3. Methodology

3.1. Literature search

We conducted an extensive search across various academic databases, including IEEE Xplore, ScienceDirect, PubMed, and Google Scholar, using keywords such as "Digital Twin," "Agriculture," "Precision Farming," "IoT in Agriculture," and related terms. The search was limited to publications from the past decade to ensure the inclusion of recent developments in the field.

3.2. Inclusion criteria

In the initial phase, we screened the retrieved literature based on relevance to the topic. Only peer-reviewed journal articles, conference papers, and reputable research reports were considered for inclusion in the review. We focused on publications that explicitly discussed the application of digital twin technology in agricultural practices, encompassing aspects related to crop management, resource optimization, predictive analytics, and decision-making.

3.3. Exclusion criteria

Publications that were not directly related to digital twin technology in agriculture, duplicate studies, and non-English articles were excluded from the review.

3.4. Data extraction

From the selected articles, we extracted key information, such as the authors, publication year, research objectives, methodologies, findings, and limitations. We organized the data in a systematic manner to facilitate a comprehensive analysis.

3.5. Synthesis and analysis

The extracted data were thoroughly analyzed to identify patterns, trends, and recurring themes related to the applications and challenges of digital twins in agriculture. We compared and contrasted different studies to gain insights into the current state of the field and the potential future directions.

3.6. Critical assessment

To ensure the credibility and reliability of the selected literature, we critically assessed the methodology, data sources, and sample size of each study. This step helped in evaluating the quality of the evidence presented in the literature.

3.7. Identification of gaps

Through the analysis, we identified gaps and limitations in the existing literature, particularly in areas where the application of digital twin technology in agriculture requires further exploration and research.

3.8. Conclusion and implications

Based on the findings from the literature analysis, we draw meaningful conclusions and discuss the implications of digital twin technology in transforming agriculture. We also highlight the potential benefits and challenges associated with the adoption of this technology in the agricultural sector.

By employing this approach, we aimed to provide a comprehensive and well-informed review of digital twin technology in agriculture, contributing to the existing body of knowledge and guiding future research efforts in this emerging field.

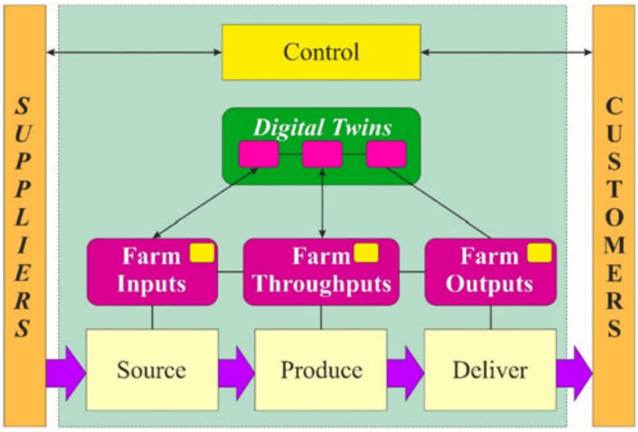
4. Results

4.1. Application of digital twins in agriculture

Agriculture is an extremely complicated and dynamic industry. It is reliant on various facets and quirks of Mother Nature, including the weather, the soil, the climate, and diseases. For farms to meet the demands of society and consumers for food safety, they must be effective and quick to adjust to changes in market conditions. To remain competitive in the market, they must also adhere to quality and environmental norms, placing a heavy load on agriculture in terms of hopes and expectations for the future of a nation's economy (Fountas et al., 2015; Sørensen et al., 2010). In order to reinforce agricultural knowledge, agricultural digital twins use a variety of production models, system rules, and feedback data collects to represent many parts of the agricultural production process as physical objects in physical space (Nasirahmadi & Hensel, 2022). With the help of these, they create dynamic virtual models that are multidimensional and multiscale and are based on agricultural entities, rendering diverse agricultural production processes in virtual reality (Figure 4).

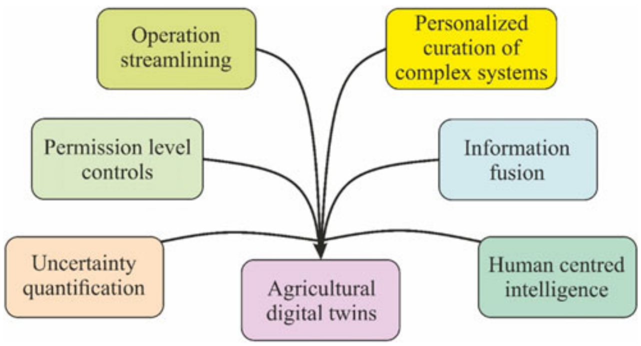
Through the association of data and learning from it, digital twins adjust to the initial conditions in each particular physical

Figure 4
Virtual control of agriculture by digital twin (adapted from Verdouw et al., 2021)



twin. With the help of the data interaction that takes place between the virtual model and the physical process, the dynamic virtual models continuously interact and optimize on their own to improve their integrity and obtain exact control over these entities. Quantitative prediction and decision feedback are carried out based on these actual agricultural entities as well as requirements. With the introduction of digital twins in agriculture, the physical agricultural entity and the digital virtual reality will be connected, perceived, and controlled (Figure 5). In the long run, this digital transformation and integration will increase agriculture's sustainability and profitability (Van der Burg et al., 2021).

Figure 5
Characteristics of digital twins that can benefit agricultural applications



By giving farmers a digital representation of their actual farm, digital twin technology can be a key component of digital farming. Using information from sensors, weather stations, and satellite photos, a digital twin is a digital depiction of a physical asset, such as a farm or a particular crop area (Purcell & Neubauer, 2023). It has its roots in the field of engineering and manufacturing. It involves creating a digital replica of a physical object or system, which can be used to simulate and test various scenarios and optimize performance. The use of digital twinning in agriculture is a more recent development, but it has quickly gained popularity due to its potential to revolutionize farming practices (Madni et al., 2019). The integration of digital twinning and digital farming has led to the development of smart farming, which involves the use of digital technologies such as sensors, IoT devices, and big data analytics to optimize farming practices and increase yields. Smart farming enables farmers to monitor and manage various aspects of their operations, such as soil health, crop growth, and livestock health, in real time (Alves et al., 2019). Digital farming and digital twinning are two technologies that have emerged in response to the increasing demand for sustainable and efficient agricultural practices. The integration of these technologies has led to the development of smart farming, which has the potential to revolutionize agriculture and increase food production to meet the growing demand for food (Abbasi et al., 2022).

While digital twins have a wider range of applications in other fields, including enhancing human–machine interaction safety (Ma et al., 2019), building cost and energy proficiency assessments (Nasirahmadi & Hensel, 2022; Teng et al., 2021), and providing insights into complex multidisciplinary systems (Bhatti et al., 2021), agronomy has not yet reached the point where they can demonstrate the same values. Digital twin applications in agriculture (Bhatti et al., 2021), animal husbandry (Neethirajan & Kemp, 2021), and apiculture (Singh et al., 2022) have not yet reached the stage of evaluation. However, the following are some uses for digital twins.

In order to monitor the impact and rotation of potatoes during harvest, Kampker et al. (2019) created a plastic "potato digital twin" in their place. The digital twin of the potato is planted online and harvested identically to actual ones in their study. It features sensors that monitor several aspects of the harvesting process, including blows, shocks, rotation speed, etc. The sensing data are used to modify the harvester machine's settings. Thus, crop damage is reduced. It is then connected to a cloud platform to calculate potato crop returns and price (Kampker et al., 2019). Digital twins were used by Linz et al. (2019) to construct field robots for crop treatment and phenotyping inside vineyards. They used real-time information to imitate the robots' autonomous behavior in a virtual 3D environment and then mirrored it to control the actual robot. They were able to cut down on the number of tests needed to evaluate crop treatment results or phenotypes, shorten development lead times, and measure sensor behavior more accurately (Linz et al., 2019). By building digital twins of the Alphonso, Totapuri, and Kesar mango kinds, Pattanaik and Jenamani (2020) were able to perfectly replicate the cooling and eminence of mangoes for trade based on airflow rate and temperature (Pattanaik & Jenamani, 2020). To research how crop quality and environmental factors interact and to manage crops, Evers et al. are developing a digital twin system of greenhouse tomato plants. The system will be improved using real-time sensor data fed from actual greenhouses (Webfixers, 2020). A digital twin system comprised of a single-view leaf reconstruction approach of plant growth using ResNet deep learning was proposed by Li et al. (2022). In order to improve animal welfare, Jo et al. (2018) developed a smart digital twin pig farm system employing their previously introduced digital twin stands called "Prefix," "Ditto," and "Watson" and conducted a feasibility study on it (Jo et al., 2018). One sustainable IoT-based model and a model for using digital twins in vertical farming were proposed by Monteiro et al. It focuses on monitoring and regulating the environment using light and misting (Monteiro et al., 2018). A farm management simulation tool called AgROS was created by Tsolakis et al. (2019) to enable field testing of autonomous agricultural robots or unmanned ground vehicles using static object layout characteristics like real fields and trees (Tsolakis et al., 2019) To assist in decision-making, Alves et al. developed an intelligent IoT-based prototype of a digital twins' farm system using data from sensors that measure soil moisture, humidity, and air temperature as well as data from weather stations, irrigation systems, and other sensory equipment. They emphasize that farmers can use a digital twin to make better decisions and lessen their impact on the environment and natural resources (Alves et al., 2019). A mechanism comprising numerous agents was put forth by Skobelev et al. (2020) for creating digital twins of plants. "A computer model that imitates its life cycle and synchronises with the living plant using examinations by agronomists and data on environmental conditions (weather, soil, etc.)" is how they described a plant's digital twin (Skobelev et al., 2020). There are less reports on digital twins for farming than there are for other industries, according to Sreedevi and Santosh Kumar (2020). They also suggested that digital twins could help hydroponic farming by forecasting potential problems. It can also manage nutrients, soil pH, illnesses, and weeds, as well as optimize the entire farming system (Sreedevi & Santosh Kumar, 2020). AgScan3D+, an autonomous dynamic crown monitoring system developed by Moghadam et al. (2020), creates digital twins of 15,000 trees and is employed in mango, macadamia, avocado, and vine orchards. In order to predict illness and crop loss, a spinning 3D camera creates a model for each tree, monitors its health, structure, pressure, fruit quality, and other indications, and gives real-time decision support.

Digital twins could ensure the natural capital of agricultural landscapes. Satellite data have a lot of potential because it could replace widely spread sensors that could give evidence. From an agricultural perspective, digital twins would enable the monitoring of functions such as river catchment, pollination, water table, and carbon. If they changed, it would be clear whether our actions or inaction caused the change. All of these use scenarios can already be partially satisfied if the proper sensors, models, and interfaces are invested in. However, because they rely on common models for crops, animals, agroecosystems, and other things, these would not quite suit our definition of a digital twin. In order to transform into a fully functional digital twin of the twinning entity, these models should develop and adapt (Smith, 2022).

To adapt digital twinning in farming, farmers can follow some steps such as identifying the problem, selecting the right technology, implementing the technology, and analyzing the data and continuous improvement. Farmers should identify the problem they want to solve or the opportunity they want to pursue using digital twinning technology. This could be optimizing crop yields, reducing waste, improving livestock management, or enhancing resource management (Neethirajan & Kemp, 2021). Once the problem has been identified, farmers should research and select the digital twinning technology that best suits their needs and budget. This could involve selecting sensors, drones, weather stations, or other technologies that can provide the necessary data. Once the technology has been selected, farmers should implement it by installing the necessary hardware and software, collecting and managing data, and integrating it into their existing farming systems (CEPAL, 2021). Once the technology has been implemented, farmers should analyze the data collected by the technology to gain insights into crop yields, weather conditions, soil health, and other factors that affect farming. This analysis can help farmers make informed decisions about when to plant, irrigate, fertilize, and harvest their crops. As farmers gain experience with digital twinning technology, they should continuously improve their use of the technology by refining their data analysis techniques, integrating additional technologies, and collaborating with other stakeholders in the farming ecosystem. In conclusion, digital twinning is an effective technology that farmers can use to optimize their farming practices and increase efficiency and productivity (El Idrissi et al., 2022). Here are some potential future aspects of digital twin farming and how they could help farmers economically.

4.1.1. Precision agriculture

Digital twin farming can enable precision agriculture by providing farmers with detailed insights into the health and growth of their crops. With this technology, farmers can use sensors and other data collection tools to monitor soil moisture, nutrient levels, and other key indicators. This information can then be used to make data-driven decisions about when to water, fertilize, or harvest crops, which can help farmers save money by reducing waste and increasing yields (Skobelev et al., 2020).

4.1.2. Predictive analytics

Digital twin farming can also help farmers predict potential issues before they become major problems. By analyzing historical data and real-time sensor data, digital twins can identify trends and patterns that may indicate issues such as pest infestations, crop diseases, or soil deficiencies. This early warning system can help farmers take proactive measures to prevent losses, which can help them save money and increase profitability (Knibbe et al., 2022).

4.1.3. Climate-smart farming

With the increasing threat of climate change, farmers need to adopt more sustainable and climate-smart practices. Digital twin farming can help by providing farmers with real-time data on weather patterns, soil conditions, and other environmental factors. With this information, farmers can adjust their practices to mitigate the impact of climate change and ensure their crops are resilient to extreme weather events. This can help farmers reduce risks and maintain their profitability over the long term (Slob & Hurst, 2022).

4.1.4. Autonomous farming

Digital twin farming can also enable autonomous farming by leveraging the power of machine learning and artificial intelligence. With autonomous farming, farmers can use robots and other automated tools to plant, harvest, and maintain crops. This can help farmers save time and money on labor costs, while also reducing the risk of human error. Additionally, autonomous farming can help farmers achieve higher levels of precision and efficiency, which can help them increase yields and profitability (Oliveira et al., 2022).

4.2. Challenges and limitations

The use of digital twin technology has been hailed as groundbreaking in numerous industrial fields. Its promise in agriculture is currently far from being realized. The more complex systems that digital twins aim to digitize are one of the key reasons why there are not more implementations. The majority of agronomical systems are complex living systems made up of intricate and dynamic agricultural practices, which makes it challenging to establish a foundation (Abbasi et al., 2022). Beyond the current capabilities of digital twins' dynamic behavior, the process dynamics demand skills. This issue is still present in the healthcare industry (Oyekan et al., 2020). In such a dynamic process, it is difficult to obtain a seamless access to object information while maintaining sufficient data integrity. Furthermore, it can be challenging to meet real-time synchronization requirements in remote locations due to a lack of funding (Botín-Sanabria et al., 2022). The fact that farming requires numerous interrelated objects, such as involvements such as seeds, fertilizers, and pesticides; materials involving objects concerned with agricultural production and resources like fields, machinery, and manpower; and different forms of agricultural output such as harvests, adds to the dynamism and complexity mentioned above. Managing the relationships between several digital twins used in farming that have varying granularity levels is difficult (Schleich et al., 2017).

Another characteristic indicating the acceptance of digital twins in agronomy is that the group must come to believe in the interaction of the components of the digital twins in order for it to be accurate. This key goal is to accurately represent a system's internal operations and to provide maintenance schedules and alternative administrative methods (Bécue et al., 2020). It is difficult to acquire this faith since many conclusions have an influence on living systems that is difficult to reverse. Additionally, the less data culture slows down adoption in agronomy, necessitates vast volumes of data to operate, and does not provide the anticipated benefits in small-scale deployments (Jones et al., 2017). The integration of digital twins' components and their real-time updating can be difficult for a culture that is highly transdisciplinary and less focused on IT (Brown et al., 2019). Due to the variance in the design of digital twins run by different customers, dynamic integration of data gathered from many stakeholders and subsequent data fusion into a single model in a virtual space is another challenge. External investors need to have secure access to digital twins, and the solution they use should enable them to add historical and future data archives and resources, such as past and satellite data inputs, weather forecast inputs, and analyses of soil, water, and air conditions to the digital twins (Lehtola et al., 2022). Although they are not exhaustive, each of these datasets provides a variety of signals. Loopholes will develop if there is a lack of information or if the parameter is not carefully examined. For instance, extrapolating these measures from other data is typically simple. As a result, digital twins often contain a computer modeling framework that fills in these gaps (Segovia & Garcia-Alfaro, 2022). These systems must go beyond simple models, like those used to forecast grass development, and accurately reflect the relevant chemical, physical, and biological processes taking place in the field. Learning capability is a need, and the model must faithfully represent the actual variety of grass species seen in the field (Pylianidis et al., 2021). Additionally, they need to make it simpler for the decision-maker to access exceedingly complex information. It is not required to have a complex digital twin. Since it would be difficult to estimate the exact amount of digestible dry matter contained in a field of grass, it is crucial that they are realistic enough (Smith, 2022).

In spite of many potential benefits for agriculture, there are also some drawbacks to consider. Here are some of the main drawbacks.

4.2.1. Cost

Digital twin can require significant investment in technology and infrastructure, such as sensors, data management systems, and software. This can be a barrier for small-scale farmers who may not have the financial resources to invest in this technology (Attaran & Celik, 2023).

4.2.2. Data privacy and security

The use of digital twin technology involves collecting and analyzing large amounts of data. These raise concerns around data privacy and security, as farmers must ensure that their data are protected from cyber threats and other unauthorized access.

4.2.3. Technical complexity

Digital twin technology can be complex, requiring specialized skills and expertise to implement and manage. This can be a challenge for farmers who may not have experience with these technologies (Lei et al., 2023).

4.2.4. Environmental impact

While digital twinning can help farmers optimize their use of resources, such as water and fertilizer, the technology itself may have an environmental impact. For example, the use of sensors and other electronic devices can create electronic waste, and the energy required to power these devices can contribute to greenhouse gas emissions (Botín-Sanabria et al., 2022).

4.2.5. Limited access to technology

In some cases, farmers may not have access to the necessary technology infrastructure, such as reliable Internet connectivity or electricity supply, to support the use of digital twin technology (Tzachor et al., 2022).

Regarding eco-friendliness, digital twin can be both beneficial and detrimental to the environment. On one hand, digital twinning can help farmers optimize their use of resources, reduce waste, and adopt sustainable farming practices. This can contribute to more eco-friendly agriculture. On the other hand, the technology itself may have an environmental impact, as mentioned above. Therefore, it is important to consider the overall environmental impact of digital twinning in agriculture and work toward minimizing any negative effects (Blair, 2021).

4.3. A hypothetical suggested model for improvement of digital twins in agricultural sector

The proposed model involves developing a digital twin model for predicting crop yield and quality in agriculture. The model will utilize data from various sources such as soil sensors, weather forecasts, and historical yield data to generate accurate predictions of crop yield and quality. This will enable farmers to optimize their crop management practices and make informed decisions regarding planting, fertilization, and irrigation.

The proposed digital twin model will differ from existing methods in several ways. First, it will leverage advanced machine learning algorithms to process and analyze large volumes of data from various sources. This will enable the model to generate more accurate predictions than traditional statistical models that rely on simpler data processing techniques. Second, the proposed model will incorporate real-time data from sensors and other sources to continuously update its predictions. This will enable farmers to make timely adjustments to their crop management practices based on the latest information. Third, the model will be designed to be highly scalable and customizable, allowing it to be adapted to a wide range of crops and farming environments. This will make it a valuable tool for farmers across different regions and climates. In summary, the proposed problem of developing a digital twin model for predicting crop yield and quality has the potential to significantly improve agricultural productivity and sustainability. The model's ability to leverage advanced machine learning algorithms, real-time data, and scalability will set it apart from existing methods and make it a valuable tool for farmers worldwide.

Here is a proposed method section for the problem of developing a digital twin model for predicting crop yield and quality in agriculture. Our proposed method is illustrated through a flow chart in Figure 6.

4.3.1. Data collection

The first step in developing the digital twin model is to collect relevant data from various sources such as soil sensors, weather forecasts, and historical yield data. These data will be used to train and validate the model.

4.3.2. Data preprocessing

Once the data are collected, it needs to be preprocessed to remove any inconsistencies and errors. This step involves data cleaning, normalization, and feature engineering to extract relevant features from the data.

4.3.3. Model development

In this step, we will develop a deep learning model that can effectively predict crop yield and quality. The proposed model will be based on a convolutional neural network (CNN) architecture that has shown promising results in image classification tasks. The model will take input data from various sources and predict crop yield and quality based on that data.

4.3.4. Model training

The next step is to train the model using the preprocessed data. We will use a combination of supervised and unsupervised learning techniques to train the model. The supervised learning will involve using labeled data to train the model, while unsupervised learning will be used to learn patterns and relationships in the data.

4.3.5. Model validation

After the model is trained, it needs to be validated using a separate dataset to ensure that it can generalize to new data. We will use k-fold cross-validation to evaluate the performance of the model.

4.3.6. Model optimization

In this step, we will optimize the hyperparameters of the model to improve its performance. We will use techniques such as grid search and random search to find the best hyperparameters.

4.3.7. Real-time integration

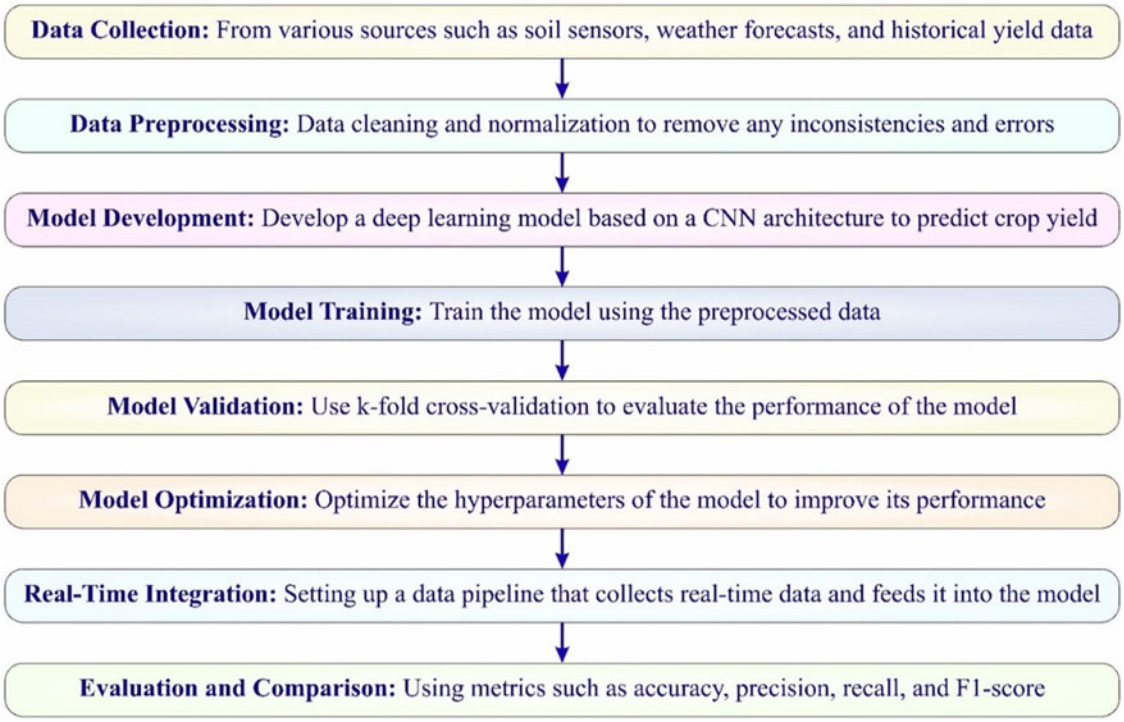
Once the model is optimized, it needs to be integrated into a real-time system that can provide farmers with up-to-date predictions of crop yield and quality. This will involve setting up a data pipeline that collects real-time data from various sources and feeds it into the model.

4.3.8. Evaluation and comparison

Finally, we will evaluate and compare the performance of the proposed digital twin model with existing methods. We will use metrics such as accuracy, precision, recall, and F1-score to evaluate the model's performance.

The proposed methodology incorporates the latest ideas in deep learning concepts such as CNNs and hyperparameter optimization techniques to achieve the best results (Bhosle & Musande, 2023). The use of CNNs enables the model to effectively process and analyze complex data from various sources, while hyperparameter optimization ensures that the model is fine-tuned for optimal performance. Additionally, the real-time integration of the model into a data pipeline ensures that farmers have access to up-to-date

Figure 6
Proposed method for revolutionizing modern agriculture through digital twins



predictions, enabling them to make informed decisions about crop management practices. Overall, the proposed methodology provides a comprehensive approach for developing a digital twin model for predicting crop yield and quality in agriculture.

5. Conclusion and Future Prospects

This article highlights the increasing significance of digital twin technology in India's agriculture sector. By utilizing advanced technologies, farmers can access tools and services to enhance crop yields, minimize wastage, and improve profitability, contributing to the overall development of the agricultural value chain. The potential of digital twins in agriculture is immense, especially with the further growth of artificial intelligence technology and virtualization in agriculture.

Digital twin technology in farming is playing an increasingly important role in India's agriculture sector. This not only benefits farmers but also contributes to the overall development of the agricultural value chain, ultimately leading to food security and economic growth for the country. This technology holds a huge amount of promise for the upcoming years to come with further growth of artificial intelligence technology and virtualization of agriculture. Some of the future scopes of digital twin technology in daily life could include:

- Healthcare: Digital twins could be used to create personalized medical treatments for patients by modeling their anatomy, physiology, and genetic makeup. This could lead to more effective and efficient treatments and better patient outcomes.
- Transportation: Digital twins could be used to simulate traffic patterns and optimize traffic flow, leading to reduced congestion and improved transportation efficiency. They could also be used to model the behavior of autonomous vehicles and optimize their performance.
- Manufacturing: Digital twins could be used to optimize the design and production processes of manufacturing plants, leading to reduced waste and improved productivity.
- Energy: Digital twins could be used to model energy systems and optimize energy usage, leading to reduced energy consumption and lower carbon emissions.

Digital twin technology will be more advanced and adopted into different agricultural sectors. It can be used as a basis for the complicated interactions of agronomical production processes to obtain agricultural information. For instance, a digital twin plant model can be created to simulate the expected life cycle of the plant based on environmental factors in advance. This technology allows for fully automated production and processing, which reduces production costs. By modeling the animals and compiling data on their living conditions, dietary needs, etc., it can be utilized to create a virtual farm breeding environment. To enable smooth data integration and operation, a standard interoperable digital twin technology must be established. We also need to provide them access to a great number of sensors and a huge amount of data to help them construct the ideal digital twin model so they can quickly analyze the data and understand the issues. To boost the effectiveness of the models, we must also create a sizable database. The development of digital twin models must be done in a way that makes them applicable in all fields, regardless of the weather and other factors. Therefore, we must provide the systems with a vast volume of unfiltered data from numerous fields globally. In order to solve the issues, it is also vital to gather data from the local population and incorporate it into the database, as doing so will improve the accuracy and effectiveness of digital twin models. To create digital twins that are more precise in the agricultural and other industries, scientists and engineers from all around the world must collaborate. The adoption of digital twin technology, particularly in agriculture, is still in its infancy; it may be inferred from this. Integrating the various forms of data that are available to effectively describe an agricultural system or object from start is a difficult undertaking for academics. While some low-level tasks can be completed without human assistance, most decision-making tasks require physical intervention. Advanced uses of digital twins for prescribing and predicting throughout the lifecycle have not yet been fully explored and require more study. Building a fully autonomous simulation without requiring human involvement is a significant problem and a future research goal.

Overall, this article emphasizes that while digital twin adoption in agriculture is still in its early stages, it holds tremendous potential. Further research is needed to explore advanced applications of digital twins throughout the agricultural lifecycle and to build fully autonomous simulations without human intervention. The potential impact of this technology on agriculture and other sectors can be transformative, promising a future of enhanced crop productivity, environmental sustainability, eco-friendly agripreneurship, and greener economic growth.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

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