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A Comprehensive Overview of Federated Learning for Next-Generation Smart Agriculture: Current Trends, Challenges, and Future Directions

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Federated Learning (FL) is an emerging technique that offers significant potential to enhance smart agriculture by enabling collaborative model training across distributed data sources while preserving data privacy. This paper provides a comprehensive overview of the integration of FL within smart agriculture, emphasizing its role in addressing key challenges, such as data privacy, security, scalability, and data heterogeneity. The paper distinguishes itself from existing reviews by systematically analyzing FL applications in specific agricultural domains, including crop monitoring, soil health management, and livestock management. In addition, it introduces new classifications of FL use cases, focusing on privacy-preserving techniques, scalability issues, and the non-IID nature of agricultural data. Case studies from real-world implementations are used to highlight practical applications and challenges. The paper also discusses recent advances, such as the integration of FL with edge computing and the adoption of personalized federated learning. By presenting a detailed analysis of trends, challenges, and future research directions, this overview fills gaps in existing literature and provides insights into how FL can be leveraged to improve precision, productivity, and sustainability in smart agriculture. Ultimately, the findings underscore the transformative potential of FL to revolutionize data-driven agricultural decision-making and contribute to the development of resilient, privacy-conscious agricultural systems.

Povzetek: Podan je pregled metod in tehnik federativnega učenja ter njihove uporabe v pametnem kmetijstvu. Federativno učenje omogoča sodelovalno učenje modelov na porazdeljenih podatkih, kar ohranja zasebnost podatkov. Kljub prednostim, kot so izboljšana zasebnost in zmanjšanje potrebe po centraliziranem zbiranju podatkov, se pri uporabi federativnega učenja pojavljajo izzivi, kot so heterogenost podatkov, zagotavljanje varnosti in zasebnosti ter obvladovanje neodvisno in neenakomerno porazdeljenih podatkov.

1 Introduction

Smart agriculture, also known as precision agriculture, marks a significant evolution in farming practices by integrating modern information and communication technologies (ICT) to enhance efficiency, productivity, and sustainability (see figure 1). Often referred to as the *Third Green Revolution*, smart agriculture leverages technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), and Big Data to enable real-time monitoring and control of agricultural processes. These technologies optimize the use of critical resources like water, fertilizers, and pesticides. The current technological landscape includes IoT devices and sensors that collect vast amounts of data from fields, offering insights into soil health, crop growth, and environmental conditions. Drones and satellite imagery provide advanced monitoring capabilities, enabling early detection of problems and timely corrective actions. AI and ML algorithms process this data to provide predictive analytics and decision support, helping farmers make informed decisions. Additionally, automation and robotics are becoming more prevalent in tasks like planting, weeding, and harvesting, enhancing operational efficiency.

Despite these technological advancements, the vast distribution of agricultural data and the need to maintain data privacy pose significant challenges. Traditional centralized approaches to data collection and processing require the transfer of large volumes of raw data to centralized servers, which raises concerns about data privacy, security, and scalability. Federated learning (FL), a decentralized machine learning approach, holds significant potential to address these challenges by allowing multiple clients (e.g., edge devices or local servers) to collaboratively train models while keeping data local. This paradigm shift allows models to be trained without transferring raw data, as each client shares only model updates (e.g., gradients or parameters)

with a central server, which aggregates these updates to improve the global model. The process iterates until the model converges.
The benefits of federated learning are manifold. By ensuring that raw data remains on local devices, it significantly enhances data privacy and security, reducing the risks associated with data breaches and unauthorized access. Furthermore, FL minimizes communication overhead and bandwidth requirements-critical concerns when handling large datasets in agriculture.

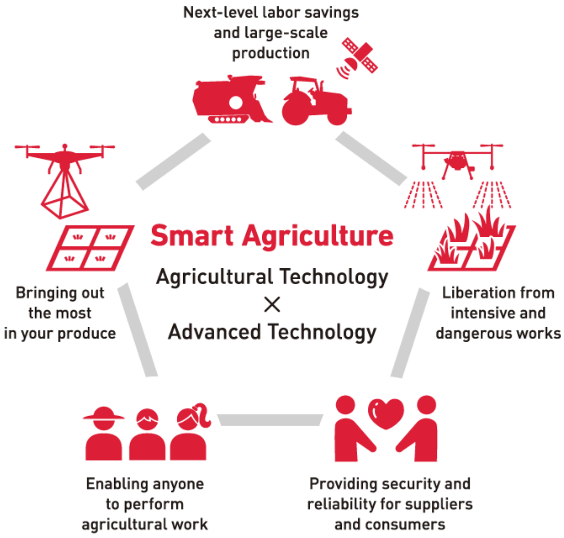

Figure 1: Smart agriculture

It also enables the use of diverse, heterogeneous data from multiple sources, improving the robustness and generalizability of trained models. However, FL presents several technical challenges, such as managing non-IID (non-Independent and Identically Distributed) data, ensuring secure and efficient communication between clients and servers, and addressing issues related to model convergence and performance. The heterogeneity of devices and data quality can also impact FL's effectiveness in agricultural environments.
The integration of federated learning into smart agriculture (see figure2) is driven by the necessity to enhance data privacy, reduce communication costs, and leverage the distributed and fragmented nature of agricultural data. In traditional centralized systems, privacy concerns and the risk of data breaches are prominent, as vast amounts of sensitive data must be transferred and stored in central servers. Federated learning mitigates these issues by keeping data local and only transmitting model updates. Furthermore, the decentralized nature of FL aligns well with the geographically dispersed and heterogeneous agricultural landscape, allowing for the development of personalized and context-aware models that cater to specific regional needs.

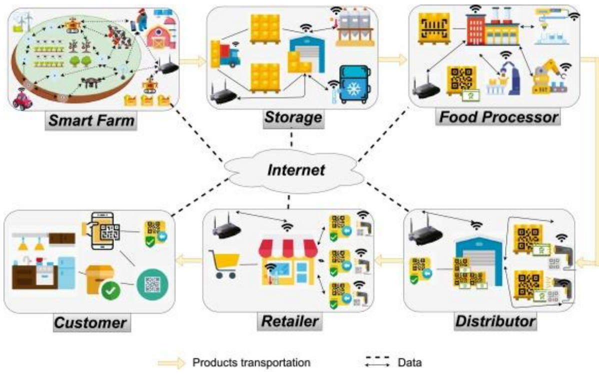

Figure 2: Federated learning for smart agriculture

The primary objective of this paper is to provide a comprehensive overview of the current state and potential of federated learning in the context of smart agriculture. Specifically, this survey reviews the existing literature on federated learning and its applications in various domains, with a focus on agriculture. It highlights the current trends and technologies in smart agriculture that can benefit from federated learning, examines the challenges and opportunities associated with its implementation, and presents case studies and real-world implementations to illustrate practical applications. In addition, the paper discusses security and privacy considerations specific to federated learning in agriculture and identifies future research directions that could further enhance the integration of FL into smart agricultural practices.
Unlike previous surveys that primarily focus on individual technical aspects of FL or specific applications in other industries, this paper aims to fill existing gaps by providing a holistic overview of FL in smart agriculture. It explores a wider range of applications, from crop monitoring and soil health management to livestock management, while also addressing emerging trends such as the integration of FL with edge computing and advanced privacy-preserving techniques. To strengthen its practical relevance, the paper includes real-world case studies that compare FL-based solutions to traditional methods, highlighting the benefits and limitations of FL in diverse agricultural contexts.
The structure of the paper is as follows: First, it explores current trends and technologies in smart agriculture, focusing on IoT, sensor networks, AI, and ML. The literature review follows, offering an analysis of existing research on federated learning in agriculture and identifying research gaps. Next, the fundamentals and techniques of federated learning are detailed, including its core concepts and methodologies. Various applications of FL in agriculture, such as crop monitoring, soil health, and livestock management, are examined. Finally, case studies and real-world implementations are reviewed to discuss practical challenges and solutions, followed by a discussion of the challenges and future directions for FL in smart agriculture. This survey aims to inform researchers, practitioners, and policymakers about the potential of federated learning to revolutionize agricultural practices.

2 Literature review

This literature review provides a comprehensive overview of the research landscape in federated learning (FL) and its integration with smart agriculture. It is organized into three main sections: (1) an overview of federated learning, (2) a review of technological advancements in smart agriculture, and (3) an exploration of how federated learning addresses specific challenges within agricultural practices. Additionally, this section includes a comparative analysis of existing overview papers on federated learning in agriculture, highlighting gaps and outlining how this paper contributes to the state-of-the-art (SOTA).

2.1 Overview of federated learning

Federated learning represents a paradigm shift in machine learning, enabling multiple participants to collaboratively train a shared model while maintaining data localization. This approach is particularly valuable in addressing data privacy concerns and minimizing the need for large-scale data transfers. The Federated Averaging (FedAvg) algorithm, introduced by McMahan et al. [1], is a cornerstone technique in FL, allowing efficient model training across numerous devices by aggregating local model updates from participants without sharing raw data.

Recent research has focused on enhancing the robustness and scalability of FL in real-world environments. A major challenge in federated learning is handling non-IID (non-Independent and Identically Distributed) data, which arises when data distribution varies across clients, as is often the case in agriculture. To address this, several studies have proposed strategies to improve the performance of FL algorithms in heterogeneous environments [2], such as modifying the aggregation process to account for variations in data distributions.

Privacy remains a critical concern in FL, especially when dealing with sensitive agricultural data. Secure aggregation and differential privacy techniques, as introduced by [3], provide strong privacy guarantees by ensuring that individual data points cannot be re-identified from the aggregated updates. These techniques are particularly useful in agricultural settings where protecting sensitive data (e.g., soil conditions or crop yields) is paramount.

In addition to privacy concerns, the emergence of personalized federated learning has gained traction. Personalized FL [4] enables global models to be fine-tuned to better align with individual clients' data, addressing the challenge of heterogeneity in local data. This method improves the relevance and accuracy of predictions, particularly in agricultural contexts where environmental conditions and farming practices can vary significantly across regions.

2.2 Research on smart agriculture technologies

Smart agriculture integrates advanced technologies to improve farming practices, efficiency, and productivity. Key among these technologies are Internet of Things (IoT) devices and sensor networks, which enable real-time monitoring of environmental conditions and facilitate data-driven decision-making. In their comprehensive review of IoT applications in precision agriculture, [5] highlighted how these technologies enhance crop yield predictions and resource management. By collecting granular data on soil moisture, temperature, and nutrient levels, IoT-enabled systems offer valuable insights that optimize agricultural practices.

Machine learning (ML) also plays a pivotal role in processing the vast amounts of data generated by IoT systems. Deep learning algorithms have been shown to significantly improve the detection of crop diseases and the prediction of crop yields. For example, [6] demonstrated that convolutional neural networks (CNNs) outperform traditional methods in identifying early symptoms of crop diseases, leading to timely interventions and improved agricultural outcomes.

Beyond deep learning, reinforcement learning (RL) has been explored as a technique for optimizing resource allocation in agriculture. For instance, [7] applied reinforcement learning to irrigation management, showing how RL models dynamically adjust water usage based on real-time environmental data, resulting in substantial water conservation.

2.3 Federated learning in smart agriculture

The integration of federated learning into smart agriculture offers several benefits, particularly in addressing challenges such as data privacy and fragmentation. In traditional centralized systems, agricultural data (e.g., from multiple farms) must be transferred to a central server, raising privacy concerns and the risk of data breaches. Federated learning mitigates these issues by allowing farms to collaboratively train models without sharing raw data, making it a powerful tool for privacy-conscious applications.

For instance, a study by [8] demonstrated the effectiveness of federated learning in collaborative crop monitoring. Their work showed that federated models improved the accuracy of disease prediction and crop management without compromising individual farm data privacy. Similarly, [9] explored the use of FL for soil health management, revealing that decentralized data from different farms could be used to develop highly accurate soil quality prediction models. By preserving data privacy, federated learning enabled better insights into soil management strategies without risking exposure of proprietary data.

However, while these studies highlight the potential of federated learning, several gaps remain in the existing literature. Most prior reviews focus narrowly on specific applications or technical aspects of FL without offering a comprehensive overview of its integration across various domains within smart agriculture. Additionally, many existing works overlook emerging trends in federated learning, such as its integration with edge computing or its application to personalized farming models that address the non-IID nature of agricultural data.

2.4 Comparative analysis of existing overview papers

To provide context for the contribution of this paper, it is essential to compare the current work with existing overviews in the field. The table below summarizes key overview papers in federated learning for smart agriculture, identifying their focus areas and highlighting the gaps they leave unaddressed.

Table 1: Comparative analysis of federated learning in smart agriculture

Overview Paper	Focus Areas	Gaps	Contribution of This Paper
[1]	General FL applications in IoT	Minimal coverage of agriculture-specific challenges, no discussion of FL integration with edge computing	Comprehensive focus on agriculture-specific use cases, emerging trends, and privacy concerns in FL
[2]	FL for data privacy in smart agriculture	Limited focus on application-specific challenges (e.g., non-IID data, regional differences)	In-depth analysis of technical challenges like data heterogeneity and model convergence in agriculture
[3]	FL for crop disease monitoring	Lacks broader application in soil and livestock management	Explores multiple agricultural domains, including soil health and livestock management
[4]	Privacy-preserving techniques in FL for agriculture	Insufficient analysis of emerging trends in FL (e.g., FL with edge computing)	Detailed exploration of emerging trends like FL-Edge integration and personalized FL for specific farm needs

As shown in the table 1, many existing reviews lack a **holistic approach** to federated learning in agriculture, focusing on either narrow technical aspects or specific applications. This paper seeks to fill these gaps by providing a more comprehensive overview of FL's integration into various agricultural domains, exploring both established and emerging trends, and presenting real-world case studies to highlight practical applications and challenges.

3 Federated learning fundamentals and techniques

Federated learning (FL) is a transformative approach in machine learning that emphasizes decentralized data processing and collaborative model training. It allows multiple clients to train a shared model locally on their data, addressing the challenges of data privacy, security, and data silos [10]. This section explores the core principles, key algorithms, and recent advancements in federated learning, including new methodologies and emerging trends that are critical for its applications in smart agriculture.

3.1 Fundamentals of federated learning

Federated learning is a decentralized machine learning paradigm designed to address privacy concerns and eliminate the need for transferring raw data between clients and central servers. It allows clients, such as IoT devices or institutions, to keep their data locally while contributing to a global model by sharing only model updates (e.g., gradients or parameters). This decentralized approach significantly enhances privacy and security while enabling collaboration across diverse data sources [11].

The FL process typically involves several steps:

- **Initialization**: A global model is initialized and distributed to all participating clients. This model, often a deep learning model, is trained locally by each client on its data [12].
- **Local training**: Each client trains the model using its local data and standard machine learning techniques (e.g., gradient descent) to update model parameters [13].
- **Aggregation**: The trained model updates from all clients are sent to a central server, where an aggregation method, such as Federated Averaging (FedAvg), combines the updates [14].
- **Update distribution**: The central server distributes the refined global model back to the clients, repeating the process until the model converges or meets a predefined performance threshold [15].
- **Model evaluation**: The global model is periodically evaluated using a validation set to ensure its generalization across different data distributions.

Federated learning addresses the need for privacy-preserving machine learning while benefiting from the diversity of data sources. However, it presents challenges in managing communication overhead, non-IID data, and ensuring efficient convergence in heterogeneous environments.

3.2 Core algorithms and techniques

3.2.1 Federated averaging (FedAvg)

Federated Averaging (FedAvg), introduced by McMahan et al. [16], is a foundational algorithm in federated learning. It aggregates local model updates from all participating clients to create a global model. The steps involved in FedAvg are:

- **Local training**: Clients train the model locally over several epochs, generating updates (e.g., gradients) based on their local data [17].
- **Aggregation**: The server aggregates these updates by calculating a weighted average, accounting for the size of each client's dataset [18].
- **Model update**: The aggregated global model is sent back to the clients for further training.

While FedAvg is effective for clients with similar data distributions, it struggles with heterogeneous environments, such as those found in agriculture, where data distributions across clients may differ significantly [19].

3.2.2 Secure aggregation

Privacy is a primary concern in federated learning, and secure aggregation techniques are essential for ensuring that individual client updates cannot be inferred from the aggregated data. **Secure aggregation** uses encryption to protect updates during transmission [20]. Key techniques include:

- **Homomorphic Encryption**: Enables computation on encrypted data, allowing the server to aggregate model updates without needing to decrypt them [21].
- **Secure Multi-Party Computation (MPC)**: MPC allows multiple clients to compute a function over their inputs while keeping those inputs private, ensuring the confidentiality of individual updates [22].

These techniques ensure privacy while preserving the utility of the aggregated global model, which is critical in privacy-sensitive applications like agriculture, where farm data can be proprietary or sensitive.

3.2.3 Differential privacy

Differential privacy offers mathematical guarantees that individual data points cannot be distinguished within a dataset, making it a crucial technique for ensuring privacy in federated learning. In FL, differential privacy is applied to model updates to prevent the extraction of sensitive information from the aggregated data [23]. Methods include:

- **Noise addition**: Random noise is added to model updates before they are sent to the server, with the amount and type of noise controlling the level of privacy [24].
- **Privacy budget**: This manages the trade-off between model accuracy and privacy by limiting the number of iterations and the amount of noise added [25].

Differential privacy is particularly valuable in smart agriculture, where protecting sensitive farm data, such as crop yields or soil conditions, is essential while still allowing for collaborative model training.

3.2.4 Personalization techniques

Personalized federated learning aims to adapt the global model to meet the specific needs of individual clients. This approach is especially useful when clients have diverse data distributions, as is common in agricultural environments where farms may differ significantly in climate, soil, and crop types [26]. Personalization techniques include:

- **Local fine-tuning**: After receiving the global model, each client can perform additional training on its local data to fine-tune the model for its specific requirements [27].
- **Meta-Learning**: This approach involves training models to learn how to adapt quickly to new tasks or data distributions, enabling clients to personalize the global model more effectively [28].

These personalization techniques improve the relevance and performance of federated learning models in heterogeneous environments like agriculture, where region-specific adaptations are necessary.

3.3 Eerging trends and techniques

3.3.1 Federated transfer learning

Federated transfer learning extends FL to scenarios where clients may have different, but related, tasks. It leverages pre-trained models from one task to improve learning on another related task, making it particularly useful in agriculture, where different farms or regions may have overlapping but distinct data needs [29]. The key aspects of federated transfer learning include:

- **Shared representation learning**: Shared model layers capture common features across tasks, enabling knowledge transfer between different agricultural tasks (e.g., pest detection in different regions) [30].
- **Task-specific fine-tuning**: Models can be customized for each client's specific task while retaining the benefits of shared learning [31].

This technique allows for improved model performance in scenarios with limited data or highly specialized tasks, such as detecting rare diseases in crops.

3.3.2 Federated multi-task learning

Federated multi-task learning allows for the simultaneous training of models on multiple tasks within a federated setting. This is highly beneficial in agriculture, where different farming operations (e.g., crop yield prediction, soil quality monitoring) may need to be optimized concurrently [32]. Techniques include:

- **Joint model training**: A single model is trained to perform multiple tasks, with task-specific heads or layers to handle different outputs [33].
- **Task aggregation**: Gradients from different tasks are combined to update the model in a way that benefits all tasks [34].

This approach improves efficiency and generalization, making it ideal for complex, multi-dimensional agricultural environments where different data sources need to be integrated.

3.3.3 **Federated** learning with edge computing

The integration of federated learning with **edge computing** is a key trend that aims to leverage computational resources at the edge of the network, such as IoT devices and edge servers. This approach reduces latency and improves the efficiency of federated learning by enabling more computation to be done locally, rather than sending data back and forth between clients and the central server [35]. Key benefits include:

- **Local computation**: Performing model training and updates locally on edge devices reduces the need for large-scale data transmission, making it particularly useful in rural or bandwidth-limited agricultural settings [36].
- **Edge aggregation**: Model updates can be aggregated at the edge before being sent to the central server, optimizing the communication process [37].

This trend is critical for smart agriculture, where IoT devices are increasingly deployed in fields for real-time monitoring of crops and environmental conditions.

4 Applications of federated learning in smart agriculture

Federated learning (FL) provides a decentralized approach to machine learning, enabling collaborative model training across multiple data sources while preserving data privacy [38]. In the context of smart agriculture, FL offers significant advantages by leveraging distributed data to enhance agricultural practices while maintaining data security. This section explores the various applications of FL in smart agriculture, focusing on its potential to improve crop management, optimize resource use, enhance livestock management, and drive innovation in precision agriculture. Additionally, this section compares the discussed applications with existing methods to highlight how FL addresses gaps left by traditional and centralized approaches.

4.1 Crop Management and Yield Prediction

4.1.1 Federated learning for crop disease prediction

Federated learning has the potential to significantly enhance **crop disease prediction** by aggregating data from various farms and research institutions without centralizing sensitive information. This approach addresses critical issues of data privacy and fragmentation that often hinder disease prediction models. Key applications include:

- **Disease detection models**: FL enables the development of robust disease detection models by training on diverse data sources, such as images from different regions. The ability to integrate data from various environmental conditions and farming practices enhances the generalization capabilities of these models, improving disease detection across different crops and regions [39].
- **Early warning systems**: Models trained through FL can analyze environmental data (e.g., temperature, humidity) and historical disease patterns to provide early warnings of potential disease outbreaks. This early detection system helps farmers take preventive measures before diseases spread, reducing crop losses and improving overall yield [40].

Compared to traditional centralized systems, FL offers a significant advantage in terms of data privacy, as raw data remains decentralized while model performance improves through collaborative training.

4.1.2 Yield prediction and optimization

Yield prediction models also benefit from federated learning by integrating diverse data from multiple farms, regions, and weather stations. Applications include:

- **Aggregated yield forecasting**: FL aggregates yield data from various sources—such as satellite imagery, weather forecasts, and historical yield records allowing for more reliable predictions. These aggregated models enable better planning and resource allocation by factoring in diverse environmental conditions [41].
- **Precision agriculture**: Federated learning improves precision agriculture by integrating data on soil conditions, crop health, and weather patterns. These models help optimize variable-rate applications of fertilizers, pesticides, and water, leading to more efficient resource use and improved crop productivity [42].

FL enables yield forecasting and optimization at a broader scale, addressing the heterogeneity of data from different regions while preserving data privacy.

4.2 Soil and irrigation management

4.2.1 Soil quality monitoring

FL enhances **soil quality monitoring** by aggregating data from a variety of sources, including sensors and research stations, allowing for a more comprehensive understanding of soil health.

- **Soil health models**: By training models on data from multiple sensors (e.g., soil moisture, nutrient sensors) and laboratory analyses, FL

can provide detailed assessments of soil quality. This approach leads to better recommendations for soil management practices, helping farmers optimize soil health across regions with different soil conditions [43].
- **Nutrient management**: FL-based models analyze soil nutrient levels and crop nutrient requirements across various regions, optimizing fertilizer application. This data-driven approach reduces waste, improves soil fertility, and promotes sustainable farming practices [44].

By preserving data privacy while enabling broader collaboration, FL provides a more effective method for soil monitoring compared to traditional centralized systems that require data aggregation at a single site.

4.2.2 Smart irrigation systems

Federated learning improves the efficiency of **smart irrigation systems** by aggregating data from diverse sensors and weather stations to optimize water use:

- **Water usage optimization**: FL models aggregate data from soil moisture sensors, weather forecasts, and historical irrigation practices, leading to more efficient watering schedules. This reduces water waste and ensures that crops receive the right amount of water based on real-time conditions [45].
- **Adaptive irrigation**: FL models continuously learn from data collected across different farms, allowing them to adjust irrigation practices in real-time based on environmental changes and crop needs. This adaptability improves water use efficiency, a critical factor in regions facing water scarcity [46].

FL's ability to aggregate data while maintaining privacy makes it ideal for optimizing irrigation systems, particularly in regions where water management is a critical concern.

4.3 Livestock management

4.3.1 Health monitoring and disease management

In livestock management, FL offers significant advantages in **health monitoring and disease management:**

- **Health prediction models**: FL models trained on data from wearable sensors (e.g., heart rate monitors, activity trackers) can predict early signs of health issues in livestock. These models enable timely intervention, reducing disease spread and improving overall herd health [47].
- **Disease outbreak prediction**: By aggregating data on livestock health, environmental conditions, and disease history, FL models can predict potential disease outbreaks. This allows farmers to implement preventive measures, leading to better disease management [48].

The decentralized nature of FL helps protect sensitive livestock data while facilitating more accurate health and disease predictions across different farms.

4.3.2 Productivity optimization

FL also supports the optimization of **livestock productivity** by integrating data on feeding patterns, growth rates, and environmental conditions:

- **Feed efficiency models**: FL-based models analyze data from automated feed systems and sensors to optimize feed formulations and delivery schedules. This improves feed efficiency, reduces costs, and enhances animal growth [49].
- **Performance monitoring**: Models trained using FL can monitor livestock performance metrics (e.g., weight gain, reproductive rates) across farms, helping identify best practices and optimize management strategies [50].

FL enables collaboration among farms without compromising proprietary data, making it an ideal solution for productivity optimization in livestock management.

4.4 Precision agriculture and resource management

4.4.1 Precision planting and harvesting

FL can significantly enhance **precision planting and harvesting** practices:

- **Planting recommendations**: FL models analyze data on soil conditions, crop varieties, and weather forecasts to provide personalized planting recommendations. These models ensure crops are planted under optimal conditions, leading to better yields and more efficient resource use [51].
- **Harvest timing optimization**: By integrating data on crop growth stages and environmental conditions, FL models predict the best times for harvesting, minimizing losses and maximizing crop quality [52].

Compared to centralized systems, FL offers a more flexible and privacy-preserving approach to precision agriculture, allowing for more tailored recommendations based on local data.

4.4.2 Resource allocation and management

FL enhances **resource allocation and management** by aggregating data on resource usage (e.g., water, fertilizer) and environmental conditions:

- **Resource efficiency models**: These models analyze data on water, fertilizer, and pesticide usage to optimize resource allocation, reducing waste and ensuring that resources are used efficiently across different farms [53].
- **Environmental impact assessment**: FL models assess the environmental impact of agricultural practices by integrating data on soil health, water usage, and emissions. This helps in developing sustainable practices that mitigate environmental impacts [54].

FL supports more sustainable agricultural practices by enabling efficient resource management while preserving sensitive data.

4.5 Emerging trends and innovations

4.5.1 Integration with edge computing

The integration of FL with **edge computing** is an emerging trend that enhances real-time decision-making in agriculture:

- **Edge-based learning**: Edge devices, such as sensors and IoT devices, can perform local federated learning to analyze data in real-time. This reduces latency and improves the responsiveness of agricultural applications, such as automated irrigation and disease detection [55].
- **Collaborative edge networks**: FL models can be deployed across collaborative edge networks, allowing farms and agricultural institutions to share insights and improve model performance without compromising data privacy [56].

4.5.2 Federated transfer learning

Federated transfer learning allows knowledge transfer across related but different tasks, further enhancing FL's capabilities:

- **Knowledge transfer**: Federated transfer learning allows for the transfer of knowledge from one agricultural task or region to another. For example, a model trained to detect pests in one region can be adapted for another region with similar pest characteristics [57].
- **Adaptation to local conditions**: Transfer learning models can be fine-tuned using local data to adapt to specific agricultural conditions, improving model performance and relevance [58].

5 Case studies and real-world implementations

Federated learning (FL) is transforming smart agriculture by enabling farms to collaboratively develop advanced machine learning models without centralizing sensitive data. This approach is particularly effective in real-world scenarios where decentralized data sources, such as farms and agricultural institutions, can be utilized to solve complex agricultural challenges. By applying FL, farms can improve predictive accuracy, optimize resource management, and enhance operational efficiency, all while ensuring data privacy and security. The following case studies illustrate the practical benefits and transformative potential of FL in modern farming.

5.1 Weather-driven pest management

- **Scenario**: In the Mediterranean region, a network of farms collaborates to improve pest management using FL. Each farm collects data on local weather conditions (e.g., temperature, humidity, rainfall) and pest occurrences. This data includes detailed records of pest populations, environmental conditions, and crop types [59].
- **Federated learning application**: Each farm trains a local model to analyze the relationship between weather patterns and pest activity. FL aggregates these local models to build a comprehensive global model that predicts pest outbreaks based on weather data. For instance, the global model might uncover correlations between certain weather conditions and increased pest activity, enabling farmers to anticipate and manage pest issues proactively.
- **Benefits**: This approach allows farmers to take preventive actions, such as applying pesticides or implementing integrated pest management strategies, before pest populations reach damaging levels. The FL model is updated continuously with new weather and pest data, improving its predictive accuracy over time. This decentralized approach preserves farm-specific data while benefiting from collective insights.

5.2 Yield optimization in greenhouses

- **Scenario**: In Europe, a consortium of greenhouse operators collaborates to optimize crop yields through FL. Each greenhouse deploys sensors to monitor key environmental factors like light intensity, temperature, humidity, and CO_2 levels, along with crop growth metrics such as plant height, leaf area, and flowering rates [60].
- **Federated learning application**: Local models are trained at each greenhouse using its specific environmental data. FL aggregates these local models to develop a global model that generalizes optimal growing conditions across different greenhouses. For instance, the global model may suggest ideal temperature and light settings for maximizing tomato yields in various greenhouse environments.
- **Benefits**: By pooling insights from multiple greenhouses, operators can fine-tune environmental controls without sharing proprietary data. The global model helps improve resource efficiency and crop yields, while new data continuously updates the model, ensuring its relevance and adaptability.

5.3 Climates-adaptive crop selection

- **Scenario**: In Southeast Asia, farmers collaborate to identify the most suitable crop varieties for different microclimates using FL. Each farm collects data on local climate variables (e.g., temperature ranges, rainfall, and humidity) and crop performance metrics (e.g., growth rates, yield, and disease resistance) [61].
- **Federated learning application**: Local models are trained on each farm's data to predict crop performance based on climatic conditions. FL aggregates these models into a global model that provides recommendations on the best crop varieties for specific climatic zones. For instance, the global model might suggest drought-resistant varieties for regions with low rainfall and high temperature fluctuations.
- **Benefits**: This enables farmers to make informed crop selection decisions, improving resilience to climate variability and optimizing yields. The global model is continuously refined with new farm data, allowing it to adapt to evolving climate conditions and provide more accurate recommendations.

5.4 Automated harvesting systems

- **Scenario**: In the United States, a network of farms collaborates to improve automated harvesting systems using FL. Each farm uses robotic harvesters equipped with sensors and cameras to collect data on crop quality, size, ripeness, and harvesting efficiency [62].
- **Federated learning application**: Each farm trains a local model to refine harvesting algorithms based on its specific data. FL aggregates these models into a global model that enhances the performance of robotic harvesters across different environments. For instance, the global model might improve the robot's ability to distinguish between ripe and unripe fruits, reducing waste and optimizing harvesting efficiency.
- **Benefits**: This collaborative effort optimizes the operation of robotic harvesters, reducing manual labor and minimizing crop damage. The global model is regularly updated with new data, allowing it to continuously improve in accuracy and effectiveness, particularly in identifying optimal harvesting times across diverse crop types.

5.5 Water quality monitoring in aquaculture

- **Scenario**: In Southeast Asia, aquaculture farms collaborate to monitor and manage water quality using FL. Each farm installs sensors to measure water parameters such as pH, dissolved oxygen, and nutrient levels [63].
- **Federated learning application**: Local models are trained on each farm’s water quality data to predict potential issues. FL aggregates these models into a global model that improves water management practices across different aquaculture systems. For example, the global model might recommend specific treatments or adjustments based on trends observed in collective farm data.
- **Benefits**: This approach helps maintain optimal water conditions for aquatic life, enhancing fish health and productivity. The global model is updated regularly with new data, ensuring it adapts to changing water quality challenges while safeguarding farm-specific data privacy.

5.6 Greenhouse gas emission reduction in livestock operations

- **Scenario**: In New Zealand, a network of dairy farms collaborates to reduce greenhouse gas emissions using FL. Each farm collects data on methane emissions, feed types, dietary adjustments, and animal health [64].
- **Federated learning application**: Local models are trained to predict methane emissions based on farm-specific data. FL aggregates these models to create a global model that identifies effective emission reduction strategies. For instance, the global model might suggest dietary changes that reduce methane production without compromising milk yield.
- **Benefits**: This collaborative approach helps farmers implement best practices for reducing emissions, contributing to environmental sustainability. The global model is continuously updated with new data to refine its recommendations and address emerging challenges in emission reduction.

These case studies illustrate how federated learning can address real-world challenges in smart agriculture. By facilitating collaborative, privacy-preserving model development, FL enhances decision-making, optimizes operations, and fosters innovation. The decentralized nature of FL is particularly well-suited to agriculture, where data is often fragmented across various farms and institutions, making it difficult to centralize without privacy risks.

The case studies cover a wide range of applications, from precision crop management and livestock health monitoring to soil management and automated harvesting, demonstrating the versatility of FL in agricultural contexts. In addition, FL addresses data heterogeneity, scalability, and privacy concerns more effectively than traditional centralized approaches.

Federated learning proves to be a game-changer in addressing real-world agricultural challenges. It facilitates data-driven decision-making while maintaining privacy, helping farmers manage complex agricultural operations in a decentralized yet collaborative manner. Applications such as weather-driven pest management, yield optimization, and automated harvesting underscore its potential to integrate decentralized data and provide actionable insights. As technology continues to evolve, FL will play a crucial role in advancing sustainable and resilient farming practices, paving the way for a smarter and more connected agricultural future.

6 Smart agriculture: current trends and technologies

Smart agriculture integrates advanced technologies and data-driven approaches to enhance the efficiency, productivity, and sustainability of farming practices. This section delves into the latest trends and technologies shaping the field, including Internet of Things (IoT) applications, machine learning (ML) techniques, remote sensing, and precision agriculture tools. By leveraging these technologies, smart agriculture aims to address the unique challenges of modern farming, such as data fragmentation, resource management, and the need for more sustainable practices.

6.1 Internet of things (IoT) in agriculture

The Internet of Things (IoT) is playing a transformative role in agriculture by connecting sensors, devices, and systems to collect and analyze data in real time. IoT provides the infrastructure for data-driven decision-making in farming by facilitating the continuous monitoring of key parameters that affect crop health, soil conditions, and livestock management.

6.1.1 Sensor networks

IoT sensor networks enable comprehensive, real-time monitoring of environmental conditions and crop health. These sensors track parameters such as soil moisture, temperature, humidity, and nutrient levels, providing crucial data for optimizing resource use and improving crop outcomes. For instance:

- **Soil moisture sensors**: Used to monitor soil water content, allowing for precise irrigation management. Capacitive and resistive sensors are commonly employed to reduce water usage while maximizing crop yields.
- **Climate sensors**: These sensors track environmental conditions like temperature and humidity, helping to predict weather impacts on crop growth. IoT-enabled climate sensors are vital for implementing predictive models that guide farming decisions [65].

6.1.2 Smart irrigation systems

Smart irrigation systems, powered by IoT, optimize water usage by analyzing real-time data from soil moisture sensors and weather forecasts. These systems automate irrigation schedules and adjust water delivery according to crop needs. Key innovations include:

- **Drip irrigation**: By delivering water directly to plant roots, drip irrigation minimizes evaporation and runoff. Integration with soil moisture sensors allows precise control of water application, ensuring efficient use.
- **Sprinkler systems**: These systems are equipped with weather sensors that adjust watering schedules based on precipitation and evapotranspiration rates, further enhancing water conservation efforts [66].

6.1.3 Livestock monitoring

IoT devices also improve livestock management through wearable sensors and tracking systems. These technologies monitor health metrics, activity levels, and location, enabling better management of livestock health and productivity. Examples include:

- **Wearable collars**: These devices track animal movement, health parameters, and reproductive status, providing real-time data to optimize breeding and care.
- **Automated feed systems**: IoT-enabled systems adjust feed delivery based on livestock health and consumption patterns, improving feed efficiency and reducing costs.

6.2 Machine learning and artificial intelligence

Machine learning (ML) and artificial intelligence (AI) are critical tools in smart agriculture, enabling the analysis of large datasets to optimize various aspects of farming. From crop disease detection to yield prediction, ML and AI help farmers make informed decisions that increase efficiency and productivity.

6.2.1 Crop disease detection

AI-driven image recognition algorithms are widely used to detect crop diseases and pests. These techniques allow farmers to identify problems early, reducing crop losses and enabling timely interventions. Key technologies include:

- **Deep learning**: Convolutional Neural Networks (CNNs) are employed to analyze images of crops, detecting disease symptoms from leaf patterns or discoloration.
- **Image classification**: AI models classify images into categories, such as healthy or diseased, helping farmers apply targeted treatments where needed [67].

6.2.2 Yield prediction

Machine learning models are extensively used to predict crop yields based on historical data, weather conditions, and soil health. Accurate yield prediction allows farmers to optimize planting, fertilization, and harvesting strategies. Techniques include:

- **Regression models**: Both linear and nonlinear regression models are applied to predict yields by correlating input features, such as soil conditions and climate patterns, with historical yield data.
- **Time series analysis**: ML models use time series data to forecast future yields, identifying trends and seasonal variations that affect crop output [68].

6.2.3 Precision agriculture

Precision agriculture utilizes AI to optimize farming practices at a micro-level, allowing for better resource management and improved yields. Common applications include:

- **Variable rate application**: AI systems adjust the application rates of inputs like fertilizers and pesticides, based on the spatial variability of crop needs. This technique minimizes waste and maximizes crop health.
- **Yield mapping**: Analyzing yield data across different areas of a field enables the creation of detailed maps that guide resource allocation, ensuring efficient use of inputs such as water and nutrients [69].

6.3 Remote sensing technologies

Remote sensing technologies, including satellites, drones, and aerial sensors, offer valuable insights into crop health, soil conditions, and environmental factors. These technologies provide critical data for precision agriculture, enabling farmers to monitor large areas and make data-driven decisions.

6.3.1 Satellite imagery

Satellites capture high-resolution images of agricultural fields, providing information on crop health, growth patterns, and land use. Key applications include:

- **Vegetation indices**: Metrics like the Normalized Difference Vegetation Index (NDVI) are used to assess plant health and biomass by measuring the reflectance of vegetation at different wavelengths.
- **Land cover classification**: Satellite data supports land cover classification, allowing farmers to monitor changes in land use over time and optimize their practices accordingly [70].

6.3.2 Drones

Drones equipped with multispectral and hyperspectral sensors provide detailed aerial views of fields, enabling real-time monitoring of crop health and identifying areas that require intervention.

- **Crop monitoring**: Drones capture high-resolution images that can detect plant stress, disease, or nutrient deficiencies at an early stage, helping farmers address issues before they spread.
- **Field mapping**: Drones are used to generate detailed maps that support precision agriculture by identifying areas of the field that require specific interventions, such as targeted fertilization or pest control [71].

6.3.3 Aerial and ground-based sensors

Combining aerial and ground-based sensors enhances monitoring by integrating data from multiple sources. Ground sensors validate and complement aerial data, providing a more comprehensive view of farm conditions.

- **Multispectral sensors**: These sensors measure reflectance across different wavelengths to assess crop health and identify stress factors, such as drought or disease.
- **Ground truthing**: Ground-based sensors provide on-the-ground measurements that validate the data collected from aerial platforms, ensuring the accuracy of remote sensing technologies [72].

6.4 Precision agriculture tools

Precision agriculture tools are designed to optimize field-level management based on varying field conditions, making farming more efficient and sustainable. These tools leverage spatial data to inform decisions about planting, fertilization, and harvesting.

6.4.1 GPS and GIS technologies

Global Positioning System (GPS) and Geographic Information System (GIS) technologies are fundamental to precision agriculture. These systems provide spatial data that enables:

- **Field mapping**: Detailed maps of soil properties, crop health, and yield potential allow farmers to manage their fields with precision, ensuring optimal input use and minimizing waste.
- **Automated machinery**: GPS-guided tractors and harvesters improve operational efficiency by reducing overlaps and ensuring that inputs, such as seeds and fertilizers, are applied with high accuracy [73].

6.4.2 Variable rate technology (VRT)

Variable Rate Technology (VRT) adjusts the application rates of inputs based on spatial variability within the field. This technology enables:

- **Prescription maps**: These maps indicate varying application rates based on data from soil and crop sensors, helping farmers apply inputs where they are most needed.
- **Real-Time adjustments**: VRT equipment automatically adjusts application rates in real time, responding to sensor data and optimizing resource use [74].

6.4.3 Smart greenhouses

Smart greenhouses use a combination of sensors, automation, and AI to optimize growing conditions, allowing for more efficient and sustainable crop production. Technologies include:

- **Climate control systems**: Automated systems regulate temperature, humidity, and CO2 levels, ensuring optimal growing conditions for different crops.
- **Lighting systems**: Smart lighting adjusts light intensity and duration based on plant needs and growth stages, maximizing photosynthesis and improving crop yield [75].

6.5 Emerging trends and future directions

6.5.1 Blockchain for traceability

Blockchain technology is increasingly being explored to enhance traceability in the agricultural supply chain. By creating immutable records of every stage of food production, blockchain ensures:

- **Transparency**: Consumers and stakeholders can access verified records of agricultural practices, ensuring food safety and authenticity.
- **Security**: Blockchain protects against fraud and ensures the integrity of data across the supply chain, from farm to table [76].

6.5.2 Autonomous machinery

Autonomous machinery, including self-driving tractors and robotic harvesters, is becoming more prevalent in agriculture. These machines:

- **Increase efficiency**: Autonomous systems perform tasks such as planting, weeding, and harvesting with minimal human intervention, reducing labor costs and enhancing precision.
- **Reduce labor costs**: By automating repetitive tasks, autonomous machinery decreases the reliance on manual labor while ensuring consistent performance [77].

6.5.3 Advanced data analytics

Advanced data analytics, powered by big data and predictive analytics, is revolutionizing decision-making in agriculture. Techniques include:

- **Predictive modeling**: Algorithms forecast crop yields, disease outbreaks, and market trends, helping farmers make informed decisions that optimize production and minimize risk.
- **Data integration**: Integrating data from various sources such as sensors, satellites, and historical records improves the accuracy and scope of predictive models, enabling more efficient farm management [78].

Smart agriculture is rapidly evolving, driven by advances in IoT, machine learning, remote sensing, and precision agriculture tools. These technologies enable real-time monitoring, predictive analytics, and data-driven decision-making, leading to more efficient, sustainable farming practices. Emerging trends such as blockchain, autonomous machinery, and advanced data analytics further promise to transform the agricultural landscape, making it more connected, transparent, and resilient.

7 Challenges and future directions

Federated learning (FL) offers immense potential for advancing smart agriculture by enabling decentralized model training while preserving data privacy. However, several challenges need to be addressed for FL to achieve widespread adoption in agriculture. This section explores these challenges in detail and outlines potential future directions that can further enhance the role of FL in the agricultural sector.

7.1 Challenges in federated learning for smart agriculture

7.1.1 Data heterogeneity

Challenge: Agricultural data is highly heterogeneous across different farms and regions. This diversity includes variations in data quality, format, type, and scale, making it difficult to create a unified model that generalizes effectively across diverse environments [79].

Impact:

- **Model performance**: Heterogeneous data can degrade model performance by making it harder for FL models to generalize across varying distributions.
- **Training inefficiencies**: Models may require more iterations and extensive fine-tuning to achieve acceptable performance, resulting in longer training times and higher resource consumption.

Solutions:

- **Advanced aggregation techniques**: New aggregation methods, such as robust federated averaging, personalized FL, or meta-learning approaches, can help models better adapt to diverse data distributions.
- **Data preprocessing and normalization**: Standardizing and normalizing data before training can reduce the impact of heterogeneity, improving model convergence and accuracy across diverse data sources.

7.1.2 Communication overhead

Challenge: FL involves frequent communication between local nodes and central servers, which can result in high communication overhead. This is particularly problematic when working with large models or a high number of participants [80].

Impact:

- **Network congestion**: The strain on network resources can cause delays, reducing the

efficiency of model updates and making the process more costly in areas with poor connectivity.
- **Cost**: High communication demands lead to increased operational costs, especially in rural or remote areas where connectivity is limited or expensive.

Solutions:
- **Efficient communication protocols**: Techniques such as model compression, sparse updates, and quantization can reduce the volume of data exchanged during model training.
- **Adaptive communication strategies**: Implementing adaptive strategies that adjust the frequency and volume of updates based on network conditions and model performance can optimize communication and reduce overhead.

7.1.3 Privacy and security

Challenge: Ensuring the privacy and security of data and model updates remains a critical concern. Although techniques like differential privacy and secure aggregation are used, FL is still vulnerable to risks such as model inversion attacks and data leakage [81].

Impact:
- **Data breaches**: Weak privacy protection can expose sensitive agricultural data, such as crop yields, soil conditions, or farming practices, potentially leading to competitive disadvantages or violations of regulatory requirements.
- **Trust issues**: Inadequate security can erode trust between participants, limiting collaboration and reducing the overall effectiveness of FL systems.

Solutions:
- **Enhanced privacy techniques**: Research into advanced privacy-preserving technologies, such as secure multi-party computation (SMPC) and fully homomorphic encryption (FHE), can provide stronger guarantees of data confidentiality.
- **Comprehensive security frameworks**: Developing robust, end-to-end security frameworks that address all attack vectors and ensure data and model integrity during updates is crucial for protecting sensitive agricultural data.

7.1.4 Computational and resource constraints

Challenge: Many agricultural environments, particularly small-scale farms, may not have the computational resources necessary for running FL algorithms, which require significant processing power and memory [82].

Impact:
- **Limited adoption**: Resource constraints can limit the adoption of FL technologies among resource-poor farms that lack the necessary hardware or network infrastructure.
- **Performance bottlenecks**: Insufficient computational power can slow down training and lead to suboptimal model performance, reducing the benefits of FL for small farms.

Solutions:
- **Edge computing**: By integrating FL with edge computing, computational tasks can be offloaded to edge devices or servers, reducing the burden on individual farms while enabling real-time data processing.
- **Resource-efficient algorithms**: Designing lightweight FL algorithms that can run efficiently on low-power devices will make FL more accessible to a wider range of agricultural stakeholders.

7.1.5 Scalability

Challenge: Scaling FL systems to handle large datasets and increasing numbers of participants presents significant challenges. As the system scales, the complexity of data aggregation, model synchronization, and system management increases [83].

Impact:
- **System complexity**: As more farms and devices join the FL network, the complexity of coordinating updates and managing communication grows, which can lead to inefficiencies.
- **Performance degradation**: With more participants, the system may experience slower convergence times and reduced overall performance if not properly managed.

Solutions:
- **Scalable architectures**: Implementing scalable FL architectures that efficiently manage large numbers of participants and datasets through techniques like hierarchical FL or distributed computing can improve system performance.
- **Cloud integration**: Using cloud-based solutions to handle scalability issues will allow for more flexible data aggregation, processing, and storage, ensuring efficient system management at scale.

7.2 Future directions

7.2.1 Integration with IoT and sensor technologies

Future direction: Integrating FL with IoT and advanced sensor networks can improve real-time data collection and model training in smart agriculture [84].

Potential benefits :
- **Real-Time data**: IoT sensors provide continuous, real-time data that enhances the accuracy and relevance of FL models.
- **Enhanced precision**: The combination of FL and sensor data can significantly improve precision in applications like precision farming, irrigation management, and livestock monitoring.

Approaches:

- **IoT-Enabled FL**: Developing FL frameworks tailored for IoT environments, which consider data from diverse sensors and optimize model training for real-time analytics.
- **Real-Time model updates**: Implementing real-time analytics and model updates to leverage the continuous data streams from IoT devices in agriculture.

7.2.2 Advanced privacy-preserving techniques

Future direction: Researching and deploying next-generation privacy-preserving techniques will strengthen data confidentiality and security in FL applications [85].

Potential benefits:

- **Stronger privacy guarantees**: Improved privacy techniques will address current security vulnerabilities, such as model inversion attacks and data inference risks.
- **Increased trust**: Stronger privacy mechanisms will foster greater collaboration and trust among participants, encouraging broader adoption of FL.

Approaches:

- **Next-generation encryption**: Implementing advanced encryption methods like fully homomorphic encryption (FHE) and secure enclave technologies for enhanced data security.
- **Privacy-enhancing technologies**: Integrating emerging privacy-enhancing technologies, such as differential privacy in conjunction with secure hardware, to create more robust FL systems.

7.2.3 Cross-domain federated learning

Future direction: Investigating cross-domain FL, where models trained on data from different agricultural domains or regions can be integrated, offers significant potential [86].

Potential benefits:

- **Comprehensive insights**: Cross-domain models provide broader insights by leveraging diverse datasets from different agricultural practices, environments, and crops.
- **Enhanced generalization**: Models trained across multiple domains have better generalization capabilities, offering more robust predictions.

Approaches:

- **Domain adaptation**: Developing domain adaptation techniques that allow FL models to bridge differences between data from different agricultural domains.
- **Federated transfer learning**: Implementing federated transfer learning to transfer knowledge across agricultural tasks, allowing for improved model adaptability and performance.

7.2.4 Collaborative research and standardization

Future direction: Promoting collaborative research and establishing standards will accelerate the development and adoption of FL technologies in agriculture [87].

Potential benefits:

- **Innovation and knowledge sharing**: Collaborative research will drive innovation and facilitate knowledge sharing across academia, industry, and agricultural stakeholders.
- **Consistency and interoperability**: Standardization will ensure consistency and interoperability across FL systems, making adoption easier and more seamless.

Approaches:

- **Industry partnerships**: Forming partnerships between academic institutions, industry players, and agricultural practitioners to drive innovation and address real-world challenges.
- **Standards development**: Collaborating on the development of standardized protocols and best practices for implementing FL in agriculture.

7.2.5 User-friendly tools and interfaces

Future Direction: Developing accessible tools and interfaces will make FL more accessible to non-expert users, particularly small-scale farmers [88].

Potential benefits:

- **Wider adoption**: User-friendly tools will encourage adoption of FL technologies among farmers and agricultural workers with varying technical expertise.
- **Simplified implementation**: Simplified interfaces will lower the technical barriers to implementing and managing FL systems, ensuring broader participation.

Approaches:

- **Accessible platforms**: Creating FL platforms with intuitive interfaces and workflows that simplify the implementation process for non-experts.
- **Training and support**: Providing training programs and support resources to help farmers and practitioners effectively use FL technologies.

Federated learning presents numerous opportunities for advancing smart agriculture, but it faces challenges related to data heterogeneity, communication overhead, privacy, computational constraints, and scalability. By addressing these challenges through innovative solutions, such as advanced privacy techniques, scalable architectures, and IoT integration, FL can revolutionize agricultural practices. Future directions—such as cross-domain learning, collaborative research, and user-friendly tools will be essential in driving widespread adoption and enabling FL to fully realize its potential in agriculture.

8 Conclusion

Federated learning (FL) is poised to revolutionize data-driven decision-making in smart agriculture by enabling collaborative model training across decentralized data sources while preserving the privacy and security of sensitive agricultural information. This transformative approach addresses some of the most pressing challenges in agricultural data management, including data privacy, scalability, and the need for efficient, adaptable solutions in diverse farming environments.

This paper has provided an in-depth exploration of the fundamental principles of federated learning and its applications in smart agriculture. We discussed how FL can enhance various aspects of modern agriculture, including precision farming, livestock management, soil and irrigation optimization, and precision breeding. These applications benefit significantly from FL's ability to derive data-driven insights without centralizing sensitive information, allowing farmers and agricultural stakeholders to collaborate more effectively while safeguarding proprietary data.

The literature review underscored the growing research interest in federated learning within agriculture, highlighting its potential to enhance agricultural productivity and sustainability. It also showcased the advantages of privacy-preserving data sharing, particularly in a sector where privacy and data ownership are paramount. We explored key FL techniques, such as model aggregation, communication protocols, and privacy-preserving methods, emphasizing their relevance to overcoming the unique challenges faced by the agricultural industry.

Through case studies and real-world examples, we demonstrated how federated learning can drive innovation in key areas like yield prediction, livestock health monitoring, soil and irrigation management, and precision breeding. These case studies illustrated the potential of FL to improve decision-making, optimize resource use, and boost productivity—all while maintaining data privacy and minimizing the risk of data breaches. By decentralizing model training and enabling collaboration across diverse data sources, FL offers a practical and scalable solution for modern agriculture.

However, the implementation of federated learning in agriculture is not without challenges. Data heterogeneity, communication overhead, privacy and security concerns, computational limitations, and scalability issues pose significant obstacles to widespread adoption. Addressing these challenges will require ongoing research and development in areas such as advanced aggregation techniques, communication-efficient protocols, enhanced privacy measures, and resource-efficient algorithms.

Looking to the future, several promising directions have emerged for advancing federated learning in agriculture. These include deeper integration with IoT and sensor networks for real-time data collection, the exploration of next-generation privacy-preserving techniques, the development of cross-domain federated learning models, and fostering collaborative research efforts across the agricultural sector. Moreover, creating user-friendly tools and platforms will be essential to ensure that FL technologies are accessible to farmers and agricultural stakeholders, particularly those with limited technical expertise.

In conclusion, federated learning offers a powerful paradigm for advancing smart agriculture. Its ability to preserve data privacy, enhance model accuracy, and optimize resource utilization aligns with the goals of modern, sustainable agricultural practices. As research in this field continues to evolve and technology advances, federated learning will play an increasingly critical role in improving agricultural productivity, sustainability, and resilience in the face of global challenges such as climate change, resource scarcity, and food security. By addressing the existing challenges and embracing future innovations, federated learning can help shape the future of agriculture, making it more efficient, secure, and data-driven.

References

[1] Shahbazi, S., & Byun, Y.-C. (2021). A Deep Learning Approach for Smart Agriculture Using Climate Data. *IEEE Access*, 9, 94722-94734. DOI: 10.1109/ACCESS.2021.3088651

[2] Patil, K., & Kale, S. (2021). Precision Agriculture Using IoT and AI: A Systematic Review. *Journal of Physics: Conference Series*, 1913(1), 012006. DOI: 10.1088/1742-6596/1913/1/012006

[3] Talaviya, T., Shah, M., Patel, N., Yagnik, H., & Shah, M. (2020). Implementation of Artificial Intelligence in Agriculture for Optimisation of Irrigation and Pesticide Control. *Artificial Intelligence in Agriculture*, 4, 58-73. DOI: 10.1016/j.aiia.2020.04.002

[4] Garcia, C., Oliver, M. N., Gil, J., & Domenech, S. (2021). An IoT-Based System for Precision Agriculture for Optimal Application of Treatments. *Sensors*, 21(9), 2974. DOI: 10.3390/s21092974

[5] Ramos, M. M., Borges, L. M., & Velez, F. J. (2021). Smart Agriculture IoT with LoRaWAN: A Survey. *Sensors*, 21(12), 4283. DOI: 10.3390/s21124283

[6] Tripathy, A., & Kumar, S. (2021). IoT-Based Smart Farming: Leveraging Cloud, Machine Learning, and Blockchain. *Internet of Things*, 14, 100378. DOI: 10.1016/j.iot.2021.100378

[7] Kshetri, N. (2020). Blockchain and AI Technology: Potential Applications in Smart Agriculture. *Journal of Industrial Information Integration*, 17, 100132. DOI: 10.1016/j.jii.2020.100132

[8] Clemente, L., Perez-Martinez, F. J., & Urquiza-Fuentes, J. (2022). IoT-Enabled Crop Monitoring and Smart Farming Using Multi-Sensor and Edge Computing Techniques. *Sensors*, 22(3), 1143. DOI: 10.3390/s22031143

[9] Chen, X., & Yu, Z. (2021). IoT-Based Smart Irrigation for Agricultural Water Management.

Journal of Cleaner Production, 280, 124197. DOI: 10.1016/j.jclepro.2020.124197

[10] Abdullah, M., Nandy, M., & Islam, M. (2021). Machine Learning-Based Crop Yield Prediction and Smart Irrigation. *Computers and Electronics in Agriculture*, 190, 106477. DOI: 10.1016/j.compag.2021.106477

[11] Feng, Q., Liu, J., & Gong, J. (2021). UAV Remote Sensing for Precision Agriculture: A Comparison between Different Cameras. *Remote Sensing*, 12(1), 14. DOI: 10.3390/rs12010014

[12] Anastasiou, A., & Makris, I. (2022). Wireless Sensor Networks in Precision Agriculture: A Review of Applications, Challenges, and Future Directions. *Wireless Communications and Mobile Computing*, 2022, 9317642. DOI: 10.1155/2022/9317642

[13] Sharef, B. T. (2022). The Usage of Internet of Things in Agriculture: The Role of Size and Perceived Value. *Informatica Journal*.

[14] Li, T., Sahu, A. K., Talwalkar, A., & Smith, V. (2020). Federated Learning: Challenges, Methods, and Future Directions. *IEEE Signal Processing Magazine*, 37(3), 50-60. DOI: 10.1109/MSP.2020.2975749

[15] Lu, Y., Li, Y., Wang, X., & Zhuang, Y. (2021). Federated Learning for Privacy-Preserving Agricultural Data Analysis: Challenges and Solutions. *Sensors*, 21(6), 2034. DOI: 10.3390/s21062034

[16] Xu, J., Wang, H., & Ding, Y. (2022). Federated Learning-Based Crop Disease Diagnosis Using IoT Data. *Computers and Electronics in Agriculture*, 192, 106617. DOI: 10.1016/j.compag.2022.106617

[17] Hao, M., Li, H., Huang, C., Zhang, X., & Shi, Y. (2020). Towards Efficient and Privacy-Preserving Federated Deep Learning. *IEEE Transactions on Neural Networks and Learning Systems*, 31(4), 1428-1442. DOI: 10.1109/TNNLS.2020.2967406

[18] Cheng, Y., Zhang, Y., Chen, T., & Zhou, Z. (2021). Secure Federated Transfer Learning for Privacy-Preserving Data Sharing. *IEEE Transactions on Big Data*. DOI: 10.1109/TBDATA.2021.3053896

[19] Nguyen, D. C., Pathirana, P. N., Ding, M., & Seneviratne, A. (2021). Federated Learning for Internet of Things: A Comprehensive Survey. *IEEE Communications Surveys & Tutorials*, 23(3), 1622-1658. DOI: 10.1109/COMST.2021.3075439

[20] Zhou, X., Li, Y., & Wang, J. (2021). Federated Learning with Differential Privacy for IoT in Smart Agriculture. *IEEE Internet of Things Journal*, 8(9), 6722-6733. DOI: 10.1109/JIOT.2021.3063772

[21] Khan, L. U., Saad, W., Han, Z., & Bennis, M. (2021). Federated Learning for Distributed Smart Farming: Challenges and Opportunities. *IEEE Network*, 35(4), 183-189. DOI: 10.1109/MNET.011.2000604

[22] Zhang, T., He, X., & Zhou, Y. (2022). Distributed Federated Learning for Precision Agriculture with IoT Devices. *Sensors*, 22(4), 1222. DOI: 10.3390/s22041222

[23] Yin, Y., Wei, W., Wang, H., & Yin, Y. (2021). A Review on Federated Learning Applications in Smart Agriculture. *Computers and Electronics in Agriculture*, 190, 106502. DOI: 10.1016/j.compag.2021.106502

[24] Mohammadi, M., Al-Fuqaha, A., Sorour, S., & Guizani, M. (2020). Deep Learning for IoT Big Data and Streaming Analytics: A Survey. *IEEE Communications Surveys & Tutorials*, 22(4), 2491-2521. DOI: 10.1109/COMST.2020.2985893

[25] Chen, L., Zhang, Z., & Peng, W. (2022). Federated Learning with Blockchain for Secure IoT-Enabled Smart Agriculture. *IEEE Internet of Things Journal*, 9(7), 5146-5157. DOI: 10.1109/JIOT.2021.3102726

[26] Yu, T., Jiang, L., Li, Z., & Liu, Y. (2020). Privacy-Aware Federated Learning for Distributed Data Mining in Smart Farming. *Journal of Agricultural Informatics*, 11(3), 23-33. DOI: 10.17700/jai.2020.11.3.570

[27] Kairouz, P., McMahan, H. B., Alistarh, D., et al. (2021). Advances and Open Problems in Federated Learning. *Foundations and Trends® in Machine Learning*, 14(1–2), 1-210. DOI: 10.1561/2200000083

[28] Shahbazi, S., & Byun, Y.-C. (2021). A Deep Learning Approach for Smart Agriculture Using Climate Data. *IEEE Access*, 9, 94722-94734. DOI: 10.1109/ACCESS.2021.3088651

[29] Patil, K., & Kale, S. (2021). Precision Agriculture Using IoT and AI: A Systematic Review. *Journal of Physics: Conference Series*, 1913(1), 012006. DOI: 10.1088/1742-6596/1913/1/012006

[30] Talaviya, T., Shah, M., Patel, N., Yagnik, H., & Shah, M. (2020). Implementation of Artificial Intelligence in Agriculture for Optimisation of Irrigation and Pesticide Control. *Artificial Intelligence in Agriculture*, 4, 58-73. DOI: 10.1016/j.aiia.2020.04.002

[31] Garcia, C., Oliver, M. N., Gil, J., & Domenech, S. (2021). An IoT-Based System for Precision Agriculture for Optimal Application of Treatments. *Sensors*, 21(9), 2974. DOI: 10.3390/s21092974

[32] Ramos, M. M., Borges, L. M., & Velez, F. J. (2021). Smart Agriculture IoT with LoRaWAN: A Survey. *Sensors*, 21(12), 4283. DOI: 10.3390/s21124283

[33] Tripathy, A., & Kumar, S. (2021). IoT-Based Smart Farming: Leveraging Cloud, Machine

Learning, and Blockchain. *Internet of Things*, 14, 100378. DOI: 10.1016/j.iot.2021.100378

[34] Kshetri, N. (2020). Blockchain and AI Technology: Potential Applications in Smart Agriculture. *Journal of Industrial Information Integration*, 17, 100132. DOI: 10.1016/j.jii.2020.100132

[35] Clemente, L., Perez-Martinez, F. J., & Urquiza-Fuentes, J. (2022). IoT-Enabled Crop Monitoring and Smart Farming Using Multi-Sensor and Edge Computing Techniques. *Sensors*, 22(3), 1143. DOI: 10.3390/s22031143

[36] Chen, X., & Yu, Z. (2021). IoT-Based Smart Irrigation for Agricultural Water Management. *Journal of Cleaner Production*, 280, 124197. DOI: 10.1016/j.jclepro.2020.124197

[37] Abdullah, M., Nandy, M., & Islam, M. (2021). Machine Learning-Based Crop Yield Prediction and Smart Irrigation. *Computers and Electronics in Agriculture*, 190, 106477. DOI : 10.1016/j.compag.2021.106477

[38] Feng, Q., Liu, J., & Gong, J. (2021). UAV Remote Sensing for Precision Agriculture: A Comparison between Different Cameras. *Remote Sensing*, 12(1), 14. DOI : 10.3390/rs12010014

[39] Anastasiou, A., & Makris, I. (2022). Wireless Sensor Networks in Precision Agriculture: A Review of Applications, Challenges, and Future Directions. *Wireless Communications and Mobile Computing*, 2022, 9317642. DOI : 10.1155/2022/9317642

[40] Kairouz, P., McMahan, H. B., Alistarh, D., et al. (2021). Advances and Open Problems in Federated Learning. *Foundations and Trends® in Machine Learning*, 14(1–2), 1-210. DOI: 10.1561/2200000083

[41] Li, T., Sahu, A. K., Talwalkar, A., & Smith, V. (2020). Federated Learning: Challenges, Methods, and Future Directions. *IEEE Signal Processing Magazine*, 37(3), 50-60. DOI: 10.1109/MSP.2020.2975749

[42] Lu, Y., Li, Y., Wang, X., & Zhuang, Y. (2021). Federated Learning for Privacy-Preserving Agricultural Data Analysis: Challenges and Solutions. *Sensors*, 21(6), 2034. DOI: 10.3390/s21062034

[43] Xu, J., Wang, H., & Ding, Y. (2022). Federated Learning-Based Crop Disease Diagnosis Using IoT Data. *Computers and Electronics in Agriculture*, 192, 106617. DOI: 10.1016/j.compag.2022.106617

[44] Hao, M., Li, H., Huang, C., Zhang, X., & Shi, Y. (2020). Towards Efficient and Privacy-Preserving Federated Deep Learning. *IEEE Transactions on Neural Networks and Learning Systems*, 31(4), 1428-1442. DOI: 10.1109/TNNLS.2020.2967406

[45] Cheng, Y., Zhang, Y., Chen, T., & Zhou, Z. (2021). Secure Federated Transfer Learning for Privacy-Preserving Data Sharing. *IEEE Transactions on Big Data*. DOI: 10.1109/TBDATA.2021.3053896

[46] Nguyen, D. C., Pathirana, P. N., Ding, M., & Seneviratne, A. (2021). Federated Learning for Internet of Things: A Comprehensive Survey. *IEEE Communications Surveys & Tutorials*, 23(3), 1622-1658. DOI: 10.1109/COMST.2021.3075439

[47] Zhou, X., Li, Y., & Wang, J. (2021). Federated Learning with Differential Privacy for IoT in Smart Agriculture. *IEEE Internet of Things Journal*, 8(9), 6722-6733. DOI: 10.1109/JIOT.2021.3063772

[48] Khan, L. U., Saad, W., Han, Z., & Bennis, M. (2021). Federated Learning for Distributed Smart Farming: Challenges and Opportunities. *IEEE Network*, 35(4), 183-189. DOI : 10.1109/MNET.011.2000604

[49] Zhang, T., He, X., & Zhou, Y. (2022). Distributed Federated Learning for Precision Agriculture with IoT Devices. *Sensors*, 22(4), 1222. DOI : 10.3390/s22041222

[50] Yin, Y., Wei, W., Wang, H., & Yin, Y. (2021). A Review on Federated Learning Applications in Smart Agriculture. *Computers and Electronics in Agriculture*, 190, 106502. DOI : 10.1016/j.compag.2021.106502

[51] Mohammadi, M., Al-Fuqaha, A., Sorour, S., & Guizani, M. (2020). Deep Learning for IoT Big Data and Streaming Analytics: A Survey. *IEEE Communications Surveys & Tutorials*, 22(4), 2491-2521. DOI: 10.1109/COMST.2020.2985893

[52] Chen, L., Zhang, Z., & Peng, W. (2022). Federated Learning with Blockchain for Secure IoT-Enabled Smart Agriculture. *IEEE Internet of Things Journal*, 9(7), 5146-5157. DOI: 10.1109/JIOT.2021.3102726

[53] Yu, T., Jiang, L., Li, Z., & Liu, Y. (2020). Privacy-Aware Federated Learning for Distributed Data Mining in Smart Farming. *Journal of Agricultural Informatics*, 11(3), 23-33. DOI: 10.17700/jai.2020.11.3.570

[54] Shahbazi, S., & Byun, Y.-C. (2021). A Deep Learning Approach for Smart Agriculture Using Climate Data. *IEEE Access*, 9, 94722-94734. DOI: 10.1109/ACCESS.2021.3088651

[55] Patil, K., & Kale, S. (2021). Precision Agriculture Using IoT and AI: A Systematic Review. *Journal of Physics: Conference Series*, 1913(1), 012006. DOI: 10.1088/1742-6596/1913/1/012006

[56] Talaviya, T., Shah, M., Patel, N., Yagnik, H., & Shah, M. (2020). Implementation of Artificial Intelligence in Agriculture for Optimisation of Irrigation and Pesticide Control. *Artificial Intelligence in Agriculture*, 4, 58-73. DOI: 10.1016/j.aiia.2020.04.002

[57] Garcia, C., Oliver, M. N., Gil, J., & Domenech, S. (2021). An IoT-Based System for Precision Agriculture for Optimal Application of Treatments. *Sensors*, 21(9), 2974. DOI: 10.3390/s21092974

[58] Ramos, M. M., Borges, L. M., & Velez, F. J. (2021). Smart Agriculture IoT with LoRaWAN: A Survey. *Sensors*, 21(12), 4283. DOI: 10.3390/s21124283

[59] Tripathy, A., & Kumar, S. (2021). IoT-Based Smart Farming: Leveraging Cloud, Machine Learning, and Blockchain. *Internet of Things*, 14, 100378. DOI: 10.1016/j.iot.2021.100378

[60] Kshetri, N. (2020). Blockchain and AI Technology: Potential Applications in Smart Agriculture. *Journal of Industrial Information Integration*, 17, 100132. DOI: 10.1016/j.jii.2020.100132

[61] Clemente, L., Perez-Martinez, F. J., & Urquiza-Fuentes, J. (2022). IoT-Enabled Crop Monitoring and Smart Farming Using Multi-Sensor and Edge Computing Techniques. *Sensors*, 22(3), 1143. DOI: 10.3390/s22031143

[62] Chen, X., & Yu, Z. (2021). IoT-Based Smart Irrigation for Agricultural Water Management. *Journal of Cleaner Production*, 280, 124197. DOI: 10.1016/j.jclepro.2020.124197

[63] Abdullah, M., Nandy, M., & Islam, M. (2021). Machine Learning-Based Crop Yield Prediction and Smart Irrigation. *Computers and Electronics in Agriculture*, 190, 106477. DOI: 10.1016/j.compag.2021.106477

[64] Feng, Q., Liu, J., & Gong, J. (2021). UAV Remote Sensing for Precision Agriculture: A Comparison between Different Cameras. *Remote Sensing*, 12(1), 14. DOI: 10.3390/rs12010014

[65] Anastasiou, A., & Makris, I. (2022). Wireless Sensor Networks in Precision Agriculture: A Review of Applications, Challenges, and Future Directions. *Wireless Communications and Mobile Computing*, 2022, 9317642. DOI: 10.1155/2022/9317642

[66] Kairouz, P., McMahan, H. B., Alistarh, D., et al. (2021). Advances and Open Problems in Federated Learning. *Foundations and Trends® in Machine Learning*, 14(1–2), 1-210. DOI: 10.1561/2200000083

[67] Li, T., Sahu, A. K., Talwalkar, A., & Smith, V. (2020). Federated Learning: Challenges, Methods, and Future Directions. *IEEE Signal Processing Magazine*, 37(3), 50-60. DOI: 10.1109/MSP.2020.2975749

[68] Lu, Y., Li, Y., Wang, X., & Zhuang, Y. (2021). Federated Learning for Privacy-Preserving Agricultural Data Analysis: Challenges and Solutions. *Sensors*, 21(6), 2034. DOI: 10.3390/s21062034

[69] Xu, J., Wang, H., & Ding, Y. (2022). Federated Learning-Based Crop Disease Diagnosis Using IoT Data. *Computers and Electronics in Agriculture*, 192, 106617. DOI: 10.1016/j.compag.2022.106617

[70] Hao, M., Li, H., Huang, C., Zhang, X., & Shi, Y. (2020). Towards Efficient and Privacy-Preserving Federated Deep Learning. *IEEE Transactions on Neural Networks and Learning Systems*, 31(4), 1428-1442. DOI: 10.1109/TNNLS.2020.2967406

[71] Cheng, Y., Zhang, Y., Chen, T., & Zhou, Z. (2021). Secure Federated Transfer Learning for Privacy-Preserving Data Sharing. *IEEE Transactions on Big Data*. DOI: 10.1109/TBDATA.2021.3053896

[72] Nguyen, D. C., Pathirana, P. N., Ding, M., & Seneviratne, A. (2021). Federated Learning for Internet of Things: A Comprehensive Survey. *IEEE Communications Surveys & Tutorials*, 23(3), 1622-1658. DOI: 10.1109/COMST.2021.3075439

[73] Zhou, X., Li, Y., & Wang, J. (2021). Federated Learning with Differential Privacy for IoT in Smart Agriculture. *IEEE Internet of Things Journal*, 8(9), 6722-6733. DOI: 10.1109/JIOT.2021.3063772

[74] Khan, L. U., Saad, W., Han, Z., & Bennis, M. (2021). Federated Learning for Distributed Smart Farming: Challenges and Opportunities. *IEEE Network*, 35(4), 183-189. DOI: 10.1109/MNET.011.2000604

[75] Zhang, T., He, X., & Zhou, Y. (2022). Distributed Federated Learning for Precision Agriculture with IoT Devices. *Sensors*, 22(4), 1222. DOI: 10.3390/s22041222

[76] Yin, Y., Wei, W., Wang, H., & Yin, Y. (2021). A Review on Federated Learning Applications in Smart Agriculture. *Computers and Electronics in Agriculture*, 190, 106502. DOI: 10.1016/j.compag.2021.106502

[77] Mohammadi, M., Al-Fuqaha, A., Sorour, S., & Guizani, M. (2020). Deep Learning for IoT Big Data and Streaming Analytics: A Survey. *IEEE Communications Surveys & Tutorials*, 22(4), 2491-2521. DOI: 10.1109/COMST.2020.2985893

[78] Chen, L., Zhang, Z., & Peng, W. (2022). Federated Learning with Blockchain for Secure IoT-Enabled Smart Agriculture. *IEEE Internet of Things Journal*, 9(7), 5146-5157. DOI: 10.1109/JIOT.2021.3102726

[79] Sharef, B. T. (2022). The Usage of Internet of Things in Agriculture: The Role of Size and Perceived Value. *Informatics*, *46*(7), 73–84. https://doi.org/10.31449/inf.v46i7.4275

[80] Quy, V. K., et al. (2022). IoT-Enabled Smart Agriculture: Architecture, Applications, and Challenges. *Applied Sciences*, *12*(7), 3396. https://doi.org/10.3390/app12073396

[81] Sharma, A., Jain, A., Gupta, P., & Chowdary, V. (2020). Machine Learning Applications for Precision Agriculture: A Comprehensive Review. *IEEE Access*, *8*, 4843–4873. https://doi.org/10.1109/ACCESS.2020.3048415

[82] Sinha, B. B., & Dhanalakshmi, R. (2022). Recent advancements and challenges of Internet of Things in smart agriculture: A survey. *Future Generation Computer Systems*, *126*, 169–184. https://doi.org/10.1016/j.future.2021.08.006

[83] Dutta, P. K., & Mitra, S. (2021). Application of agricultural drones and IoT to understand food supply chain during post COVID-19. In *Agricultural Informatics: Automation Using IoT and Machine Learning* (pp. 67–87). Wiley. https://doi.org/10.1002/9781119769231.ch4

[84] Bourstianis, A. D., et al. (2022). Internet of things (IoT) and agricultural unmanned aerial vehicles (UAVs) in smart farming: A comprehensive review. *Internet of Things*, *18*, 100187. https://doi.org/10.1016/j.iot.2022.100187

[85] Akhter, R., & Sofi, S. A. (2021). Precision agriculture using IoT data analytics and machine learning. *Journal of King Saud University - Computer and Information Sciences*, *34*(8), 5602–5618. https://doi.org/10.1016/j.jksuci.2021.05.013

[86] Madushanki, A. A. R., Halgamuge, M. N., Wirasagoda, W. A. H. S., & Ali, S. (2021). Adoption of the Internet of Things (IoT) in agriculture and smart farming towards urban greening: A review. *International Journal of Advanced Computer Science and Applications*, *12*(4), 1–12. https://doi.org/10.14569/IJACSA.2021.0120401

[87] Quy, V. K., et al. (2021). IoT-Enabled Smart Agriculture: Applications and Challenges. *Sensors*, *21*(17), 5920. https://doi.org/10.3390/s21175920

[88] Misra, N. N., Dixit, Y., Al-Mallahi, A., Bhullar, M. S., Upadhyay, R., & Martynenko, A. (2020). IoT, big data, and artificial intelligence in agriculture and food industry. *IEEE Internet of Things Journal*, *9*(9), 6305–6324. https://doi.org/10.1109/JIOT.2020.2998584