# Privacy-Preserving AI in Agriculture: A Review of Federated Learning Approaches

**Jigar A. Soni[1], Nitin R. Pandya[2], Rajan B. Patel[3], Jinit S. Raval[4]**

Assistant Professor, Dept. of ICT, Sankalchand Patel College of Engineering, Sankalchand Patel University,Visnagar, India[1]
Assistant Professor, Dept. of IT, Sankalchand Patel College of Engineering, Sankalchand Patel University,Visnagar, India[2]
Assistant Professor, Dept. of B.Sc. IT, Sankalchand Patel College of Engineering, Sankalchand Patel University,Visnagar, India[3]
Teaching Intern, Dept. of CE, Sankalchand Patel College of Engineering, Sankalchand Patel University Visnagar, India[4]

jasoniict_spce@spu.ac.in[1], nrpce_spce@spu.ac.in[2], rbpbscit_spce@spu.ac.in[3], jsrvalce_spce@spu.ac.in[4]

**Abstract**: Federated Machine Learning (FML) is a revolutionary approach for training machine learning models while ensuring data privacy and security. This paper provides a comprehensive analysis of FML and its applications in agriculture. We examine how FML enhances predictive analytics, fosters collaborative learning among agricultural stakeholders, and addresses challenges such as communication constraints and data heterogeneity. Additionally, we explore real-world implementations and present relevant datasets that highlight the impact of FML on modern agricultural practices.

**Keywords**: Federated Learning, Machine Learning Agriculture, Precision Agriculture, Smart Farming, IoT in Agriculture, Crop Monitoring

## I. INTRODUCTION

### 1. Digital Transformation in Agriculture

Digital transformation of agriculture is being accelerated through technological innovations that support productivity, sustainability, and resource use. Emerging technologies including Machine Learning (ML), the Internet of Things (IoT), and remote sensing are at the heart of the transformation of modern agriculture - allowing for real-time monitoring, predictive analytics, and informed decisions about data-driven practices in agriculture to improve production functions, such as optimizing crop yields; improving soil and land quality; and managing water resources[1]. Machine learning is particularly important in precision agriculture by utilizing data collected from ground-based sensors, drones, and satellite imagery to identify patterns, predict pathogenic diseases, optimize fertilizer use, and utilize a data-driven supply chain management approach. While there is much promise in utilizing machine learning in agriculture, a number of barriers still exist for large-scale adoption of machine learning is agriculture[2].

### 2. Challenges in Machine Learning Adoption in Agriculture

- While machine learning (ML) has illustrated potential applications in the agricultural domain, there are numerous important barriers to its integration [3]:

- **Fragmentation of data:** Agricultural data is largely dispersed across different entities (e.g., individual farmers, cooperatives, government agencies, research institutions), and the absence of a shared data platform or system makes it impractical to design useable ML models that can be generalized across crop types and agronomic regions.



http://doi.org/10.63766/spujstmr.24.000030

- **Privacy:** Agricultural professionals and agribusinesses are often reluctant to share their data due to privacy and competitive concerns. Standard practice in machine learning is for models to require a centralized data system for storage and the use of this data which raises additional privacy and security challenges and limits involvement of multiple groups to share the data or the storage of data.

- **Expensive centralized processing and storage**: Building machine learning models typically require a considerable number of computational resources to store and process data. The cost of storing and processing vast amounts of data could be prohibitive for smaller to medium size farms to invest in cloud services or other high-performance computing investing services.

## 3. Federated Machine Learning: A Decentralized Solution

To address these difficulties, Federated Machine Learning (FML) has arisen as a decentralized alternative to traditional machine learning. FML enables various organizations to collaborate in the training of machine learning models without needing to exchange raw data[4]. Instead of sending data to a central repository, it enables local devices—such as farm sensors, edge devices, or regional data centers—to train models independently and provide only model updates to a central aggregator. This method preserves data privacy, minimizes communication costs, and facilitates collaboration among diverse stakeholders[2].

### 3.1 Fundamental Principles of Federated Machine Learning

FML is based on these principles:

**1. Training locally:** All data stays on local devices containing the specific model, and that device performs the machine learning training at the edge.

**2. Model combining:** Rather than send all the data used for training, the only things sent to the global model are any model changes (e.g., weight changes).

**3. Protecting privacy:** Because you are not sending the raw data, the risk associated with data security is reduced and privacy protection is increased.

4. **Decentralized collaboration:** Different entities (such as farmers, agribusinesses, and research organizations) can share data and train models together without actually seeing each other's private data.

These principles enable FML to be a scalable and privacy-protected approach to meeting the demands of the new data-driven agricultural production paradigm[5].

## 4. Applications of FML in Agriculture

FML can transform various aspects of agriculture by giving data-driven insights without compromising data privacy. Major applications are[6]:

### 4.1 Detection of Crop Diseases

Centralized data gathering for traditional ML models might be difficult for small farmers. FML enables individual farmers to train localized models for disease detection while feeding a global model with improved accuracy without compromising data privacy.

### 4.2 Yield Prediction

Accurate yield prediction is necessary for supply chain planning and efficient allocation of resources. FML allows farms to share work in developing training models for yield prediction based on local weather, soil type, and past yields.

### 4.3 Soil Health Monitoring

By combining information from soil sensors on various farms, FML can improve soil health evaluations while keeping data ownership at the farm level. This optimizes fertilizer application and minimizes environmental impact.

### 4.4 Smart Irrigation Systems

FML can amplify smart irrigation by aggregating localized information from various farms to enhance water management practices. This can be beneficial in water-scarce areas, where optimized irrigation will result in meaningful savings in water use.

### 4.5 Livestock Health Management

With the use of IoT devices and wearables, livestock health information can be processed using FML models to achieve early disease identification and optimal herd management with guaranteed data security.

Federated Machine Learning provides an innovative platform for agriculture, supporting collaborative model training while maintaining data security. With the solution to problems like data fragmentation, privacy, and computation costs, FML facilitates scalable and efficient AI-powered solutions in agriculture. Future research can emphasize how to enhance the efficiency of communication in FML, increase model resistance to adversarial attacks, and extend its applicability to other agricultural fields.

## II. RESEARCH METHODOLOGY

The research takes a systematic and comprehensive approach to investigate the use of Federated Machine Learning (FML) in agricultural science. The procedures adopted are meant to provide literature that is relevant, updated, and of high quality. The steps undertaken are database selection, search strategy, inclusion/exclusion criteria, screening, quality assessment, data extraction, synthesis, and the final selection of literature, each to be outlined below[7].

### 1. Database Selection

To identify relevant literature, the following academic databases and digital libraries were utilized due to their comprehensive coverage of computer science, agriculture, and interdisciplinary research:

- Google Scholar
- IEEE Xplore
- PubMed
- SpringerLink
- ScienceDirect
- ACM Digital Library
- arXiv
- Web of Science

These platforms were chosen for their extensive repositories of peer-reviewed journal articles, conference papers, and preprints, ensuring a broad and diverse collection of studies.

**2. Search Strategy**

A systematic search strategy was employed to identify studies related to Federated Machine Learning and its applications in agriculture. The search terms were categorized into two groups:

- **Federated Machine Learning Terms**: "Federated Learning," "Decentralized Machine Learning," "Privacy-Preserving Machine Learning," "Collaborative Learning."
- **Agriculture Terms**: "Precision Agriculture," "Crop Monitoring," "Yield Prediction," "Livestock Management," "Climate Resilience," "Agricultural IoT."

Boolean operators (AND, OR) were utilized to combine these terms. Examples of search queries include:

- ("Federated Learning" OR "Decentralized Machine Learning") AND ("Precision Agriculture" OR "Crop Monitoring")
- ("Federated Learning") AND ("Livestock Management" OR "Climate Resilience")

The investigation focused on articles from peer-reviewed journals, conference proceedings, and preprints released between 2016, when FML began, and 2024.

**3. Inclusion and Exclusion Criteria**

In order to ensure that studies included were relevant and written to a certain quality, we included studies according to the following criteria:

**Inclusion Criteria**

- FML Relevance: The studies should explicitly include Federated Machine Learning or variants of such methods.
- Use in Agriculture: The studies should show an application of Federated Machine Learning methods in agriculture or agricultural-related domains, for example, precision agriculture, crop monitoring, livestock management, or climate adaptability.
- Peer-Reviewed Studies: Only peer-reviewed journal articles, conferences, and reputable sources of preprint materials (e.g., arXiv) were covered.
- Sufficient Technical Details: the studies should provide enough technical depth on the FML framework, algorithms, or implementation.
- Most Recent Studies: The researchers placed preference on studies that had been published in the last 5 years ((2019-2024) in order to stay as current with the most recent advancements in the field.

**Exclusion Criteria**

- Irrelevant: Studies that did not explicitly focus on Federated Machine Learning (or an unnamed variant) applied to agriculture were ruled out from the inclusions.
- No Technical Detail: Studies that were purely conceptual or simply lacked technical depth were ruled out.
- Duplicating Studies: Complete duplications of studies, or papers with significant duplication were ruled out.

- Outdated Studies: Studies that had been published before 2016, unless they were considered foundational were ruled out.

**4. Screening Process**

The review process was divided into two stages: -

**Phase one:** Title and Abstract Review: All studies identified were screened on their titles and abstracts for relevance according to the inclusion and exclusion criteria, and excluded if they were clearly not applicable.

**Phase two:** Full-Text Review: The full text of the remaining studies was evaluated for consideration of relevance, technical rigour, and suitability to the research purpose. Those studies that met all inclusion requirements were selected for full review.

**5. Quality Assessment**

To ensure the reliability and validity of the selected studies, a quality assessment was performed based on the following criteria:

- **Methodological Rigor**: The study should employ a robust methodology for implementing and evaluating FML.
- **Reproducibility**: The study should provide sufficient details for reproducibility, such as datasets, algorithms, and evaluation metrics.
- **Impact and Citations**: Preference was given to studies with high citation counts or those published in high-impact journals/conferences.
- **Novelty**: The study should contribute novel insights or advancements to the field of FML or its applications in agriculture.

**6. Data Extraction**

For each selected study, the following data was extracted:

- Authors and Publication Year
- Title and Source
- Key Objectives
- FML Framework and Algorithms
- Application in Agriculture
- Key Findings and Contributions
- Limitations and Future Directions

**7. Synthesis and Analysis**

The extracted data was analyzed to identify recurring themes, emerging trends, and gaps in the existing literature. The findings were organized into sections such as principles of FML, applications in agriculture, advantages, challenges, and future directions.

**8. Final Selection**

After the screening, quality assessment, and data extraction, a final set of studies was selected for inclusion in the review.

## III. LITERATURE REVIEW

Federated Machine Learning (FML) has revolutionized agriculture with its decentralized, privacy-enhancing, and collaborative data analysis. The current developments in FML applications in agriculture are discussed in this section with an emphasis on precision farming, crop monitoring, livestock management, and climate resilience. Summary in a tabular structure is presented below:

TABLE I:
LITERATURE REVIEW SUMMARY

| Year | Title | Authors | Summary |
|---|---|---|---|
| 2024 | Exploring Machine Learning Models for Federated Learning: A Review of Approaches, Performance, and Limitations[8] | Elaheh Jafarigol, Theodore B. Trafalis, Talayeh Razzaghi & Mona Zamankhani | Surveys ML algorithms (supervised/unsupervised, reinforcement learning) in FL contexts. Privacy-preserving ML techniques, blockchain integration, crisis management applications. |
| 2021 | The Role of Cross-Silo Federated Learning in Facilitating Data Sharing in the Agri-Food Sector[9] | Aiden Durrant, Milan Markovic, David Matthews, David May, Jessica Enright, Georgios Leontidis | This research presents a federated learning method aimed at improving data sharing in supply chains while avoiding the exchange of raw data, with an emphasis on predicting soybean yields. The results demonstrate improved model performance through decentralized data utilization[10]. |
| 2024 | Federated Learning in Food Research[11] | Zuzanna Fendor, Bas H. M. van der Velden, Xinxin Wang, Andrea Jr. Carnoli, Osman Mutlu, Ali Hurriyetoglu | This systematic review examines the use of federated learning within the food sector, addressing topics like the evaluation of water and milk quality, cybersecurity for water treatment, analysis of pesticide residue risks, and identification of weeds. It emphasizes the prevailing concentration on centralized horizontal federated learning while pointing out deficiencies in vertical or transfer federated learning and decentralized frameworks. |
| 2023 | Model Pruning Enables Localized and Efficient Federated Learning for Yield Forecasting and Data Sharing[12] | Andy Li, Milan Markovic, Peter Edwards, Georgios Leontidis | The paper introduces a method combining model pruning with federated learning to address data heterogeneity and communication efficiency in agriculture. Experiments with soybean yield forecasting show improved inference performance and reduced model sizes and communication costs[13]. |
| 2023 | Federated Learning: Crop Classification in a Smart Farm Decentralised Network[14] | Godwin Idoje, TasosDagiuklas, Muddesar Iqbal | The research explores how federated learning can be utilized in smart agriculture, specifically for classifying crops based on climatic factors. It assesses the performance of decentralized models against centralized ones, revealing that decentralized models reach convergence more quickly and provide greater accuracy. |
| 2024 | Federated Learning Architectures: A Performance Evaluation with Crop Yield Prediction Application[15] | Anwesha Mukherjee, Rajkumar Buyya | This study applies both centralized and decentralized federated learning models to predict crop yields utilizing Long Short-Term Memory Networks. It assesses the performance based on prediction accuracy, precision, recall, F1-Score, and training |

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|---|---|---|---|
| | | | duration, showing improved prediction accuracy and shorter response times compared to conventional cloud-based methods. |
| 2024 | Crop Irrigation Advisory System Using Federated Logistic Regression[16] | Deepthi Gardas, R. Karthi | The study develops a federated irrigation advisory system using logistic regression to predict irrigation needs based on field parameters. It employs a client-server architecture with the Flower framework and evaluates the model's performance, discussing factors affecting federated learning in agricultural applications. |

The studies examined evidence of growing influence and adoption of Federated Machine Learning in agriculture, due in part to its possibilities for addressing data privacy, scalability, and collaboration issues. There are several notables' uses of FML in agriculture including precision farming, crop surveillance and monitoring, animal husbandry and livestock management, and climate resilience. Smart farming technologies consisting of FML are increasingly prevalent in agricultural applications despite recognized limitations and barriers associated with their use, such as communication overhead, heterogeneous models, and data imbalance. Future research should incorporate optimization and applicability of FML systems in agricultural settings, and also consider adoption and integration possibilities with emergent technologies, such as blockchain or edge computing.

This review identifies FML based system as a considerable opportunity for innovating current agricultural practices while supporting concerns associated with data privacy and supervision, and emphasizing greater collaboration between agricultural stakeholders.

## IV. PRINCIPLES OF FEDERATED MACHINE LEARNING

Federated Machine Learning (FML) is a collaborative framework of training models in a decentralized manner so that multiple participants can collectively train a machine learning model without revealing their original data. FML methodology provides data privacy and security and utilizes distributed computational power. The core principles of FML are[17]:

1. **Decentralized Model Training**: In contrast to conventional centralized ML models, FML enables edge devices or local servers to independently train models on their own datasets and share only the model updates[4].
2. **Privacy Preservation**: As raw data stays at the origin, FML complies with privacy laws like GDPR and HIPAA, rendering it appropriate for delicate sectors such as healthcare and agriculture[18].
3. **Model Aggregation**: A main server combines local model updates through methods like Federated Averaging (FedAvg) or Federated Proximal (FedProx), guaranteeing an enhanced global model[18].
4. **Data Heterogeneity Management**: FML handles non-IID (Independent and Identically Distributed) data from various devices by employing sophisticated optimization and regularization methods[18].
5. **Efficient Communication**: FML reduces bandwidth consumption by only transmitting model parameters instead of entire datasets, making it feasible for resource-constrained environments like remote farms[4].
6. **Robustness and Security**: Methods like differential privacy, secure aggregation, and homomorphic encryption reduce risks associated with data breaches, model inversion attacks, and adversarial manipulations[4].

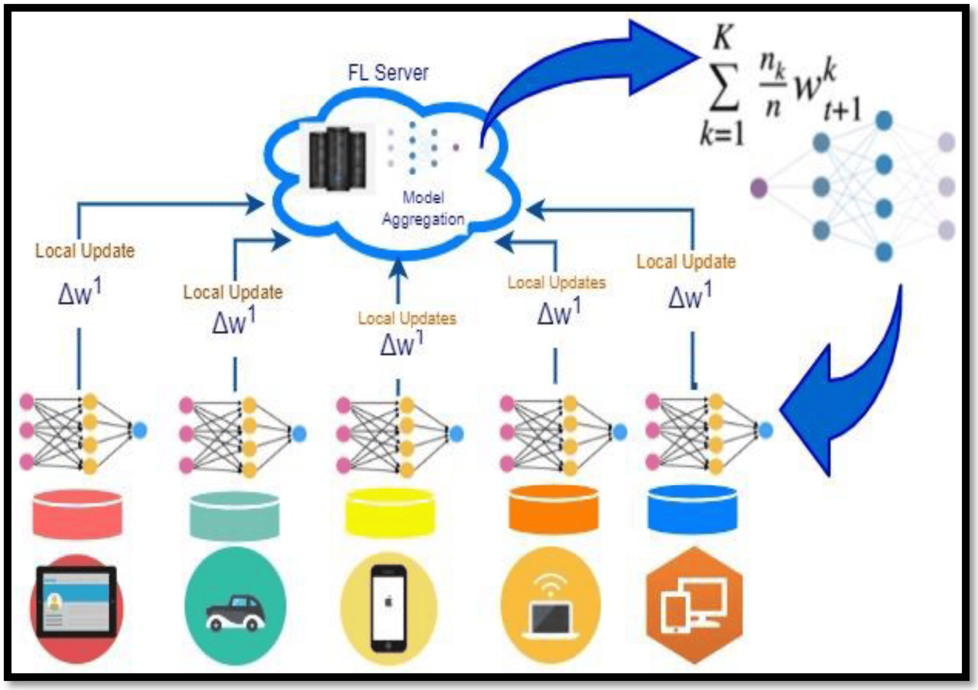


Fig.1 Federated learning methodology for an iterative process [19]

## V. ADVANTAGES OF FEDERATED MACHINE LEARNING IN AGRICULTURE

**Advantages**

**1. Privacy and Security**

- FML eliminates the need for data centralization, reducing the risk of data breaches and ensuring compliance with privacy laws[4].
- Secure aggregation techniques ensure that individual contributions remain anonymous.

**2. Scalability and Efficiency**

- FML allows large-scale collaboration between farms, agricultural research institutions, and agritech firms without requiring massive centralized infrastructure.
- It reduces data transfer costs, making it suitable for real-time applications like pest identification and crop yield prediction.

**3. Handling Data Heterogeneity**

- Traditional ML models struggle with variations in climate, soil, and farming practices across different locations. FML enables region-specific training while maintaining a globally optimized model.
- It accommodates non-uniform data distribution across different farms, ensuring more representative and generalizable predictions.

**4. Improved Model Performance**

- FML enhances the accuracy of agricultural ML models by incorporating diverse datasets from multiple locations while mitigating biases associated with limited data sources.
- Domain-specific adaptations, such as federated pruning or transfer learning, improve inference speed and reduce computational demands.

**5. Cost-Effectiveness**

- Eliminates the need for expensive cloud-based data processing and storage.
- Enables low-power edge computing on IoT devices, drones, and farm sensors, reducing dependency on high-end infrastructure.

**Disadvantages**

**1. High Communication Overhead**

- Secure raw data transmission is compromised, but iterative model updating involves several communication rounds between the local devices and the aggregator, with latency.

- The resource-constrained environment will have issues with flaky network connectivity, resulting in inconsistency in FML training.

**2. Model Aggregation Complexity**

- Model inconsistency can be induced by aggregating updates from extremely heterogeneous datasets and must be tackled with some aggregation methods.
- System heterogeneity (e.g., variation in the capabilities of devices) is another problem to be encountered.

**3. Vulnerability to Security Threats**

- FML is vulnerable to attacks from attackers, i.e., exposures to poisoning attacks, where malicious nodes provide erroneous updates to poison the global model.
- Secure Multi-Party Computation (SMPC) and Differential Privacy (DP) involve computational overhead, impacting the efficiency of the model.

**4. Limited Availability of Standardized Datasets**

- As compared to classical ML, which has well-curated centralized datasets, FML lacks any standard datasets and therefore is restrictive for benchmarking.

- Variation in model performance can be attributed to differences in data collection techniques between different agricultural stakeholders.

## VI. CONCLUSION

Federated Machine Learning presents a revolutionary approach to combining AI and ML for agriculture to support collective learning and data privacy[4]. Precision farming and livestock production to climate resilience and supply chain optimization are some of the key challenges of modern farming solved by FML. The literature presents great contributions toward yield estimation, pest detection, soil monitoring, and irrigation scheduling using FML-based models.

However, the high communication cost, security attacks, and data heterogeneity are still challenges. Further research on efficient aggregation algorithms, privacy-preserving techniques, and real-time FML deployments will be important to realizing its full potential. Regardless of the future challenges, FML will be a foundation of AI-based agriculture, enabling sustainable, data-driven, and smart agricultural practice.

## VII. FUTURE DIRECTIONS

1. **Optimized Communication Strategies**
   Research should focus on reducing communication overhead using compression techniques, such as sparsification and quantization, to make FML viable for real-time agricultural applications.

2. **Privacy-Enhancing Technologies**
   Integrating advanced privacy mechanisms like secure federated learning (SFL), differential privacy, and blockchain-based FML can enhance trust and security in agricultural collaborations.

3. **Federated Transfer Learning**
   Integrating FML with transfer learning can mitigate data heterogeneity by enabling pre-trained models to be fine-tuned for specific agricultural regions or crop types.

4. **Edge Computing and IoT Integration**
   Future studies should explore deploying FML on IoT-enabled edge devices such as smart tractors, drones, and greenhouse sensors to enable localized and low-latency decision-making.

5. **Adaptive Aggregation Methods**
   Developing dynamic aggregation techniques that account for varying farm conditions and resource constraints will improve the reliability and accuracy of federated models.

6. **Real-World Deployment and Benchmarking**
   There is a need for standardized agricultural FML datasets and real-world pilot programs to validate the effectiveness of proposed frameworks in diverse farming conditions.

7. **Multi-Modal Data Fusion**
   Future FML applications should incorporate diverse data sources, such as satellite imagery, weather forecasts, and soil sensors, to develop robust predictive models for sustainable agriculture[20]

By addressing these challenges and leveraging advancements in AI and ML, FML has the potential to revolutionize digital agriculture, making farming more efficient, productive, and environmentally sustainable.

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