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Privacy-Preserving Intelligent Framework for Soil-Fertility Prediction in Precision Agriculture †

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Abstract

Context: Using sophisticated data-driven technologies, precision agriculture has emerged as a crucial strategy for enhancing agricultural production, sustainability, and resource management. In centralized learning approaches, farmers must share their farm data with a central server. This raises issues of data ownership, security, and privacy in distributed agricultural settings. Objective: In this paper, our primary objective is to develop a privacy-preserving intelligent framework for soil-fertility prediction in precision agriculture. This study aims to compare the predictive performance of several intelligent models and assess federated learning's ability to enable safe, decentralized, and collaborative agricultural analytics. Materials and Methods: This study utilized 10 classical machine learning models (MLs) and five centralized MLP architectures (deep learning (DL) models) and evaluated them using performance metrics such as accuracy, precision, recall, F1-score, and Cohen's Kappa for soil fertility. We also developed a privacy-preserving intelligent framework, adopting federated MLP training using the FedAvg (federated learning (FL) mechanism) with five clients and 20 communication rounds, using FedAvg (federated averaging aggregation). The dataset was divided into different farms to simulate real-world distributed agriculture systems. Results: From our experimental observations, the Extra Tree (ET) classifier obtained the highest accuracy of 93.94%, an F1-score of 93.99%, and a Kappa value of 0.90%. Similarly, the Shallow MLP model from DLs obtained an accuracy of 93.18% and a Kappa value of 0.8977. The FL framework achieved 84.47% accuracy and a Kappa score of 0.76. In addition, our framework preserves farm-level data privacy and removes the need for centralized data sharing. The experimental work demonstrates that distributed learning is a secure and collaborative option for smart agriculture. We have compared centralized classical ML, centralized MLP, and federated MLP training. The Shallow MLP model with a 128-64 neuron architecture achieved better performance.

Keywords: soil-fertility prediction; machine learning; deep learning; federated learning; privacy preservation

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1. Introduction

The agriculture sector is one of the most important sectors in the world, and farmers are continuously monitoring different types of crops. To meet the needs of the global population, farmers provide utmost care in farming, facing new challenges every day. In traditional farming, it is very difficult to identify problems in different crops. Now, in this era, farmers are adopting digital farming, where they are aware of the inputs on their farmland, such

as fertilizer, water, and pesticides, and know the right time, place, and quantity to grow crops properly. In soil-fertility prediction, farmers need to provide essential nutrients and conditions (nitrogen, phosphorus, potassium, organic matter, pH balance, and micronutrients) correctly for optimal growth. Accurate and efficient decisions play a crucial role in soil fertility. Traditional soil-fertility predictions are based on laboratory-based physicochemical analysis of different soil samples. But this approach is time-consuming, expensive, and difficult when huge amounts of data are available. Nowadays, MLs and DLs help process large amounts of data for analysis, making informed decisions possible. This helps farmers make effective decisions. In particular, ensemble and deep learning models play an important role in predicting and classifying whether the soil is fertile or not. Models such as RF, XGB, SVM, and attention-based neural architectures are frequently used in this work. Farm-level data is most important in precision agriculture because it contains raw data collected from different locations, such as field location, input cost, and soil composition, which is sensitive and legally protected in many jurisdictions. That is why this study presents federated learning, where farmers' raw data is more secure. Raw data does not need to be sent to the central server. Farmers train the model on their local machines, and only the weights and biases are sent to the global server for updating. Privacy-preserving machine learning (PPML) approaches, including federated learning (FL), differential privacy (DP), secure multi-party computation, and homomorphic encryption, can reconcile these competing objectives. This paper fills that gap by proposing a privacy-preserving intelligent framework for soil-fertility prediction that combines IoT-based soil and environmental sensing with federated and differentially private learning mechanisms, all while retaining the predictive power of modern ensemble and deep learning models.

This paper is organized as follows. Section 2 presents the literature review on ML, DL, and FL for soil-fertility prediction and privacy-preserving distributed learning in agricultural and IoT environments. Section 3 presents the proposed soil-fertility model. Section 4 presents the experimental work and dataset description. Section 5 discusses the results, followed by the conclusion and future scope.

2. The Literature Review

Behera et al. [1] showed how ML can predict whether soil is fertile. The authors used several MLs and conducted statistical tests. The RF model achieved the highest accuracy of 90.91% compared with the other models used for soil-fertility prediction. Rao, R. R., & Reddy, U. S. conducted experimental work based on DL for soil-fertility prediction. Along with this, the authors used SMOTEs to balance their dataset. The authors proposed a framework called AMIFP that compares MLs with DL baseline models. They reported an accuracy of 98.65%, a precision of 98.73%, and a recall of 98.65% [2]. Chaudhary, P. et al. [3] discussed briefly a systematic literature review(SLR) on soil analysis using ML techniques. The authors mainly considered supervised ensemble learning and deep models, such as RF, SVM, GBM, and CNN, utilized for this study. This study found that these algorithms performed well. The SLR strictly followed the PRISMA guidelines to analyze soil in IoT environments. The study covered 2019 to 2024. Helfer, G. A. et al. [4] presented a model that helps predict soil using Partial Least Squares Regression methods and obtained the results. The best results for predicting organic matter and clay were R2 = 0.9345, RMSECV = 0.54%, and R2 = 0.9239, RMSECV = 5.28%, respectively. The author Ajith, S., Vijayakumar, S., & Elakkiya, N [5] reviewed agricultural work where ML and DL help analyze data. The authors predicted yield and pests and detected diseases using sophisticated ML and DL algorithms. In addition, this study also predicted food quality assessment in precision agriculture. Senapaty, M. K. et al. [6] discussed how soil-fertility prediction is possible through ML classifiers. From their experimental observations, LoGR and DT performed

well. The authors proposed FL techniques to preserve the data and obtained precision, recall, and accuracy of 87%, with an F1-score of 86%. This study utilized an IoT environment to collect data from different sources and emphasized feature selection techniques.

Dembani, R. et al. [7] presented a systematic literature review on agricultural data. The authors used the federated learning technique to investigate how to preserve data on pest and disease detection, crop production prediction, and resource management. Their findings highlight federated learning's potential to transform privacy-preserving data analysis in agriculture by enabling better decision-making through aggregated insights from multiple farms while maintaining data confidentiality. Cooray, L. et al. [8] presented a systematic literature review on deep federated learning. The review evaluates fundamental methodological developments, such as advanced model aggregation methods, techniques to improve communication efficiency, such as model compression and decentralized training, and strategies to mitigate statistical heterogeneity due to non-IID data.

Additionally, it explores advanced architectural models, including hierarchical and blockchain-based systems, as well as emerging paradigms like federated meta-learning and federated reinforcement learning. Islam, M. B. et al. [9] presented an SLR on sensor-based soil moisture forecasting. The authors presented recent advancements, including LLMs, FL, and TL. This study follows the PRISMA methodology, in which 189 papers were reviewed and screened against inclusion/exclusion criteria. This work highlights interesting areas for future research, such as using TinyML for edge deployment, explainable AI to improve clarity, and privacy-aware model training. D. A. & Padhy, N. [10] presented that how federated learning helps to detect the weeds and also achieved a balance between prediction accuracy, interpretability, and sustainability in precision agriculture. Mahapatro, P. K. et al. [11] mainly focused on privacy preservation. The authors utilized DL models to detect the plant and presented whether the plant is healthy or not. Their first objective was to identify whether the soil is fertile or not.

3. Proposed Model for Privacy-Preserving Federated Multi-Layer Perceptron (Fed-MLP) Framework for Soil-Fertility Prediction in Precision Agriculture

Phase 1: Distributed Data Sources and On-Client Preprocessing: In this phase, we divided our dataset into different partitions, such as client 1, client 2, ..., client N. Here, each client has farm data with field measurements. Each client maintains its private local data Di. We have downloaded this dataset from the publicly accessible Kaggle repository at https://www.kaggle.com/datasets/rahuljaiswalonkaggle/soil-fertility-dataset, accessed on 15 January 2026. This dataset contains 12 features, which are soil physicochemical attributes such as macronutrients (nitrogen (N), phosphorus (P), potassium (K)), chemical properties such as soil pH, organic carbon (0c), etc., and secondary and micronutrients [sulphur, zinc, iron, copper, manganese, boron, etc.]. There are 881 records available, with the target attribute output having three classes. Figure 1 presents the federated learning framework for soil-fertility prediction in precision agriculture.

$$x \in R12: x = [N,P,K,pH,EC,OC,S,Zn,Fe,Cu,Mn,B]T \quad (1)$$

We used the Flower Framework with the version of v1.42.0 and rest the free open sources software like Googlecolab, tensor flow for tis work. Initially, the data was not cleaned, so we applied data-processing techniques to remove noise on the client side and address distribution heterogeneity across clients. We observed many duplicate records, so we performed data cleaning and imputation. Here, we removed the duplicate records. In addition, we performed Z-score normalization to rescale feature values. To balance the dataset, we used SMOTE (Synthetic Minority Over-sampling), and finally, the dataset was

split in such a way that 80% of the data was used for local training and the rest for validation and testing. In order to prevent data leakage, we divided the dataset into two parts, i.e., training and evaluation subsets, before applying the Synthetic Minority Over-sampling Technique (SMOTE). To prevent synthetic observations from affecting the evaluation data, SMOTE was limited to the training data. The test subset maintained the original class distribution, as appropriate for the evaluation protocol. Data that were not utilized to generate synthetic training observations were employed to evaluate model performance. The purpose of this procedure was to mitigate the risk of data leakage and to offer a more dependable evaluation of predictive performance.

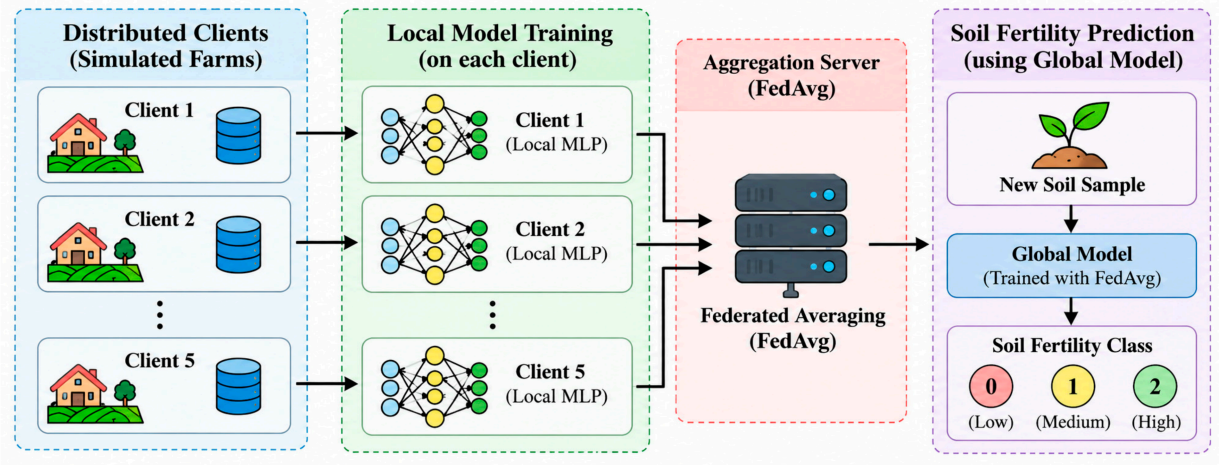


Figure 1. Proposed federated learning framework for soil-fertility prediction in precision agriculture.

Phase 2: Local Model Training and Privacy-Preserving Encryption: In this phase, we used machine learning and deep learning for soil-fertility prediction. This study used federated learning for privacy preservation, where the farmer (client) trains a local model. Our objective was to avoid sharing farm data. This approach preserves data and ensures privacy in line with data governance regulations. We independently trained the proposed Multi-Layer Perceptron (MLP) locally using the farm's soil data. There are 12 input features considered, with 64 hidden neurons and three output classes, i.e., 12 input features → 64 hidden neurons → 3 output classes. Input layer: 12 nodes, each corresponding to one of the soil features.

- Hidden layer: We considered the MLP architecture featuring dense layers, which is equipped with ReLU (Rectified Linear Unit) activation functions and dropout regularization.
- Output layer: The softmax classification layer with three nodes was used to represent the soil-fertility classes. It consists of three different classes: Class 0—low fertility, Class 1—medium fertility, and Class 2—high fertility. Encrypted model weights: After completing local training epochs (EEs), clients extract only the modified model parameters/weights (wi) and encrypt them before uploading to the aggregation server. Here, the model weights (w) and bias (b) are sent to the global model, not the raw data. The main difference between local training and traditional centralized machine learning is that the local training process uses the client's private dataset directly. After that, only the learned model information is sent to the federated learning system.

Phase 3: Federated Learning Process (Server Aggregation): In this paper, we have developed a framework that uses five simulated clients. It further represents the distributed agricultural data sources. For the purpose of classifying soil fertility, each client keeps the assigned soil observations locally and trains an MLP. We used the FedAvg algorithms to update the clients' communication model and send updates to an aggregation server. The

federated averaging (FedAvg) technique aggregates the data from 20 rounds of transmission. The global model is sent back to the clients for subsequent predictions. We have not implemented a separate encryption mechanism, differential privacy, or secure aggregation. The architecture is thus presented as a federated learning approach with local data retention, and its formal privacy protection remains an open question for further exploration. This study uses the FedAvg (federated averaging) algorithm, which is run on the central aggregation server. It provides global knowledge shared across clients through iterative learning. Steps: The first step of FedAvg is model initialization, where the server initializes the baseline global model (W0). Next, the server broadcasts the current weights to selected clients. In local training, the clients update the local parameters using their local training data for E epochs. Then, the clients transmit the local weight updates to the server. Then, in FedAVG, the server aggregates the client weights proportional to their dataset sizes. Lastly, the global model is updated. In this case, the aggregated model is distributed to the clients in place of the server model. These processes are continuous for T communication rounds until model convergence is achieved.

We have not implemented a separate encryption mechanism, differential privacy, or secure aggregation. The architecture is thus presented as a federated learning approach with local data retention, and its formal privacy protection remains an open question for further exploration. We have removed unsupported implications of encryption-based protection and clarified that a comprehensive threat model and evaluation of additional privacy-enhancing mechanisms are important directions for future work.

Phase 4: Soil-Fertility Prediction Using the Global Fed-MLP: After the FL rounds, the global model is used to predict soil fertility. Once the model achieves optimal performance, it is deployed to evaluate unseen soil samples. A sample of 12 different soil properties has been input into the global model.

$$X = [N,P,K,pH,EC,OC,S,Zn,Fe,Cu,Mn,B] \quad (2)$$

Further, this input was pre-processed and transformed for model development and passed to the global MLP. The model finally produced an AE probability distribution that classified the soil samples into one of the three features target. Class 0 is defined as low fertility; Class 1 is defined as medium fertility, where less maintenance of fertilization is required; and Class 2 presents high fertility, which is defined as the optimal condition for high crop yield in precision agriculture.

$$y \in \{0,1,2\} \quad (3)$$

4. Results and Discussion

This study presents ten machine learning models for soil-fertility prediction in a federated learning environment. These models are Extra Trees, Random Forest, XGBoost, LightGBM, Gradient Boosting, CatBoost, Decision Tree, SVM, KNN, and Logistic Regression. In addition to these MLs, we also used five deep learning models: Shallow MLP (128-64), Wide MLP (512-256-128), Deep MLP (256-128-64), Tiny MLP (64-32-16), and Medium MLP (256-128). All models are trained under the FL settings for soil-fertility prediction. The Table 1 above presents the soil-fertility prediction under the FL environment.

The ET model performed well, with an accuracy of 0.9394, a precision of 0.9424, a recall of 0.9394, and an F1-score of 0.9091. The ET model is the best for centralized learning compared to the other models.

Table 2 presents the centralized DL models for soil-fertility prediction. This study used five DL models and found that the Shallow MLP model achieved the highest accuracy

of 93.18%. The architecture contains two hidden layers with 128 and 64 neurons and an F1-score of 0.9313.

Table 1. Machine learning model performance.

Rank	ML Model	Accuracy	Precision	Recall	F1-Score	Kappa
1	**ET**	**0.9394**	**0.9424**	**0.9394**	**0.9399**	**0.9091**
2	RF	0.9318	0.934	0.9318	0.932	0.8977
3	XGBoost	0.9318	0.9327	0.9318	0.9316	0.8977
4	LightGBM	0.9318	0.9326	0.9318	0.9318	0.8977
5	GB	0.928	0.9288	0.928	0.9277	0.892
6	CatBoost	0.9167	0.9169	0.9167	0.9165	0.875
7	DT	0.8864	0.8864	0.8864	0.8854	0.8295
8	SVM	0.8485	0.8477	0.8485	0.8477	0.7727
9	KNN	0.7841	0.7904	0.7841	0.7725	0.6761
10	LoGR	0.7462	0.7459	0.7462	0.746	0.6193

Table 2. Centralized deep learning model performance.

Rank	DL Model	Architecture	Accuracy	F1-Score	Kappa
1	**Shallow MLP (128-64)**	2 hidden layers: 128, 64 neurons	**0.9318**	**0.9313**	**0.8977**
2	Wide MLP (512-256-128)	3 wide hidden layers with high dropout	0.9129	0.9124	0.8693
3	Deep MLP (256-128-64)	3 hidden layers with batch normalization	0.9091	0.9089	0.8636
4	Tiny MLP (64-32-16)	3 small hidden layers	0.9091	0.9089	0.8636
5	Medium MLP (256-128)	2 hidden layers with moderate capacity	0.8939	0.8925	0.8409

Table 3 presents the client distribution data for soil-fertility prediction under the FL settings. Here, we divide the entire dataset into five clients and briefly present the distribution among the samples.

Table 3. Federated learning client data distribution.

Client/Farm	Total Samples	Training Samples	Validation Samples
Client 1	213	170	43
Client 2	213	170	43
Client 3	210	168	42
Client 4	210	168	42
Client 5	210	168	42
Total	**1056**	**844**	**212**

Figure 2 presents the FL performance for soil-fertility prediction. The figure demonstrates the proposed privacy-preserving Fed-MLP framework across 20 communication rounds, from T1 = 1 to T = 20. As the number of communication rounds increased, the global model performed well, with a peak classification accuracy of 84.47% at round 20. Figure 3 presents a brief comparison of three different learning approaches for soil-fertility prediction: the first is machine learning, the second is DL, and the third is FL. This study

presents the best model for ML and FL. It has been observed that the best model for ML is ET.

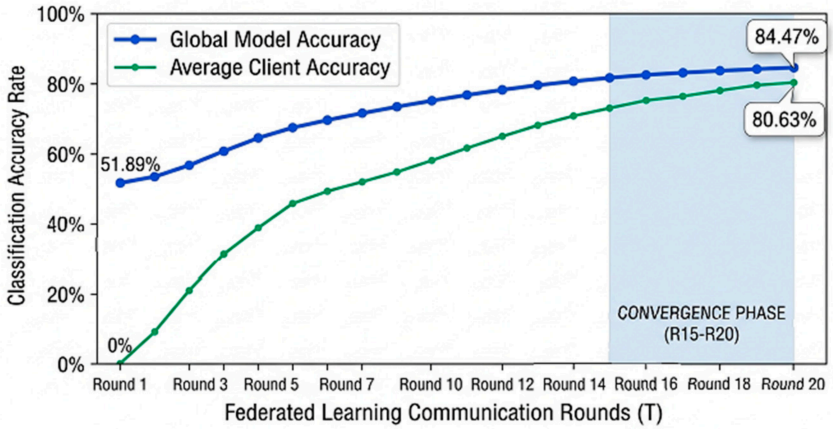
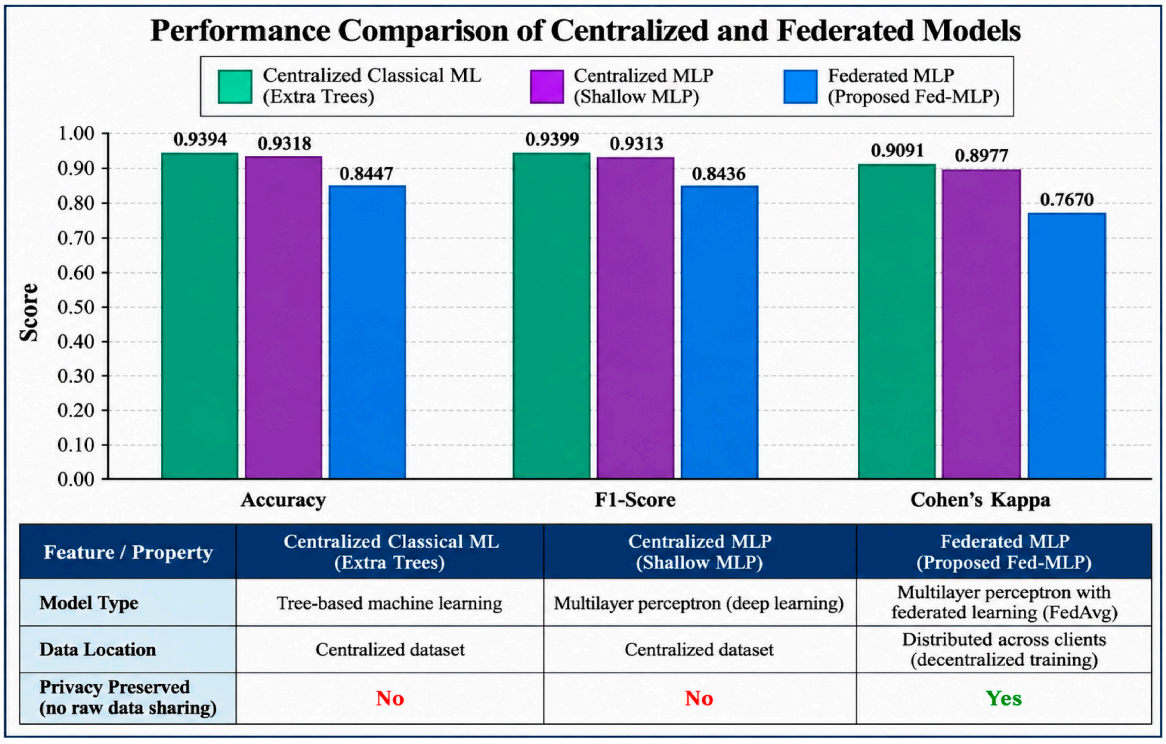


Figure 2. FL performance across the communication rounds for soil-fertility prediction.



Feature / Property	Centralized Classical ML (Extra Trees)	Centralized MLP (Shallow MLP)	Federated MLP (Proposed Fed-MLP)
Model Type	Tree-based machine learning	Multilayer perceptron (deep learning)	Multilayer perceptron with federated learning (FedAvg)
Data Location	Centralized dataset	Centralized dataset	Distributed across clients (decentralized training)
Privacy Preserved (no raw data sharing)	**No**	**No**	**Yes**

Figure 3. Performance comparison of centralized classical machine learning, centralized MLP, and federated MLP for soil-fertility prediction.

Figure 3 presents a comprehensive comparison of three different paradigms for soil-fertility prediction. Figure 3 presents the best traditional ML model (ET), the best centralized DL model (Shallow MLP), and our proposed FL framework (Fed-MLP) for the classification task. This may lead to vulnerability to data breaches, but our proposed decentralized Fed-MLP model achieves an accuracy of 84.47%. This proposed approach helps maintain data privacy. This performance–privacy trade-off demonstrates that Fed-MLP provides reliable, accurate soil-fertility classification, appropriate for practical precision agriculture applications where data security and sovereignty are crucial.

Figure 4 presents the relationship between centralized ML and DL vs. FL. It has been observed that centralized learning achieves the highest performance accuracy of 93.9% and

an F1-score of 94.0%. The below mentioned Figure 4 presents the performance comparison. Apart from this, FL achieves an accuracy of 84.5% and an 84.4% F1-score.

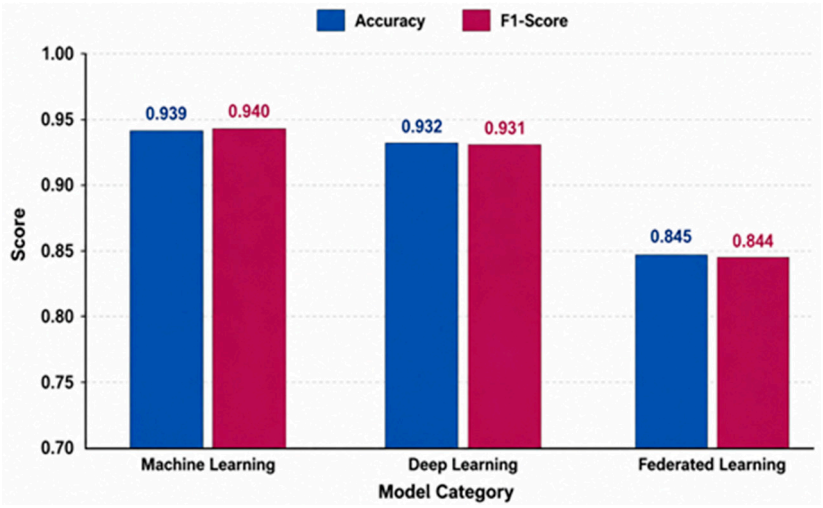


Figure 4. Performance comparison of centralized classical ML, centralized MLP, and federated MLP.

5. Conclusions

This study presents 10 ML and five DL models to determine whether the soil is fertile. Our study proposes a privacy-preserving intelligent framework for soil-fertility prediction in precision agriculture by combining all three learning approaches. We used SMOTE to balance the classes. From our experimental results, the ET model achieved the best centralized accuracy (93.94%), and in DL, the Shallow MLP (128-64) achieved 93.18% accuracy. The entire dataset was divided into five clients for federated learning using the FedAvg algorithm. The selected lightweight MLP improved global model accuracy from 51.89% in the first communication round to 84.47% after 20 rounds, achieving an F1-score of 84.36% and a Kappa of 0.7670 without participating farms sharing raw soil data. The federated model performed worse than centralized learning, but it provides a privacy-preserving mechanism for collaborative soil-fertility prediction in resource-constrained agricultural situations with a lightweight architecture.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

Model Acronym/Name	Full Form/Architecture
ET	Extra Trees
RF	Random Forest
XGBoost	Extreme Gradient Boosting
LightGBM	Light Gradient Boosting Machine
GB	Gradient Boosting
CatBoost	Categorical Boosting
DT	Decision Tree
SVM	Support Vector Machine
KNN	K-Nearest Neighbors
LoGR	Logistic Regression
Shallow MLP (128–64)	Multi-layer Perceptron with Two Hidden Layers Containing 128 and 64 Neurons
Wide MLP (512–256–128)	Multi-layer Perceptron with Three Hidden Layers Containing 512, 256, and 128 Neurons
Deep MLP (256–128–64)	Multi-layer Perceptron with Three Hidden Layers Containing 256, 128, and 64 Neurons
Tiny MLP (64–32–16)	Multi-layer Perceptron with Three Hidden Layers Containing 64, 32, and 16 Neurons
Medium MLP (256–128)	Multi-layer Perceptron with Two Hidden Layers Containing 256 and 128 Neurons

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