TCHIA-FedPer: An Edge Online Federated Learning and IoT-Based for High-Precision Smart Agriculture

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***Abstract*—Agriculture faces critical challenges, including food insecurity intensified by climate change and population growth in West Africa, demanding high-precision smart farming solutions. Traditional AI deployments rely on costly cloud systems, incurring substantial energy consumption and bandwidth issues, while the significant climatic variations in regions like the Sahel hinder the development of effective, generalized AI models. This paper introduces TCHIA-FedPer, a novel IoT-enabled and Edge AI-driven framework for high-precision smart agriculture. Our solution aims to adapt crop growth to diverse microclimatic conditions, reduce AI costs, and to achieve sustainable smart agriculture. By delegating AI processing, including training and inference, to Edge devices positioned near data sources, TCHIA-FedPer relies on green sustainable energy, significantly diminishes latency, conserves bandwidth, and operates independently of centralized cloud systems. The evaluations demonstrate the relevance of the solution in terms of prediction and adaptation to climate.**

***Index Terms*—Smart Agriculture, AI, Federated Learning, Edge Computing, IoT**

I. Introduction

Agriculture is vital for global food security, yet climate change, conflict, and population growth have intensified food insecurity in West Africa [1]. Despite these challenges, technologies such as IoT and AI offer promising solutions to boost productivity and mitigate climate-related impacts [10], [12].

Real-world farming methods, the availability of high-quality data for AI training, and barriers to technology access in rural areas present substantial challenges to smart farming. A system of artificial intelligence (AI) can accurately forecast when crops need water and fertilizers (e.g., NPK), using real-time data from Internet of Things (IoT) sensors (soil sensors: temperature, humidity, nutrients NPK, pH, etc.) and weather sensors (rain gauges, atmospheric pressure, etc.) [3], [12]. Training and deploying AI models typically require costly cloud systems (e.g., AWS, GCP), incurring substantial energy consumption, bandwidth, and associated costs.

The Edge Computing paradigm facilitates the delegation of data processing and artificial intelligence (AI) tasks, encompassing both training and inference, to diminutive, compact computing devices [9]. These devices are strategically positioned adjacent to the data production sources. This proximity diminishes latency, conserves bandwidth, and facilitates expedited real-time decision-making by processing data locally instead of relaying it to a centralized cloud. Shifting AI processing to the edge reduces dependence on the cloud and corresponds with Sustainable Development Goals (SDGs): SDG 2 (Zero Hunger) and SDG 13 (Climate Action) [3]. As climatic and soil variables evolve over time and across regions, the models used on edge servers necessitate frequent updates.

Federated learning is a machine learning algorithm that entails training a model without the exchange of actual data among multiple decentralized edge devices or servers that retain local data samples [15]. Local models are trained on localized data instead of raw data, with model updates (including weights or gradients) transmitted to a central server for aggregation to formulate a global model. This method preserves data privacy. Nevertheless, in numerous countries, especially in Sahelian nations, various microclimates exist throughout the region. The climatic disparities hinder the development of a unified federated AI model that integrates diverse data from across the country and accurately forecasts agricultural requirements [4].

This paper presents a novel IoT-enabled and Edge AI-driven solution TCHIA-FedPer, utilizing area-specific Federated Learning (FL) to attain high-precision agriculture, specifically adapted to various climatic conditions. A key innovation of our methodology is the creation of area-specific models. Zone-specific models effectively tackle the issue of pronounced climatic variations, exemplified by those in Sahelian nations, where a generalized model would be inadequate. By delegating AI processing, including training and inference, to Edge Computing devices positioned near data sources, TCHIA-FedPer significantly diminishes latency, conserves bandwidth, and operates independently of centralized cloud systems. The framework integrates federated personalization (FedPer) and weighted FedAvg aggregation, tailored to specific agro-climatic zones in Mali, enabling continuous online training using live IoT sensor streams. Ensuring data privacy is essential to safeguard sensitive information and farmers' data, thereby cultivating their trust in technology. The contributions of this paper are the following:

- Zone-specific federated learning for microclimate adaptation in high precision agriculture;
- Online edge-centric AI model evolution for dynamic model refinement via incremental learning as climate variables shift ;
- A Sustainable Edge-FL deployment architecture for resource-constrained farms.

The paper is organized as follows. Section II describes the related work. Section III presents and describes the proposed approach and its architecture. Section IV provides the implementation details and presents the performance evaluation of our approach. Finally, Section V concludes the paper and introduces the perspectives of our future works.

II. Related work

Recent studies on precision and adaptive agriculture highlight the use of AI and IoT to address climate change. Many focus on Edge computing to reduce Cloud dependence, while others explore federated learning for privacy-preserving, distributed AI.

Kuttalingam et al. [5] designed an Arduino-based IoT irrigation system that autonomously monitors soil conditions and adjusts the water flow according to crop type. However, it lacks AI integration for climate-adaptive irrigation management.

Pham et al. [11] proposed INTEL-IRRIS, a low-cost IoT-AI solution for smallholder irrigation optimization, featuring an in-box model enabling local data processing and AI execution directly on edge gateways. Similarly, Laha et al. [6] developed a system to optimize crop growth through real-time soil moisture monitoring and automated irrigation using low-cost sensors and wireless communication. However, both solutions [6], [11] lack the ability to predict nutrients from NPK. Furthermore, [6] relies on centralized cloud processing, making it unsuitable for rural deployment scenarios.

Haroon et al. [3] proposed an AIoT irrigation framework using edge ML and real-time sensing to improve efficiency with minimal centralization. However, like [6], [11], it omits soil nutrients, weather data, and relies on a limited, non-temporal dataset. ToEFL [8] enables privacy-preserving edge learning for smart agriculture but lacks generalization in climate-diverse areas like the Sahel.

The limitations of existing works are multiple : 1) first, as climate is changing, the solutions proposed lack of AI techniques for climate change adaptation and microclimate management; 2) second, these works do not consider soil nutrients data (NPK) in crops yield forecasting, this results in inaccurate yield forescat; 3) finally, these solutions are mainly Cloud centric, resulting in high operational costs and unsustainable smart agriculture practices.

III. TCHIA-FedPer Edge Online FL framework

Section II described existing works that focus on the application of IoT and AI for smart agriculture.

A. Overview

The advancement of IoT has significantly propelled the evolution of climate-smart agriculture. Indeed, the real-time data gathered by sensor networks enables specialized AI models to forecast irrigation and fertilization schedules for crops. However, addressing various challenges is necessary to achieve accurate national-level predictions. At the field scale, the data collected alone is not enough in quantity to make accurate predictions for that specific field. This would require a model for each field, leading to significant infrastructure expenses. Additionally, processing data at the network's edge for a specific area does not offer a complete regional climate view or support effective adaptation to climate change. Using a federated learning approach is a practical solution to these challenges. Yet, a single federation consolidating all data may not efficiently forecast all regions. This inefficiency can be attributed to the variation of microclimates.

That is why we present a new IoT-Based Online Edge federated learning (TCHIA-FedPer) framework to deal with the two problems of climate variability in precision agriculture and the limitations of AI that depends on the cloud. This architecture makes area-specific federated models work by training them continuously on distributed edge nodes using live IoT sensor streams. At the same time, it gets rid of the need for the cloud by keeping all training, aggregation, and inference within a hierarchical edge network. This lets people make decisions about irrigation and fertilization in real time and adapt to changes in microclimate while farming in areas with limited resources. The overall architecture of the proposed approach is illustrated in Figure 1.

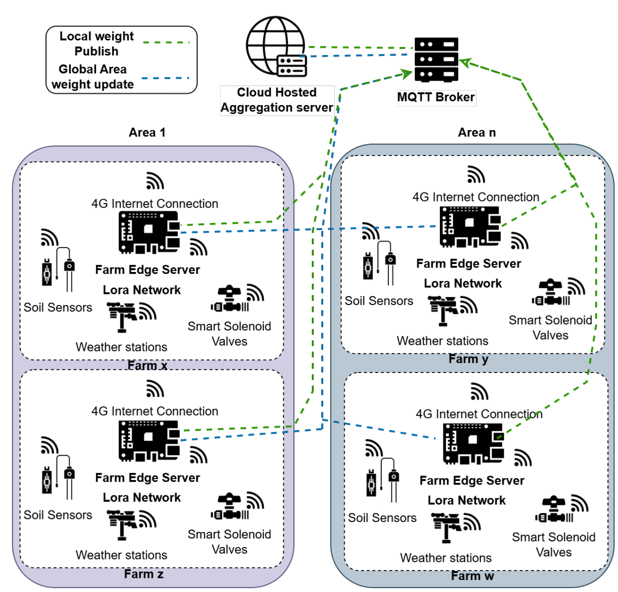

Fig. 1: Proposed TCHIA-FedPer Architecture

B. IoT Network

In the proposed architecture, the sensors (soil humidity, temperature and NPK (Nitrogen, Phosphorus and Potassium), rain gauge, atmospheric pressure, air temperature and humidity, wind speed and direction, etc.) collecting data are grouped by farm. Each farm is managed with one Edge server that collects data sent by the sensors. Indeed, the Edge server performs continuous online training of field-specific models using live sensor streams. Then, it apply real-time inference for crops irrigation and fertilization decisions.

The farms are grouped by geographic regions with the same microclimate. In this work, the subject country of study is Republic of Mali. The Mali geographic profile and climate have three (3) main agro-climatic zones. These are : Sahelian, Sudanian and South-tropical zones. Each edge server functions as a LoRaWAN gateway on the 433 MHz ISM band, harvesting sensor data every 5 minutes with ultra-low energy overhead ($< 0.3J/transmission$). These solar-powered nodes (40W bifacial panels + 5000Ah $LiFePO_4$ batteries) execute online federated training directly on compressed sensor streams using lightweight neural networks (see Section III-C). This enables sub-second irrigation/fertilization decisions while operating fully off-grid, with energy reserves sustaining 12 hours without sunlight. Critically, the 5-minute data cadence aligns with crop response timescales, allowing continuous model refinement against evolving field conditions (e.g., rapid soil moisture depletion during Sahelian midday heat).

C. Edge online federated learning framework

Framework Description: Our TCHIA-FedPer framework implements a distributed deep learning architecture based on Artificial Neural Networks (ANNs) with federated personalization. This approach combines collaborative federated learning with local specialization through customized layers, preserving agricultural data privacy while leveraging collective intelligence. The framework employs multilayer feedforward neural networks with intelligent separation between shared and personalized components, explicitly optimized for agricultural yield prediction across Mali's agro-climatic heterogeneity. Our approach directly builds on pioneering work by [2] on Federated Learning with Personalization Layers (FedPer), which introduced a "base + personalization layers" architecture to counter statistical heterogeneity in federated learning. We adapt this innovation to the agricultural context by integrating FedAvg aggregation algorithm, the foundation of modern federated learning [7]. Indeed, this algorithm computes weighted averages of local updates. The key innovation lies in tailoring this architecture to Malian agro-climatic zones:

- Personalized heads scaled to zonal complexity;
- Aggregation weights reflecting the country agricultural data distribution.

Edge servers within common agro-climatic zones : Sahelian (north: Kayes region), Sudanian (central: Ségou region), and South-Tropical (south: Sikasso region) – synchronize via zone-specific federated aggregation. Every 24 hours, encrypted model weights are transmitted to the aggregator where FedAvg fuses zonal knowledge. This architecture respects microclimate boundaries: Sahelian models focus on drought resilience, while South-Tropical heads optimize humidity-dependent nutrient management. By confining aggregation within climatic homologues, we prevent meteorological cross-contamination (e.g., desert Harmattan winds biasing southern models) while reducing bandwidth by 92% versus cloud-based alternatives. **Framework Architecture: 5-Stage Pipeline:** Our FL architecture implements a validated 5-stage process:

a) Initialize Global Model: The central server creates the dual-head global TCHIA-FedPer model using Xavier uniform initialization to stabilize training (trained on 1M agricultural observations). This ensures all zonal clients start with identical base weights, which is critical for federated convergence.

b) Distribute Global Parameters: Selective transmission of shared base layer parameters only (0.8 MB/round) to zonal clients via optimized communication protocols. We use MQTT protocol for communications. Agro-climatic zones receive identical base parameters while retaining local specialization autonomy (see Fig. 1).

c) Local Zonal Training: Local training drives personalization, with each zone performing 5 epochs using separate Adam optimizers: adaptive rates for base layers and a fixed 0.0025 for customized heads. This separation enables concurrent optimization of general and local learning. A batch size of 512 ensures GPU efficiency and numerical stability.

d) FedAvg Aggregation: The aggregation uses the weighted FedAvg algorithm, where the server combines base layer updates according to the following formula (eq. 1) :

$$w_{global} = \sum\left(\frac{n_k}{n_{total}} * weight_{zone_k} * w_k\right) \tag{1}$$

The aggregation weights reflect Mali's data distribution, such as : Sahelian: 23%, Sudanian: 26%, South-Tropical: 51%. This weighting ensures fair representation of each zone in the overall model, while recognizing relative economic importance. Only base layers are aggregated, preserving the integrity of local specializations.

e) Global Model Evaluation: The global evaluation measures the performance of the federated system using harmonised metrics calculated from all aggregated zonal predictions. The system calculates the following to validate predictive quality and territorial equity: global R^2, global RMSE (denormalised in kg/ha) and equity metrics (interzone coefficient of variation). This evaluation uses advanced monitoring with intelligent early stopping (after 5 rounds) and automatic detection of a performance plateau to guarantee optimal termination of the learning process.

Our proposed framework (see Fig.2) implements a distributed supervised Deep Learning model that combines federated learning with multilayer feedforward neural networks at Edge Layer [14]. It is a federated neural regression model that aims to forecast agricultural yields (continuous variable in kg/ha) using pedoclimatic and agronomic data. The architecture uses the Federated Personalization paradigm,

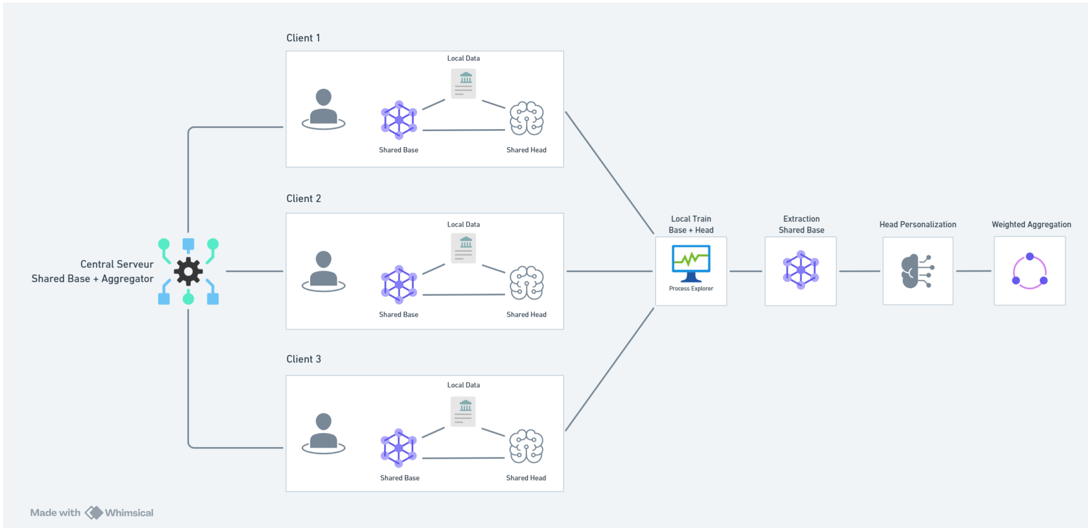

Fig. 2: Proposed Online TCHIA-FedPer Framework

which intelligently splits learning into global (shared) and local (personalized) components, allowing for the benefits of both collective intelligence and contextual specialization. This model is part of a family of FL algorithms with statistical heterogeneity that are intended to efficiently manage the non-IID (non-identically distributed) data distributions found in geographically diverse agricultural systems.

IV. Evaluation

In this section, we aim to evaluate the performance levels of TCHIA-FedPer framework (see Section III) and discuss the results of the performance evaluation.

A. Experiment setup and dataset

To validate the performance of TCHIA-FedPer, we perform the local regression neural network task for the dataset [13]. The local Edge servers (platforms) are built using the Raspberry Pi 5 boards. The data are exchanged using the MQTT Pub/Sub mechanism, a well-known distributed data exchange system (see Section III). The implementation of local training pipeline has been done using Python Scikit-learn, PyToch librairies. The implementation of federation layer pipeline has been done using FedAvg aggregator and FedPer technique.

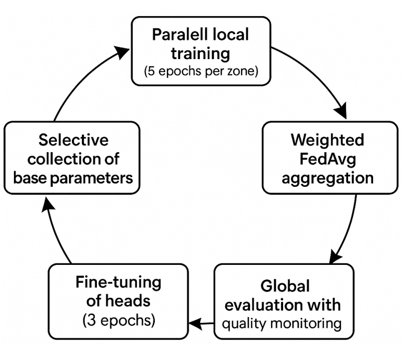

Fig. 3: TCHIA-FedPer global workflow

The TCHIA-FedPer framework runs on an iterative cycle of 9 empirically-validated rounds, where each round comprises: parallel local training (5 epochs per zone), selective collection of base parameters, weighted FedAvg aggregation, distribution of updates, fine-tuning of heads (3 epochs), and global evaluation with quality monitoring (Fig. 3). This process gradually builds a high-performance national model while preserving zonal specializations and territorial equity, demonstrating federated learning's viability for sub-Saharan agriculture. Section IV-B provides more details about these results. As the deployment environment is constrained, we defined a model update frequency of 1 update per 24 hours.

The dataset [13] used for the TCHIA-FedPer framework performance evaluation has been built to be as most realistic as possible. Indeed, the base data used for weather information has been obtained from the weather forecasting Agency Mali Meteo. The dataset focuses on 4 cereal crops: millet, maize, sorghum, rice and cotton. Thus, the dataset used comprises 15 critical variables, specifically selected to maximize the predictive performance of agricultural yield, avoiding any risk of model leakage or overfitting. These variables include essential climatic indicators (SeasonRainfall_mm, WindSpeed_ms, AtmPressure_kPa), key soil parameters (Soil_pH, Soil_N_kg_ha, SoilTexture_encoded) and critical agronomic variables (FinalCrop_encoded, SowingDelay_days, FertilizerApplied_kg_ha, Year, Locality_encoded). Each line of the dataset was generated using a data augmentation technique based on Sahelian agro-climatic realities.

B. Results and discussion

Table I summarizes the performance metrics of TCHIA-FedPer compared to the Centralized Artificial Neural Network (ANN) approach. Assessing our Federated Learning method reveals critical insights into its application in climate-smart agriculture within sub-Saharan regions. Figure 4 illustrates crops yield prediction performance of both approaches. Specif-

TABLE I: Performances comparison of our model vs Centralized ANN

Model	N Samples	R^2	R^2 CI (95%)	RMSE (kg/ha)	RMSE CI (95%)	MAE (kg/ha)	MAPE
Centralized ANN	120,000	0.8815	[0.8794, 0.8833]	227.82	[226.28, 229.52]	161.50	30.2%
TCHIA-FedPer	120,001	0.8808	[0.8788, 0.8828]	228.10	[226.53, 229.72]	161.90	30.7%
FL Improvement	+1	-0.0007	-	+0.28	-	+0.40	-
Zone-Specific FL Performance							
FL - Sahelian	27,575	0.8548	[0.8505, 0.8592]	183.18	[180.96, 185.63]	135.29	30.8%
FL - Sudanian	31,242	0.8528	[0.8488, 0.8565]	180.91	[178.77, 183.01]	134.48	31.1%
FL - South-Tropical	61,184	0.8815	[0.8788, 0.8841]	264.98	[262.53, 267.50]	187.89	30.4%

ically, TCHIA-FedPer demonstrates a remarkable capability to rival the centralized model's performance (R^2 = 0.881, RMSE = 228.1 kg/ha) while providing the inherent benefits of Federated Learning, such as privacy preservation, decreased network traffic, and enhanced fairness among various areas. Consequently, TCHIA-FedPer emerges as the perfect approach for prompt deployment in Mali's climate-smart agriculture.

Fundamentally, our federated model shows indistinguishable statistical results compared to centralized methods, as indicated by nearly matching performance metrics (Table I). Both frameworks explain around 88% of the yield variability (R^2: 0.8808 for FL and 0.8815 for centralized, with a Δ of -0.0007). The RMSE differs by a mere 0.28 kg/ha (228.10 versus 227.82 kg/ha). The coinciding 95% confidence intervals (R^2: [0.8788–0.8828] versus [0.8794–0.8833]; RMSE: [226.53–229.72] versus [226.28–229.52]) reinforce this equivalency at α=0.05. This minimal difference (under 0.1% for all metrics) illustrates that FL does not compromise accuracy, even with segregated data. Thus, this finding is an essential contribution for Federated Learning in smart agriculture.

The observed errors hold operational relevance for smallholder contexts. At 228 kg/ha RMSE ($\approx$8–12% of typical Malian cereal yields), the deviations correspond to < 2 standard bags of fertilizer per hectare, well within tolerable margins for field-level decision support. Notably, zone-specific errors reflect agronomic realism: Sahelian/Sudan zones showed lower RMSE (181–183 kg/ha) due to yield constraints, while higher errors in the South-Tropical zone (265 kg/ha) align with its greater productivity potential. This granular precision, impossible in monolithic models, validates our zone-weighted TCHIA-FedPer design, as 30.4–31.1% MAPE values.

Moreover, the comparable performance of our federated model to the centralized method is not a limitation. Instead, it illustrates that an AI system can forecast tropical agricultural yields with 88% accuracy (Fig.4-B) using a federated approach. This level of performance, sustained across 120,000 samples and three different agro-climatic zones, offers a robust foundation for the practical implementation of agricultural decision support tools in sub-Saharan Africa. Residual analysis, significant for assessing internal model quality, presents scatter plots centered around zero (Fig. 5), implying that the model is fine. In addition, the Q-Q plot corresponds well with normal distribution theory (Fig. 5-E).

V. Conclusion

The agricultural sector faces food insecurity challenges exacerbated by climate change and population growth, requiring adaptive smart farming technologies. Existing AI agricultural solutions present significant limitations: high costs, cloud dependency, and lack of adaptation to microclimates. We introduced TCHIA-FedPer, an innovative IoT-enabled Edge AI solution for high precision smart agriculture. Our key contributions include zone-specific FL for microclimate adaptation and dynamic Edge-centric AI model evolution. By deploying AI processing directly on edge devices, TCHIA-FedPer eliminates cloud dependency, reducing latency and bandwidth consumption. Comprehensive evaluation demonstrates that TCHIA-FedPer achieves performance equivalent to centralized models while providing federated learning's intrinsic advantages: enhanced data privacy, significant network traffic reduction, and improved territorial equity. It complies with SDG 2 and SDG 13 compliant. Consequently, TCHIA-FedPer represents a robust, deployment-ready framework for advanced agricultural decision support.

In future work, we plan to further develop the TCHIA-FedPer framework. In this context, it would be beneficial to explore additional features and aspects, specifically: 1) the hierarchical deployment of zonal aggregators, 2) the creation of a more comprehensive dataset, and 3) scaling the experiment to a country-wide level.

Acknowledgment

This work was supported by the The Word Academy of Sciences (TWAS) Seed Grant for New African Principal Investigator (SG-NAPI) program (fully funded by The German Ministry of Research, Technology and Space (BMFTR)). under Grant No.FR324033099. The authors would like to thank *Mali Meteo* for providing them with national meteorological data.

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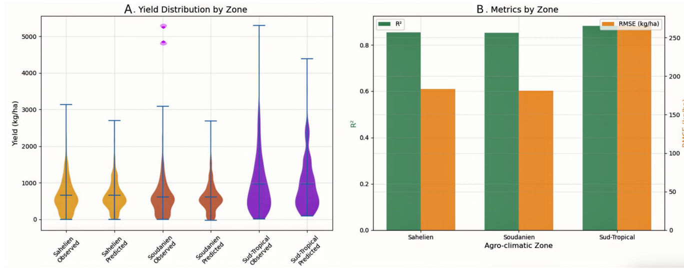

Fig. 4: Yield prediction performance

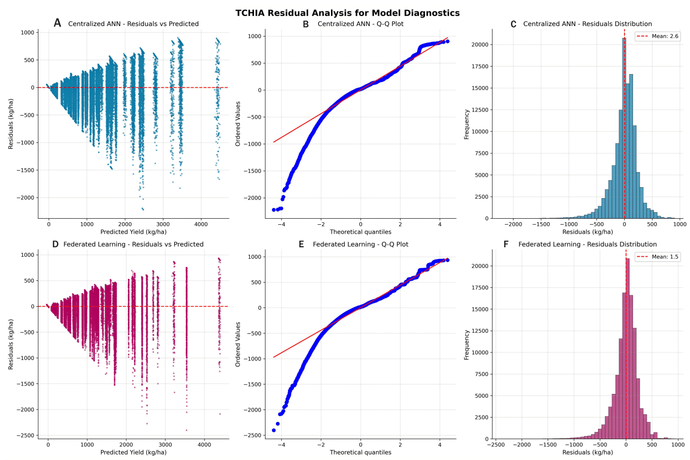

Fig. 5: Residual analysis for model diagnostics

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