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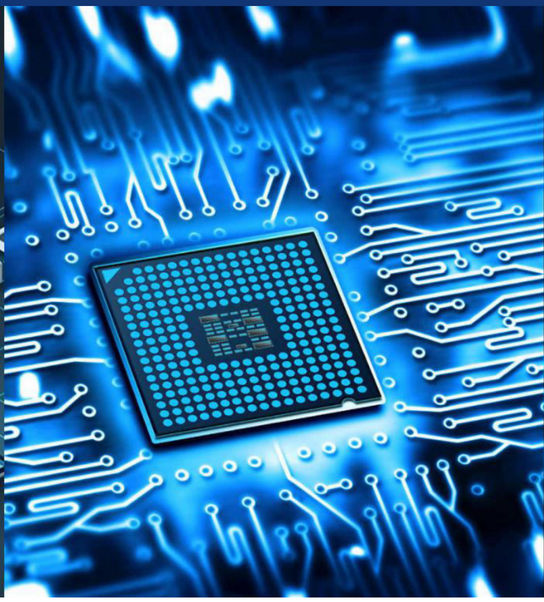

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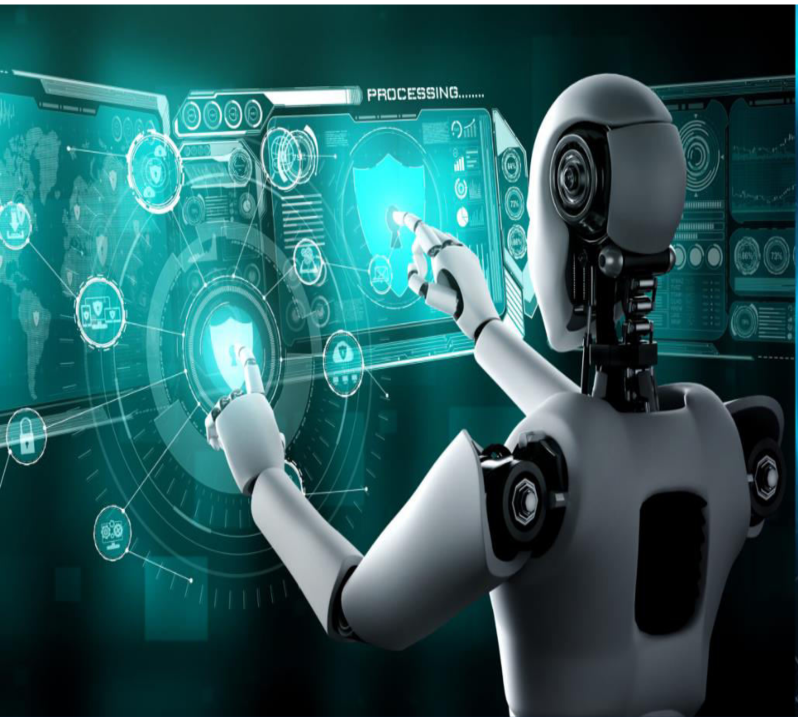

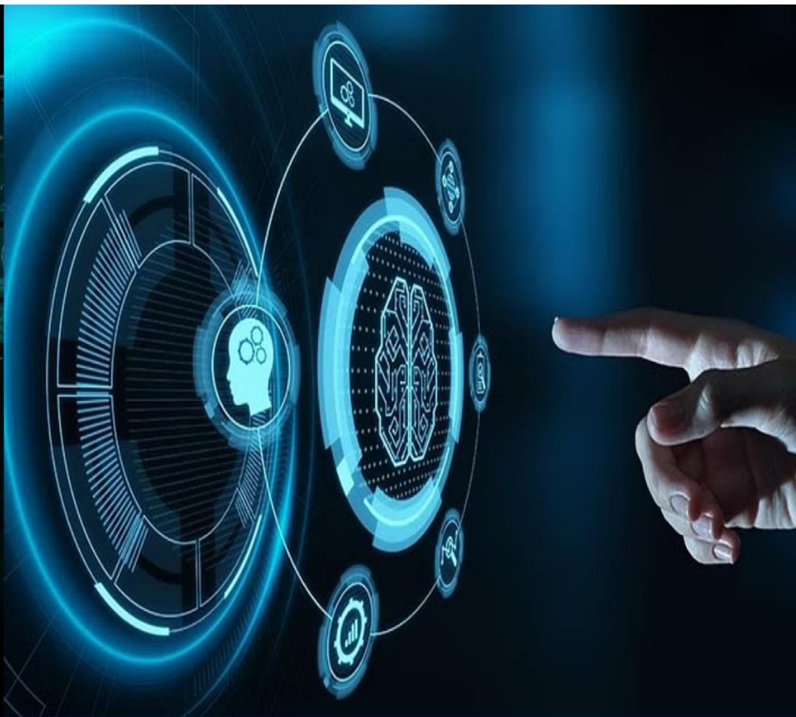

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Neuro-Fuzzy Driven Client Selection for Efficient Federated Learning

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ABSTRACT: Federated Learning (FL) enables multiple distributed devices to collaboratively train a shared machine learning model while retaining data locally, thereby improving privacy and reducing the need for centralized data collection. However, the effectiveness of FL is strongly influenced by the heterogeneous characteristics of participating clients. Variations in battery capacity, communication bandwidth, computational capability, data quality, and device reliability often lead to inefficient client participation, increased communication overhead, and slower model convergence. Conventional client selection strategies such as random or static threshold-based approaches are unable to adapt to continuously changing device conditions.

Neuro-Fuzzy client selection framework for heterogeneous Federated Learning environments. The proposed framework integrates an Adaptive Neuro-Fuzzy Inference System (ANFIS) with the Federated Averaging (FedAvg) algorithm to evaluate client suitability using multiple resource-aware features. Fuzzy reasoning captures uncertainty in device characteristics, while adaptive learning continuously refines the selection policy based on feedback obtained during successive communication rounds. The framework further incorporates realistic device simulation, including dynamic battery variation, bandwidth fluctuation, client churn, and both IID and Non-IID data distributions, to emulate practical mobile computing environments.

Experimental evaluation demonstrates that the proposed Neuro-Fuzzy strategy consistently selects more suitable clients than conventional selection methods, leading to faster convergence, improved mean model accuracy, reduced energy consumption, lower training time. The proposed approach provides an adaptive and resource-aware client selection mechanism that enhances the efficiency and scalability of Federated Learning in heterogeneous edge and mobile networks.

KEYWORDS: Federated Learning, Neuro-Fuzzy Systems, ANFIS, Client Selection, Federated Averaging (FedAvg), Resource-Aware, Heterogeneous Devices, Machine Learning.

I. INTRODUCTION

The rapid expansion of mobile devices, edge computing, and Internet of Things (IoT) applications has resulted in massive amounts of distributed data. Conventional machine learning approaches require collecting this data at a centralized server for model training, which raises concerns regarding privacy, communication overhead, and storage requirements. Federated Learning (FL) addresses these challenges by enabling multiple clients to collaboratively train a global model while keeping their local data on their own devices. Only model updates are exchanged with the server, significantly improving data privacy and reducing unnecessary data transmission.

Although Federated Learning offers several advantages, its performance is greatly affected by the heterogeneous nature of participating devices. Clients differ in battery level, computational capability, communication bandwidth, data quality, and network reliability. These dynamic variations make client selection a critical factor influencing model convergence, energy consumption, and overall training efficiency. Random or static threshold-based client selection methods often fail to adapt to changing resource conditions, resulting in inefficient participation and increased communication costs.

To overcome these limitations, this paper proposes a Neuro-Fuzzy client selection framework for heterogeneous Federated Learning environments. The proposed approach employs an Adaptive Neuro-Fuzzy Inference System (ANFIS) to evaluate client suitability based on multiple resource-aware parameters, including battery level, bandwidth, computational capability, data quality, and device reliability. By combining fuzzy reasoning with adaptive learning, the proposed framework effectively handles uncertainty while continuously improving the client selection process across communication rounds. Selected clients perform local training, and their model updates are aggregated using the Federated Averaging (FedAvg) algorithm to generate an improved global model.

A realistic simulation environment is developed to model heterogeneous devices, dynamic resource variation, client churn, and both IID and Non-IID data distributions. The proposed method is evaluated against conventional client selection strategies using metrics such as classification mean accuracy, convergence speed, energy consumption and training time. Experimental results demonstrate that the Neuro-Fuzzy approach achieves more efficient client participation, faster convergence, improved mean accuracy, and better resource utilization, making it suitable for practical privacy-preserving Federated Learning applications.

The main contributions of this work are summarized as follows:
• A Neuro-Fuzzy client selection framework for heterogeneous Federated Learning.
• ANFIS-based adaptive evaluation of clients using battery level, bandwidth, computational capability, data quality, and reliability.
• A realistic Federated Learning simulation supporting heterogeneous devices and IID/Non-IID data distributions.

II. RELATED WORK

Federated Learning has emerged as a promising distributed learning paradigm that enables collaborative model training while preserving data privacy. The Federated Averaging (FedAvg) algorithm introduced in [1] established the foundation for decentralized model aggregation and significantly reduced communication overhead. However, the client selection process primarily relied on random participation, without considering variations in device resources or network conditions.

Several studies have focused on improving client selection by incorporating resource-aware decision mechanisms. The authors in [2] proposed a fuzzy logic-based approach that evaluates client suitability using parameters such as battery level, communication bandwidth, and computational capability. Although the method improved resource utilization, its manually designed membership functions and fixed inference rules limited its adaptability to dynamic environments.

A fuzzy inference-based client selection strategy for vehicular Federated Learning was presented in [3], where client participation was determined using data freshness, computational capability, network throughput, and sample availability. The proposed method achieved faster model convergence in vehicular networks but lacked an adaptive learning mechanism capable of refining the decision process over time.

To improve energy efficiency, hierarchical Federated Learning combined fuzzy logic with communication optimization in [4]. The proposed framework reduced energy consumption and communication cost by selecting resource-capable clients. Nevertheless, the selection policy remained dependent on predefined fuzzy rules, making it difficult to respond effectively to continuously changing client conditions.

Motivated by these limitations, this work proposes a Neuro-Fuzzy client selection framework that integrates an Adaptive Neuro-Fuzzy Inference System (ANFIS) with Federated Learning. Unlike existing approaches, the proposed method simultaneously considers multiple client characteristics, including battery level, bandwidth, computational capability, data quality, and device reliability, while continuously refining the client selection strategy using learning feedback from previous communication rounds. This adaptive mechanism enables more efficient client selection, resulting in improved model convergence, reduced energy consumption, lower training time, and resource-aware participation in heterogeneous Federated Learning environments.

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III. PROPOSED METHODOLOGY

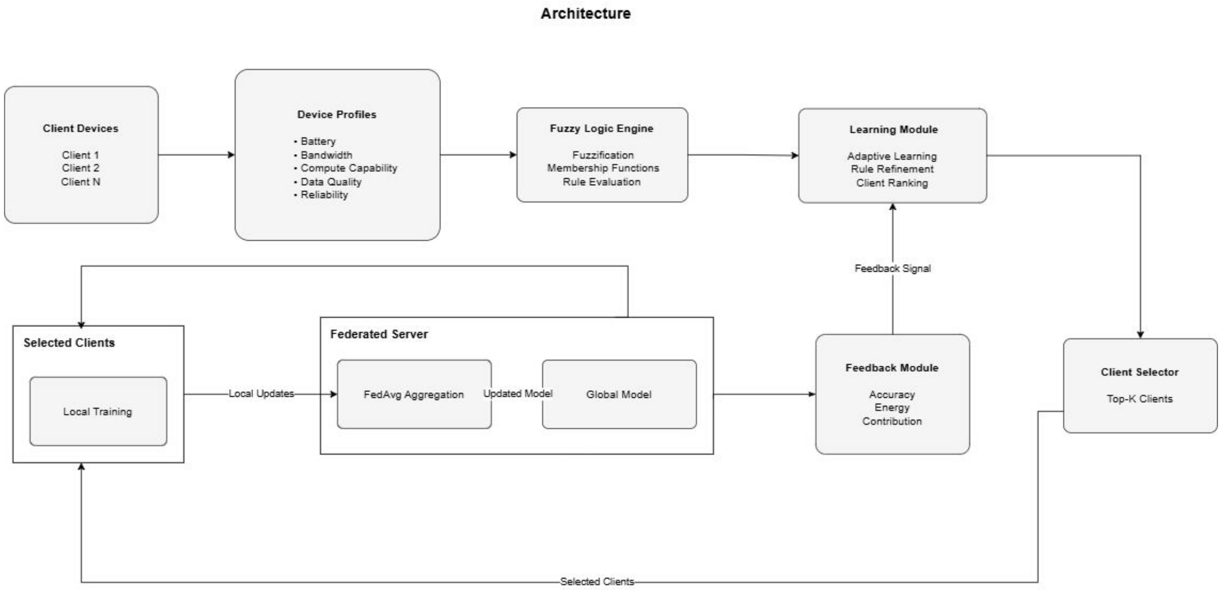

Figure 1: Architecture

A. *System Architecture*

Figure 1 presents the architecture of the proposed Neuro-Fuzzy Federated Learning framework. Multiple heterogeneous client devices participate in the Federated Learning process while keeping their local datasets private. Each client is characterized by five dynamic features: battery level, communication bandwidth, computational capability, data quality, and device reliability.

These features are processed by the Neuro-Fuzzy decision engine, where fuzzy inference evaluates the suitability of each client. The adaptive learning module refines the client scoring mechanism using feedback obtained after every communication round. Based on the updated suitability scores, the client selector chooses the Top-K clients for local model training.

The selected clients train the global model using their local datasets and transmit only the updated model parameters to the federated server. The server aggregates these updates using the Federated Averaging (FedAvg) algorithm to generate an improved global model. A feedback module then evaluates each client's contribution based on metrics such as accuracy improvement and energy consumption. This feedback is used to update the Neuro-Fuzzy model, enabling more accurate client selection in subsequent communication rounds. The process repeats until the global model converges.

B. Neuro-Fuzzy Client Scoring

The proposed framework employs an Adaptive Neuro-Fuzzy Inference System (ANFIS) to evaluate the suitability of each client before every Federated Learning communication round. Unlike conventional threshold-based methods, the proposed approach combines fuzzy reasoning with adaptive neural learning to estimate the participation capability of heterogeneous clients under dynamically changing resource conditions.

Each client is represented by a five-dimensional feature vector

$$X_i = [B_i,\ BW_i,\ CC_i,\ DQ_i,\ R_i]$$

where

- (B_i) denotes the battery level,
- (BW_i) represents the communication bandwidth,

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- (CC_i) indicates the computational capability,
- (DQ_i) denotes the data quality, and
- (R_i) represents the device reliability.

These resource features are periodically updated before every communication round to reflect the current operating conditions of each client.

Gaussian Membership Function

Each input feature is transformed into fuzzy membership values using Gaussian membership functions. The membership degree is computed as $\mu(x) = \exp\left(-\frac{(x-c)^2}{2\sigma^2}\right)$
where (c) represents the learnable center of the membership function and (σ) denotes its learnable spread. Unlike conventional fuzzy systems with manually defined parameters, both values are optimized automatically during training.

Rule Evaluation

The firing strength of each fuzzy rule is obtained by multiplying the membership values of all input features

$$w_j = \prod_{k=1}^{5} \mu_{jk}(x_k)$$

The normalized firing strength is calculated as: $\overline{w}j = \frac{w_j}{\sum m=1^M w_m}$ where (M) is the total number of fuzzy rules.

Consequent Layer

Each fuzzy rule produces a first-order Takagi-Sugeno consequent: $f_j = p_{j1}B + p_{j2}BW + p_{j3}CC + p_{j4}DQ + p_{j5}R + q_j$ where (p_{jk}) and (q_j) are trainable consequent parameters.

Client Suitability Score

The final Neuro-Fuzzy output is computed by combining the normalized rule outputs $S_i = \sum_{j=1}^{M} \overline{w}_j f_j$
The obtained value is passed through a sigmoid activation function to produce the final suitability score
$Score_i = \frac{1}{1+e^{-S_i}}$ where $(Score_i \in [0,1])$.
Clients with higher suitability scores possess better resource availability and are therefore considered more suitable for participation in the current Federated Learning round.

C. *Adaptive Feedback Learning*

To continuously improve the client selection strategy, the proposed framework employs an adaptive feedback learning mechanism after every Federated Learning communication round. Instead of relying on static fuzzy rules, the Neuro-Fuzzy model learns from the actual performance of the selected clients and updates its parameters accordingly.

Client Contribution Evaluation

After local training, the contribution of each selected client is estimated by measuring the improvement in validation accuracy.

$$C_i = A_i^{after} - A_i^{before}$$

where

- (A_i^{before}) is the validation accuracy before local training,
- (A_i^{after}) is the validation accuracy after local training.

The contribution values are normalized to eliminate scale variations between communication rounds.

Utility Score Computation

The proposed framework evaluates every participating client using three criteria: Normalized validation accuracy improvement, Data quality, Normalized energy consumption.
These factors are combined to compute a utility score

$$U_i = \sigma(w_c C_i + w_q Q_i - w_e E_i)$$

where

- (C_i) is the normalized contribution,
- (Q_i) is the data quality,
- (E_i) is the normalized energy consumption,
- $(w_c), (w_q), and (w_e)$ are weighting coefficients, and
- $(\sigma(\cdot))$denotes the sigmoid activation function.

A higher utility score indicates that the client provides significant model improvement while consuming fewer computational resources.

Experience Buffer

For every participating client, the corresponding feature vector and utility score are stored as a training sample

$$(X_i, U_i)$$

These samples are accumulated in an experience buffer and are later used to retrain the Neuro-Fuzzy model.

ANFIS Parameter Update

The ANFIS model is periodically updated by minimizing the Mean Squared Error (MSE) between the predicted suitability score and the computed utility score: $L = \frac{1}{N}\sum_{i=1}^{N}\left(\hat{U}_i - U_i\right)^2$

where

- (U_i) represents the target utility score,
- $(\hat{U}_i)$ denotes the predicted output of the ANFIS model.

The trainable parameters are updated using the Adam optimization algorithm according to $\theta_t - \eta\nabla_\theta L$
where θ represents the ANFIS parameters and (η) is the learning rate.
After updating the model, the client suitability scores become more representative of actual client performance. Consequently, subsequent communication rounds select clients that contribute more effectively to the global model while reducing energy consumption and improving overall training efficiency.

IV. PSEUDO CODE

Algorithm: Neuro-Fuzzy Client Selection Mechanism
Step 1: Initialize the global model, Neuro-Fuzzy (ANFIS) model, and all participating client devices.
Step 2: Partition the training dataset among clients using IID or Non-IID distribution.
Step 3: Update the resource profile of each client by obtaining battery level, communication bandwidth, computational capability, data quality, and device reliability.
Step 4: Check the availability of every client.
    If (Battery Level < Minimum Threshold OR Client is Offline)
        Exclude the client from the current communication round.
    Else
        Include the client for evaluation.
Step 5: Normalize the resource features of all available clients.
Step 6: Compute the suitability score of each client using the Neuro-Fuzzy (ANFIS) decision engine.
Step 7: Rank all available clients according to their suitability scores and select the Top-K highest-ranked clients.
Step 8: Distribute the current global model to the selected clients and perform local model training.
Step 9: Collect the updated local model parameters from all participating clients.
Step 10: Aggregate the received model updates using the Federated Averaging (FedAvg) algorithm to obtain the new global model.
Step 11: Evaluate each participating client based on its contribution, validation performance, and energy consumption to generate a feedback (utility) score.
Step 12: Update the ANFIS parameters using the feedback obtained from the current communication round.
Step 13: Repeat Steps 3–12 until the maximum number of communication rounds is completed or the global model converges.
Step 14: End.

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V. SIMULATION RESULTS

The proposed Neuro-Fuzzy client selection framework was evaluated through extensive simulations and compared with Random Selection, Round Robin, Static Fuzzy Logic, and Hierarchical Fuzzy Joint Optimization (HFJO). The experiments were conducted under four different scenarios, namely Normal, IID, Non-IID, and High Churn, to evaluate the robustness of the proposed approach in heterogeneous Federated Learning environments.

A. Mean Accuracy Analysis

Mean accuracy is one of the primary performance metrics used to evaluate the effectiveness of the proposed client selection strategy. Figure 2 compares the mean classification accuracy achieved by Random Selection, Round Robin, Static Fuzzy Logic, Hierarchical Fuzzy Joint Optimization (HFJO), and the proposed Neuro-Fuzzy method under the Normal, IID, Non-IID, and High Churn scenarios.

The proposed Neuro-Fuzzy framework consistently achieves higher mean accuracy by selecting clients based on battery level, communication bandwidth, computational capability, data quality, and device reliability. The adaptive feedback learning mechanism further refines the client selection process after each communication round, enabling the framework to identify clients that contribute more effectively to global model optimization.

B. Energy to Reach Target Accuracy

Energy to Reach Target Accuracy represents the amount of energy consumed by participating client devices before the global model achieves the predefined target accuracy. Lower energy consumption indicates a more efficient client selection strategy because fewer computational and communication resources are required during the Federated Learning process. Figure X compares the energy required by Random Selection, Round Robin, Static Fuzzy Logic, Hierarchical Fuzzy Joint Optimization (HFJO), and the proposed Neuro-Fuzzy client selection strategy under the Normal, IID, Non-IID, and High Churn scenarios.

As shown in Figure 3, the proposed Neuro-Fuzzy framework consistently consumes less energy than the existing methods across all experimental scenarios. The proposed approach achieves energy reductions of 37.89%, 42.56%, 28.03%, and 26.23% compared with Random Selection under the Normal, IID, Non-IID, and High Churn scenarios, respectively, while also outperforming Round Robin, Static Fuzzy Logic, and HFJO. These improvements are achieved through intelligent client selection based on battery level, communication bandwidth, computational capability, data quality, and device reliability, enabling the framework to reduce unnecessary participation of resource-constrained clients and improve the overall energy efficiency of the Federated Learning process.

C. Total Energy Consumption

Total Energy Consumption represents the cumulative energy consumed by all participating client devices throughout the entire Federated Learning process. Unlike the Energy to Reach Target Accuracy metric, which measures the energy required only until the target accuracy is achieved, this metric evaluates the overall energy expenditure during all communication rounds. Figure X compares the total energy consumption of Random Selection, Round Robin, Static Fuzzy Logic, Hierarchical Fuzzy Joint Optimization (HFJO), and the proposed Neuro-Fuzzy client selection strategy under the Normal, IID, Non-IID, and High Churn scenarios.

As illustrated in Figure 4, the proposed Neuro-Fuzzy framework consistently achieves lower total energy consumption than the existing client selection strategies across all experimental scenarios. Compared with Random Selection, the proposed approach reduces total energy consumption by **26.98%**, **27.20%**, **16.32%**, and **23.18%** under the Normal, IID, Non-IID, and High Churn scenarios, respectively, while also outperforming Round Robin, Static Fuzzy Logic, and HFJO. The reduction in energy consumption is achieved through adaptive client selection, which prioritizes resource-efficient clients and minimizes unnecessary computation and communication, thereby improving the overall energy efficiency of the Federated Learning system.

D. Total Training Time

Total Training Time measures the overall execution time required to complete all Federated Learning communication rounds, including local model training, model transmission, and global model aggregation. Lower training time indicates a more efficient client selection strategy with reduced computational and communication overhead. Figure X compares the total training time of Random Selection, Round Robin, Static Fuzzy Logic, Hierarchical Fuzzy Joint Optimization (HFJO), and the proposed Neuro-Fuzzy client selection strategy under different simulation scenarios.

As shown in Figure 5, the proposed Neuro-Fuzzy framework achieves lower training time in most scenarios by selecting resource-capable clients with better computational capability and communication bandwidth. Compared with Random Selection, the proposed approach reduces training time by **19.04%**, **37.29%**, **3.02%**, and **13.43%** under the Normal, IID, Non-IID, and High Churn scenarios, respectively. These results demonstrate that intelligent client selection improves the overall efficiency of the Federated Learning process by reducing unnecessary delays during model training and communication.

E. Participation Fairness Analysis

Participation fairness is evaluated using Jain's Fairness Index (JFI), which measures how uniformly client devices participate in the Federated Learning process. Figure X compares the participation fairness of Random Selection, Round Robin, Static Fuzzy Logic, Hierarchical Fuzzy Joint Optimization (HFJO), and the proposed Neuro-Fuzzy client selection strategy under different simulation scenarios.

As shown in Figure 6, the proposed Neuro-Fuzzy framework achieves slightly lower fairness than some baseline methods because client selection is based on resource suitability rather than equal participation. Only clients that satisfy the required resource conditions, such as adequate battery level, communication bandwidth, computational capability, data quality, and device reliability, are selected for training. Consequently, resource-constrained or unavailable clients participate less frequently, leading to a lower JFI. This selective participation improves overall model accuracy, convergence speed, and energy efficiency while ensuring that only eligible clients contribute to the Federated Learning process.

E. Rounds Required to Reach Target Accuracy

The number of communication rounds required to reach the target accuracy reflects the convergence efficiency of a Federated Learning system. Fewer communication rounds indicate faster model convergence with lower communication and computational overhead. Figure X compares the communication rounds required by Random Selection, Round Robin, Static Fuzzy Logic, Hierarchical Fuzzy Joint Optimization (HFJO), and the proposed Neuro-Fuzzy client selection strategy under different simulation scenarios.

As shown in Figure 7, the proposed Neuro-Fuzzy framework reaches the target accuracy in fewer communication rounds than the existing methods across most scenarios. By selecting clients with higher resource availability and better data quality, the proposed approach accelerates model convergence while reducing communication overhead and improving the overall efficiency of the Federated Learning process.

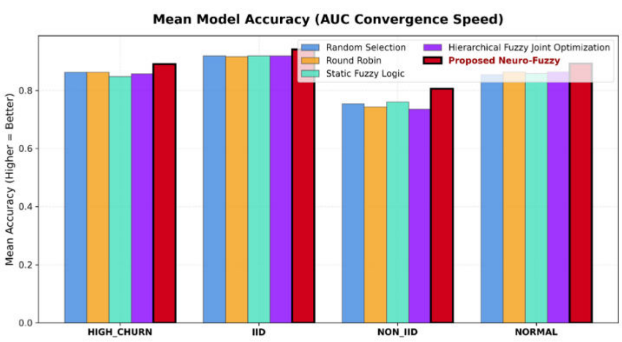

Fig.2. Mean Accuracy Comparison

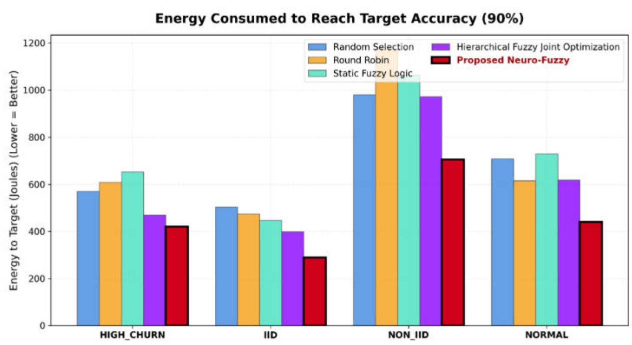

Fig. 3. Energy to Reach Target Accuracy Comparison

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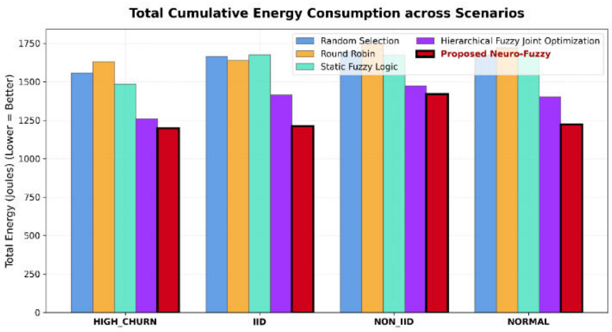

Fig. 4. Total Energy Comparison

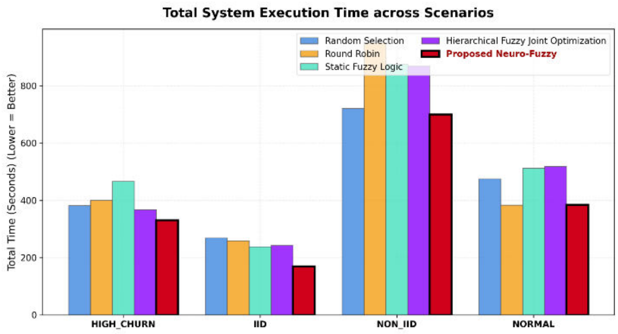

Fig 5. Total Training Time Comparison

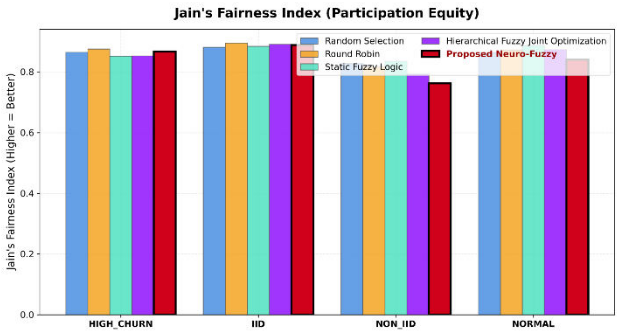

Fig. 6. Participation Fairness (Jain's Fairness Index) Across Different Scenario

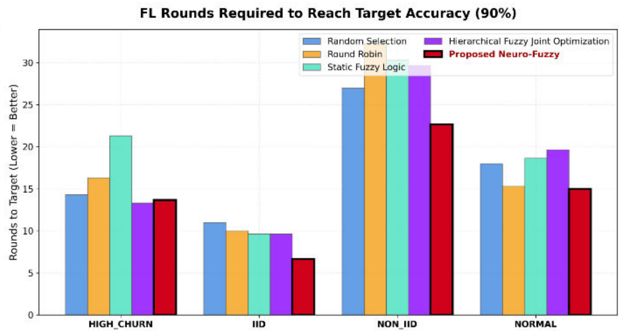

Fig 7. Rounds Required to Reach Target Accuracy

VI. CONCLUSION AND FUTURE WORK

This paper presented a Neuro-Fuzzy client selection framework for heterogeneous Federated Learning environments by integrating an Adaptive Neuro-Fuzzy Inference System (ANFIS) with the Federated Averaging (FedAvg) algorithm. The proposed framework intelligently selects participating clients based on battery level, communication bandwidth, computational capability, data quality, and device reliability, while an adaptive feedback learning mechanism continuously refines the client selection strategy using training performance. Experimental results under Normal, IID, Non-IID, and High Churn scenarios demonstrated that the proposed approach consistently achieved higher mean accuracy, reduced energy consumption, lower training time, and fewer communication rounds compared with Random Selection, Round Robin, Static Fuzzy Logic, and Hierarchical Fuzzy Joint Optimization (HFJO). Although the selective client participation results in slightly lower participation fairness, it ensures that only eligible and resource-capable clients contribute to model training, thereby improving the overall efficiency of the Federated Learning process. Future work will focus on validating the proposed framework in large-scale real-world edge computing environments, incorporating additional context-aware parameters such as network latency and client mobility, and exploring advanced learning techniques to further enhance adaptive client selection.

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