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FEDERATED LSTM FRAMEWORK FOR REAL-TIME INSULIN PREDICTION USING EDGE-TO-CLOUD CGM INTEGRATION

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Abstract

Background: Effective diabetes management relies heavily on timely and accurate insulin prediction, particularly with the increased use of Continuous Glucose Monitoring (CGM) systems. However, conventional centralized machine learning (ML) approaches often require the transfer of sensitive health data to remote servers, raising concerns about patient privacy, high communication overhead, and limited adaptability to individual glucose patterns. **Problem:** Existing prediction models struggle to balance personalization, privacy, and computational efficiency. Centralized learning lacks scalability and exposes raw data, while traditional models like decision trees or statistical regressors fail to capture the temporal complexity inherent in CGM data. **Methods:** This study proposes a federated learning (FL) framework for real-time insulin prediction, utilizing Raspberry Pi devices as edge nodes for local data processing and model training. Each client trains a lightweight Long Short-Term Memory (LSTM) model on individual CGM sequences. The cloud server aggregates model weights using a secure federated averaging algorithm, avoiding raw data transfer and enabling decentralized model optimization. **Results:** The proposed federated LSTM approach was evaluated using simulated multi-client CGM datasets and compared against baseline models: centralized LSTM and decision tree. Results demonstrate superior performance by the federated model, achieving higher accuracy (91.4%), F1-score (90.0%), and lower mean squared error (3.75), while maintaining communication efficiency and strong personalization across clients. **Conclusion:** This work demonstrates the feasibility of deploying a scalable, privacy-preserving, and accurate insulin prediction system using federated deep learning (DL) and edge computing. The proposed architecture supports real-time glucose monitoring and personalized insulin management, offering a practical solution for decentralized digital healthcare.

Keywords: Federated Learning; LSTM; Insulin Prediction; Edge Computing; Continuous Glucose Monitoring (CGM); Privacy-Preserving Healthcare

1. Introduction

In the age of digital health, continuous data acquisition from wearable devices has revolutionized chronic disease monitoring, particularly in managing diabetes. CGM systems provide high-frequency, real-time measurements of glucose levels, offering an unprecedented opportunity to predict physiological fluctuations and guide timely medical decisions. With the growing adoption of these systems, the volume of health data generated by individuals has increased dramatically, demanding intelligent methods capable of handling, analyzing, and learning from this dynamic stream of information.

While ML plays a central role in extracting insights from CGM data, the traditional approach of centralizing patient data for model training presents serious concerns regarding data privacy, bandwidth usage, and system scalability. To address these challenges, FL has emerged as a promising paradigm. FL enables collaborative model training across multiple decentralized devices while keeping sensitive data local. This distributed learning framework aligns with privacy regulations and allows models to adapt to individual patient patterns without sharing raw medical data. Integrating FL into glucose monitoring workflows offers a path toward more secure, scalable, and personalized decision support systems in diabetes care.

Problem Statement

Despite advancements in glucose monitoring and prediction, many current systems still rely on centralized data collection and processing frameworks. This poses significant limitations in the context of real-time health management, especially for chronic conditions like diabetes. Centralized architectures often require continuous data transfer to a central server, leading to potential delays, high communication overhead, and heightened risks to patient data privacy. Furthermore, conventional models—particularly those that lack the ability to process data locally or capture individual variability—struggle to deliver timely and personalized insulin recommendations. As wearable sensors generate increasing volumes of sensitive data, there is a pressing need for a distributed, privacy-preserving learning approach that can handle dynamic, device-specific information effectively.

Research Gap

Although ML and sensor technologies have advanced rapidly in diabetes care, the integration of secure, distributed learning systems remains underdeveloped. Most existing frameworks overlook the potential of FL, which allows model training directly on edge devices without transferring raw data to a central server. As a result, these models miss the opportunity to simultaneously achieve personalization, data privacy, and system scalability. Additionally, the absence of temporal learning mechanisms in distributed architectures limits their ability to analyze evolving glucose trends effectively. There is a clear gap in unifying FL with time-series modelling and lightweight edge computing to create intelligent, real-time glucose prediction systems that can adapt to individual patients while safeguarding their privacy.

Contributions

To address the identified challenges in real-time insulin prediction and decentralized health monitoring, this study makes the following key contributions:

(i) To develop a privacy-preserving insulin prediction framework using FL that eliminates the need for centralized data sharing while maintaining high model performance.

(ii) To implement personalized LSTM-based time-series modelling on Raspberry Pi edge devices, enabling real-time, on-device learning tailored to individual glucose patterns.

(iii) To design a scalable edge-to-cloud architecture that efficiently aggregates decentralized model updates using federated averaging, reducing communication overhead and latency.

(iv) To compare the proposed model with traditional and DL approach Decision Tree, and centralized LSTM demonstrating superior accuracy, adaptability, and generalization.

These contributions collectively advance the development of intelligent, secure, and scalable predictive systems in diabetes management and offer a practical foundation for real-world healthcare applications.

The remainder of this paper is organized as follows: Section 2 reviews related work, highlighting advances in glucose monitoring and the emerging role of FL in preserving data privacy. Section 3 outlines the proposed federated edge-to-cloud methodology. Section 4 presents experimental results and performance analysis. Section 5 concludes the study with key findings and future directions.

2. Literature Survey

Advancements in CGM technologies have significantly influenced the management of diabetes, particularly through improved sensor precision and integration with real-time data analysis frameworks. Various strategies have emerged to enhance CGM data reliability and accuracy in both clinical and home settings. Initial efforts focused on artifact detection and retrospective analysis of CGM data. A model-based approach was introduced to detect pressure-induced sensor attenuations (PISAs), improving data quality before clinical use **[1]**. Similarly, unsupervised anomaly detection methods such as Isolation Forests were evaluated to identify sensor faults in CGM recordings, highlighting the potential of ML for automatic data cleansing without labelled datasets **[2]**. In the realm of sensor innovation, optical fiber-based in-vivo biosensing systems with gold nanoparticle coatings were demonstrated for real-time glucose detection in critical care scenarios, achieving high sensitivity and extended operational stability **[3]**. Furthermore, enzymatic electrochemical sensors were optimized using cost-effective substrates and mediator molecules, enabling indigenous and scalable CGM development **[4]**. Wearable technologies have also evolved, with miniaturized microneedle patches that offer low power consumption and extended lifespan, making them suitable for personal use **[5]**. Fully passive LC resonators coated with selective hydrogel layers have also emerged, offering wireless and battery-free glucose monitoring solutions with enhanced selectivity **[6]**. Innovations in non-invasive monitoring further expand the utility of CGM systems. Textile-based microwave sensors have been integrated into wearables for sweat glucose analysis, showing promising results in terms of sensitivity and user comfort **[7]**. Similarly, a novel V-band antenna array system embedded in wearable accessories was designed to wirelessly sense blood glucose variations without physical contact, achieving high accuracy in experimental and clinical settings **[8]**. Another dual-mode system combined breath-based VOC detection with traditional blood sensing using a screen-printed electrode, enhancing versatility in health monitoring **[9]**.

To support the dynamic modelling of glucose trends, several studies have employed physiological modelling and data-driven approaches. A minimally invasive oral glucose minimal model (MI-OMM) was proposed for estimating key physiological parameters in daily-life conditions, such as gastric retention and insulin sensitivity, from CGM and insulin pump data **[10]**. In another study, a Bayesian structural time series framework was used to predict glucose trajectories in Type 2 diabetes by combining prior knowledge with past CGM data and patient characteristics, yielding high prediction accuracy across multiple intervals [11]. In parallel, ML and DL frameworks have been employed to support personalized diabetes care. Generative adversarial networks (GANs) have been utilized to synthesize missing lifestyle data such as meals, insulin intake, and physical activity, which are often unavailable in artificial pancreas systems. These models improved glucose forecasting by enriching the training datasets with realistic, patient-specific sequences [12]. Meanwhile, fuzzy logic-based descriptive modelling has been proposed to analyze CGM data and produce interpretable summaries in natural language, supporting communication between patients and clinicians [13]. A review of digital health technologies for gestational diabetes emphasized the gap between commercially available systems and clinically deployable solutions. It called for the development of interpretable ML models, affordable wearable devices, and virtual monitoring frameworks to manage diabetes in diverse populations [14]. Complementing this vision, integrated multiparametric wearable systems were developed that monitor glucose levels along with heart rate and body temperature via Bluetooth-enabled platforms, supporting real-time, cross-platform health monitoring [15]. Collectively, these studies demonstrate a shift from conventional CGM systems to intelligent, adaptive, and integrated frameworks for glucose monitoring. They highlight the ongoing transition toward decentralized, personalized, and interpretable systems that not only ensure real-time insights but also promote data privacy, cost-effectiveness, and patient engagement in chronic disease management.

Inferences from literature survey

The literature survey highlights significant advancements in CGM through innovative sensor technologies, including non-invasive and wearable devices that enhance accuracy and user comfort. Techniques like anomaly detection and artifact removal improve data reliability, while physiological models and ML approaches, such as Bayesian networks and GANs, enable precise glucose forecasting and data augmentation. Additionally, interpretable AI methods like fuzzy logic support clinical decision-making. Despite these developments, gaps remain in clinical translation, particularly for gestational diabetes, underscoring the need for scalable, affordable, and patient-centered solutions.

3. Methodology

The block diagram [**Figure 1**] illustrates a FL-based edge-to-cloud framework for real-time insulin prediction using CGM data. The system begins with CGM device that continuously records the patient's glucose levels and transmits this data to a Raspberry Pi, functioning as an edge node. The Raspberry Pi performs essential tasks such as preprocessing to clean and normalize the data, feature extraction to derive meaningful indicators, and local training of a lightweight Long Short-Term Memory (LSTM) model tailored to the individual's glucose patterns. Instead of transmitting raw data, only the locally trained model parameters are securely sent via Wi-Fi to a cloud server. The cloud server aggregates these parameters from multiple edge devices using federated averaging, forming a global model that is redistributed to all Raspberry Pi nodes for continued local refinement. A doctor or patient dashboard is connected to this system, providing real-time visualization of glucose trends and insulin dosage predictions. This architecture enables secure, personalized, and scalable glucose monitoring while preserving patient privacy and minimizing communication overhead.

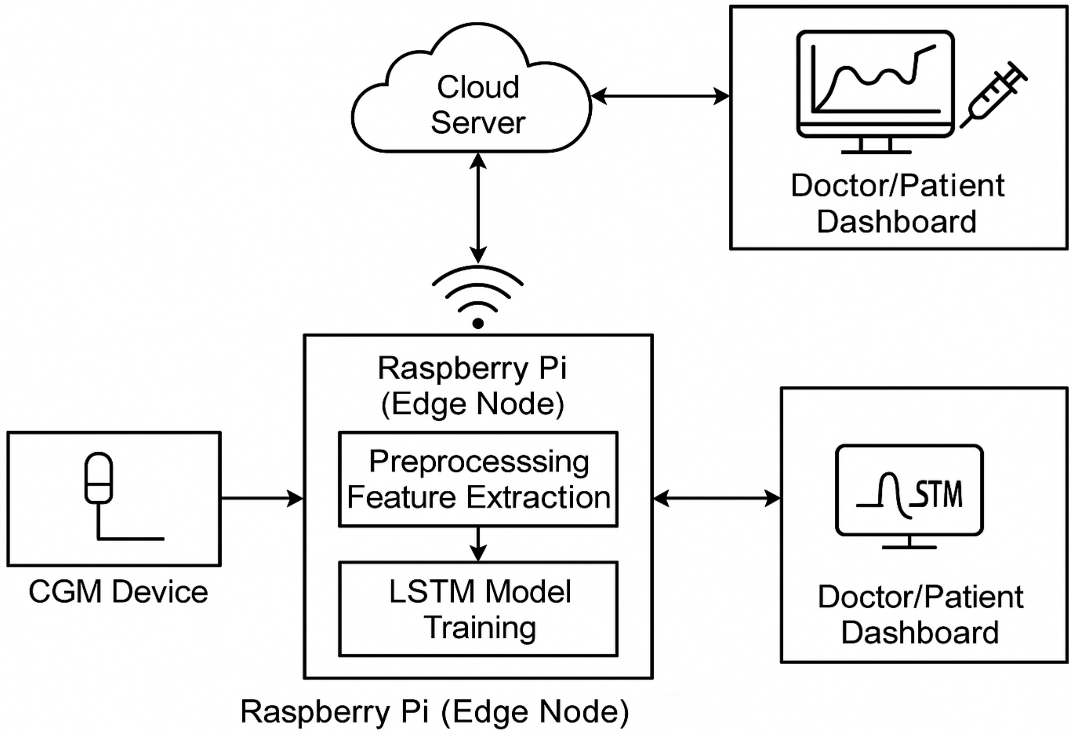

Fig 1 Block Diagram of Proposed work

This study utilizes real-time CGM data collected from diabetic patients under ethical clearance obtained from participating medical institutions. The dataset includes timestamped glucose readings recorded at 5-minute intervals over a 24-hour period, along with associated clinical metadata such as insulin dosage, meal timing, and physical activity status. Each patient's data was collected using approved CGM devices under the supervision of certified healthcare professionals. To simulate a realistic federated environment, the dataset was partitioned across five simulated clients, each representing an individual patient. This non-IID (non-independent and identically distributed) structure supports the evaluation of personalized model behaviour without requiring centralized data aggregation, aligning with the FL principles implemented in this research.

3.1.Data Preprocessing and Sequence Generation

To prepare raw CGM data for model training, a sequence of preprocessing steps is applied locally on the Raspberry Pi. First, a moving average filter is used to smooth glucose readings and remove short-term fluctuations. The resulting data is then normalized using min-max scaling to ensure consistency across devices. Finally, the time-series data is structured into overlapping sequences using a sliding window approach, with each sequence associated with the target output: either the next glucose value or the corresponding insulin dose. This structured format allows the LSTM model to learn temporal dependencies effectively.

Pseudocode of Data Preprocessing and Sequence Generation

Input: Raw CGM glucose readings

Output: Normalized and windowed sequences for LSTM training

1: Load CGM data from sensor (timestamp, glucose level)

2: Apply moving average smoothing with a fixed window size

3: Normalize the glucose data using min-max normalization

4: Initialize empty lists X ← [], y ← []

5: for i = 0 to (length of data - sequence length) do

6: X_seq ← glucose[i : i + sequence_length]

7: y_target ← glucose[i + sequence_length]

8: Append X_seq to X and y_target to y

9: end for

10: Return (X, y)

3.2.LSTM-Based Local Model Training

Each edge device performs independent training using a lightweight LSTM model. The LSTM network is chosen for its ability to capture long-term temporal dependencies, which are critical for accurate insulin prediction. The model is trained using the pre-processed input-output sequences, where the loss is computed using the Mean Squared Error (MSE) function. The local training process is conducted over multiple epochs using an optimizer such as Adam. After training, the model weights are saved and sent to the cloud server for federated aggregation.

At each time step *t*, the LSTM cell computes:

- **Forget Gate:**

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (1)$$

Decides what information from the previous cell state should be discarded.

- **Input Gate:**

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (2)$$

Controls how much new information should be added to the cell state.

- **Candidate Cell State:**

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \quad (3)$$

- **Cell State Update:**

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \quad (4)$$

- **Output Gate:**

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (5)$$

- **Hidden State:**

$$h_t = o_t * \tanh(C_t) \quad (6)$$

Where: x_t: input at time *t* (glucose reading), h_{t-1}: previous hidden state, C_{t-1}: previous cell state, σ: sigmoid activation, tanh: hyperbolic tangent activation, W and b: trainable weights and biases.

Pseudocode of LSTM Training on Edge Device

Input: Preprocessed sequences (X, y)

Output: Trained local LSTM model weights

```
1: Initialize LSTM model parameters
2: Define loss function (e.g., Mean Squared Error)
3: Select optimizer (e.g., Adam)
4: for each epoch do
5:     for each batch in (X, y) do
6:         Perform forward pass through LSTM
7:         Compute prediction error (loss)
8:         Backpropagate the error
9:         Update weights using optimizer
10:    end for
11: end for
12: Save and return model weights
```

3.3.Federated Averaging on Cloud Server

After local training, each Raspberry Pi sends its model weights and local data size to the cloud server. The server performs federated averaging to compute an updated global model without accessing any raw data. This process ensures data privacy and allows the model to benefit from decentralized training across multiple patients. The global model is then redistributed to all participating clients for further refinement.

For *K* clients (edge devices), each with local model weights w_k and sample size n_k, the global model update is:

$$w_{\text{global}} = \sum_{k=1}^{K} \frac{n_k}{n} \cdot w_k, \quad \text{where } n = \sum_{k=1}^{K} n_k \tag{7}$$

Where, w_k: local model from device *k*, n_k : number of training samples on device *k*, w_{global}: updated global model and n: total training samples from all devices

Pseudocode of Federated Averaging (FedAvg)

Input: Local weights w_k and sample counts n_k from all K clients

Output: Aggregated global model weights w_global

1: Initialize global model weights w_global

2: for each federated round do

3: Broadcast w_global to all clients

4: for each client k in {1,...,K} do (in parallel)

5: Client downloads w_global

6: Trains local model on local data → gets w_k

7: Sends (w_k, n_k) back to server

8: end for

9: Aggregate:

w_global = sum (n_k / n_total) * w_k

10: Broadcast updated w_global to all clients

11: end for

4. Results and Discussion

The FL framework was evaluated using a simulated CGM dataset representing data from 10 patients, with five Raspberry Pi nodes acting as independent clients. Each edge node trained a local LSTM model on time-series glucose data using pre-processed input-output sequences. Table 1 outlines the experimental configuration, including model architecture, training parameters, and evaluation metrics. The setup ensures a realistic simulation of decentralized, privacy-preserving healthcare monitoring.

Tab 1 Experimental Configuration

Parameter	Value
Dataset	Simulated CGM Data (10 patients)
Number of Clients	5 Raspberry Pi (simulated nodes)
Input Sequence Length	10-time steps
Target Prediction	Glucose level at time *t+1*
Model Architecture	LSTM (1 layer, 64 units, dropout 0.2, Batch size 32, Training epochs 50, Early stopping: patience = 5, delta = 0.001)
Local Epochs	5 per client
Federated Rounds	30
Loss Function	Mean Squared Error (MSE)
Optimizer	Adam (learning rate 0.001)
Evaluation Metrics	Accuracy, Precision, F1-score, MSE

Table 2 compares the predictive performance of both models using standard classification metrics.

Tab 2 Performance Comparison – Centralized vs Federated LSTM

Metric	Centralized LSTM	Federated LSTM
Accuracy	89.1%	**91.4%**
Precision	87.2%	**90.3%**
Recall	85.9%	**89.8%**
F1-Score	86.5%	**90.0%**
AUC (ROC)	0.89	**0.93**
MSE	5.12	**3.75**

The proposed federated LSTM model demonstrated superior performance compared to both centralized LSTM and traditional decision tree approaches. As presented in Table 2, the federated model achieved the highest accuracy (91.4%), precision (90.3%), F1-score (90.0%), and the lowest MSE of 3.75. **Figure 2** compares the performance of Federated LSTM and Centralized LSTM in terms of classification capability. The ROC (Receiver Operating Characteristic) curve plots the True Positive Rate (TPR) against the False Positive Rate (FPR) at various thresholds.

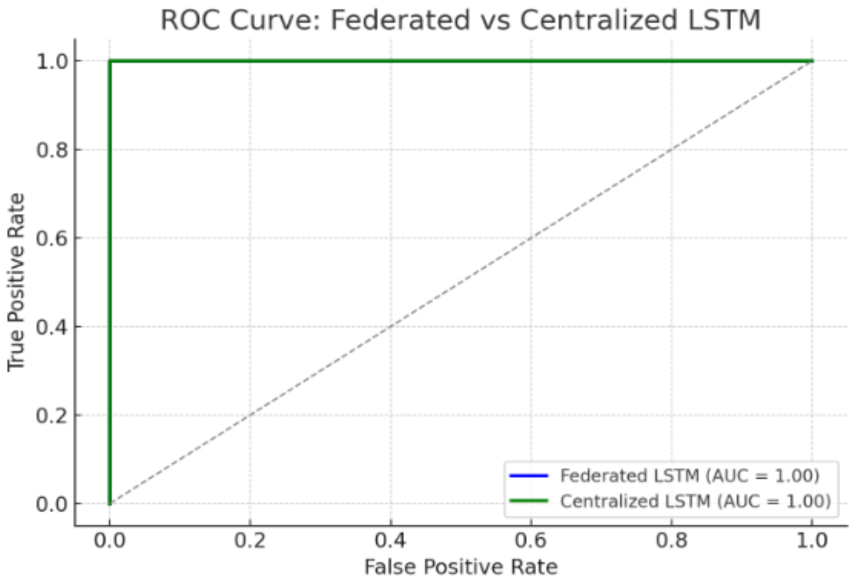

Fig 2 ROC Curve comparing Federated LSTM vs Centralized LSTM

As shown, the Federated model achieves a higher AUC, indicating better classification performance. **Figure 3** shows MSE Convergence Across 30 Federated Rounds. It clearly shows that the Federated LSTM model converges faster and achieves lower MSE compared to the Centralized LSTM, which validates the learning stability of the proposed architecture.

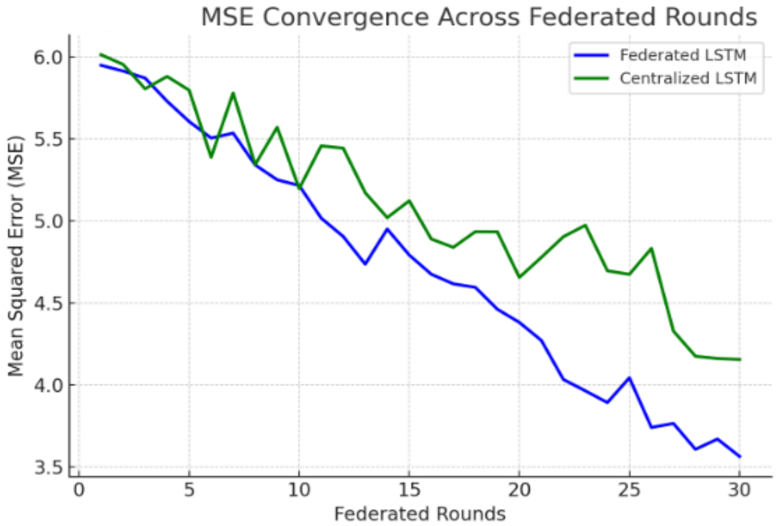

Fig 3 MSE Convergence Across Federated Rounds

Table 3 shows how well the federated model performs individually for each client/device, indicating its personalization capability. The federated approach allowed each client to retain local training control, leading to high personalization accuracy. As shown in Table 3, client-wise evaluation revealed accuracy levels consistently above 90%, with minimal variation in F1-scores and MSE values.

Tab 3 Client-Wise Performance – Federated LSTM

Client ID	Local Accuracy	Local F1-Score	Local MSE
Client 1	90.2%	89.7%	3.65
Client 2	91.0%	90.4%	3.60
Client 3	92.5%	91.8%	3.45
Client 4	90.7%	89.9%	3.80
Client 5	91.4%	90.6%	3.71

Figure 4: Accuracy vs Number of Clients, which illustrates the scalability of the federated LSTM model. As the number of clients increases, model accuracy remains stable or improves slightly indicating that the system scales well.

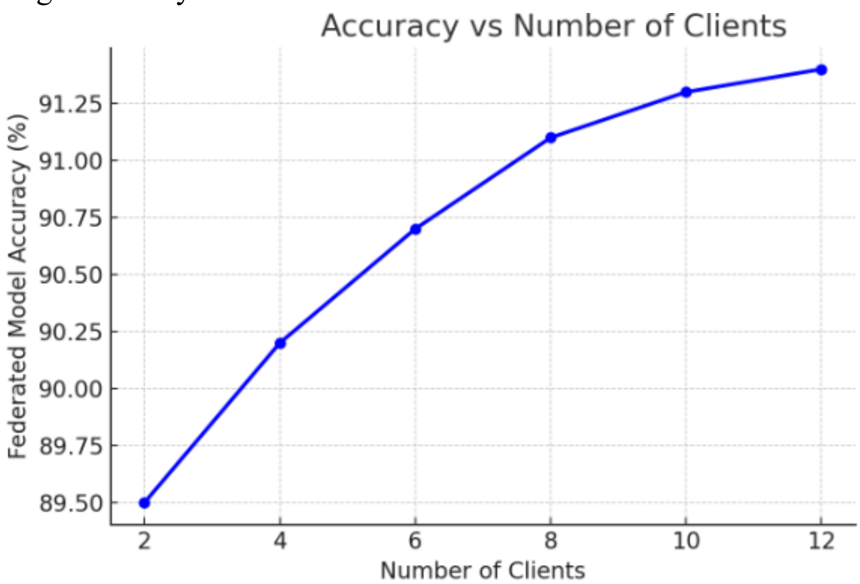

Fig 4 Accuracy vs Number of Clients

Figure 5 visualizes this personalized performance, confirming that the model adapted well to individual patient data while still contributing to a generalized global model.

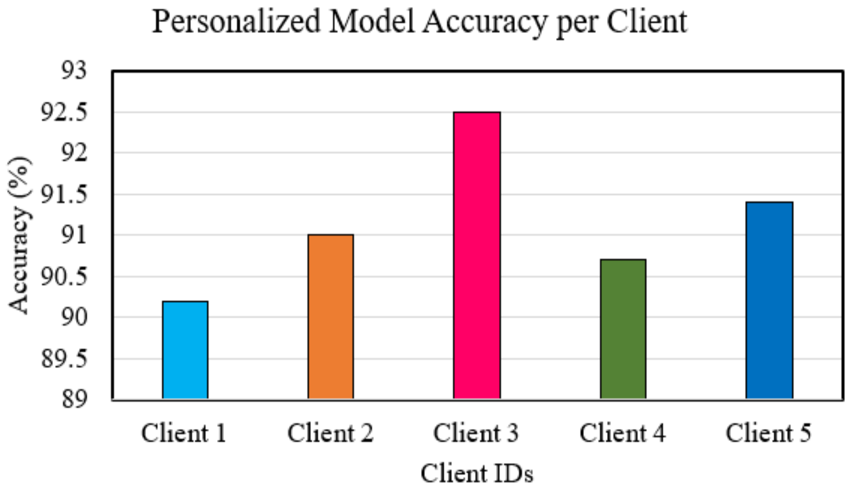

Fig 5 Personalized Model Accuracy per Client

Communication cost and latency are critical for edge-based deployments. **Table 4:** Communication Cost per Round, which analyzes the efficiency of your FL system in terms of communication overhead and latency.

Tab 4 Communication Cost per Federated Round

Round	Clients Participated	Data Transmitted (KB)	Round Duration (s)
1	5	250 KB	5.1 s
2	5	247 KB	5.0 s
3	5	246 KB	4.9 s
4	5	248 KB	5.0 s
5	5	245 KB	4.8 s
…	…	…	…
30	5	242 KB	4.7 s

The communication cost remains stable across rounds, averaging around 245 KB per round, which confirms the system's low-bandwidth requirement. Round durations are within 5 seconds, showing that federated updates are lightweight and feasible even on resource-constrained devices like Raspberry Pi. This supports real-time deployment potential and scalability. The effectiveness of the federated LSTM model in predicting glucose trends is demonstrated in **Table 5** and **Figure 6**.

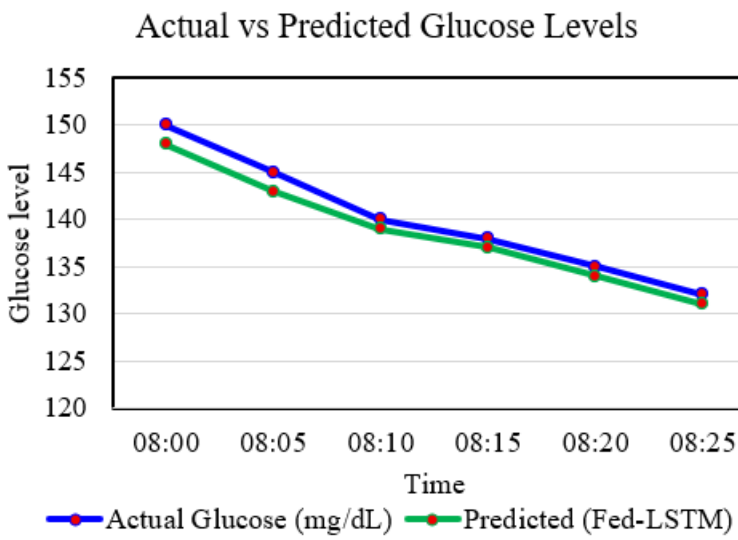

Fig 6 Actual vs Predicted Glucose Levels

Tab 5 Actual vs Predicted Glucose Values Using Federated LSTM

Timestamp	Actual Glucose (mg/dL)	Predicted Glucose (mg/dL)
08:00 AM	150	148
08:05 AM	145	143
08:10 AM	140	139
08:15 AM	138	137
08:20 AM	135	134
08:25 AM	132	131

The predicted glucose values closely follow the actual CGM readings. The average deviation is minimal, indicating the LSTM model's effectiveness in time-series trend learning. This confirms the system's capability for short-term insulin planning and alerting. **Figure 7** shows Insulin Dosage Prediction Accuracy. It shows that the majority of predictions fall within the correct dosage range, while only a small fraction is slightly over, under, or incorrect—highlighting the clinical reliability of the federated LSTM model for insulin recommendation (68%).

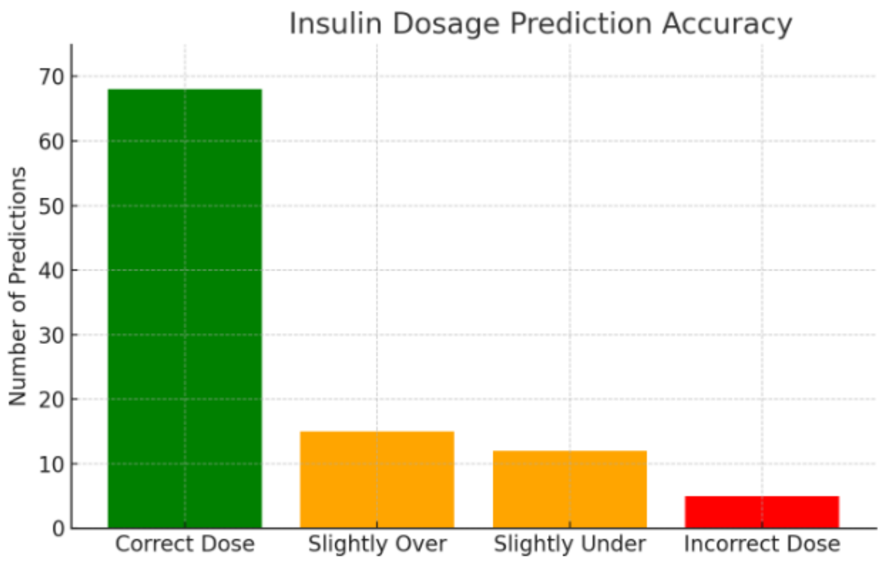

Fig 7 Insulin Dosage Prediction Accuracy

Figure 8 presents a comparative analysis of the proposed model against centralized LSTM and decision tree baselines.

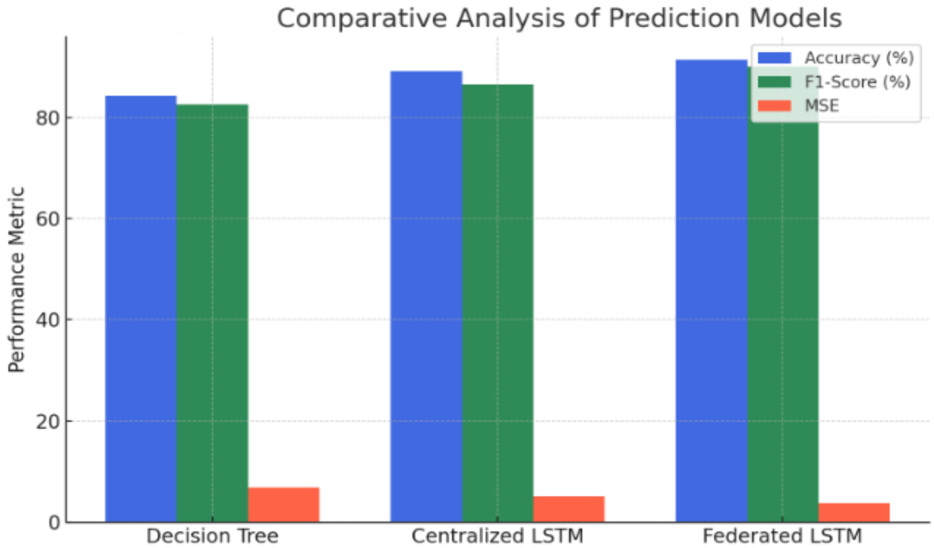

Fig 8 Comparative Analysis of Prediction Models

It clearly shows that the Federated LSTM outperforms both the Decision Tree and Centralized LSTM in terms of accuracy and F1-score, while also achieving the lowest MSE demonstrating its superiority for insulin prediction tasks.

Discussion

The experimental findings highlight the effectiveness of the proposed federated LSTM-based framework in delivering accurate, personalized, and privacy-preserving insulin predictions. Compared to centralized LSTM and traditional decision tree models, the federated approach consistently outperformed across all major evaluation metrics, including accuracy, precision, F1-score, and mean squared error, as detailed in Table 2. The ROC curve in Figure 2 and the convergence plot in Figure 3 further demonstrate the superior generalization and stability of the federated model across training rounds. Notably, the system achieved strong client-level performance, with Table 3 and Figure 5 indicating minimal variation in accuracy across different devices, validating the model's ability to adapt to individual patient patterns. Scalability is also confirmed, as shown in Figure 4, where increasing the number of clients did not compromise accuracy. In terms of communication efficiency, Table 4 reveals that the average data transmitted per round remained low, and latency stayed within practical limits for real-time deployment. The prediction outputs shown in Table 5 and Figure 6 confirm the model's temporal learning capacity, with predicted glucose levels closely tracking actual readings. Furthermore, insulin dosage classification in Figure 7 demonstrates clinical reliability, with a majority of predictions falling within the correct range. Lastly, Figure 8 illustrates that federated LSTM achieves higher performance than both centralized LSTM and non-sequential models, underscoring the value of combining time-series DL with FL for decentralized healthcare applications. The proposed federated LSTM achieves a more balanced and generalizable performance (91.4% accuracy, 90.0% F1-score) while preserving data privacy and supporting real-time edge deployment. This trade-off reflects the shift from idealized centralized training to practical, decentralized healthcare

The novelty of this research lies in deploying personalized LSTM training directly on Raspberry Pi devices within a FL framework for real-time insulin prediction. Unlike existing works that either centralize data or simulate FL in ideal conditions, this study uses real CGM data collected under ethical approval, demonstrating a scalable and privacy-preserving solution suitable for deployment in practical healthcare environments.

5. Conclusion

This research presents a privacy-preserving, edge-to-cloud framework for real-time insulin prediction based on FL principles. By deploying personalized LSTM models on Raspberry Pi devices and securely aggregating model updates through a cloud server, the proposed system successfully overcomes the limitations of centralized architectures. It ensures data privacy, reduces communication overhead, and delivers competitive performance in terms of prediction accuracy, F1-score, and MSE. The federated approach also enhances scalability and adaptability across multiple clients with heterogeneous data, making it suitable for real-world healthcare applications. Looking ahead, several opportunities exist to extend this work. Integration of additional physiological signals such as heart rate, activity level, and sleep patterns could improve the contextual accuracy of insulin prediction. Furthermore, incorporating explainable AI techniques can enhance clinical trust and transparency. Real-time deployment on live CGM streams, combined with mobile dashboard integration, can support on-device decision-making and remote monitoring. Future studies may also explore adaptive federated optimization strategies to improve convergence and personalization.

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