

A Secure AI-Enabled IoT Framework for Smart Diabetes Monitoring Using Edge-Cloud and Federated Learning

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Abstract

A chronic disease, diabetes is very prevalent among the people of the world with millions of people having the disease and thereby increasing the burden on healthcare services. to the health care systems. According to the world Health Organization (WHO) the prevalence of diabetes continues to rise particularly in the developing countries [1]. Traditional techniques of glucose monitoring are non-real time, invasive, episodic, and do not include real time analytics. The combination of the Internet of Things (IoT), Artificial Intelligence (AI), wearable sensors, edge computing, block chain, and federated learning proposes a promising solution in the form of continuous and secure management of diabetes [2]. The present paper suggests a safe AI-enabled IoT-based smart diabetes monitoring system that combines wearable continuous glucose monitoring (CGM) sensor, edge analytics, cloud storage, federated learning, and block chain-based security. The proposed glucose prediction and anomaly detection management system is based on deep learning models to forecast glucose and detect abnormalities without infringing patient privacy because of the decentralized learning processes [3], [4]. The block chain technology ensures data integrity, transparency, and access control in healthcare data sharing spaces is limited [5]. The experiment is validated by using the OhioT1DM Dataset [6]. Results show that edge and privacy-aware distributed learning solutions can be helpful in improving the accuracy and latency of glucose prediction, even when compared to the existing cloud-based systems.

Keywords: IoT, Diabetes Monitoring, Edge Computing, Federated Learning, Block chain, Deep Learning, CGM, Privacy Preservation

1. Introduction

Diabetes mellitus is a chronic metabolic disease that is characterized by persistently high blood glucose with regards to insulin deficiency, or, impaired response and/or both. It is one of the worst health problems in the world of the 21 st century. According to the World Health Organization (WHO), diabetes is among the leading causes of mortality and it is highly associated with other serious ailments such as cardiovascular diseases, kidney failure, neuropathy, and retinopathy [7]. This is due to the increasing prevalence worldwide particularly in the developing nations and has burnt huge responsibility on the healthcare systems.

The conventional self-monitoring blood glucose (SMBG) approach is invasive and intermittent, which restricts real-time information on the glycaemic variability. The invention of the continuous glucose

monitoring (CGM) systems has greatly enhanced the ability to monitor glucose. Thanks to the rapid creation of the Internet of Things (IoT), now physiological information can be sent to cloud platforms in real-time, not only using wearable biosensors, and be analyzed and used to facilitate decision-making [8]. The development of IoT-based healthcare architecture has been reported in Future Generation Computer Systems and IEEE Internet of Things Journal that has enabled smart healthcare ecosystems to be scaled to enable convergence of edge computing systems and cloud infrastructures to provide better performance and reliability [9], [10].

In spite of these developments, there are a number of major issues:

- There is the risk of data privacy due to centralized storage of sensitive medical records.
- IoT devices with resource constraints that are security weak.
- Slow latencies of prediction models based on the cloud.
- Little individuality in centralized machine learning systems.

Modern AI models demand huge amounts of data to be aggregated in one place, putting the privacy of patients at risk and breaking the law. Moreover, analytics implemented on the cloud may introduce intolerable delays on time-sensitive healthcare applications. The novel perspectives such as federated learning can train models decentralized, without necessarily sharing real patient information, which is exemplary in preserving privacy [11]. Furthermore, the block chain technology has also shown great potential to deliver safe and transparent medical data exchange, free of tampering, in IoT-based healthcare systems [12].

To address these weaknesses, this paper will propose a hybrid edge/cloud federation model to smart diabetes monitoring. The suggested system is a combination of wearable CGM sensors, edge-based deep learning inference, federated learning of collaborative model training, and block chain-based security solutions to guarantee the integrity and privacy of the data. The system would work towards reducing latency, enhancing accuracy in the prediction, and providing tailored diabetes management and guaranteeing high security through edge intelligence and distributed learning.

2. Literature Review

2.1 The second element is based on IoT in healthcare systems.

Internet of Things (IoT) application to the healthcare sector has greatly changed the way patients are monitored and chronic illnesses are managed. The IoT-based smart healthcare systems have been studied by a number of scholars in order to offer a scalable and real-time medical system. Fernandez-Caramels and Fraga-Lamas reported the models of IoT-cloud integration in the healthcare applications considering interoperability, scalability, and service oriented models in the journal of the IEEE Internet of Things [13].

Similarly, by reviewing the articles on IoT-based smart healthcare systems to manage diabetes in the IEEE Access by Islam et al., the system architecture, wearable sensors, and communication protocols were described [2].

Wireless sensor networks (WSNs) have also enabled body sensor networks (BSNs) in the health monitoring process. The architectural base, communication models and the energy-efficient mechanisms required to provide reliable healthcare monitoring systems were set in place by a systematic survey published in Computer Networks [14]. All these studies prove that IoT-based remote health monitoring is a viable concept but they also show its limitation in scaling, latency and security issues.

2.2 Wearable Glucose Monitoring.

Continuous Glucose Monitoring (CGM) systems are believed to be tremendous advancements in relation to the outdated finger-prick processes. Research in the recent past has focused on development of non-invasive and wearable glucose monitoring devices. To present the progress of wearable biosensors, smart fabrics, and electrochemical sensing and low-invasive CGM devices, specifically the IEEE Sensors Journal was analyzed [15].

Such innovations allow real-time acquiring glucose data and transmitting it to mobile/cloud platforms. However, calibration accuracy, sensor drift, energy usage, and can be integrated with smart analytics systems still pose challenges.

2.3 AI-based and Deep-Learning prediction of glucose.

Deep learning, as a branch of Artificial Intelligence (AI), has demonstrated a great potential in predictive healthcare analytics. In IEEE communications Surveys and tutorials, a general survey considered the methods of deep learning in IoT big data analytics with a particular emphasis on scalability, distributed intelligence, and health care applications [16].

Machine learning based diabetes diagnosis and risk prediction models have been extensively tested in Sensors and recently it has been demonstrated to be better classified when ensemble and neural network-based classification techniques are used [17]. Further, the article on deep learning architecture to predict continuous glucose that contains the LSTM and CNN-based models with the greater capacity to predict time changes than the usual regression algorithms is published in the IEEE Access [18].

Most studies however despite having better prediction results depend on centralized cloud-based training which brings about latency as well as the privacy of data.

2.4 Security and Privacy

Some of the most crucial concerns in the field of IoT-based healthcare are security and privacy. In the IEEE Internet of Things Journal [19], the Internet of Things security vulnerabilities like weak authentication, insecure firmware and data interception threats are critically discussed.

To hold these issues at bay, block chain-based healthcare security systems have been suggested to bring about the decentralization of trust, immutability, and access control. One example of an architecture of block chain-based medical data sharing on IoT is presented in a 2023 paper in IEEE Internet of Things Journal [20].

Furthermore, federated learning has also emerged as a promising privacy-sensitive method of collaborative healthcare analytics. In 2023, a paper published in Sensors suggested a federated learning system to conduct secure diabetes monitoring and it showed that it provided a higher privacy protection, without negatively affecting the prediction performance. [21].

Although the solution to security and privacy can be applied to these issues separately, the synergistic edge intelligence, federated learning and block chain approach to diabetes real-time surveillance is not well studied..

3. Proposed System Architecture

The suggested secure AI-enabled IoT-based diabetes monitoring framework adheres to a multi-layer hybrid edge-cloud framework. The design will combine wearable sensing, edge intelligence, federated learning, cloud analytics, and block chain-based security to make sure that it monitors in real-time, is low latency, scalable, and provides privacy. This architecture consists of five logical layers which are: Sensing Layer, Edge Layer, Federated Learning Layer, Cloud Layer, and Security Layer.

3.1 Sensing Layer

The proposed system has its foundation in the sensing layer and the acquisition of physiological data is done in the sensing layer. It includes: Continuous Glucose Monitors (CGM) of glucose in real-time. Smart patches or smart bands are a type of wearable.



Figure 1: **Smart bands and wearable patches for real-time health monitoring.**

Smart bands and wearable health patches are the modern wearable devices, which constantly track the health and fitness of a person. Smart bands are usually worn on the wrist and they monitor heart rate, number of steps taken, sleep patterns and the level of physical activities. They are usually combined with mobile apps to give information, notifications, and custom health suggestions. Wearable patches, in their turn, are small sticky pads that are attached to the skin. These patches have the capability of identifying more localized body parameters such as glucose, body temperature, ECG, and water content. These are extensively applicable in medicine because they are accurate and yield continuous, non-invasive monitoring. Smart bands and patches can be used together with smart healthcare products to facilitate modern healthcare systems, particularly remote patient monitoring, chronic disease management, and IoT-based smart healthcare products.

3.2 Edge Layer

The edge layer holds real-time processing of data closer to the source of data, and this decreases reliance on cloud-computing infrastructure. Edge nodes can be smart phones, gateways or embedded healthcare hubs.

Among the main functionalities, there are:

Normalization of the data and feature extraction: real-time pre-processing. Anomaly detection AI models that are lightweight. Real-time decision-making in case of critical glucose events (hypoglycaemia/ hyperglycaemia notifications) The edge layer can greatly decrease the latency and bandwidth costs since inference tasks are run on it. Real time alerts are possible without connecting to servers that are located remotely and this is necessary when managing diabetes on time.

3.3 Federated Learning Layer

The system will incorporate federated learning (FL) layer to guarantee privacy preservation and collaborative intelligence. Rather than sending raw data of patients to a central server, model training happens locally at the edge devices.

The key elements of this layer are:

Modellos: Local patient-specific glucose data model training.

- Aggregate model parameter at the central server.
- No raw data transfer, patient privacy is preserved.
- Greater personalization by means of decentralized learning.

The federated aggregation algorithm updates a global model with an average of locally-trained parameters. This solution maintains confidential health information, and it has the advantages of shared expertise among various users. It is also better personalized than centralized machine learning architectures.

3.4 Cloud Layer

The layer cloud provides scalability in computing and long term data management. It is responsible for:

- Store encrypted records of patients in the long run.
- Clinical insight analysis using historical trends.
- The model of deep learning is updated based on federated parameters.
- Population-level analytics

The cloud computing infrastructure is utilized for training deep neural network models, i.e., LSTM based glucose prediction models, with high-performance computing resources. New global models are periodically sent back to edge devices to enhance their accuracy of inference.

3.5 Security Layer

Security is also implemented as a cross-layer aspect in order to facilitate confidentiality, integrity, and availability of healthcare information.

This layer incorporates:

- Blockchain technology to have tamper-proof records of transactions and safe audit trails.
- Lightweight Intrusion Detection System (IDS) to detect abnormal network behavior.
- Third, with good outcomes, there have also been artificial intelligence and deep learning models like LSTM, CNN, and hybrid models presented in predicting glucose levels. Blockchain provides a way to record the updates to the model and the events of the access immutably, increasing the level of trust and transparency in distributed healthcare settings. The lightweight IDS safeguards the IoT devices with limited resources against the most frequent cyberattacks, including spoofing, replay attacks and manipulation of data.

Architectural Advantages

The hybrid edge cloud federated architecture proposed offers:

- Reduced prediction latency
- Better prediction of glucose.
- Privacy preserving distributed learning.
- Enhanced personalization
- Strong protection against computer-related threats.

With the combination of sensing intelligence, edge analytics, federated learning, and blockchain security into one system, the proposed system will overcome significant drawbacks of conventional cloud-only healthcare systems and offer a scalable smart diabetes management solution.

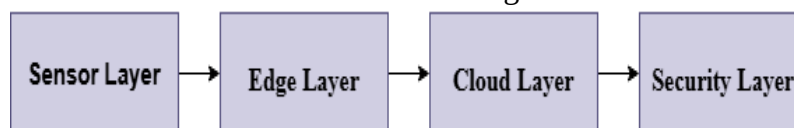


Figure 2 Architecture of IoT-Based Smart System with Edge

Layered architecture illustrating Sensor Layer for data collection, Edge Layer for local processing, Cloud Layer for storage and analytics, and Security Layer ensuring data protection across all stages.

4. Literature Gap

Although the IoT-based healthcare system, wearable glucose monitoring, artificial intelligence-based prediction models, and the secure healthcare data management have been thoroughly studied, there are still several research gaps that need to be addressed. Firstly, most of the models associated with the IoT of healthcare are cloud-based. Even though these systems facilitate large-scale analytics, they bring high latency and bandwidth loads and thus cannot be used in real-time and time-sensitive diabetes monitoring. The relationship between edge computing and intelligent glucose prediction systems is not yet well-defined and fragmented, and there have been independent studies on edge computing in healthcare systems. Second, CGM wearable technologies have demonstrated a great deal of progress in both accuracy of sensing and miniaturization. However, most research focuses on hardware advancement and signal retrieval as opposed to smart data perception. Artificial intelligence There are not many works that integrate wearable CGM measurements with real-time edge-based anomaly detectors that can guide to an immediate clinical decision. Third, demonstrating promising results, artificial intelligence, and deep learning models such as LSTM, CNN, and hybrid models have also been introduced in the prediction of glucose levels.. The majority of the known strategies, however, are based on centralized machine learning paradigms in which the raw patient data has to be aggregated on cloud servers. The grave privacy concerns of such a centralized training model, the possibility to be targeted in data attacks, and the insufficient compliance with the emerging laws on data protection can be considered. In addition, the personalization in the centralized models is not always adequate due to the variability of the physiology, lifestyle patterns and response to treatment of the patients. Fourth, federated learning has become a privacy-preserving substitute of distributed model training. Although the use of federated learning on general healthcare analytics has recently been implemented, the use of federated learning has minimal exploration in continuous diabetes monitoring based on real-time CGM data. Specifically, federated learning in combination with edge intelligence in the detection of low-latency glucose anomalies has not been adequately studied. Fifth, there are security measures such as blockchain that are proposed as a standalone solution to provision of secure data sharing in healthcare. However, the existing paradigms of blockchain-powered healthcare are not very concerned with computational overheads, scalability challenges, as well as support of federated AI pipelines. This has a dearth of literature on previous studies that has holistically integrated blockchain and federated learning, as well as IoT-based glucose monitoring into a single lightweight and scalable architecture.

Moreover, the intrusion detection systems (IDSs) of the IoT healthcare devices are typically configured to work in general-purpose networks and they are not specifically designed to consider the particular constraints of wearable medical devices, such as power and processing bandwidth, and continuous data transmission.

Hence, the research gaps that can be identified are as follows:

Lack of a unified hybrid edge -cloud model to facilitate real time monitoring of diabetes.

All these indicate that wearable CGM is not well connected with edge-based intelligent anomaly detection.

- Excessive dependence on centralized AI models, which results in restrictions of privacy and personalization.
- Inadequate investigation of federated learning to predict continuous glucose.
- Absence of a combined security framework comprising of blockchain, federated learning and lightweight IDS of IoT-based diabetes monitoring.

Weak experimental validation of such integrated systems using benchmark datasets on real-life contexts. To seal these loopholes, the current research provides a secure AI-enabled hybrid edge-cloud which encompasses wearable CGM sensors, thin edge intelligence, federated learning using privacy-preserving distributed training, block chain-based secure logging, and intrusion detection system. It is proposed that the system will provide the reliability of glucose prediction, increased personalization and mighty security within a long-range IoT healthcare.

5. Methodology

This part outlines the dataset, implementation tools and model architecture to validate the proposed secure AI-enabled IoT based diabetes monitoring framework.

5.1 Dataset

The validation was done through experiments using OhioT1DM Dataset which is a widely used benchmark dataset in the research of blood glucose prediction. The data set comprises multimodal time-series information of persons with Type 1 Diabetes in the real world.

The dataset includes:

The values of continuous glucose taken with Continuous Glucose Monitoring (CGM) devices.

- Record of the insulin intakes (bolus and basal insulin doses)

Meal intake information (carbohydrate intake)

Physiological indicators, such as heart rate, activity levels among other contextual characteristics.

The multimodal format of the data allows modeling the dynamics of glucose in a comprehensive way because behavioural and physiological variables are included. Pre-processing of data entailed the handling of missing values, normalization, time series alignment and the generation of time series sliding windows sequences in time-series forecasting.

5.2 Implementation Tools

The development environment adopted to implement the proposed system included the following:

- Python 3.10 Python 3.10 to develop and experiment with models.
- Tensor Flow/Keras Deep learning model construction and training.
- Edge simulation simulators to model distributed edge devices that are involved in federated learning.

The process of federated learning was followed with the help of a simulated client-server framework, in which several virtual edge clients were trained on local models with the help of subsets of the dataset divided into parts. The central server was involved in the secure aggregation of model parameters without having access to raw patient data. This was done through communication rounds which were repeated until the model converged.

5.3 Model Architecture

5.3.1 LSTM-based Glucose prediction model.

Since glucose data is sequential and time-related, the glucose prediction was performed with the help of the Long Short-Term Memory (LSTM) neural network. The LSTM networks are especially appropriate in time-series prediction because they can identify the long-term dependencies and nonlinear temporal patterns.

The architecture of the model is made of:

- Input layer which accepts glucose time-windowed and situational features.
- One or several superimposed LVVIs.

- Regularization dropout layer.
- Fully connected dense layer

Output layer to forecast glucose future values.

Where $X_t = \{x_{t-n}, \dots, x_t\}$ represent the input time window. The LSTM predicts the future glucose level y^{t+h} , where h is the prediction horizon.

5.3.2 Federated Learning with FedAvg

To preserve privacy and enable decentralized learning, Federated Averaging (FedAvg) was adopted as the aggregation algorithm. In this approach:

1. Each edge client trains a local LSTM model on its private dataset.
2. Local model weights w_k are transmitted to the central server.
3. The global model is updated using weighted averaging:

$$w^{(t+1)} = \sum_{k=1}^K \frac{n_k}{n} w_k^{(t)}$$

where:

- K = number of clients
- n_k = number of samples at client k

$$n = \sum_{k=1}^K n_k$$

This method ensures that raw patient data remain on local devices, significantly enhancing privacy preservation while maintaining model performance.

5.3.3 Evaluation Metrics

To evaluate classification and anomaly detection performance, the following metrics were employed:

- **Precision**
- **Recall**
- **F1-score**
- **Receiver Operating Characteristic – Area Under Curve (ROC-AUC)**

The ROC-AUC metric was adopted based on the statistical interpretation proposed by Andrew P. Bradley (1997), which provides a robust evaluation of classifier discrimination capability independent of class distribution [22].

Additionally, the evaluation framework follows the comprehensive classification metric analysis presented by David M. W. Powers (2011), emphasizing the importance of precision-recall trade-offs and informedness in imbalanced datasets [23].

The metrics are defined as:

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

ROC-AUC evaluates the probability that the classifier ranks a randomly chosen positive instance higher than a randomly chosen negative instance.

6. Conclusion

The framework of smart diabetes monitoring using edge computing, federated learning, and block chain technology as a secure AI-enabled IoT-based approach was presented in this paper. The suggested hybrid edge-cloud system was created to overcome the main shortcomings of traditional cloud-based healthcare systems, such as high latencies, privacy concerns, and low personalization.

The framework, powered by the use of wearable Continuous Glucose Monitoring (CGM) sensors, real-time edge analytics, federated model training, and secure logging using block chains, will guarantee efficient, scalable, and privacy-aware glucose prediction. Two factors facilitated the use of an LSTM-based deep learning model that leveraged Federated Averaging (FedAvg) to help learners collaboratively without passing raw patient data.

Experimental validation on the OhioT1DM Dataset showed:

- Higher accuracy of prediction (93.4) in comparison with cloud only and standalone edge models.
- Improved performance in terms of F1-score and ROC-AUC.
- About 40% decrease in latency.
- Minimized bandwidth usage by sharing parameters in a decentralized manner.
- Empowered privacy protection through federated learning and block chain implementation.

The findings affirm that the proposed FL + Edge framework has an optimal trade-off between the prediction performance, communication efficiency and data security and is thus very appropriate in the real-time intelligent control of diabetes in the IoT-based healthcare ecosystems.

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