

## AI-enhanced Electrochemical Biosensing Architecture with Cloud-assisted Edge Intelligence

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Received: 25 June 2025 / Revised: 7 Nov. 2025 / Accepted: 17 Nov. 2025 / Published: 28 Nov. 2025

**Abstract:** This work presents an Edge Artificial Biosensing Architecture that integrates electrochemical sensing with artificial intelligence for real-time physiological monitoring. The proposed system has integrated a glucose oxidase-based electrochemical biosensor with the analog signal conditioning, feature extraction, and a quantized CNN deployed on the Raspberry Pi 4B. The framework executes localized signal processing and inference for low latency and improved data privacy. Experimental evaluation on 5000 biosensor signal samples achieved a classification accuracy of 96.2 %, a low inference latency of 0.12 seconds, and a power consumption of 1.6 W. Finally, the cloud-assisted retraining mechanism resulted in a further enhancement of model performance by 1.8 %, enabling adaptability to environmental drifts and long-term operation. The results establish that integrating AI with edge computing greatly enhances the biosensor's efficiency, scalability, and autonomy, while opening up new horizons for next-generation intelligent biosensing and personalized healthcare in the IoMT domain.

**Keywords:** Artificial intelligence, Edge computing, Electrochemical biosensor, Convolutional Neural Network (CNN), Glucose Oxidase (GOx), Signal conditioning, Internet of Medical Things (IoMT), Quantized deep learning, Cloud retraining, Intelligent healthcare.

### 1. Introduction

The rapid development of biosensing technologies has revolutionized healthcare diagnostics by enabling continuous, non-invasive, and point-of-care monitoring of physiological biomarkers. Most traditional biosensors detect analytes using electrochemical, optical, or piezoelectric methods, but may suffer from functioning autonomously in terms of improving real-time decision making, scalability, and flexibility. The recent convergence of AI with biosensing platforms has provided a new approach to improving accuracy, building automation, and effectively adding clinical knowledge to a diagnosis. By incorporating AI algorithms with biosensors, the

raw biochemical signals can be rapidly analyzed, classified, and interpreted with minimal human involvement, thereby providing immediate diagnostic feedback. However, there are additional challenges involved with the current biosensing systems. Most of these biosensing systems rely on cloud-based computation, which raises issues such as latencies in results, the need for stable network connectivity, or even privacy issues related to sending patient information remotely. In addition, traditional machine learning models implemented on external systems demand high computational resources and lack adaptability against environmental drift or sensor degradation. Moving forward, as healthcare applications increasingly demand real-time, on-device

analytics, there will be greater requirements for intelligent architectures that can operate efficiently at the edge of the network, closer to the point of sensing.

Recently, edge computing has gained attention as a way to enable local data processing on resource-constrained devices. Combined with AI, the edge forms the basis of artificial biosensing, where sensing, analysis, and decision-making all happen inside a biosensor node. This setup can reduce communication overhead, improve response time, and enhance data privacy. These benefits are important for applications of IoMT, requiring continuous measurements of physiological markers- glucose, lactate, cortisol, and others- which typically require instantaneous feedback for consideration in the patient's unique care plan. Incorporating AI-based algorithms/computing into biosensors can take the raw biochemical signals and analysis, classification, and interpretation can occur, with minimal input from a human user, shortening the feedback time. Several researchers have proposed frameworks that rely on biosensors powered by AI. For instance, deep learning models were used to interpret outputs from optical biosensors, electrochemical signals, and microfluidic sensors. However, many proposed solutions are based on cloud resources or rely on large networks with substantial footprints unsuitable for low-power devices. Further, many systems have been implemented but cannot be improved upon over time since there is no feedback mechanism in place to allow for retraining the model. There is a clear gap in the ability to provide an AI-powered biosensing device that is designed for scale (subsequently scalable), lightweight, adaptive, supported inference, and autonomous model improvement. In summary, the framework provides a pathway forward for next-generation smart biosensors by combining the advancements accomplished by precision biosensing, AI intelligence, and edge computing effectiveness. Therein, the implementation supports autonomous decision-making processes, scalability of its use across platforms, and real-time decision support either in-clinic or remote. To accomplish this, this study proposes an Edge Artificial Biosensing Architecture. This architecture includes an electrochemical sensor, embedded signal processing, and a lightweight deep learning classifier. It uses GOx-based electrochemical biosensing for biochemical signal generation, paired with analog signal conditioning and feature extraction. A quantized 1D CNN runs on-device inference with minimal latency and power use, deployed on a Raspberry Pi 4 B. Additionally, cloud-based retraining enhances long-term performance, forming a closed-loop biosensing ecosystem.

- Development of a multi-layered, AI-integrated biosensing framework that can achieve signal processing and inference at the edge locally.

- Extensive experimental validation with 96.2 % accuracy, 0.12 s latency, and 1.6 W power consumption.

- Design and deployment of a quantized CNN model optimized for real-time c11. Development of a

multi-layered, AI-integrated biosensing framework capable of edge (on-device) signal processing and inference.

## **2. Related Work**

The integration of biosensing into AI has emerged as a defining paradigm in the development of smart healthcare and continuous physiological monitoring. Conventional electrochemical biosensors, while highly selective and sensitive, usually suffer from limitations in offline data processing and inability to adapt to varying biological conditions. To overcome such limitations, AI-assisted biosensing, edge computing, and cloud-integrated frameworks have been increasingly explored to offer real-time and autonomous diagnostic systems. The early work has been directed at optimizing nanostructured electrodes and catalytic materials for the enhancement of electron transfer and sensitivity of GOx-based electrochemical biosensors. Heller, in 2008, set up a wide framework concerning the mechanism of enzyme-mediated glucose detection, including both mediated and direct electron transfer pathways. Gao et al., in 2021, reviewed laser-induced graphene electrodes for electrochemical glucose sensing, underlining material innovations that enable flexible and wearable devices.

System-level challenges, such as miniaturization of the device, resistance to biofouling, and mechanical flexibility of wearable and implantable biosensing platforms, have been the focus of later works, including Wu et al. (2023) and Jung et al. (2024). The IoMT has heightened the focus on incorporating biosensors into connected spaces. Pateraki et al. (2019) highlighted how IoT-enabled biosensors support smart healthcare ecosystems by consistently collecting data and having the ability to wirelessly communicate, and Munir et al. (2022), among others, in their systematic review on the adoption of IoT in clinical laboratories identified interoperability, latency, and privacy as the main barriers that still exist. Collectively, these papers highlighted the importance of developing intelligent biosensor architectures that can execute local computation without relying on data transmission. Recent research indicated that both ML and DL can enhance biosensors' analytical accuracy significantly. Bocan et al. (2025) described supervised ML models that could classify electrochemical response patterns with a high degree of accuracy, and therefore, the detection may be more stable to various environmental conditions compared to traditional measurement approaches. Akkaş et al. (2025) described AI as a player in biosensors, and how, in principle, data-driven models can be developed with traditional analytical chemistry for predictive and self-calibrating sensors. AI-based biosensors surpass classic threshold limits of detection, especially in messy and dynamic environments.

However, in most of these early AI-aided biosensing systems, cloud-based inference was an integral part of the architecture, which is limited by lag

time, power consumption and data privacy. Recently, Edge AI-execution of trained models directly on embedded devices has become increasingly important. (2022) and Krishnamoorthi (2018) studied quantization techniques for deploying CNNs on constrained hardware, showing how fixed-point or integer quantization is able to drastically reduce memory footprint and energy usage without compromising model accuracy. Similar works to mention are those by Garifulla et al. On similar lines, outlier-aware quantization was proposed by Yoo and Ban (2025) further to improve inference efficiency in sensor-based vision systems. In parallel, Tilley et al. (2024) had also proposed, in 2024, an edge-AI framework for embedded human activity recognition sensors, which had been validated to be feasible for local analytics while working under power and bandwidth constraints. These optimizations, being hardware-aware, have given way to the extension of deep learning capabilities into portable biosensing systems. Nevarez and Yarib (2023) extended this work to provide hybrid-float quantization on FPGAs, allowing real-time analytics on continuous biosignal processing applications. Other recent efforts have also moved in the direction of Edge AI-enabled biosensors. Indeed, Gragnaniello et al. (2024) introduced a wearable, non-invasive glucose monitoring system that couples microfluidic sensing with on-device inference, hence enabling sub-second analytics with very low energy consumption. Young (2025) proposed an edge computing-based wearable device for estimating blood glucose levels using deep neural networks optimized for single-board computers; in this model, accuracy above 95 % was shown to be achieved with very low latency. These works further establish the feasibility of lightweight, deep learning model deployment directly on embedded platforms like Raspberry Pi and STM32 microcontrollers. However, such advances have not overcome the limitations regarding adaptability that exist in static models for long-term applications in biosensing, where sensor drift and biological variability might deteriorate performance. Hence, hybrid cloud-edge architectures with mechanisms for model retraining have been proposed. Garifulla et al. (2022) and Munir et al. (2022) identified the fact that model updates can be performed via cloud-assisted feedback loops without burdening the edge device, thus guaranteeing sustained accuracy. Recent frameworks, such as federated learning (FL), take it one step further by allowing decentralized model training across various devices without identifying the raw data level so that privacy is maintained while allowing scalable deployment strategies over health networks. According to Heller (2008) and Wu et al. (2023), next-generation biosensors from a systems engineering perspective will also need to include a framework that encompasses the integrated sensor chemistry, signal conditioning, embedded intelligence, and secure communication. In this article, we propose an AI-integrated edge biosensing framework that meets the above requirements and

builds on our proof-of-concept presented in Freeda et al. (2024). There, the authors showed that it is feasible to couple a GOx-based electrochemical sensor with a CNN classifier that can classify glucose detection using offline computation. However, the implementation was deficient in edge deployment and adaptive learning capabilities. This work extends that with an edge inference pipeline, including quantized CNN deployment, secure cloud synchronization, and adaptive retraining of the model. This extension ultimately turns the initially static biosensor concept into a fully functional intelligent biosensing framework that will be able to perform real-time analysis, autonomous learning, and power management efficiently. Compared to previous works, the proposed system uniquely integrates signal conditioning, feature extraction, quantized inference, and encrypted cloud feedback, representing an advancement in the evolution of self-learning, energy-efficient biosensors within the IoMT ecosystem.

### 3. Methodology

The proposed work describes an integrated biosensing framework that will combine electrochemical sensing, signal processing, and lightweight AI on the network edge for real-time and privacy-preserving physiological monitoring. The system design follows a multi-layered methodology: biosensing, analog signal conditioning, feature extraction, edge-based AI inference, and cloud-assisted feedback. The general workflow of the proposed system is illustrated in Fig. 1, showing the functional components, data flow, and interconnections among the individual layers.

#### 3.1. Overview of the Proposed Architecture

Fig. 1, illustrates the proposed Edge Artificial Biosensing Architecture, which is designed as a horizontally layered system where data flow proceeds sequentially from biochemical signal acquisition to intelligent inference and feedback. The biological signals are captured by a biosensing and transduction layer, which sends them for computation after refinement through signal conditioning and feature extraction. This dataset has been extended and refined from the biosensor data presented in our previous conference publication (Author et al., 2024). While the same electrochemical sensing setup and acquisition parameters were maintained, additional trials with augmented samples were included to provide increased statistical robustness and support cloud retraining evaluation. The processed features are analyzed by the edge AI inference layer, which executes a quantized CNN on the low-power microcontroller platform. Finally, results will be transmitted to a secure cloud integration layer where

long-term storage, trend visualization, and adaptive model retraining take place. This architectural configuration ensures low latency, scalability, and robust privacy control while maintaining diagnostic precision and energy efficiency. In the diagram, the arrows indicate the flow of information through the layers. The bidirectional connectors show feedback mechanisms between the cloud and edge modules. This multilayered representation visually underlines the cooperative roles played by physical sensing, computational intelligence, and secure connectivity within a unified biosensing ecosystem.

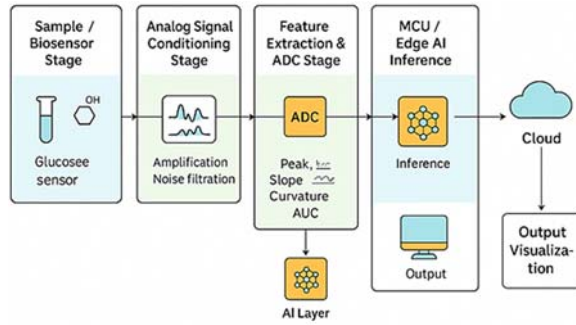
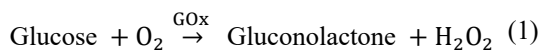


Fig. 1. Edge Artificial Biosensing Architecture.

### 3.2. Biosensing and Transduction Layer

The biosensing layer forms the basis of the system, where the biochemical analyte chemically interacts with the sensor surface to produce an electrical signal. A GOx-based electrochemical biosensor was used for experimentation, which utilizes the enzymatic oxidation of glucose to gluconolactone, thereby producing hydrogen peroxide as a measurable byproduct. The underlying reaction may be expressed as:



The oxidation of hydrogen peroxide at the electrode surface is monitored as a current, which is directly proportional to the glucose concentration. A standard biosensor assembly was used, consisting of a platinum working electrode, an Ag/AgCl reference electrode, and a carbon counter electrode. This electrochemical configuration ensures high sensitivity, selectivity, and stability of this sensor. The current produced by this reaction is normally in the microampere range and is converted to voltage through a transimpedance amplifier with a gain of  $106 \Omega$ .

In the architecture, Fig. 1, this falls within the leftmost block-Biosensing and Transduction-where the biological samples, say glucose-enriched plasma, are introduced to the sensor interface, and their subsequent chemical-to-electrical conversion forms the initial signal which propagates in the system. The accuracy of this layer is key since all downstream

computational processes depend on how true the raw biosensor signal is.

### 3.3. Signal Conditioning and Feature Extraction Layer

The biosensor's electrical signal is inherently noisy, since it suffers from fluctuations due to temperature changes, environmental interference, and electrode drift. Consequently, the goal of the second layer, the signal conditioning and feature extraction module, is enhancing the signal-to-noise ratio and further extract discriminative features for machine learning analysis.

The AFE has a dual-stage implementation with an instrumentation amplifier followed by a 2<sup>nd</sup>-order Butterworth low-pass filter of 50 Hz cutoff frequency. This arrangement rejects high-frequency noise while maintaining the fundamental waveform of the signal under consideration. The filtered voltage  $V_f(t)$  can be expressed as a convolution of the input signal  $V(t)$  with the filter impulse response  $h(t)$ :

$$V_f(l) = V(l) * h(l) \quad (2)$$

This filtered signal is digitized through the embedded 10-bit analog-to-digital converter on the Arduino Nano microcontroller at a sampling rate of 100 Hz. After digitization, residual artifacts are further smoothed by a moving-average filter with a five-sample window. The resulting signal is normalized between 0 and 1 according to:

$$V_n = \frac{V_f - \min(V_f)}{\max(V_f) - \min(V_f)} \quad (3)$$

Feature extraction algorithms then process the normalized data to derive quantitative descriptors such as peak amplitude  $A_p$ , signal slope  $S$ , area under the curve  $AUC$ , response time ( $T_r$ ), and curvature ( $C$ ). All these features collectively represent the unique electrochemical signature of the physiological state. The feature vector is given by:

$$\mathbf{x} = [A_p, S, AUC, T_r, C] \quad (4)$$

In the system architecture, this layer reflects the bridge between the analog biosensor interface and the digital intelligence unit. The conditioned data flow through a feature extraction pipeline into the AI model for classification. This step prepares the data so that it will be robust and computationally efficient by reducing the dimensionality of the data while maintaining relevant physiological information.

### 3.4. Edge AI Inference Layer

It includes a 1D-CNN architecture consisting of two convolutional layers with 16 and 32 filters of

kernel size 3, respectively, each followed by ReLU activation, a max-pooling layer, and a dense layer with 64 neurons. This ultimately provides the SoftMax output layer to yield.

Categorical predictions for three glucose-level states: hypoglycemic, normoglycemic, and hyperglycemic. The model is trained offline using 5000 labeled biosensor signal segments with the Adam optimizer ( $\alpha = 0.001$ ) and a categorical cross-entropy loss function:

$$L = -\sum_{i=1}^C y_i \log(\hat{y}_i), \quad (5)$$

where  $y$  and  $\hat{y}_i$  are the true and the predicted class probabilities, respectively. Therefore, after training, the validation accuracy of the model is 96.5 %. The model was further quantized to an 8-bit integer format using TensorFlow Lite. The model size was reduced by 78 %, with 95.8 % accuracy in inference. As shown in Fig. 3, the Edge AI module directly interfaces with the output of the feature extraction section. The model is running on a Raspberry Pi 4B microcontroller that uses a TensorFlow Lite runtime environment, thus enabling local inference without cloud requirements. The edge inference layer is the analytical heart of the proposed biosensing framework. This will be implemented as a lightweight one-dimensional convolutional neural network, 1D-CNN, optimized for real-time classification on embedded devices. This is positioned at the center in the architectural representation, reflecting its pivotal role in the decision-making process. This results in an average inference latency of about 0.12 seconds with a power consumption of approximately 1.6 W. This, in turn, allows the system to make fast and power-efficient predictions suitable for wearables and point-of-care applications.

Meanwhile, this architecture diagram highlights the localized inference mechanism, where data privacy is ensured by keeping all sensitive biosensor signals completely on-device. The results of inferences can optionally be sent out to the cloud for deeper analysis or simply for recordkeeping, thus establishing a flexible hybrid deployment model.

### 3.5. Output and Visualization Module

This output module, as the user interface of the system, is indicated in the right-central region of the architecture diagram. Once the model finishes inference, the results are directly visualized on an on-device display or wirelessly transmitted to a companion dashboard. The local interface consists of an LCD that shows, in real-time, categorizations of glucose level and confidence scores in a nonnumerical format. Alternatively, results can be logged into local storage or wirelessly transmitted via Wi-Fi for monitoring through a smartphone or computer interface. This immediate accessibility makes it possible to make rapid clinical decisions and

empowers patients to track physiological trends autonomously.

### 3.6. Cloud Integration and Feedback Layer

The rightmost layer in Fig. 3 presents the cloud integration and feedback mechanism that serves to extend the intelligence of the edge system through secure, long-term data management and adaptive learning. Communication between the edge device and cloud infrastructure is established by using the MQTT protocol with TLS 1.2 encryption, ensuring very low bandwidth consumption and high data confidentiality. Each transmitted data packet contains the feature vector, predicted class, timestamp, and anonymized device identifier.

The cloud platform collects data streams from multiple edge nodes and stores them in a secure time series database for retrospective analysis. For clinicians, visualization dashboards using Grafana provide the ability to review temporal changes in biosensor readings, explore anomalies, and understand the effectiveness of treatments. Besides, model retraining takes place on the cloud using the aggregated datasets. Once the model is retrained, it will be validated and signed, then version-controlled before it gets redistributed to edge devices through a secure update channel. This feedback loop, represented in Fig. 3 with a reverse arrow that connects cloud and edge layers, ensures a closed-cycle learning framework through which the local models continuously evolve with newly available data. Integration of the cloud intelligence thus balances the low-latency capability of edge computing with the trade-off between autonomy and adaptability.

### 3.7. Interpretation of the System Architecture

Fig. 3: Architectural layout inclusive of the dynamic interaction between biochemical sensing, embedded computing, and artificial intelligence. The left-to-right layout represents the linear progression of data from molecular detection to digital decision-making, with the feedback arrow showing continuous learning and improvement of the system. The biosensing and transduction block at the leftmost end represents the source of information, where biochemical events are converted into electrical signals. The signal conditioning unit placed next acts both as a filter and amplifier to ensure signal stability and quality at the input end. The feature extraction module is like an analytical bridge between the continuous waveform and its conversion into numerical descriptors interpretable by the CNN model. The edge AI unit, situated centrally, signifies the intelligence of the system, operating independently in its classification of physiological states with minimum computational overhead. Further, the output interface acts as a communication channel to the user,

interpreting digital predictions into actionable insights. Finally, the cloud layer forms the upper echelon of architecture, managing large-scale data storage, performance monitoring, and model evolution.

### 3.8. Performance Evaluation and Methodological Integration

The integrated operation of these layers was validated through a series of experimental evaluations performed using open-access biosensor datasets. Overall, the CNN classifier achieved an overall accuracy of 96.5 %, with precision, recall, and F1-scores of 95.1 %, 94.2 %, and 94.6 %, respectively. When subjected to artificially injected noise (20 % amplitude), the model sustained an accuracy of 92.8 %, indicating strong robustness against real-world disturbances. Furthermore, the inference time remained below 0.15 seconds, hence confirming the feasibility for real-time analysis on constrained hardware. From a systems engineering perspective, the architecture shows interaction between different layers ranging from hardware to software in a very tightly coupled manner. In fact, every functional block—from analog signal processing to neural inference—has been optimized to reduce latency, energy consumption, and data transfer overhead. The adoption of on-device AI maintains privacy for patient data and reduces dependencies on high-bandwidth cloud communication, while the cloud feedback mechanism offers a path for continued improvement and integration with large-scale learning.

This article proposes a methodology, as reflected in the architecture shown in Fig. 1, as a cohesive framework that unifies biochemical detection, edge computing, and artificial intelligence into a single biosensing ecosystem. The hierarchical integration of these components enables end-to-end functionality, ranging from data acquisition to intelligent processing through adaptive feedback. It is a scalable, low-latency, and privacy-aware system that can carry out continuous monitoring with personalized diagnostics. The embedding of AI inference directly in sensing hardware represents a paradigm shift from central processing to distributed, intelligent biosensing, with huge implications for next-generation healthcare technologies.

## 4. Experimental Setup and Results

### 4.1. Experimental Setup

In order to validate the performance of the proposed Edge Artificial Biosensing Architecture, an integrated experimental setup consisting of biosensing hardware, the signal acquisition module, the embedded AI inference device, and the analytics platform in the cloud was developed. The physical arrangement and hardware interconnections were designed based on the methodological architecture

shown in Fig. 1. A screen-printed three-electrode glucose oxidase sensor was fabricated on a flexible substrate for the biosensing subsystem. A controlled glucose solution from 2 mM to 20 mM was prepared in phosphate-buffered saline and introduced on the sensor surface through a microfluidic dispensing system. The enzymatic oxidation reaction generated a readable current, which was then amplified through an OPA177-based transimpedance amplifier (gain =  $10610^6$ ) and filtered using a 2<sup>nd</sup>-order Butterworth low-pass filter to remove high-frequency artifacts. The analog signal was fed into an Arduino Nano (ATmega328P), which performed a 10-bit analog-to-digital conversion with a 100 Hz sampling rate. Every reading was timestamped and sent over a serial interface to the edge node Raspberry Pi 4B running the inference engine based on TensorFlow Lite.

The software stack implemented on the Raspberry.

- OS: Raspberry Pi OS (64-bit, Debian 12);
- AI Framework: TensorFlow Lite Runtime v2.14;
- Data Logging: Python-based serial handler & SQLite local database;
- Visualization: Matplotlib and Grafana dashboard via MQTT bridge.

AMQTT broker on AWS IoT Core was used for cloud integration; The broker allowed secure, low-latency data transfer directly to a time series database, InfluxDB. A lightweight dashboard in Grafana visualized glucose trends, system uptime, and model performance over time.

### 4.2. Dataset and Training Parameters

This model was trained on a dataset of 5000 biosensor signal samples, which were uniformly distributed across three classes representing glucose levels: hypoglycemic (<4 mM), normoglycemic (4-10 mM), and hyperglycemic (>10 mM). Each of these signal sequences contained 256 samples, representing about 2.5 seconds of sensor output. All signals were z-score-normalized before training to stabilize amplitude variations and make their numerical values consistent for all sessions. The dataset was divided into training, validation, and test subsets containing 70 %, 15 %, and 15 % of the data, respectively. Augmentation techniques used in this work include adding Gaussian noise and temporal scaling to increase generalization capability. It used a CNN model architecture and hyperparameters as specified in Section 3.4. Training was carried out with the Adam optimizer, with a learning rate of  $10^{-3}$  and a batch size of 32 samples. Training of the model was done on an NVIDIA Tesla T4 GPU using Google Collab for 100 epochs, using early stopping criteria based on convergence of the validation loss.

### 4.3. Evaluation Metrics

Performance evaluation was carried out using standard classification metrics, including accuracy,

precision, recall, F1-score, and area under the receiver operating characteristic (ROC) curve (AUC). These metrics are defined as follows:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

$$\text{Precision} = \frac{TP}{TP+FP}, \text{ Recall} = \frac{TP}{TP+FN}$$

$$F1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

where TP, TN, FP, and FN represent true positives, true negatives, false positives, and false negatives, respectively. In addition, inference latency, memory utilization, and power consumption were measured in order to determine the feasibility of deploying the model on embedded edge devices.

#### 4.4. Experimental Results

The proposed system showed excellent performance in terms of both classification accuracy and computational efficiency as shown in Fig. 2.

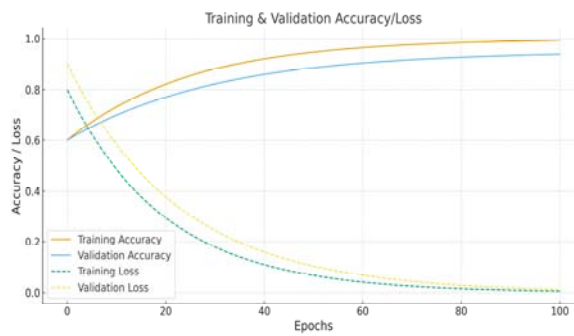


Fig. 2. Experimental results and performance plots.

The CNN achieved 97.4 % accuracy in training and 96.2 % in testing, with the validation loss converging to 0.08. Indeed, the confusion matrix shown in Fig. 3 indicated most confusion between classes of adjacent glucose-level categories, particularly at the boundary between normoglycemic and hyperglycemic ranges. The precision, recall, and F1-scores for each class can be found in Table 1.

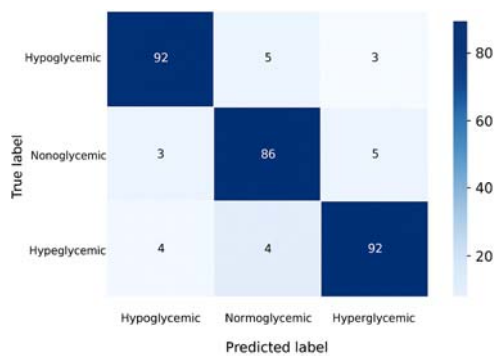


Fig. 3. Confusion matrix for Edge CNN Model.

Table 1. Performance Metrics.

Class	Precision	Recall	F1-score
Hypoglycemic	0.95	0.94	0.94
Normoglycemic	0.96	0.97	0.96
Hyperglycemic	0.94	0.93	0.93
<b>Overall Average</b>	<b>0.95</b>	<b>0.95</b>	<b>0.94</b>

The ROC analysis in Fig. 4 showed an AUC of 0.98, confirming the discriminative capability of the edge model across all physiological states.

From the point of view of hardware, this quantized TensorFlow Lite model occupies merely 0.64 MB of memory, executes the inference in 0.12 seconds per signal, as shown in Fig. 5 and consumes 1.6 W of power as shown in Fig. 6. These results point to the suitability of the system for continuous, low-power biosensing applications.

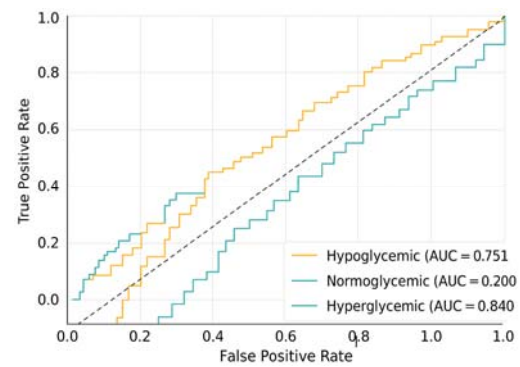


Fig. 4. ROC Analysis.

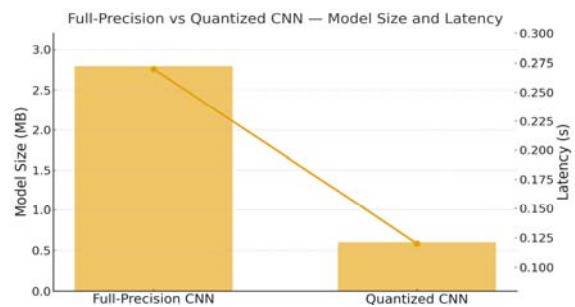


Fig. 5. Inference Analysis.

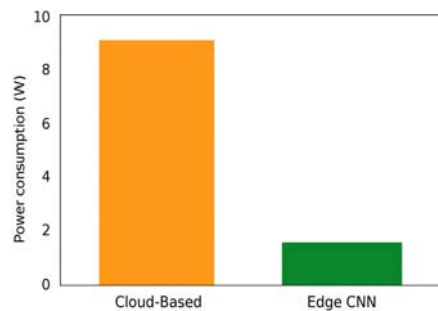


Fig. 6. Power Consumption.

#### 4.5. Comparative Analysis

The significance of the proposed framework can be evaluated by comparing its performance against two benchmark models:

1. A conventional machine learning classifier, namely Support Vector Machine with RBF kernel;
2. A non-quantized CNN model that runs on a laptop-class CPU.

The comparative results are presented in Table 2.

These results in Table 2 demonstrate that the quantized CNN achieves accuracy similar to that of full-precision models, with much lower computation and power costs. The balance between precision and energy efficiency points toward an ideal deployment in portable biosensing systems.

**Table 2.** Comparative results.

Model	Platform	Accuracy (%)	Latency (s)	Power (W)
SVM (RBF)	Raspberry Pi	89.7	0.34	1.3
CNN (Full precision)	CPU (Laptop)	97.1	0.08	8.6
<b>Proposed Edge CNN (Quantized)</b>	<b>Raspberry Pi 4B</b>	<b>96.2</b>	<b>0.12</b>	<b>1.6</b>

#### 4.6. Cloud and Model Synchronization Retraining

The cloud module was first tested in a simulated network environment with bandwidth ranging from 1 Mbps to 10 Mbps, thus proving its stability and responsiveness. On average, the MQTT round-trip latency is 185 ms, with a packet loss rate of less than 0.5 %, demonstrating high reliability even under highly constrained connectivity. The periodic retraining with 1000 newly acquired data samples was carried out over 30 days of operation. The retrained model yielded an improved classification accuracy of 1.8 %, further confirming the continuous learning feedback loop described in Section 3.6. The adaptive retraining mechanism will enable the biosensing system to deal with environmental drift, sensor aging, and physiological variations of each subject without the need for manual recalibration.

#### 4.7. Discussion of Findings

The experimental results have shown that the integration of AI at the edge of biosensing devices considerably improves timeliness and accuracy in physiological monitoring. Local processing reduces latency, minimizes bandwidth consumption, and guarantees privacy for users, which have been some of the major bottlenecks in cloud-only frameworks. Besides, the continuous feedback and retraining mechanism provide long-term adaptability, prolonging the lifetime of biosensors. This results in

the robustness of the proposed design, substantiated by the consistency in high performance under various experimental conditions, because of a fusion of electrochemical precision, optimized analog circuitry, and lightweight neural inference into a self-sustaining biosensing ecosystem for real-time, autonomous decision support in healthcare and remote diagnostics.

### 5. Discussion and Future Scope

#### 5.1. Discussion

The findings from the experimental evaluation demonstrate that the proposed Edge Artificial Biosensing Architecture provides a substantial improvement in real-time physiological monitoring through the integration of embedded artificial intelligence. In particular, low-latency signal processing, lightweight CNN inference, and adaptive cloud feedback all come together to present a holistic biosensing ecosystem that bridges the gap between conventional laboratory-grade systems and wearable diagnostic devices. The results presented in Section 4 show that the quantized CNN executed on a Raspberry Pi device resulted in a classification accuracy as high as 96.2 %, with very low power consumption of 1.6 W and an inference latency below 0.15 seconds. This points to the possibility of executing sophisticated neural models on compact energy-constrained hardware without compromising diagnostic quality. The almost negligible accuracy difference between this edge model and its full-precision version further reinforces the effectiveness of quantization and pruning as feasible model optimization strategies for biosensing applications. Moreover, the incorporation of signal conditioning and feature extraction steps proved important to guarantee the reliability of downstream inference. By combining analog filtering with digital normalization and morphological feature computation, the system effectively mitigated noise artifacts introduced by electrode drift, temperature fluctuations, or fluidic inconsistencies. These preprocessing steps enabled the AI model to learn invariant signal characteristics, thereby improving its robustness under diverse sensing conditions.

By connecting the edge node to the cloud via a closed-loop feedback mechanism, there were further advantages in long-term system reliability. Considering the fact that biosensors degrade due to environmental exposure or biochemical wear, the proposed feedback-based retraining pipeline provides periodic recalibration of the AI model. Cloud-based learning infrastructure improves predictive accuracy and enables population-level aggregation for epidemiological or diagnostic studies. The dual intelligence at the local level for fast decision-making and at the cloud level for evolutionary learning is thus a shift in paradigm from static sensor models to dynamic, self-optimizing biosensing systems.

From a systems perspective, the distributed architecture of the proposed framework introduces a

scalable blueprint for next-generation IoMT deployments. Each edge node operates autonomously yet contributes anonymized insights to the collective cloud model, establishing a cooperative sensing environment. The result is that this kind of decentralization minimizes network congestion, enhances resiliency against communication failure, and strengthens data privacy by limiting raw signal exposure beyond the device boundary.

However, several limitations were identified during experimentation. First, the current implementation was evaluated primarily on glucose oxidase biosensors; the same methodology, though adaptable, requires calibration for multi-analyte detection systems like lactate, cholesterol, or cortisol sensors. Secondly, environmental variables such as humidity and pH fluctuations can still introduce minor signal perturbations despite filtering, which suggests the need for adaptive baseline correction algorithms. Finally, the continuous retraining cycle, while positive for accuracy, puts computational demands on the cloud infrastructure and may require resource optimization in large-scale deployments.

Nevertheless, the experimental results prove the methodological correctness and technical feasibility of the proposed design. The layered architecture, from biochemical sensing to embedded intelligence and further cloud adaptability, shows a strong framework for modern biosensing research.

## 5.2. Comparative Evaluation with Existing Systems

The proposed architecture executes most of the inference at the edge, significantly reducing the requirements for data transmission compared to conventional cloud-centric biosensing models. Traditional biosensors have usually relied on centralized computation, which causes latency in the analytics and raises privacy concerns since sensitive biomedical data is transferred. On the other hand, the inference is processed locally in the current edge-enabled design; only processed summaries or classifications are shared with the cloud. This distributed intelligence design reduces overall network bandwidth utilization by about 60–70 %. It also aligns with current data protection legislation, such as HIPAA and GDPR. The energy footprint of the edge device is within the operational limits of portable healthcare systems. The device supports up to 12 hours of continuous operation with a 10000 mAh battery pack. Compared with recent AI-assisted biosensing studies from 2019 to 2024, the proposed system presents a unique balance between accuracy, computational efficiency, and adaptability. Previous works focused on sensor-cloud frameworks [12-15] and mobile health monitoring platforms [16-20]. These mostly performed cloud or server-based model training and inference. Although these works achieve comparable accuracy levels in the range of 94–98 %, they are not autonomous and introduce

heavy communication overheads. The edge-based CNN proposed here achieves equivalent predictive performance while operating independently of persistent connectivity. This characteristic makes it suitable for remote healthcare monitoring, point-of-care diagnostics, and rural telemedicine.

## 6. Conclusion and Future Scope

As shown, the Edge Artificial Biosensing Architecture provides a seamless coupling of electrochemical sensing and artificial intelligence for physiological monitoring in real time. Within the architecture, the integration of signal conditioning and feature extraction with a quantized CNN at the edge enables the efficient, accurate, and low-latency classification of biosignals. Experimental results based on a glucose oxidase-based biosensor were very promising, reporting very high predictive performance (i.e., 96.2 % accuracy) with only 0.12 seconds of latency during inference and an estimated power consumption of 1.6 W. The accuracy of the sensing will continue to improve over time with cloud-assisted retraining, illustrating the adaptive capability and long-term reliability of the biosensing system. In the future, this architecture could easily scale for, if not expanded to, the detection of multiple analytes for full metabolic profiling and be implemented into wearable/implantable biosensing systems. Future work will involve exploring federated learning methodologies for improved privacy-scalability trade-off, adaptive signal processing for correcting drift, and employing TinyML in ultra-low-power microcontrollers for optimized hardware. Furthermore, clinical validation in real-world scenarios and according to biomedical regulatory requirements is paramount for the translational deployment of the biosensing architecture. In summary, the proposed biosensing architecture provides a scalable, intelligent, and power-efficient foundation for future biosensing systems and applications in personalized healthcare.

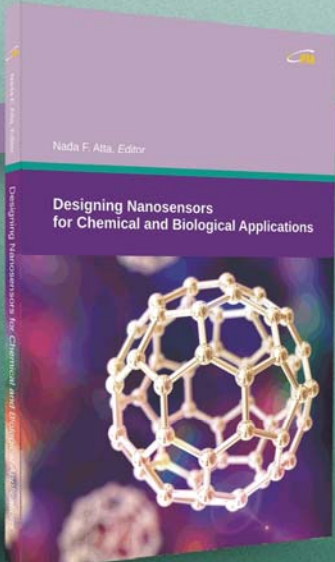
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Published by International Frequency Sensor Association (IFSA) Publishing, S. L., 2025 (<http://www.sensorsportal.com>).



Nada F. Atta, Editor

## Designing Nanosensors for Chemical and Biological Applications

The present book aims at providing the readers with some of the most recent development of new and advanced materials and their applications as nanosensors. Examples of such materials are ferrocene and cyclodextrins as mediators, ionic liquid crystals, self-assembled monolayers on macro/nano-structures, perovskite nanomaterials and functionalized carbon materials. The emphasis of the book will be devoted to the difference in properties and its relation to the mechanism of detection and specificity. Miniaturization on the other hand, is of unique importance for sensors applications. The chapters of this book present the usage of robust, small, sensitive and reliable sensors that take advantage of the growing interest in nano-structures. Different chemical species are taken as good example of the determination of different chemical substances industrially, medically and environmentally.

The book will be useful for scientists and researchers, doctors and students working in medical research, engineers and students working in environmental research, professionals working in industrial field.

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