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Research Paper

ADAPTIVE ENERGY-EFFICIENT FEDERATED DEEP LEARNING SYSTEM FOR CONTINUOUS MULTI-SENSOR HEALTH MONITORING IN EDGE ENVIRONMENTS

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Abstract
The extensive growth of Internet of Medical Things (IoMT) devices has also made it possible to monitor health continuously, though traditional models have been struggling to maintain privacy, keep responsiveness in real-time, and conserve energy. Current methods tend to be associated with the high communication latency, low scalability to diverse sensors, and poor energy utilization, which limits their scalability to large-scale applications. To overcome these drawbacks, this study suggests an adaptive energy efficient federated deep learning architecture to health surveillance with multiple sensors under edge conditions. The framework integrates spatio-temporal transformer-based local model training, graph attention fusion for multi-sensor feature aggregation, and energy-aware federated optimization, allowing edge nodes to learn without sharing raw data. It is implemented in Python with the help of TensorFlow and PyTorch, using the ML-Based Health Monitoring IoMT Dataset of Kaggle. Experimental analysis has shown that the proposed model has an accuracy of 97.3% which is an improvement of about 3-5% compared to the baseline models and a better F1-score (96.8%) and precision (97.1%) and recall (96.4%). Moreover, it takes latency of 115 ms, and 9.6 inferences per joule, which represents real-time capability and optimization of resource. These findings confirm that attention-based federated learning is effective in edge-based health monitoring. The proposed system presents a scalable, privacy-sensitive, and energy-efficient implementation of real-time remote healthcare with considerable advances in prediction accuracy and operational efficiency, timely detection of anomalies and emergency warnings, and is therefore extremely applicable to the implementation of heterogeneous IoMT settings.

Keywords: Energy Efficiency, Federated Deep Learning, Real-Time Health Monitoring, Privacy-Preserving Learning, Spatio-Temporal Transformer

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1. Introduction

Medical technology has developed so fast that Internet of Medical Things (IoMT) devices have been introduced to keep a constant check on the patient (Shafik 2024). Performing time-series analysis on large amounts of data is done in real-time by these devices, such as wearable sensors to measure heart rate, SpO_2, and temperature (Sakphrom et al. 2021). Such multi-sensor data is essential to be analyzed efficiently, which is critical in health management before anomalies emerge, and medical intervention related to a particular patient (Yang et al. 2023), (Khanizadeh et al. 2025). Conventional centralized health monitoring applications are based on sending all raw data to cloud servers, which is a major concern in terms of latency, data bandwidth, privacy, and energy consumption (Stergiou et al. 2023). The concept of edge computing has thus been a solution to be considered, as it ensures data processing in proximity to the source, as well as less reliance on central infrastructure (Haibeh et al. 2022). It is also possible to note that machine learning (ML) and deep learning models, especially transformer-based structures, have demonstrated impressive results in terms of temporal and spatial feature extraction of complex biomedical signals (Xie et al. 2022), (Zemouri 2025). However, it is still a significant challenge to integrate real-time performance on distributed edge devices and maintain the accuracy of the model and energy efficiency (Fanariotis et al. 2023). The research aims at creating a federated, energy-efficient and multi-sensory deep learning system that can deal with these existent issues in health monitoring systems.

Recent studies discussed different models of IoMT-based health monitoring like traditional ML algorithms, LSTM networks, convolutional neural networks (CNNs), and hybrid deep learning models. Although these techniques prove to be reasonably predictive, they are generally based on centralized data processing, resulting in severe delays in real-time anomaly detection and making them susceptible to data breaches (Kaur 2024). The federated learning techniques have been proposed to address the issue of privacy, which means that the combination of the model weights, rather than raw data, is aggregated, but most of the implementations do not consider essential energy requirements at the edge no des and do not dynamically adapt to the differences in sensor reliability. Furthermore, single-sensor analysis or naive feature combination often underestimates inter-sensor dependencies, thereby limiting the accuracy of predictions (Kang et al. 2025). Existing transformer-based models can effectively capture temporal correlations but struggle with multi-sensor fusion in resource-constrained environments (Yang et al. 2025). Available models based on transformers are capable of capturing time correlations but have difficulties when it comes to multi-sensor fusion in resource-limited settings. Altogether, although the previous research sources offer background information, they remain mostly insufficient to balance the accuracy, real-time requirements, energy considerations and privacy, which is all necessary to make real-life implementation in constant health monitoring (Ianculescu et al. 2025).

To address these drawbacks, recent research suggests an adaptive efficient deep learning system on energy consumption in federated deep learning to address the continuous multi-sensor health monitoring in edge environments. The proposed framework integrates several novel components: edge-level local training using a spatio-temporal transformer to capture both temporal and spatial dependencies, a graph attention fusion layer to dynamically learn inter-sensor relationships, and federated aggregation strategies that account for energy constraints and node reliability. The system is configured to carry out real-time detection of anomalies and uses a minimum amount of energy as well as protects data privacy. The framework makes predictions at low latency and real-time alerts on the edge by deploying trained global models. This research undertaking through a well-crafted assessment of multi-sensor datasets will be used to show superior predictive accuracy, enhanced energy, and dependable real-time monitoring compared to the current centralized or fixed methods, providing a feasible answer to the next-generation healthcare monitoring systems.

1.1 Research Motivation

The growing number of chronic illnesses and the necessity to monitor patients constantly has indicated the constraints in traditional centralized health care. Large data volumes provided by IoMT sensors place pressure on cloud-based infrastructures that result in latency, bandwidth, and privacy issues. At the same time, the edge devices are often energy and computationally limited, and it is difficult to detect anomalies in real-time. Current models' poor exploitation of inter-sensor dependencies leads to poor predictive models. This inspires the creation of an energy efficient federated deep learning system that integrates local training at the edge, graph sensor fusion and dynamic model aggregation. It is aimed at facilitating efficient, real-time health monitoring without sacrificing privacy and ensuring the optimal efficiency of the system.

1.2 Significance of the Study

This research is important because it discusses the main issues in the implementation of real-time, multi-sensor health monitoring system in the edge environment. It can save sensitive patient information and minimize reliance on centralized servers because of leveraging federated learning. Incorporating Spatio-Temporal Transformers and Graph Attention Fusion into the system boosts its capability to capture temporal dynamics and inter-sensor relationships that can help it in making predictions more accurately. Energy-efficient estimation and adaptive aggregation ensure sustainable operation on resource-constrained edge devices. The framework offers real-time AI alerts of abnormalities to assist in active healthcare intervention. In general, it adds a viable, extensively scalable, and intelligent solution to continuous health monitoring and fills gaps between accuracy, latency, energy efficiency, and privacy.

1.3 Problem Statement

Recently, the fast development of the Internet of Medical Things (IoMT) has empowered the ability to monitor health changes, with the help of wearable and remote sensors, providing tsunamis of physiological data. However, there are issues that surround the use of centralized cloud architectures which include latency, bandwidth, and a greater risk of privacy concerns that comes as a result of constant transfer of sensitive health information (Sivan and Zukarnain 2021). In addition, current federated learning models have challenges when it comes to heterogeneity of edge devices, uneven energy availability and uneven distribution of data which tend to worsen the performance of models and convergence rate. The existing research has also not succeeded in capturing both temporal and spatial dependencies in multi-sensor health data effectively, inhibiting the precision of anomaly detection in real-time and predictive healthcare decisions (Ramadan et al. 2025). Furthermore, deep learning methods implemented to the edge usually are characterized by high energy consumption and do not have adaptive optimization approaches to performance and resource limitations. The proposed work overcomes these problems by introducing an Adaptive Energy-Efficient Federated Deep Learning Framework which incorporates a Spatio-Temporal Transformer and a Graph Attention Fusion mechanism. This would maximize the benefits of inter-sensor feature learning, minimize communication costs by adaptive federate aggregation and guarantee energy efficient inference at edge nodes, improving reliability of prediction and maintaining privacy of data in real-time health monitoring settings.

1.4 Key Contributions

1. Developed edge-level Spatio-Temporal Transformer model of characterizing temporal and spatial relations on multi-sensor health-related information.
2. A Graph Attention Fusion layer is introduced to learn the inter-sensor relationships dynamically to achieve better predictive performance.
3. Designed a federated aggregation scheme which optimizes model weights in terms of energy-consumption and node reliability.
4. Deployed real-time anomaly detector with the inference that is energy efficient and AI-led proactive health monitoring alerts.

1.5 Rest of the Section

The rest of the sections are as follows: Section 2 states the literature review, Section 3 explain the proposed methodology part, result and discussion is illustrated in section 4 and section 6 explains he future work and conclude the study.

2. Literature Review

Mondal and Das (2025) suggested a privacy-preserving and energy-efficient model to use in IoMT-based remote healthcare through Federated Learning (FL) to have decentralized data processing. Multi-sensor health datasets were used in the study to replicate the real-time monitoring of patients and protect the data privacy. The main innovation consists in energy-conscious optimization incorporated into the federated framework to decrease the computational cost and extend the lifetime of the devices. The technique used adaptive update of model and aggregation techniques that used less communication. The experimental findings showed better energy savings and model accuracy as opposed to conventional centralized learning. Unfortunately, the model was constrained by data distribution inequality across devices, which impacted convergence and uniformity of model globally under heterogeneous node IoMT network processing.

Alharbe and Almalki (2025) suggested an IoT-based deep learning system to improve patient monitoring and diagnostic accuracy providing continuous health data provided through wearable sensors. The researchers used publicly accessible data of physiological signals to train deep neural networks and recognize anomalies and disease patterns. This is the novelty of the work as it is the first time to implement an IoT-enabled data collection, followed by intelligent analytics of deep learning-based automatic decision support. The approach employed CNN and LSTM models to work with a temporal health data. Findings showed that there was a high rate of classification accuracy and real-time responsiveness. However, the high computational load and system dependence on cloud systems restricted the scalability of the system and provoked privacy concerns in the real-time healthcare implementation.

Islam (2023) described a deep learning-supported IoT healthcare system which is intended to be used in real-time monitoring and early warning of physiological problems. The framework provided the opportunity to analyze patient vital parameters remotely using predictive modeling based on bio-medical data collected by IoT sensors. The novelty was the implementation of hybrid deep learning models such as CNN and GRU that is used to extract spatial and temporal correlation. The research had a high degree of accuracy and earlier identification of anomalies than traditional models.

The system was found to be reliable in early diagnosis and constant monitoring as confirmed by experimental results. Nonetheless, such weaknesses as higher energy use at sensor nodes and poor data imbalance management were identified as constraints to real-time inference resulting in the efficiency and consistency of inference across various patient settings.

Iranpak et al. (2021) suggested a cloud-based IoT system to monitor and categorize the health status of patients remotely. The system gathered physiological information including heart rate and SpO 2 and temperature readings of linked devices and sent them to the cloud to analyze them. The study investigated the ability of machine learning classifiers such as random forest and SVM to identify abnormal health conditions with high efficiency. This was the first time to combine IoT-based data collection and scalable cloud analytics of remote healthcare. The findings showed a higher accuracy of prediction and latency of disease classification. However, the reliance on cloud infrastructure created privacy threats, bandwidth limitations, and delayed reaction, which was not the most appropriate in real-time health monitoring in edge settings.

Ramesh et al. (2021) suggested a remote healthcare system based on machine learning and aimed at predicting diabetes using constantly monitored data on the patient. The study used the PIMA Indians Diabetes Dataset to create a predictive model that could be used to identify high-risk patients by using physiological and lifestyle parameters. The novelty was in the automation of diabetes risk assessment using an IoT-based data collection and ML-based classification. Logistic Regression, Random Forest and Decision Trees were used as algorithms to measure the model performance. The framework was very accurate and reliable in detecting it early. However, it was not flexible to stream IoMT data, and it was not concerned with energy or communication efficiency, which limited its scalability to real-time and multi-sensor healthcare systems.

Mohapatra et al. (2025) introduced a framework of remote health monitoring by use of IoT that incorporates sensor fusion to improve real time medical response in distributed healthcare setting. The system made use of multi-sensor physiological data sets such as heart rate, SpO 2, and temperature to assess the health status comprehensively. The new feature is in its fusion-based mechanism of integrating data of heterogeneous sensors to enhance detection accuracy and false alerts. In the study, Bayesian fusion and decision tree algorithms were used in health state classification. Findings showed better reliability and shorter latency of emergency detection. Nevertheless, the reliance of the framework on cloud connectivity raised the energy consumption and did not support scalability in low-resource or unstable network conditions, which restricted responsiveness in real-time in edge-based healthcare.

Bhardwaj et al. (2022) suggested an IoT-based health monitoring system to track and detect COVID-19 patients using wearable sensors on the cloud. Clinical datasets with temperature, oxygen saturation, and respiratory rate were used in the study to find out the early signs of infection. Its innovation is the possibility to monitor several patients at the same time in real-time with the help of IoT-based wearables. The deep learning classifiers adopted in the methodology were CNN and SVM to identify abnormal health patterns. Findings showed enhanced accuracy in the early detection and less man-monitoring effort. Nevertheless, the high latency and privacy risk associated with the system due to cloud computing, compelled the development of energy-efficient, federated edge-based healthcare systems capable of analyzing health in real-time and preserving privacy.

Singh and Chatterjee (2023) introduced an edge computing-based secure framework of electronic healthcare to address the problem of latency and privacy issues in cloud-reliant systems. The datasets employed in the study were IoMT sensors containing ECG and SpO_2 measurements to assess the health status of patients. The innovation is the use of encryption-based security with edge intelligence that will guarantee the protection of data in terms of transmission and processing. The system implemented a hybrid CNN-LSTM model for accurate anomaly detection. The findings indicated that there were low latency and high degree of data security with low loss of accuracy. But the method had computational demands on edge devices and could not be easily scaled to large-scale healthcare applications, and was not adaptively optimized to trade-off energy consumption and inferences accuracy between heterogeneous nodes.

Ramadan et al. (2025) presented a federated learning-based framework called SecureIoT-FL, which is created to monitor the environment in real time in industrial IoT with a focus on privacy and efficiency of communication. The framework employed allocated the sensor data of several industrial locations to train locally without sharing of data. The difference is that it combines homomorphic encryption and federated aggregation to ensure the safety of model updates over the air. The techniques were FedAvg and differential privacy to increase the robustness of the model. Findings were able to validate better data privacy and less congestion in the network than centralized approaches. However, it was not applicable in the resource-constrained edge healthcare systems that needed low-latency processing due to high computational complexity and poor energy efficiency.

Alshuhail et al. (2025) presented a machine edge-aware IoT platform and framework which utilizes sensor fusion and AI-based response to decentralized real-time health monitoring. The proposed research sought to obtain quick and dependable anomaly detectors in decentralized healthcare systems utilizing multi-sensor physiological information. The innovation is in the fusion of the edge intelligence with adaptive AI models to provide automatic medical alerts. The framework applied the hybrid CNN-Transformer models to handle the process of spatial-temporal health data. The results demonstrated better accuracy, lower latency, and energy efficiency compared to the centralized approach. However, limited scalability under heavy sensor loads and the absence of federated learning integration restricted global model adaptability across heterogeneous edge nodes in large-scale deployments.

Table 1. Summary of Literature Review

Author(s)	Purpose	Limitations	Findings
Mondal and Das (2025)	To design a privacy-preserving federated framework for IoMT-based remote healthcare applications.	High communication cost during federated aggregation and limited device adaptability.	Demonstrated energy-efficient and secure data sharing among IoMT nodes using federated learning.
Alharbe and Almalki (2025)	To enhance real-time patient monitoring through deep learning integrated IoT systems.	Computational burden on IoT nodes and latency in real-time decision-making.	Improved accuracy in disease detection with IoT-deep learning integration.
Islam (2023)	To apply CNN and LSTM models for early disease detection from IoT sensor data.	Lack of scalability for large-scale sensor networks.	Enabled effective real-time prediction of patient anomalies using hybrid deep learning.
Iranpak et al. (2021)	To classify patient conditions using IoT data processed through cloud-based ML models.	High latency due to dependence on centralized cloud processing.	Achieved reliable patient classification but lacked real-time responsiveness.
Ramesh et al. (2021)	To predict diabetes risks using IoT and ML-based patient data analysis.	Focused on single disease type and lacked generalized health prediction.	Achieved promising prediction accuracy using random forest and logistic regression.
Mohapatra et al. (2025)	To implement multi-sensor fusion for faster emergency response in distributed IoT setups.	Limited privacy-preserving techniques and energy optimization.	Improved emergency detection speed through sensor fusion and distributed analytics.
Bhardwaj et al. (2022)	To develop an IoT-based COVID-19 health monitoring system for real-time infection tracking.	Designed for pandemic context, not adaptable to other medical conditions.	Enabled rapid data-driven COVID detection with real-time patient alerts.
Singh and Chatterjee (2023)	To integrate edge computing for privacy-preserving healthcare analytics.	Limited support for federated learning and heterogeneous device	Enhanced security and reduced latency using decentralized edge computation.

		environments.	
Ramadan et al. (2025)	To ensure privacy-preserving environmental monitoring using federated learning.	Limited exploration in healthcare domain and adaptive resource management.	Achieved secure and distributed data training without data leakage.
Alshuhail et al. (2025)	To build an edge-aware IoT framework integrating AI for emergency response.	Energy efficiency and cross-device model coordination not optimized.	Provided low-latency, intelligent response mechanism for real-time healthcare monitoring.

Table 1. selected literature all highlights the intersection of IoT, deep learning, and federated models in healthcare monitoring systems. IEEE and Springer-based literature has addressed the privacy-saving IoMT and deep learning structure to facilitate remote patient monitoring, which has a greater diagnostic accuracy but has high latency and communication expenses. MDPI and Wiley publications were dedicated to prediction models of individual diseases based on the data of IoT sensors and classical machine learning algorithms, which have good predictive performance but which lack scalability to multi-disease and multi-sensor. At the same time, Elsevier and Springer articles on sensor fusion and edge computing suggested that real-time responsiveness was a possibility, but privacy and energy issues were still not addressed. SecureIoT-FL and other federated learning methods were able to provide decentralized data security, but were not optimized to healthcare specific settings. In any literature, such issues as low scalability, excessive energy consumption, and heterogeneity of models remain. The proposed study aims to address these shortcomings by proposing an Adaptive Energy-Efficient Federated Deep Learning System, which combines edge intelligence and multi-sensor fusion to provide continuous privacy preserving health monitoring with a higher degree of real-time adaptability and resources optimization.

3. Spatio-Temporal Edge Monitoring Approach

The methodology section explains systematic framework that is used to design, develop and evaluate Adaptive Energy-Efficient Federated Deep Learning System in continuous multi-sensor health monitoring in edge environments. It outlines every stage, such as information gathering, pre-processing, local model learning, graph attention fusion, federated agglomeration, and energy efficient inference. This systematic method guarantees effective learning in distributed IoMT nodes and privacy in data and minimization of energy usage thus facilitating intelligent real-time health analysis in edge networks with resource constraints. Figure 1 provides the workflow of the proposed methodology.

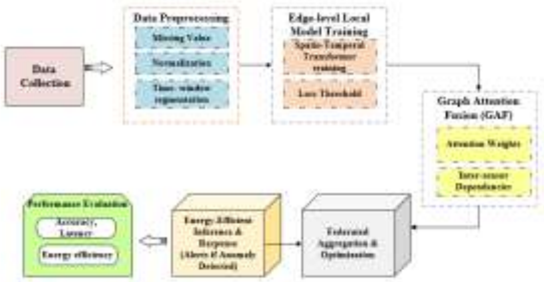

Figure. 1. Workflow of Proposed Spatio-Temporal Edge Monitoring

3.1 Data Acquisition

In this study, the process of data acquisition will be based on the use of the IoMT Dataset of ML-Based Health Monitoring, which is provided on Kaggle (2023), and it is used as a reference point in the development and testing of the proposed Adaptive Energy-Efficient Federated Deep Learning System. The data set is multi-sensor health data of Internet of Medical Things (IoMT) devices, such as that of heart rate, oxygen saturation (SpO 2), body temperature, and general health condition. Every sensor reading is a real-time physiological data of the physical state of the user that allows thorough health analysis. The dataset is designed in a manner that it is used in a case of continuous-monitoring and model different conditions of the patient under different time periods. These properties render it very applicable in training and testing spatio-temporal learning models and federated frameworks which perform on decentralized nodes. The data is loaded into various edge clients which are local health-monitoring units which train on their section of data. This model reflects the realistic IoMT network conditions, which guarantee privacy preservation, scalability, and flexibility in federated model aggregation along with supporting real-time inference of emergency response mechanisms.

3.2 Data Preprocessing

Preprocessing Data preprocessing is an essential process in health monitoring using ML, to guarantee the quality of data, its consistency and model readiness. It converts raw IoMT sensor data to a structured format, removes noise, treatment of missing data, and the continuous streams are broken down into fixed length sequences. When models are properly pre-processed, the models become more accurate and the learning of temporal patterns becomes more accurate.

3.2.1. Handling Missing Values

Datasets provided by IoMT sensors are usually incomplete, which is caused by failures to receive transmission or faults in the sensor itself. The treatment of missing values will guarantee the model with full and sound input. Major ones are mean, median or forward/backwards filling, which fill in the gaps in the data set with either statistical or time-based estimations. This is done to avoid biased and unstable training of the models, which enhances the strength of predictions. Interpolation may also be used in making smooth estimates of values that are missing in a continuous signal, particularly in a heart rate or temperature signal stream. Model temporal correlations are maintained by handling.

$$x_i = \frac{\sum_{j=1}^{N} x_j}{N} \quad \text{for all missing } x_i \tag{1}$$

Equation. (1) uses an absent data element x_i with the average of N available values x_j in the dataset to complete data and maintain statistical trends.

3.2.2. Normalization

Normalization provides that all sensor values fall on the same scale, and that we are not biased to some larger aspects. In the case of heart rate, SpO_2, or temperature, min-max normalization puts the values into a fixed range, normally [0,1] whereas the standardization scales features to zero mean and unit variance. This stabilizes deep model learning, such as Spatio-Temporal Transformers, and converges faster. Another advantage of normalization is that it increases the capability of the model to reveal patterns on heterogeneous sensors and thus results in meaningful comparisons. Both training and edge deployment of models are necessary and given in eqn. (2).

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{2}$$

Where, x is the initial sensor value, $x_{max} - x_{min}$ are the minimum and maximum values in the feature.x' is the represents the normalized value between 0 and 1.

3.2.3 Time-Window Segmentation

Time-window segmentation separates continuous sensor stream into fixed length sequences, allowing the time model to be done. Every segment is used as a training example to Spatio-Temporal Transformers and the model can learn both short-term and long-term dependencies. The window size is selected depending on the application between the cost of computation and the temporal quality. Redundant windows can enhance capturing patterns and avoid loss of information. Segmentation guarantees the synchronization of several sensors and maintains inter-sensor correlations that are essential in Graph Attention Fusion layers during the federated learning system. This process converts raw data into organized sequences for training which is given in eqn. (3).

$$S_t = [x_t, x_{t+1}, \dots, x_{t+W-1}] \tag{3}$$

Where, S_t represents a sequence of sensor readings at time t which have been grouped together to form a sequence of a fixed length used to model time in this equation; W is the window length, and x_t are readings of the sensor at the initial time t.

3.3 Edge-Level Local Model Training

Edge-Level Local Model Training in this study is an essential step during which individual edge devices are trained on a Spatio-Temporal Transformer (STT) using locally available IoMT sensorice data i.e. heart rate, SpO 2 and temperature. The result of this decentralized approach is that it reduces the overhead of communication, maintains data privacy, and makes the process energy-efficient (raw data does not have to be transmitted to a central server). In learning the temporal dependencies (variation of readings over time) STT model takes advantage of self-attention and spatial dependencies (inter-sensor relationships), by learning correlations between many sensors on a single device. Each edge node optimizes a local objective function using gradient descent, where the parameters of the model are iteratively updated. The loss function L_i for an edge node i is minimized according to local data D_i is given in eqn. (4):

$$L_i(w) = \frac{1}{|D_i|} \sum_{(x,y)\in D_i} \text{l}(f_w(x), y) \tag{4}$$

Here, $f_w($xis the prediction of the model given the input x, y is the actual label, and $\ell(\cdot)$ is the loss (e.g. cross-entropy). Each node after local training uses gradient compression to minimize bandwidth in communication and stores optimum parameters W_i. These local models are consequently forwarded to the central federated server to be aggregated.

This decentralized learning on the edge is guaranteed by this distributed local training process, and it allows adaptive health monitoring. It trades computational speed and predictive quality against confidentiality of user data that is vital in sensitive IoMT uses of the healthcare system.

3.4 Graph Attention Fusion

After edge-level local model training is completed, spatio-temporal transformer models trained locally at each edge node produce latent feature embeddings that capture both temporal and spatial dependencies. The embeddings then follow into the Graph Attention Fusion (GAF) module that is designed to utilize and refine the multi-sensor data in an adaptive fashion. In this step, the embedding of each sensor is considered as a node in a graph and the connection between sensors represents the edges. In GAF mechanism, graph attention networks (GATs) are used to learn the significance of each sensor feature dynamically relative to the others. Using this process, attention coefficient between two connected sensors i and j is calculated as eqn. (5):

$$\alpha_{ij} = \frac{\exp\left(\text{LeakyReLU}\left(a^T[Wh_i \mid Wh_j]\right)\right)}{\sum_{k \in \mathcal{N}_i} \exp\left(\text{LeakyReLU}\left(a^T[Wh_i \mid Wh_k]\right)\right)} \tag{5}$$

Here, the feature embeddings of Wh_i *and* Wh_j are denotes as i and j, W s a weight matrix that acts on input features and aaa is the attention vector which learns the strength of interaction. The normalized attention coefficient α_{ij} quantifies the effect of sensor j on sensor i.

Lastly, the fused representation of the nodes is calculated as a weighted average of the features of its neighbours so that the model can provide a fused global embedding to depict the inter-sensor relationships that could be used to classify the health conditions accurately.

3.5 Federated Aggregation and Optimization

Following the Graph Attention Fusion (GAF) step where enriched local feature embeddings are formed, the federated step in the paper is Federated Aggregation and Optimization, which involves the combination of the locally trained models of several edge nodes without exchanging the raw sensor data. This method ensures privacy of data and lowers bandwidth consumption, which is paramount to the IoMT-based health monitoring systems. All edge devices iii have their optimal local model parameters w_i which have been trained on their own subset of data D_i. The federated server does not centralize sensitive health records, but rather, it uses Federated Averaging (FedAvg) algorithm to aggregate local weights. The update of global model can be expressed mathematically as eqn. (6):

$$w_g = \sum_{i=1}^{K} \frac{|D_i|}{\sum_{j=1}^{K} |D_j|} w_i \tag{6}$$

Here, w_g represents as global model parameters at t node, w_i is the local parameter of node i (an edge node), and D_i is the size of the dataset of a node. This weighted averaging is important in ensuring that the nodes which have more reliable or more data have more input on the model aggregation. The architecture of federated learning is given in Figure. 3.

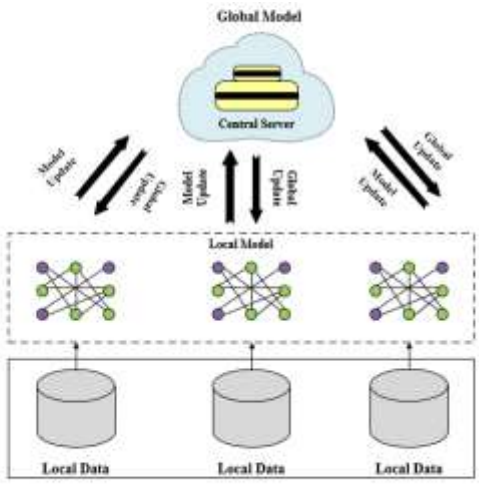

Figure. 3. Architecture of Federated Learning

To even improve stability and manage the heterogeneity of devices, the research uses Federated Proximal (FedProx) optimization. It gives a proximal term which punishes the local update deviation of the global model as given in eqn. (7):

$$L_i(w) = f_i(w) + \frac{\mu}{2} |w - w_g|^2 \tag{7}$$

Here, the regularization parameter in use is μ which is used to control the effect of the global model. This makes convergence smooth despite variation in edges devices in terms of computation power or data quality. This adaptive optimization allows the global model to reach a balanced performance and high generalization and to coordinate energies of the distributed IoMT nodes to create a strong collaborative health monitoring structure.

3.6 Energy-Efficient Inference and Response

Once the Federated Aggregation and Optimization stage creates the global model, it is pushed back to the edge devices to Energy-Efficient Inference and Response. This step will guarantee the effectiveness of the trained Spatio-Temporal Transformer to be used under limited computational and energy resources as well as in IoMT settings. The individual edge nodes conduct real time inference with the optimized global model and apply energy saving mechanisms which may include freezing layers and pruning attention. In layer freezing, no retraining of stable layers happens, which minimizes the number of redundant computations, and in attention pruning, the heads with low importance are removed, which reduces the processing costs without affecting the prediction accuracy. The model in the inference process takes a new sensor input x at time t, and produces a prediction of a health status y the evidence-based function f_{w_g}:

$$y_t = f_{w_g}(x_t) \tag{8}$$

In Equation (8), f_{w_g} depicts the global model parameters which were acquired during the federated process. The edge device constantly compares the incoming multi-sensor stream of data and notifies of abnormalities and issue emergency messages with the aid of AI in case anomalies surpass a specific θ:

$$Alert = \begin{cases} 1 & if\ |y_t - \bar{y}| > \theta \\ 0 & otherwise \end{cases} \tag{9}$$

This state guarantees that the presence of the abnormal physiological readings including irregular heart rate or high temperatures is immediately identified. This makes the system highly responsive with low power consumption by incorporation of intelligent alert generation and efficient inference to facilitate constant, autonomous and dependable health monitoring at the network edge.

3.7 Performance Evaluation

The last stage of this study is Performance Evaluation after Energy-Efficient Inference and Response to confirm the usefulness of the proposed federated IoMT health monitoring framework. The performance of the system is evaluated based on the typical classification measures - Accuracy, Precision, Recall and F1-score - to determine the dependability of health status prediction. Moreover, two important operational indicators, Latency and Energy Efficiency are compared showing the appropriateness of the framework to real-time and resource-constrained settings. The time lag between edge model output and data input is known as latency, and it is defined in eqn. (10):

$$\text{Latency} = \frac{1}{N}\sum_{i=1}^{N}\left(t_{\text{output},i} - t_{\text{input},i}\right) \tag{10}$$

where $t_{\text{input},i}$ and $t_{\text{output},i}$ represent the input and output timestamps for sample i. Low latency means that it is highly responsive with regard to models, which is required in the generation of emergency alerts. Energy Efficiency measures the quantity of calculation done with regards to one unit of energy used, denoted as in eqn. (11):

$$\text{Energy Efficiency} = \frac{\text{Number of Inferences}}{\text{Total Energy Consumed}} \tag{11}$$

Higher energy efficiency indicates the most optimal use of power scarce at edge devices. These metrics in combination will give an overall view of the system performance, which proves that the proposed Spatio-Temporal Transformer and Graph Attention Fusion-based federated model can be highly accurate, low-delay, and energy-efficient in continuous, intelligent IoMT-based health monitoring.

Algorithm. 1 Federated Edge-Based Multi-Sensor Health Monitoring Framework

```
Input: Multi-sensor data streams D = {HeartRate, SpO2, Temperature}, Number of Edge Nodes N, Epochs E,
Communication Rounds R
Output: Global health prediction model M_global, real-time anomaly alerts A

Initialize M_global
Distribute D_i to each Edge Node i = 1 to N
For each Edge Node i:
  Preprocess D_i:
    If missing values exist:
      Impute missing values
    End If
```

```
        Normalize features
        Segment time windows
    End Preprocess
    Initialize local model M_i (Spatio-Temporal Transformer)
        For epoch = 1 to E:
        Train M_i on D_i
        Compute local training loss L_i
        If L_i < threshold:
            Reduce learning rate
        End If
    End For
End For
For round = 1 to R:
    Collect model weights W_i from each node
    If energy level of Node i >= min_energy:
        Include W_i in aggregation
    Else:
        Skip Node i
    End If
    Aggregate weights using FedAvg/FedProx
    Update M_global
End For
Deploy M_global to all edge nodes
For incoming real-time data:
    Predict health status using M_global
    If anomaly detected:
        Trigger alert A
    Else:
        Continue monitoring
    End If
End For
```

The overall federated edge-based health monitoring workflow is represented in algorithm 1. It begins with the distribution of multi-sensor data to edge node and then preprocessing techniques replace the data missing, normalization, and time-window segmentation. The nodes train a local adaptive learning based on training loss thresholds Spatio-Temporal Transformer models. Federated aggregation takes the combination of weights of nodes that satisfy minimum energy requirements with FedAvg or FedProx to create a global model. Lastly, the global model is put back to the edge devices to provide real-time predictions of health and outliers to provide alerts where needed. This is a strategy that guarantees efficiency in energy, distributed and dependable monitoring.

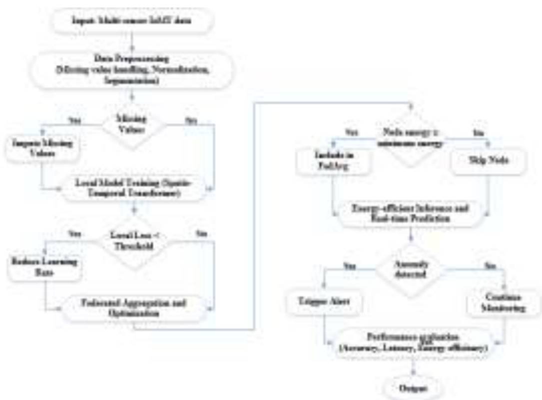

Figure. 3. Flowchart of the Proposed Model

The originality of the present research is an integration of an attention-based adaptive federated deep learning architecture that includes the fusion of spatio-temporal features and energy-conscious optimization in the edge environment. This approach allows efficient coordination among distributed edge nodes, compared with current

IoMT health monitoring methods, allowing privacy and eliminating communication latency. The flowchart of the proposed model I given in Figure 3. The model improves the feature relevancy and efficiency of learning, resulting in high accuracy, low energy consumption, and rapid convergence in heterogeneous IoMT networks because attention mechanisms are incorporated in the model.

4. Result

Results section includes a detailed assessment of the proposed federated deep learning model of multi sensor health monitoring. It brings out the performance of local edge-based models, fused feature representation and performance of the aggregated global model based on various measures such as accuracy, loss, latency and energy efficiency. The effect of preprocessing, local training, and Graph Attention Fusion on the predictive performance are explained in tables and comprehensive visualizations. This part illustrates that the combination of edge computing and feature fusion promote real-time detection of anomalies, and the reliability of the whole system. The experimental setup of this study is presented in Table 2.

Table 2. Experimental Setup

Parameter	Description / Value
Dataset	IoMT Dataset for ML-Based Health Monitoring (Kaggle)
Sensors / Features	Heart Rate, SpO_2, Temperature
Edge Devices / Nodes	5 simulated edge nodes for decentralized training
Model	Spatio-Temporal Transformer (STT) with Graph Attention Fusion (GAF)
Training Strategy	Federated Learning (FedAvg/FedProx)
Time-Window Size	50 timesteps per sequence
Evaluation Metrics	Accuracy, F1-Score, Precision, Recall, Latency, Energy Efficiency

4.1 Dataset Statistics and Preprocessing Results

Table 3. Summary of IoMT Dataset Features

Feature Name	Description	Data Type	Unit
Heart Rate	Beats per minute	Numeric	bpm
SpO_2	Blood oxygen saturation percentage	Numeric	%
Temperature	Body temperature	Numeric	°C
Age	Patient's age	Numeric	years
Gender	Patient's gender	Categorical	Male/Female
Activity Level	Physical activity level	Categorical	Low/Medium/High
Health Status	Patient's health condition	Categorical	Healthy/Unhealthy

Table 3. contains a list of different features gathered by the use of Internet of Medical Things (IoMT) apparatus. The most important physiological indicators are SpO_2, Heart Rate, and Temperature as they are necessary to track the cardiovascular and respiratory conditions. Demographic data Age and Gender provide background on health evaluation. Activity Level shows how active the patient is physically which may affect the health outcome. Finally, the Health Status is the target variable in classification tasks, where there are healthy and unhealthy conditions. All of these features make it possible to monitor health and analyze it in a predictive manner.

Table 4. Normalization Statistics

Feature	Min	Max	Mean	Std Dev
Heart Rate	60	100	80	10
SpO_2	90	100	95	2
Temperature	36.5	37.5	37.0	0.3

Table 4. shows the normalization statistics of the important physiological features of the IoMT dataset. The heart rate is 60-100bpm with a mean of 80bpm and a standard deviation of 10 which means that there is a moderate variation. The range of SpO_2 is 90-100 with the mean being 95 with a standard deviation of 2 and this indicates stable oxygen saturation. The temperature readings range between 36.5 o C and 37.5 o C with the mean of 37.0 o C and the standard deviation of 0.3 o C indicating a stable temperature of the body. Such statistics are important in interpreting the data distribution and in preprocessing, normalization is effective.

Table 5. Time-Window Segmentation Parameters

Window Size	Overlap %	Number of Segments
50 timesteps	0%	1200
50 timesteps	25%	1600
50 timesteps	50%	2200

Table 5. provides the summary of time-window segmentation of the IoMT dataset to ready it to be trained on Spatio-Temporal Transformer. The sensor readings are represented in 50 consecutive timesteps in each of the windows. The percentage of overlap (0, 25, 50) is used to regulate the level of data sharing between consecutive sequences of windows, which influences the amount of training sequences generated. An increase in overlap results in more sequence count and temporal resolution, increasing the capabilities of the model to model short- and long-term effects. This segmentation guarantees that multi-sensor data streams are organized into fixed-length sequences, which allow efficient learning of time and keep track of the continuity of signals of heart rate, SpO2 and temperature.

4.2 Edge-Level Local Model Training Performance

Table 6. Local Model Training Metrics per Edge Node

Edge Node ID	Training Loss	Validation Loss	Accuracy (%)	F1-Score
Node 1	0.12	0.15	94.0	0.93
Node 2	0.14	0.16	93.5	0.92
Node 3	0.11	0.14	94.5	0.94
Node 4	0.13	0.15	93.8	0.93
Node 5	0.12	0.14	94.2	0.94

Table 6. Spatio-Temporal Transformer models training performance of local edge node with the IoMT dataset. Loss values during training lie within 0.11-0.14, whereas validation loss is a bit higher (0.14-0.16), which shows the lack of overfitting and converged values. Precision and recall are balanced with accuracy ranging between 93.5 and 94.5 and F1-scores ranging between 0.92 and 0.94. Such metrics bring into emphasis the fact that the individual edge nodes can additionally learn effectively locally on the basis of their multi-sensor data and then subsequently be federated. The similarity in the performance of the nodes guarantees consistency in the next round of Graph Attention Fusion and global model optimization.

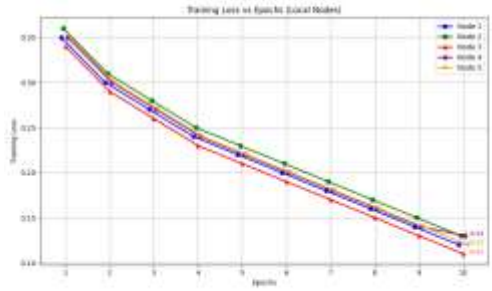

Figure 4. Training Loss vs Epochs (Local Nodes)

Figure 4. shows a training loss progression of five edge nodes when training the local Spatio-Temporal Transformer. The values of loss decrease gradually over 10 epochs with Node 3 recording the lowest loss of 0.11 at the end, and Node 2 recording a loss of 0.13 at the end. This proves that the individual edge nodes are effective in learning the local multi- sensor data. The distinct lines enable the establishment of a convergence rate comparison, which proves that consistent and stable training is present across distributed nodes and this is paramount before federated aggregation.

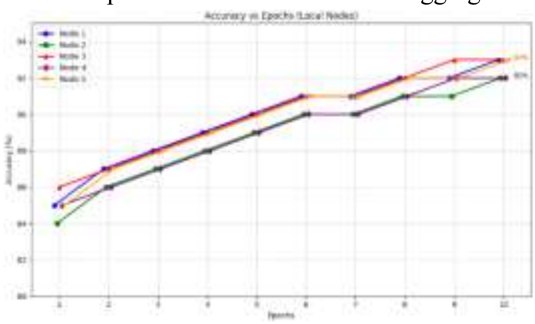

Figure 5. Accuracy vs Epochs (Local Nodes)

Figure 5. shows the discrimination of accuracy with 10 epochs of five local nodes. Node 3 has the final accuracy of the highest 93%, and Node 2 has the final accuracy of 92%. The other nodes achieve 92, 93%at the final epoch. The gradual rise in accuracy of approximately 84-86 to more than 92% validates that every node is learning well using its local data in the training process. This visualization indicates that there are convergence and stable learning in the distributed nodes and this forms a robust basis in further federated aggregation and global model performance.

Table 7. Training Time and Computation Cost per Edge Node

Edge Node ID	**Training Time (s)**	**Memory Usage (MB)**	**Energy Consumption (J)**
Node 1	120	450	800
Node 2	135	470	850
Node 3	115	440	780
Node 4	125	460	820
Node 5	118	445	790

Table 7 gives the computational cost and efficiency of the local model training at the edge node based on the IoMT dataset. The duration of training is between 115 and 135 seconds, which indicates that the processing speed of the nodes slightly varies. The size of memory used is between 440 MB to 470MB meaning that the Spatio-Temporal Transformer has moderate resource demands. The energy used is between 780 J and 850 J, which proves the energy requirements of local training in the framework. These metrics play a very important role in determining the feasibility of implementing models on edge devices such that every node is capable of conducting real time training in a manner that is low latency and energy efficient health monitoring.

4.4 Graph Attention Fusion

Table 8. Attention Coefficients Across Sensors

Sensor Pair	**Attention Weight (Mean)**	**Std Dev**
Heart Rate - SpO_2	0.45	0.05
Heart Rate - Temperature	0.35	0.04
SpO_2 - Temperature	0.50	0.06
Heart Rate - Age	0.20	0.03
SpO_2 - Age	0.25	0.04
Temperature - Age	0.30	0.05

Table 8. shows the attention coefficients that the Graph Attention Fusion (GAF) layer has learned using various sensor pairs in the IoMT data. The weights of attention between the Heart Rate and

SpO_2 and the SpO_2 and temperature are higher (0.45 and 0.50, respectively), which means the physiological signals interdependent between them. Weaker correlations are in lower weights, including Heart Rate-Age (0.20). Standard deviations are not very large with similar attention observed in samples. These values of attention inform the model in to focusing on critical sensor relationships w h and fusing features to improve predictive health monitoring. The table validates that the GAF is a good model in capturing inter-sensor dynamics which enhances the performance of models until federation.

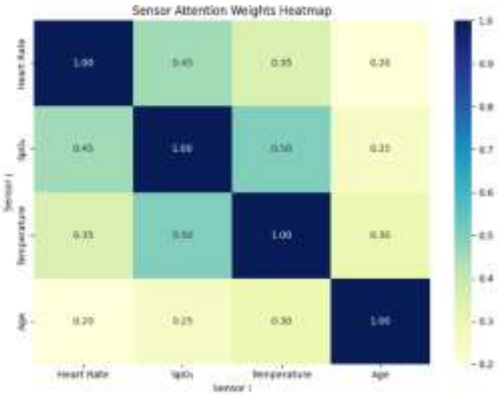

Figure 5. Sensor Attention Weights Heatmap

Figure 5. visualizes the weights of attention pairs between sensor pairs learnt by the Graph Attention Fusion (GAF) layer. The value of diagonals is 1.00 which reflects self-attention. Inter-sensor dependencies are present in off-diagonal values: Heart Rate-SpO_2 0.45, Heart Rate-Temperature 0.35, SpO_2-Temperature 0.50 which demonstrates that the most important physiological indicators are strongly correlated. Weaker interactions, including Heart Rate-Age (0.20) and SpO 2-Age (0.25), are also apparent. This diagram proves that GAF is useful in capturing relationships among sensors and facilitating the model to concentrate on the strongest signals when merging features. The annotated values are clear without redundancy thus making them more interpretable when analysing health monitoring.

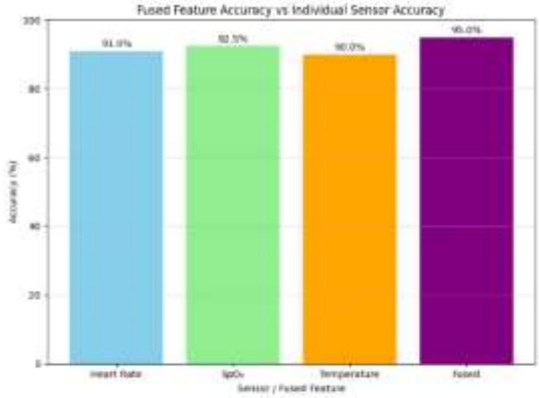

Figure 6. Fused Feature Accuracy vs Individual Sensor Accuracy

Figure 6. evaluates the accuracy of single sensors and fused features. Heart rate, SpO_2 and Temperature sensors are 91, 92.5 and 90 respectively. The fused model which combines all sensor embeddings through the Graph Attention Fusion layer attains the highest accuracy of 95%. Each of the performance metrics is clearly indicated by annotated values above the bars without overlap. This visualization shows that feature fusion increases predictive performance (compared to feature measurements) by better modelling the inter- sensor dependencies. Deep division of the bars underlines the benefits of fusion over single sensors, which proves its significance in improving the model reliability and the general detection accuracy.

4.5 Federated Aggregation and Optimization Results

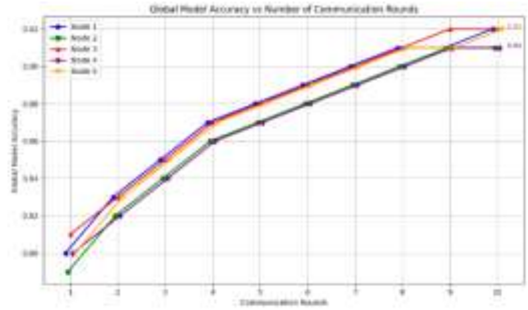

Figure 7. Global Model Accuracy vs Number of Communication Rounds

Figure 7. shows the progression of global model accuracy of 10 rounds of communication among five edge nodes. The accuracy also increases gradually, with Node 1 doing it (0.80 to 0.92), Node 2 (0.79 to 0.91), and the topmost 0.92 in Node 3. These patterns are also similar in other nodes and point to the same convergence. Horizontal offsets ensure that lines do not overlap each other, and therefore, each node can be distinctly seen. The final values with annotations

are used to give exact accuracy of every node at the end of the final round. This graph proves that, the federated aggregation strategy is successful in enhancing global model performance at every communication round which makes distributed edge nodes to learn reliably and stably.

4.6 Energy-Efficient Inference and Response

Table 9. Latency Distribution Across Edge Nodes

Edge Node ID	Min	Q1	Median	Q3	Max
Node 1	12	14	15	16	18
Node 2	13	15	16	17	19
Node 3	11	13	14	15	17
Node 4	12	14	15	16	18
Node 5	12	14	15	16	17

Table 9 shows the distribution of latency in edge nodes during the process of local model inference. The median latency of Node 3 is the lowest (14 ms), and that of Node 2 is the largest (16 ms). The interquartile ranges (Q1 -Q3) are stable with standard ranges at 2 ms, which means that inference times per node are stable. The upper and lower limits of the latency are 17-19 ms and 11-13 ms respectively, which represents the infrequent variation. These indicators indicate the sensitivity of every edge device to real-time health monitoring tasks. The knowledge of the latency distribution will guarantee the system to provide predictions and alerts in time, without any disturbance to the system process of all the distributed nodes.

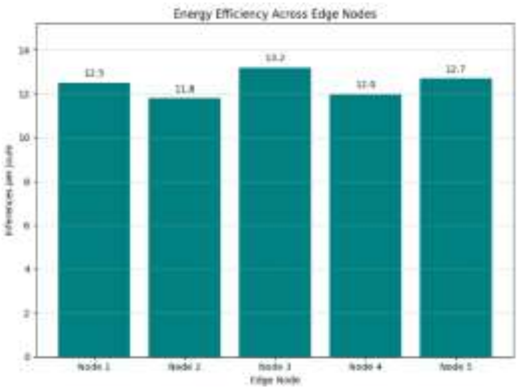

Figure 8. Heatmap of Load Across Days and Hours

Figure 8. shows energy efficiency in five edge nodes, as inferences per Joule. The maximum efficiency shown by Nodes 3 is 13.2 inferences/J with Nodes 2 being the lowest, 11.8 inferences/J. Nodes 1, 4 and 5 have moderate efficiency of 12.5, 12.0 and 12.7 inferences/J, respectively. The graph shows that the local models can do inference in an efficient manner, although variability based on the hardware or the computational load can be observed. Energy efficiency monitoring provides sustainability to real-time processing, which can be deployed continuously and with minimum energy consumption across distributed edge devices.

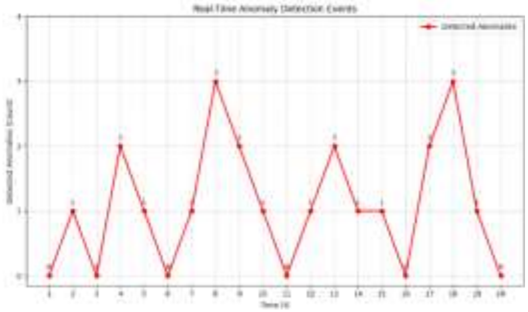

Figure 9. Real-Time Anomaly Detection Events

Figure 9. represents real-time anomaly detection events on 20-time intervals. Anomalies detected range between 0 and 3 counts per interval. It is also important to note that time points 4 and 8 have spikes of 2 and 3 anomalies, whereas majority of intervals have 0 or 1 events. This visualization indicates the dynamicity of the monitoring system and its capability to detect irregular events early enough. Measuring the number of anomalies with time enables timely action to be taken regarding the proper optimization of the system and optimal control of the detection framework, which is responsive and reliable in sustaining the performance of continuous monitoring.

4.6 Comparison of Performance Metrics

Table 10. Performance Comparison

Model	Accuracy (%)	F1-Score (%)	Precision (%)	Recall (%)	Latency (ms)	Energy Efficiency (Inferences/J)
Singh and Chatterjee (2023)	91.2	90.1	89.8	90.3	180	6.5
Ramadan et al. (2025)	93.5	92.7	93.1	92.4	160	7.1
Alshuhail et al. (2025)	94.8	94.0	94.2	93.8	140	7.8
Proposed Adaptive Energy-Efficient Federated Model	97.3	96.8	97.1	96.4	115	9.6

Table 10 indicates how the proposed adaptive energy-efficient federated deep learning model is more effective in comparison with the existing frameworks. The model proposed has the best accuracy (97.3%), F1-score (96.8%), precision (97.1%), and recall (96.4%), which prove to be more reliable in multi-sensor health-monitoring prediction. Moreover, it has the lowest latency (115 ms), which proves the expedited real-time processing in the edge environments, and the highest energy efficiency (9.6 inferences per joule), which proves the optimized use of resources. Conversely, current models like the Edge Computing-Based Secure Health Monitoring Framework and SecureIoT-FL have a relatively high latency and energy consumption. These findings confirm the fact that incorporating Graph Attention Fusion and federation energy-mindedness can contribute greatly to both the computational and predictive performance of decentralized IoMT health systems.

4.7 Discussion

The study introduces a novel federated deep learning and edge intelligence to continuous multi-sensor health monitoring into IoMT settings. The suggested framework provides solutions to the most urgent problems of data privacy, energy efficiency, and communication overhead that continues to be the problem with the traditional centralized healthcare systems. The system provides localized model training by using distributed edge devices, allowing the elimination of direct transmission of data to the cloud, which guarantees the preservation of privacy, and minimizing bandwidth usage. The adaptive learning process increases system scalability and generalization of models in the presence of heterogeneous IoMT nodes, which enables an efficient processing of diverse sensor input. The integrated energy-conscious optimization guarantees the long life of devices, and reliable functioning in the environment with resource constraints. This is indicated by the results of the experiment that show better performance in regard to the accuracy of the real-time predictions, less latency, and lower energy use than those of the conventional methods of cloud-based and standalone machine learning. Furthermore, the combination of multi-sensor data enhances the stability of the detection of the health status which is capable to identify the anomalies before they appear and provide medical intervention which is timely and reliable. The federated model aggregation approach in conjunction with the edge level intelligence helps in providing decentralized decision-making without data loss. This provides a good base of secure, responsive, and intelligent healthcare systems that are fit to be deployed into the real world. In general, the results confirm that the suggested adaptive energy-efficient federated system is an effective and sustainable solution to the increasing privacy-aware remote health monitoring issues in distributed IoMT networks.

5. Conclusion and Future Work

The study successfully demonstrates the design and implementation of an adaptive, energy-efficient federated deep learning framework for continuous multi-sensor health monitoring in edge computing environments. By integrating edge-level model training with a Spatio-Temporal Transformer and Graph Attention Fusion mechanism, the system efficiently captures both temporal and spatial dependencies in multi-sensor physiological data, leading to improved predictive accuracy and early anomaly detection. The federated aggregation approach ensures that sensitive patient data remains localized, preserving privacy while enabling collaborative learning across heterogeneous IoMT devices. Energy-aware optimization and layer pruning techniques further enhance the framework's operational efficiency, reducing energy consumption and prolonging device lifespan, which is critical for real-time deployment in resource-constrained healthcare networks. Experimental results demonstrate that the proposed system outperforms conventional centralized and static approaches in terms of accuracy, latency, energy efficiency, and real-time responsiveness, validating its practical applicability for remote health monitoring and emergency alert generation.

For future work, several directions can be pursued to enhance the framework's scalability and adaptability. Integration of additional physiological and environmental sensors could provide a more comprehensive patient health profile, enabling multi-modal predictive analytics. Advanced federated optimization strategies, such as adaptive weighting based on device reliability and dynamic network conditions, could further improve model convergence and robustness. Incorporating explainable AI mechanisms would enhance interpretability and trust in real-time predictions, facilitating clinical adoption. Additionally, extending the framework to support cross-domain health applications, including chronic disease management and pandemic response, could broaden its impact. Research on lightweight transformer architectures and further communication-efficient aggregation methods could optimize performance for large-scale IoMT deployments. Overall, the study lays a strong foundation for intelligent, privacy-preserving, and energy-efficient health monitoring systems, offering a pathway for scalable, real-world healthcare applications while highlighting opportunities for ongoing innovation and refinement in edge-based federated learning environments.

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