Design of a Secure Edge-AI IoT Framework for Real-Time Healthcare Monitoring and Predictive Analytics

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ABSTRACT

Wearable sensors and IoT supporting healthcare devices are becoming more common for continually monitoring patients' health. Such devices provide large amounts of data on body saturation with oxygen, heart rate, glucose level, blood pressure, etc. However, sending all this data straight to the cloud servers poses challenges related to latency and bandwidth and privacy risks. Even small delays in data processing can affect timely medical judgments in crucial healthcare circumstances. An integrated computing approach is needed to solve these issues. By processing data locally, the application of edge and fog computing technologies, minimizing the reliance on centralized cloud resources. However, sophisticated machine learning models are required to analyze real-time health information and identify signs of medical conditions. A secure Edge-AI-based IoT framework is suggested which enables healthcare monitoring in real-time and predicting the future health situations. Deep learning models are deployed at the edge nodes to detect medical anomalies and foretell health issues. Lightweight encryption technologies ensure reliable transfer of sensitive information, while blockchain technology is employed to create reliable logs of data access. The system actively allocates tasks to edge and cloud locations in terms of performance and efficiency. Tests show less latency, better predictive ability, and improved data protection compared to older, cloud-only methods of facilitating healthcare. The system makes possible the large-scale implementation of the technology in hospitals, remote monitoring facilities, and nursing homes, facilitating effective healthcare delivery.

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1. INTRODUCTION

In recent years, the Internet of Things (IoT) paradigm has increasingly gained traction that resulted in the existence of millions of connected devices employed in everyday situations in different fields of industry [1]. Different researchers, as well as industry stakeholders, have been working on implementing IoT technologies in diverse applications aimed at building smart environments, including smart cities, smart factories, and smart homes. For the reason above, the healthcare and wellness sector has also been benefitting from the increased use of wearable devices caused by the increase in demand for personalized health care solutions, continuous improvement in the development of miniaturized flexible sensing technologies, and expanding application of IoT technologies in the modern world [2].

In contrast, due to the technological advancements in healthcare that prolong the human lifespan, the number of elderly people in many developed countries is on the rise. With the increasing elderly population comes an intense load on current healthcare systems as old people need permanent care, assistance, and monitoring [3], thanks to numerous chronic diseases and conditions that go along with aging. Though the population of elderly people grows and in general, the number of people suffering from chronic diseases increases, healthcare infrastructures suffer from a lack of employees [4]. Many governments spend a lot of money and effort on creating high-tech solutions to guarantee high-quality, cheap, and painless services, which ultimately will make citizens' lives easier and better. Thus, there are many kinds of modern architectures based on IoT-allowing technologies and wearable devices to provide better healthcare services to people and reduce the load on existing healthcare systems [5].

Several of the proposed systems rely on the use of wearables which employs multiple physiological and environmental data provided by the sensors worn by the patients for the purpose of medical diagnosis and offering assistance to the patient in certain cases. In doing so, various algorithms of Machine Learning (ML) and Artificial Intelligence (AI) have been utilized in order to derive relevant insights from the data [7]. In most frameworks, methods and algorithms that require huge computational power and depend on Cloud-based technologies are used to infer insights and trends from the data collected. Hence, to ensure the operation of these Cloud-based systems, the data gathered from wearable technology must be transmitted frequently between the wearables and the data centers serving as the Cloud solutions, leading to concerns regarding privacy and latency issues [8]. The use of Wide Area Network (WAN) communication systems, such as WiFi or 4G technologies in providing Cloud-based systems, presents barriers to the realization of secure transmission, thus contributing to privacy concerns.

On the contrary, the major reason behind latency issues is the extensive separation of the data origins and Cloud data centers. Cloud architecture suffers from slow response times as warning or intervention services come from the faraway Cloud data centers. Therefore, this characteristic restricts their usage in real-life scenarios, where the response is not required to be immediate. As a result, the scope of healthcare services that can be provided using Cloud IoT services is limited. Nevertheless, Edge and Fog computing technologies resolved the problems discussed above and contributed to the development of IoT-based healthcare application frameworks characterized by quicker responses and preservation of confidentiality.

AI technologies such as ML, Deep Learning (DL), Federated Learning (FL), and Continual Learning (CL) systematize Edge/Fog Computing networks for an effective and rapid processing of raw data at the network edge [9]. Along with the aforementioned benefits it contributes to shortening response times when accessing applications and enhancing users' privacy. Shortened response times take on a special significance for the real-time applications like healthcare systems where it is of the utmost importance to receive right data from sensors as soon as possible because any delays can threaten lives.

In addition to the previously mentioned computational considerations, employing sophisticated technologies for precise and accurate measuring methods in the appropriate combinations for their applications increases the overall capacities, accuracy, and reliability of IoT healthcare systems as well. To achieve this goal, cutting edge research has been conducted in the last years in order to develop sensors allowing for monitoring of important physiological signals with high accuracy and precision involving minimum energy consumption. Sensors made from bio-compatible materials, easily attached to skin and manufactured in a comfortable form factor, are critical for wearable healthcare systems as they ensure the minimal or even complete absence of interference in the user's everyday activities. Besides, incorporating several advanced sensors into the given system allows for gathering significant information for better forecasting. Consequently, IoT healthcare technologies based on wearable technology and different advanced sensors are becoming less difficult, more reliable, and more robust [10]. As a result, the introduction of tiny e flexible skin-conforming sensors raises the issue of the possibility of measuring human body parameters that can't be measured with the conventional and commercially available wearable devices. In the end, this makes it possible to define an IoT healthcare technology that permits the long-term monitoring of significant indicators in prevention, diagnosis, and rehabilitation.

Different scenarios involving Edge/Fog Computing concepts have been successfully utilized in healthcare-related areas through telemedicine, and e-health as well as mobile health applications. Other domains have also seen that using intelligence within devices causes the applications to react more quickly and guarantees data safety in IoT systems. Thus, besides applying artificial intelligence algorithms to the Edge/Fog/Cloud nodes, smart devices are able to analyze data on-device and thus increase the volume of information gathered and analyzed through the use of sensors. Integrating intelligence within devices can help reduce the amount of data sent by various elements of the framework, making the system more efficient in terms of power usage and privacy. The IoT frameworks usually work with communication technologies such as ZigBee or Bluetooth Low Energy (BLE), which limits the transmission distance. In this sense, implementing the idea of local processing with the help of AI and ML could facilitate the speed of response and power efficiency of the system. Nevertheless, this approach is still nascent in the sphere of healthcare. Thus, it is essential to figure out how to integrate it into the current state of the art with the help of methods, tools, and technical requirements.

The emergence of on-device AI, sensing technologies, and the successful implementation of IoT applications on Edge, Fog, and Cloud platforms prompt us to combine these technologies and develop a framework in the healthcare domain. Thus, in this article we present a comprehensive review of existing IoT architectures using wearable devices for different applications in the healthcare domain. Furthermore, we will provide the framework and requirements for a multi-layer IoT-aware system that utilizes an advanced multi-sensor network, including Edge Computing technologies and on-device intelligence for time-critical healthcare applications. The proposed architecture employs state-of-the-art smart sensing technologies that ensure precise biosignal measurement, advanced communication technologies to develop low-cost wearables, Edge Computing in combination with Edge Computing and on-device intelligent technologies for secure real-time applications, and Cloud technologies to perform complex data processing.

2. RELATED WORKS

[11] Propose a cutting-edge IoT-based healthcare system that utilizes sensors for real-time monitoring of blood pressure and heart rate. The architecture gathers medical data from patients, sends it over the IoT cloud for secure storage, and performs sophisticated analytics to provide doctors with health alerts and reports. The architecture of the system lays emphasis on reliability, scalability, and safety and overcomes major barriers in IoT healthcare systems. The robust cloud computing-based analytics engine processes the information from sensors with the use of optimized algorithms, enabling strong accuracy of data and lower latency. The effectiveness of the system has been proven with the help of performance assessments, which achieved latency in data transfer less than 50 milliseconds, accuracy higher than 95% with respect to regular clinical devices, and efficient use of resources under diverse network conditions. The comparison with the existing Internet of things (IoT) healthcare solutions reveals significant advances in throughput, reliability, and scalability. The current research lays the groundwork for future developments in the field of predictive diagnostics based on artificial intelligence (AI), integration of more sensors and improving security mechanisms of patient data.

[12] Presents an innovative system that integrates edge computing, artificial intelligence techniques, and Internet of Things technologies to provide an effective and low-latency healthcare ecosystem. The suggested system emphasizes the use of distributed edge systems to process health information on the spot, eliminating the need for constant connectivity to the cloud, while delivering fast processing and security of data. The implementation of AI methods at the edge makes it possible to conduct vital parameters monitoring in real-time mode, detect symptoms of diseases in advance, and predict diseases beforehand. This allows health care experts to make timely choices even in remote locations or areas with insufficient health care. On top of that, this approach addresses certain problems like data protection and security and the system's capability for scaling. By means of the integration of sensors of the Internet of Things, wearables and portable platforms, uninterrupted patient monitoring is realized thus improving the decision-making process and relieving health care institutions. The paper explores the effect of Edge AI and IoT on remote health care and possible usages, advantages, and drawbacks of the changes in the worldwide healthcare system.

[13] Suggests an architecture that uses Edge-AI technology, combining Wireless Body Sensor Networks (WBSNs), lightweight models for deep learning, Federated Learning (FL), and Blockchain in a bid to resolve the limitations present in biomedical signal processing. The architecture makes use of improved models for CNN-GRU and quantization methods for processing signals like ECG and sugar levels at edge node. FL is beneficial for updates to the model without exchanging raw data and Blockchain offers the necessary security measures. The experimental tests on standard datasets show that our method has a disease prediction rate of 85%, a decrease in energy consumption of 45%, and a latency index improvement of more than 80% when compared to traditional solutions. This method highlights the necessity of developing secure, low-latency, and scalable eHealth systems and will allow implementing intelligent and privacy-preserving monitoring systems in healthcare of the future.

[14] Presents an effective Edge AI framework to perform real-time analytics in smart health care and wearable computing systems. Its pioneering concept combines federated learning with an edge gateway architecture allowing decentralized model training with preserved patient privacy. The suggested solution uses local model updates coming from the distributed wearable devices, which are collected via the edge gateway to enhance communication efficiency and resource utilization. Experimental evaluation through simulations and real-world deployment

demonstrates a 40% reduction in latency and a 15% improvement in model accuracy compared to centralized methods. The results highlight the system's scalability, energy efficiency, and ability to preserve privacy in large-scale healthcare applications. This work underscores the significance of Edge AI as a viable and secure solution for low-latency, privacy-preserving analytics in personalized and remote healthcare environments.

3. METHODOLOGY

3.1. Sensor Data Acquisition Layer

The Hybrid Edge-AI and Cloudlet-Driven IoT Framework is constructed on the Sensor Data Acquisition Layer, which allows wearable IoT devices to obtain real-time healthcare information. These instruments utilize advanced sensors, which can measure key health metrics such as heart beat rate, blood pressure, blood sugar, and SpO2 levels. Such devices may include smart watches, oxygen saturation monitors, glucose monitors, and electrocardiogram devices. Wearables allow active monitoring, meaning that information is being gathered on the go. Moreover, these devices exhibit a combination of high accuracy content measurements and low power consumption achieved by using miniaturization technology, making them suitable for prolonged application in real medical settings. Figure1 demonstrates the working process of the proposed model.

CoAP and MQTT-SN are two examples of IoT protocols that conduct data transmission between IoT devices and processing layer. These two protocols guarantee efficiency and speed of communication in wireless networks. They are designed for situations with limited resources. In case of MQTT-SN, publish-subscribe principle allows working with the protocols that consume minimum bandwidth and provide reliable connectivity, while CoAP uses the RESTful communications technique for smooth integration into existing IoT environments. Both protocols achieve the required scalability and energy efficiency for real-time data transmission from many IoT devices in case study of healthcare.

The information that is delivered to the edge nodes is rich and still raw, and has to be treated and normalized immediately. For example, noise and sensor calibration may lead to variations in heart rate values, which can be dealt with by applying filtering and smoothing techniques. Time-series methodology helps to retain the temporal order of information vital for future analysis, including anomaly detection and disease forecasting. The system uses protocol driven error handling techniques, thus preventing packet loss or corruption during transmission.

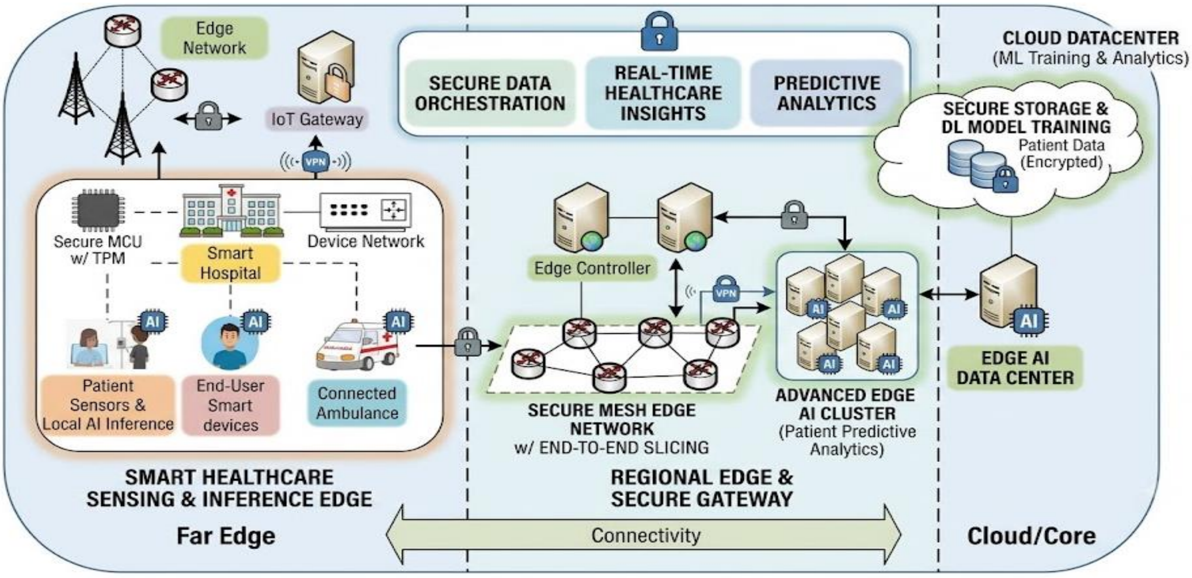

Figure 1. Architecture of the proposed model

Also, this layer has edge gateways connecting edge-AI systems and wearables. They ensure secure communications between various sensors through encryption technology. They also enable localized processing, thereby reducing the workload for IoT systems and preparing data for analysis. Thus, the Sensor Data Acquisition Layer plays a vital role in linking modern analytics and real patient data, providing precision and promptness for medical applications. The time to transmit a packet T_τ over a network is:

$$T_\tau = \frac{P_S}{B} + D \tag{1}$$

Here, P_S stands for packet size (bytes), B for bandwidth (bytes/second), and D for network latency (seconds). When a sensor transmits data, its energy consumption E is:

$$E = V \cdot I \cdot T_\tau \tag{2}$$

In Eq. (2), T_τ is the transmission time (seconds), V is the voltage (volts), and I is the current (amperes).

3.2. Edge-AI Processing Layer

The layer responsible for Edge-AI processing plays a key role in enhancing system responsiveness, reducing delay, and facilitating real-time data analysis at the edge of the network. By utilizing advanced artificial intelligence algorithms such as Temporal Convolutional Networks (TCNs) and transformer architectures, this layer processes healthcare data that has been collected through wearable Internet of things devices. Because Edge AI performs computation locally and sends only necessary information to cloudlets for future processing, there is less dependency on cloud resources.

In multi-dimensional healthcare data, transformer-based models excel at discovering complex patterns and anomalies because they make use of attention mechanisms to focus on the most relevant parts of the data. For example, a Transformer can detect rare ECG patterns and variations in heart rates that may indicate some health problem. However, TCNs are specially designed for sequence processing and do well with time-series data, including such factors like oxygen saturation readings or continuous readings of blood glucose. Since precise anomaly detection is based on the idea that the displayed output does not depend on the upcoming data points, the architecture of TCNs includes causal convolutions. Different techniques of pre-processing such as normalisation, noise reduction, and feature extraction are used to acquire data with less influence of anomalies.

Edge-AI processing is capable of removing repetitive and useless information. This ensures the immediate detection of any abnormalities and significantly cuts back the amount of information sent to cloud processors. In healthcare, this impairment period serves as a way to get rid of internet congestion and facilitate prompt decision making. What is more, Edge-AI allows carrying out immediate actions through localized processing without the need of waiting for cloud processing to be complete. The Edge-AI Processing Layer combines advanced AI technologies and computing capabilities, thereby enhancing the IoT healthcare system's scalability and responsiveness and creating opportunities for early personalized treatment. The attention weight A for a query, key K, and value V is calculated as:

$$A = soft \max \left(\frac{Q \cdot K^T}{\sqrt{d_k}}\right) V \quad (3)$$

Now $Q \cdot K^T$ is the dot product of the query and key vectors, and d_k is the key dimension. A TCN layer's output Y is:

$$Y = \sigma(W * X + b) \quad (4)$$

In Eq. (4), W is Convolution kernel weights, X denotes Input data, b shows Bias term, σ is Activation function

3.3. Edge-AI Driven IoT Computing Layer

The framework of Edge-AI Driven IoT acts as an important connection between edge systems and cloud computing infrastructure. The idea behind this layer is to increase the efficiency of processing of contemporary healthcare data by cloudlets placed near edge nodes that facilitate the integration and processing of healthcare data from many IoT devices. This layer acts as an important filtering step for anomalous inputs from edge-AI systems and moves the computation intensive processes to cloud computing including modeling diseases as well as predicting diseases. By acting as a bridge between edge and cloud, cloud computing systems reduce response time for healthcare solutions, thereby making the workload of edge devices and cloud computing systems smaller.

In healthcare environments where timing is critical, the event-driven design of Flink allows fast analysis and the identification of anomalies. The model can focus on important healthcare data and remove unnecessary information through advanced filtering and classification methods. Additionally, cloudlets also host intermediate machine learning algorithms for applications such as patients monitoring and health risk appraisal systems like random forests or lightweight deep neural networks. Doing so improves network efficiency and reduces the amount of data transmitted by ensuring that only relevant and defined data will be sent to the cloud.

The Edge-AI Driven IoT layer governs real-time data transfer and gives immediate data which helps enhance the scalability & responsiveness of IoT healthcare framework. Apart from bridging edge devices and cloud analytics, Cloudlet processing enables faster detection of certain health problems. In order to ensure an efficient and low-latency data flow in today's healthcare ecosystems, Edge-AI Driven IoT layer combines advantages of Flink with effective anomaly detection and machine learning techniques. The task execution time T_e in a cloudlet is:

$$T_e = \frac{c_t}{P_c} + L \quad (5)$$

Now $P_c$is the cloudlet processing power (cycles/second) and $C_\tau$is the task complexity (CPU cycles). L stands for latency overhead.

$$U = \frac{\sum R_i}{T} \quad (6)$$

In Eq. (6), T is the cloudlet's total resource capacity and R_i is the resource consumption by task i.

3.4. Cloud-Based Analytics Layer

In the framework of Edge-AI IoT, the Cloud-Based Analytics component is tasked as the main computing unit for data processing. This enables thorough healthcare data analysis and retention of medical data for a prolonged time. The cloud layer executes all key processes related to disease forecasting, trend analysis, and personalized health recommendations, by processing vast volumes of data coming from cloudlets.

The structured healthcare data processed by ensemble learning techniques can include electronic health records and demographics, among others. These methods use a variety of parameters to classify and predict patients' results, based on their symptoms, diagnostic findings, and medical history. The cloud layer also acts as a common site where real-time and historical data can be collected for long-term health monitoring. Also, it simplifies the process of rolling out the models and facilitates high-level data processing by allowing the personalized data processes to run through some complicated analytics pipelines based on distributed frameworks like Apache Spark. Thanks to the implementation of cloud-made technologies along with the provision of robust storage means, the data processing framework allows the healthcare sector to make accurate data-driven decisions that help in achieving the best healthcare results.

3.5. Classification

The prediction $f(x)$ for input x using n decision trees is:

$$f(x) = \frac{1}{n}\sum h_i(x) \quad (7)$$

From the equation, $h_i(x)$ is the i^{th} decision tree's output. For model predictions $\hat{y}$, the error E is:

$$E = \frac{1}{n}\sum (y_i - \hat{y})^2 \quad (8)$$

In Eq. (8), $\hat{y}$ and y_i are the predicted and actual values.

3.6. Secure Data Exchange Layer

In order to protect and secure healthcare data across all communication channels involving IoT devices, cloudlets, and the cloud, the Secret Data Exchange Layer plays a vital role in the Hybrid Edge-AI and Cloudlet-Driven IoT Framework. Since healthcare data is confidential in nature, the involvement of blockchain technology in the operation of this layer makes it possible to set up decentralized and resilient communication channels. The unique feature of blockchain is that it allows the validation and authentication of each data transaction and enables compliance with HIPAA and other healthcare standards and regulations.

Every data set is transformed into fixed-length cryptographic hashes by the Secure Data Exchange Layer using hashing technologies like SHA-256. Thus it becomes almost impossible to change the initial data secretly. There are timestamps for every transaction concerned, and the data is registered in blocks right after it is sent from the IoT devices to a cloudlet or a cloud. Only those devices and nodes that have obtained approval are entitled to interact with the network thanks to a consensus process that is used to confirm the block in such mechanisms as Proof-of-Stake (PoS) or Practical Byzantine Fault Tolerance (PBFT).

Secure Data Exchange Layer is integrated with smart contracts to implement security policies previously set, such as granting or revoking access depending on the user's activities and level of responsibility. Those contracts ensure that security and privacy policies are applied immediately as specified conditions apply. In addition, AES-256 and other encryption standards protect the data, while anomaly detection algorithms monitor the network's behavior for any signs of malicious activities.

Secure Data Exchange Layer is providing a comprehensive architecture for protection of the health care-related data by combining new cryptographic techniques with decentralized architecture of blockchain data. Thus, secure and seamless collaboration of IoT-based health care ecosystem can take place and trust can be obtained from all the parties involved, from patients to healthcare service providers and administrators. The hash H for block B is:

$$H = SHA - 256(B) \tag{9}$$

Now, B is a transaction data block and SHA-256 is a secure hash algorithm. T_c , the overall consensus time, is:

$$T_c = T_p + T_v \tag{10}$$

In Eq. (10), T_v and T_p are the verification and propagation time.

To prepare for analysis, the first step is to initialize both the models and the data streams. During the Edge Processing stage, the Edge-AI models make use of normalized sensor data to identify the presence of anomalies in real-time with low latency. Cloudlet Processing comes into play when more comprehensive data analysis is required, where more advanced models are used to improve insights. The Secure Logging mechanism relies on blockchain technology, which allows the generation of a highly secure log of all alarms and anomalies. With the detection of faults at the edge, the system can ensure efficiency by redirecting tasks to cloudlets, which allows for better error handling capabilities.

4. EXPERIMENTAL OUTCOMES

The experiments results showcase the advantages of the given Secure Edge-AI IoT framework using thorough performance analysis. The data show improvements in the areas of real-time monitoring, predictive analytics accuracy, and efficiency of the entire system. The comparative analysis has shown that the system surpasses current healthcare system-enabling solutions based on various metrics of the evaluation process.

4.1. Real-Time Monitoring Performance

The proposed Secure Edge-AI Internet of Things model delivers stable real-time monitoring with consistently low latencies and rapid artificial intelligence insight. The model is capable of processing continuous streams of health data with negligible fluctuations in performance. Thanks to edge computing, the system reduces communication delays and allows timely clinical decision-making. These findings prove that the model is suitable for continuous and time-critical health monitoring applications.

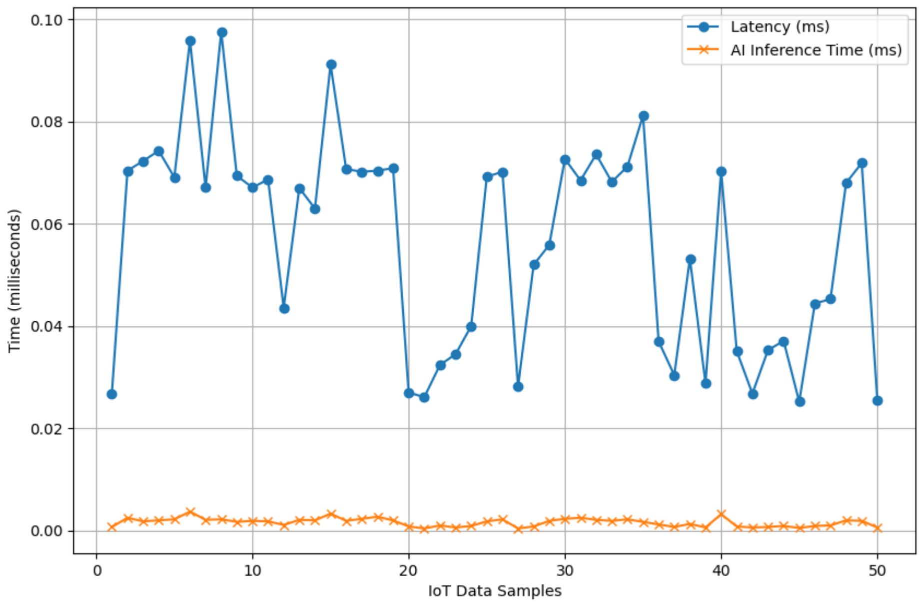

Figure 2. Real-Time Edge-AI Healthcare Monitoring Performance

According to the graph illustrated in Figure 2, both latency and AI inference time remain consistently low throughout the monitoring period. The results show that both of these parameters remain fairly steady with only slight fluctuations across all samples from the Internet of Things. The results show the effectiveness of the system for processing medical data using edge computing.

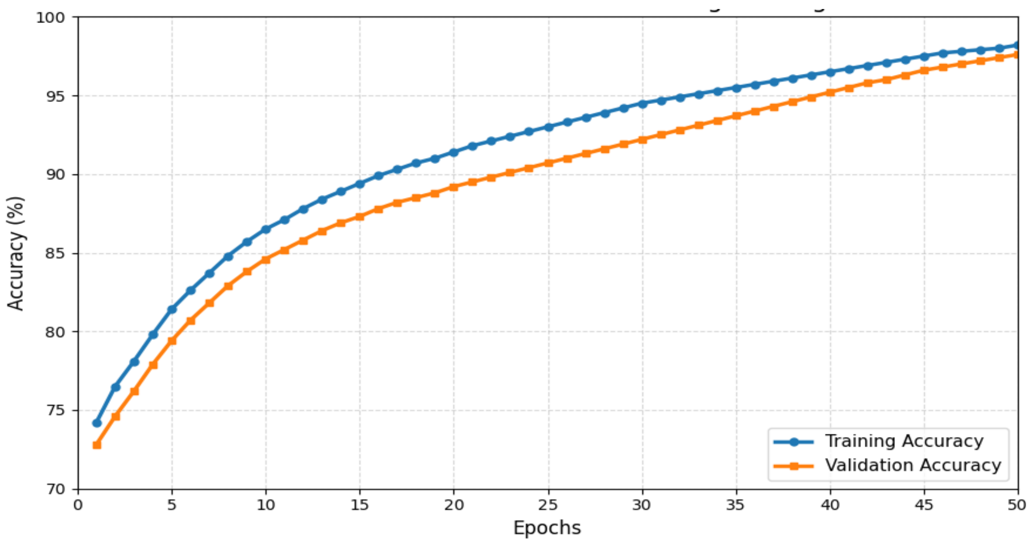

Figure 3. Predictive Model Performance During Training

Training as well as validation accuracy keep improving across all 50 epochs, implying that the model learns correctly (see Figure 3). The best training accuracy is equal to 98.2% and validation accuracy is equal to 97.6%. The small difference between the training and validation curves suggests sufficient generalization capability of the model and very little overfitting. This shows strength of the suggested predictive analytics model. The performance of the proposed model compared with other effective methods is represented in Table 1.

Table 1. Performance Comparison

Method	**Accuracy**	**Precision**	**Recall**	**F1-Score**
CNN	93.4	92.8	92.1	92.4
LSTM	94.6	94.1	93.8	93.9
IoT-Cloud	95.2	94.7	94.4	94.5
Edge-AI	96.4	95.8	95.5	95.6
Proposed Method	98.2	97.9	97.6	97.7

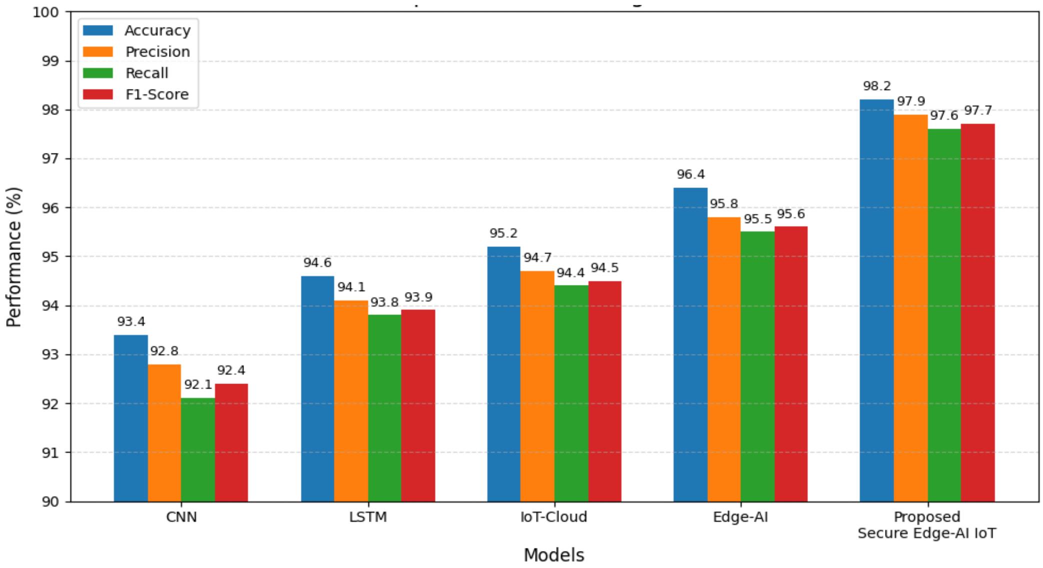

Figure 4. Comparison with Existing Methods

As shown in Figure 4, the proposed framework is compared with CNN, LSTM, IoT-Cloud, and Edge-AI in terms of the grouped bar graph. According to the findings, the suggested method has achieved the maximum Accuracy (98.2%), Precision (97.9%), Recall (97.6%), and F1-score (97.7%). The improved performance indicates the effectiveness of implementing Edge-AI along with secure IoT communication. Thus, generally speaking, the proposed framework shows better results compared to the existing approaches for healthcare monitoring.

5. CONCLUSIONS

In this study, a secure Edge-AI-based IoT framework is suggested which enables healthcare monitoring in real-time and predicting the future health situations. Deep learning models are deployed at the edge nodes to detect medical anomalies and foretell health issues. Lightweight encryption technologies ensure reliable transfer of sensitive information, while blockchain technology is employed to create reliable logs of data access. The system actively allocates tasks to edge and cloud locations in terms of performance and efficiency. Tests show less latency, better predictive ability, and improved data protection compared to older, cloud-only methods of facilitating healthcare. The system makes possible the large-scale implementation of the technology in hospitals, remote monitoring facilities, and nursing homes, facilitating effective healthcare delivery.

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