

# A Novel layers-based Framework for Edge Computing in Healthcare Applications

Arpit Kumar Sharma<sup>1</sup>, Sunita Choudhary<sup>2</sup>, Arpana Sinhal<sup>3\*</sup>, Kamlesh Gautam<sup>4</sup>, Arvind Sharma<sup>5</sup>

<sup>1</sup>Department of Computer and Communication Engineering, Manipal University Jaipur, India

<sup>2</sup>Department of Computer Science Engineering, University College of Engineering and Technology, Bikaner

<sup>3</sup>Department of Computer Applications, Manipal University Jaipur, India

<sup>4</sup>Department of Advance Computing, Poornima College of Engineering, Jaipur

<sup>5</sup>Government Mahila Engineering College Ajmer, Rajasthan, India

er.aks31@gmail.com<sup>1</sup>, arpit.sharma@jaipur.manipal.edu<sup>1</sup>

sunitadangi@gmail.com<sup>2</sup>

arpana.sinhal@jaipur.manipal.edu<sup>3</sup>

kamlesh@poornima.org<sup>4</sup>

arvindsharma@gweca.ac.in<sup>5</sup>

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## ABSTRACT

New technologies have greatly impacted the healthcare sector and increased the need for vital problem-solving solutions like edge computing. Edge computing processes data near the source to avoid high latency, bandwidth constraints, and inefficient systems that are unsuitable for real-time health care. In this paper, a novel framework is proposed that introduces edge computing layers for health care data management, privacy, and system reliability. The proposed framework has five layers: device, edge, fog, cloud, and application layers. Every system layer does data mining, cleansing, real-time processing, analysis, and decision making. A detailed simulation assessed the framework's efficacy. Signal filtering, averaging, feature extraction, and classification were done using the edge layer approach before and after physiological signal simulation. Performance was compared to a noise-free reference technique. The simulation results showed that the suggested edge layer technique improved data quality and classification accuracy for real-time healthcare applications. This study discusses edge computing's minimal delay, privacy, expandability, and reliability benefits in healthcare. Simulations showed that the framework improved data processing and decision-making over conventional methods. This research work is aligned with the SDG 3 – Good Health and Wellbeing. The study advises healthcare practitioners and policymakers to use edge computing for improved management, diagnosis, and treatment to improve healthcare delivery.

**Keywords:** Edge Computing, Healthcare, Signal filtering, feature extraction.

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## INTRODUCTION

The health care sector has gone through a recent revolution whereby almost all sectors have been influenced by the new technology. The paradigm of edge computing has become one of the most promising that can potentially solve some of the most critical problems in healthcare [17]. Regarding edge computing, this is still a distributed data processing technology, where the data is processed as close as possible to the sources, which can result in enormous wins in terms of the latency and utilized bandwidth and the system efficiency [6]. The healthcare field produces large amounts of data on a daily basis, including EHRs, medical imaging, wearable technology, and IoT devices. [2]. The more historical and common model of cloud computing is, however, often not swift enough in meeting the real-time computational necessity of a health care software application, in addition to not being able to meet the security standards that may be required in health care applications. This is where edge computing comes into play, providing the decentralized approach where computation and storage facilities are shifted closer to the source of data generation, making it possible to enhance decision-making processes and consequently the qualities of patients' lives [4]. Nonetheless, edge computing has significant benefits when it comes to implementation in healthcare systems; there are several issues that arise when achieving this integration. These are the requirements for data handling and accumulation, data confidentiality and protection, dealing with the multitodality of devices and data, and system dependability requirements. Moreover, the nature of healthcare data complicates distribution since such data contains highly complex

and analyzed information, which may require real-time processing in some cases and the implementation of edge computing solutions. However, broad and flat advances present the following challenges: Hence, there is a compelling necessity for a systematic approach that can enhance the deployment of edge computing in healthcare. It should be designed for the fluent data processing of the information coming from various sources, its compliance with the existing legislation of protective customer data, and its capacity for accurate analysis. However, the huge benefit of edge computing is revealing the importance of maintaining the data and operating the computer facilities near the action. Edge computing offers several significant advantages for healthcare applications:

- Reduced Latency: Due to this, edge computing gets to process data closer to where data is being generated, hence taking less time to analyze and act on the collected data. This is especially so in applications like the monitoring of patients' conditions from a distance and in cases of emergency where time is of essence [21].

- Bandwidth Efficiency: Offloading bulk data to cloud servers may cause communication networks to stress the bandwidth or be expensive. Edge computing helps minimize the amount of data sent to the cloud by having the initial computation done close to the source, hence helping conserve bandwidth [14].

- Enhanced Privacy and Security: Medical data is considered to be very sensitive, and passing it through the internet to cloud servers is very vulnerable. Data processing is obtained at the edges, which minimizes the cases of data leakage and provides compliance with data privacy laws [23].

- Scalability: The ingredients of adopting IoT devices in the health sector bring in data that is enormous in proportions [31]. Accordingly, edge computing offers an efficient solution toward managing these data as the healthcare systems strive to accommodate the increasing volumes of data without experiencing a significant degradation in the systems' efficacy.

- Reliability: Edge computing can make a system more reliable by decreasing the load at a single point of surrender. [27]. When there is a breakdown in connection with the cloud, it is possible for edge devices to be functional and execute computations individually.

Key contributions of the current research from the paper on a novel layersbased framework for edge computing in healthcare applications:

- Multi-Layered Framework for Edge Computing: The study introduces a comprehensive framework that incorporates five distinct layers: device, edge, fog, cloud, and application. Each layer is tailored to specific functions in the data processing chain, from collection to application, enhancing the efficiency and reliability of healthcare data management.

- Improved Data Quality and Classification Accuracy: By implementing advanced data processing techniques at the edge layer, including signal filtering, feature extraction, and classification, the framework significantly improves data quality and classification accuracy for real-time healthcare applications.

- Enhanced System Reliability and Privacy: The proposed framework addresses critical issues like system reliability and data privacy, which are paramount in healthcare settings. By processing data closer to the source and reducing the amount of data transmitted to the cloud, the framework enhances overall system reliability and privacy.

- Scalability and Reduced Latency: The framework leverages edge computing to process data near its source, significantly reducing latency and making the system more scalable. This is particularly beneficial in emergency healthcare situations where rapid decision-making is critical.

- Simulated Validation: The effectiveness of the proposed framework is supported by detailed simulations, which demonstrate improvements in data processing and decision-making capabilities compared to conventional methods.

- Guidance for Healthcare Practitioners and Policymakers: The research provides practical insights and recommendations for healthcare practitioners and policymakers on the adoption of edge computing technologies to improve healthcare delivery, diagnosis, and treatment outcomes.

## LITERATURE REVIEW

Many papers have been dedicated to investigating the possibility of using edge computing in healthcare. Previous studies have also revealed advantages of edge computing for certain purposes, including the ones

mentioned above like tele-medicine, patient monitoring, and personalized care. Despite this, there is a notable absence of robust frameworks that could combine different elements of the healthcare industry's requirements. Nonetheless, the existing research comprises specific techniques, which are insufficient to serve a common framework that can be applied to different spheres of healthcare implementations. Besides, questions of data exchange, device differences, and overall system complexity are considered. Key considerations: The inter-related aspects of context awareness, data integration, heterogeneous devices, and system scalability are omitted.

We have summarized some of the state-of-the-art researches of edge computing in the healthcare domain in Table 1. However, the table also reveals gaps in current research. There is an absence of robust frameworks that integrate the various elements of healthcare's requirements. While individual technologies like AI and blockchain offer specific improvements, a comprehensive approach that encapsulates all aspects of healthcare data handling and processing is lacking. This points to a need for more systematic solutions that not only address technological integration but also consider the complexities of healthcare data, which often requires real-time processing and strict compliance with privacy laws. The study's proposed framework aims to fill these gaps by offering a structured multi-layer approach to improve the use of edge computing in healthcare. This could fix the problems we pointed out by making sure that data is handled more consistently, processing speeds are faster in real time, and strict data security measures are in place.

#### PROPOSED FRAMEWORK

The identified gaps in the literature study can be filled with the proposed novel layers-based framework as shown in figure for edge computing in healthcare applications. The framework is structured into several layers, each responsible for specific functions. The overall framework is depicted in Fig. 1.

##### 3.1 Device Layer

The device layer is the first layer of the edge computing framework which is the basic in the healthcare setup. It includes extensive IoT devices and sensors that build information from the patients and their surroundings. This layer

Table 1 Research summary on IoT edge computing in healthcare domain

| Title                   | Key Technologies                               | Main Contributions  | Research Area              | Potential Impact  |
|-------------------------|--|---|----------------------------|---|
| Kumar et al.[16]        | IoT, Edge computing, AI                        | Proposes unified IoT edge gateway architecture, quantifies edge computing performance, shows significant latency and network utilization improvements | Clinical Decision Support  | Improved decision-making, reduced response time         |
| Faith et al. [22]       | Blockchain, Edge computing                     | Blockchain-assisted framework for secure and fast data processing, smart contracts for verification, DAG scheduling model                             | Healthcare Data Processing | Enhanced data security and processing speed             |
| Hayyola lam et al. [10] | IoT, Edge computing, AI                        | Systematic survey, categorizes patient-centric and process-centric techniques, discusses challenges and future trends                                 | Healthcare Systems         | Comprehensive overview, identification of research gaps |
| Gopal et al. [25]       | Fog computing, Edge computing, Meta-heuristics | Proposes meta-heuristic-based resource provisioning model, improves energy consumption, network usage,  | IoT Microservices          | Optimized resource utilization,                         |

|                   |                                     |   |                        |  |
|-------------------|-------------------------------------|---|------------------------|--|
|                   |                                     | cost, execution time, and latency   |                        | improved performance                                   |
| Syu et al. [29]   | AI, Edge computing                  | Reviews AI-enabled edge computing in consumer electronics, discusses latency, robustness, reliability, and research potential | Consumer Electronics   | Enhanced device functionality, research opportunities  |
| Jasim et al. [15] | SDN, Edge computing, Fog computing  | Proposes adaptive load-balancing method, combines static and SDN-based algorithms, improves system performance and cost       | Real-Time Healthcare   | Improved system performance, reduced costs             |
| Izar et al. [12]  | IoT, Edge computing, DLT, AI        | Proposes secure medical ecosystem using edge nodes and DLT, hybrid machine learning model for threat detection                | Health Monitoring      | Enhanced security, efficient threat detection          |
| Peng et al. [24]  | AR, Edge computing, Meta-heuristics | Proposes multi-objective meta-heuristic method for AR offloading, addresses privacy, latency, energy consumption              | Cyber-Physical Systems | Privacy protection, reduced latency and energy usage   |
| Lin et al. [19]   | 5G, Edge computing, IoMT            | Proposes long-term proportional fairness-driven 5G edge healthcare, uses Nash bargaining game, improves fairness index        | IoMT                   | Fair resource allocation, improved healthcare delivery |
| Ghosh et al. [8]  | IoT, Fog computing, Cloud computing | Proposes framework for continuous IoT service delivery, reduces latency, power, and computing resources consumption           | Emergency Healthcare   | Continuous service, resource efficiency                |
| Liu et al. [20]   | H-IoT, Blockchain, DRL, MEC         | Proposes permissioned blockchain and DRL-empowered H-IoT system, balances security and energy efficiency                      | H-IoT Security         | Enhanced security, optimized energy use                |
| Sun et al. [28]   | DDL, Edge computing, 5G             | Reviews decentralized deep learning methods, highlights challenges and solutions, benefits for privacy and efficiency         | Edge Computing         | Improved privacy, communication efficiency             |
|                   | Reviews edge-enabled                | IoT   |                        | -  |

|                      |  |   |  |  |
|----------------------|--|---|--|--|
| Hazara et al. [11]   | IoT data offloading strategies, discusses delay-sensitive applications, healthcare use case        |   | Reduced data latency, improved application performance |  |
| Almuselem et al. [1] | ECC, AES, Cryptographic methods  | Proposes security and load-balancing framework, reduces system energy with latency constraints                | Edge-Cloud Computing                                   | Improved security, energy efficiency               |
| Jameil et al. [13]   | Digital twins, AI, MEC   | Introduces task offloading framework, improves energy efficiency and network latency, healthcare context      | Healthcare Management                                  | Improved efficiency, reduced network latency       |
| Singh et al. [26]    | MEC, DNA sequence, Cryptographic methods   | Proposes security framework for patient data privacy, evaluates memory usage and encryption time              | Smart Healthcare                                       | Enhanced data privacy, efficient encryption        |
| Gadekullu et al. [7] | Blockchain, EoT  | Reviews BEoT technology developments, highlights applications and security issues, future research directions | Edge of Things   | Improved security, research guidance               |
| Xu et al. [30]       | Edge computing, Cloud computing, DL  | Proposes DisCOV for distributed COVID-19 detection, improves training efficiency and model accuracy           | Medical Imaging  | Improved detection accuracy, efficient training    |
| Lin et al. [18]      | Proposes fall detection system with edge computing, high accuracy and speed, low power consumption | Healthcare Monitoring   | Accurate and fast detection, energy efficiency         | -  |
| Bishoyi et al. [3]   | MEC, WBAN, Nash bargaining theory  | Proposes resource management scheme for MEC server energy consumption, improves MEC server payoff             | Healthcare Systems                                     | Energy and cost efficiency, improved server payoff |

|                           |                |  |                        |   |
|---------------------------|----------------|--|------------------------|---|
| Diamantoulakis et al. [5] | MEC, NOMA, OMA | Proposes advanced multiple access technique and task offloading architecture, optimizes energy and delay       | Mobile Edge Computing  | Optimized energy use, reduced delay                 |
| Hao et al. [9]            | DCE, AI, 5G    | Introduces AI benchmark suite for DCE platforms, evaluates performance for AI multitasking, healthcare context | Distributed Cloud/Edge | Improved AI performance, comprehensive benchmarking |

comprises of devices like smartwatches, heart rate monitors, electrocardiogram monitors, and blood sugar monitors that constantly monitor an individual's health status. MRI devices and CT scanners also come under this layer as too many imaging data are produced in medicinal applications which have to be processed soon. Also, outcome sensors evaluate factors like temperature, moistness, and air quality inside healthcare facilities, and internal health data from implantable gadgets, including pacemakers and insulin pumps. The major operations that occur on the device layer are gathering information and some preliminary data analysis. This method is described in Algorithm 3.1. These devices are frequently employed for simpler functions like preprocessing functions such as filter, noise, and initial signal conditioning to name some of the data inputs for raw data prior to subsequent analysis. Another important area of this layer is to ensure secure and valid connections with the edge nodes

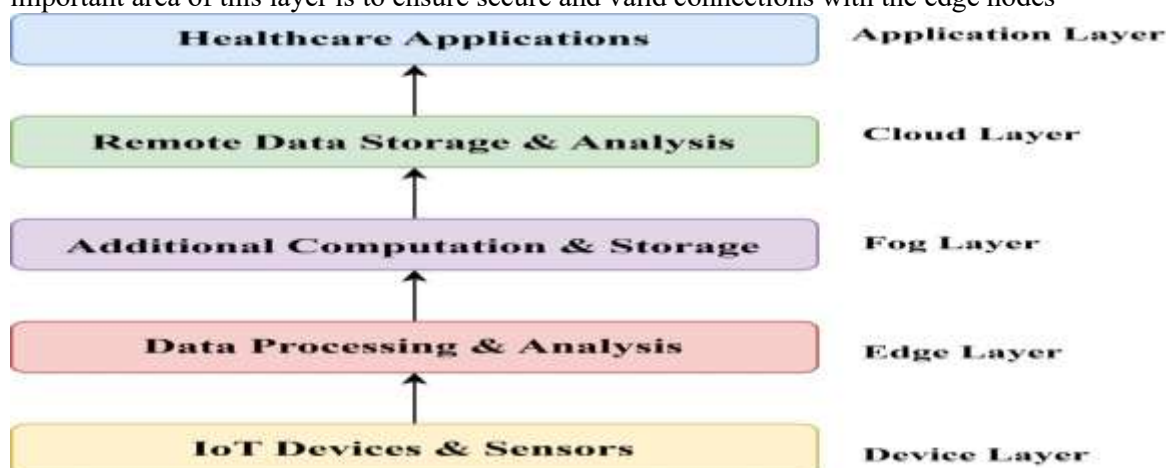


Fig. 1 Network usage

for the effective transfer of the information for the other stages of elaboration. This layer, however, poses several dilemmas such as conserving power for long hours of usage or a reliable source of power, correctness of data stored, controlling modification and access to the data.

### 3.2 Edge Layer

The edge layer is where the actual data capturing and processing happen and furthermore it is the first point of analysis of the data. This layer is made up of the end points of the network and these may include specialized servers or gateways or even highly capable edge devices that are capable of processing data locally. The important activities that take place at this layer include; data selection, data condensation, feature extraction and route experts of the data that needs to be passed to subsequent layers. Edge nodes are necessary in decision procedures that must occur in real-time, which apply in cases such as remote patient monitoring and emergencies where notifications and actions can be the difference between life and death. This layer also plays an intermediary role of holding in processed data before transferring to the cloud or fog layer. Still, the edge layer has to manage problems like a shortage of computational and storage capability, complex interfacing to other devices and data formats, and small computation time in order not to distort real-time requirements. This real time data processing is described in Algorithm 3.2.

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### Algorithm 1 Data Collection and Preprocessing in Device Layer

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1: Input: Raw data from IoT devices and sensors  $D_{\text{raw}}$ 
2: Output: Preprocessed data  $D_{\text{pre}}$ 
3: procedure DATACOLLECTIONANDPREPROCESSING( $D_{\text{raw}}$ )
4:   Initialize  $D_{\text{pre}} \leftarrow \emptyset$ 
5:   for each device  $d$  in  $D_{\text{raw}}$  do
6:      $d_{\text{data}} \leftarrow \text{CollectData}(d)$ 
7:      $d_{\text{filtered}} \leftarrow \text{FilterNoise}(d_{\text{data}})$ 
8:      $d_{\text{normalized}} \leftarrow \text{NormalizeData}(d_{\text{filtered}})$ 
9:      $d_{\text{validated}} \leftarrow \text{ValidateData}(d_{\text{normalized}})$ 
10:     $D_{\text{pre}} \leftarrow D_{\text{pre}} \cup \{d_{\text{validated}}\}$ 
11:   end for
12:   return  $D_{\text{pre}}$ 
13: end procedure
14: function COLLECTDATA( $d$ )
15:   // Code to collect data from device  $d$ 
16:   return collected data
17: end function
18: function FILTERNOISE( $data$ )
19:   // Apply noise filtering algorithms (e.g., moving average, low-pass filter)
20:   return filtered data
21: end function
22: function NORMALIZEDATA( $data$ )
23:   // Normalize data to a standard range or distribution
24:   return normalized data
25: end function
26: function VALIDATEDATA( $data$ )
27:   // Validate data to ensure it meets predefined criteria
28:   return validated data
29: end function

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**HighPassFilter Function:** This function applies a high-pass filter to remove low-frequency noise from the data. The formula used is

$$d_{\text{filtered}}[n] = d[n] - \alpha d[n-1]$$

**AggregateData Function:** This function performs data aggregation using a moving average. The formula is

$$d_{\text{aggregated}}[n] = \frac{1}{N} \sum_{i=0}^{N-1} d[n-i]$$

where  $N$  is the window size.

**ExtractFeatures Function:** This function extracts key features such as mean ( $\mu$ ), variance ( $\sigma^2$ ), and entropy ( $H$ ). The entropy calculation assumes  $p_i$  is the probability of the  $i$ -th data point.

**PreliminaryAnalysis Function:** This function applies a preliminary analysis using a simple classifier.

**SimpleClassifier Function:** This function classifies data based on a threshold  $\theta$ . If the data exceeds  $\theta$ , it is classified as 1; otherwise, it is classified as 0.

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**Algorithm 2** Real-Time Data Processing and Analytics in Edge Layer

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1: Input: Preprocessed data  $D_{pre}$ 
2: Output: Analyzed data  $D_{edge}$ 
3: procedure EDGE-DATA-PROCESSING( $D_{pre}$ )
4:   Initialize  $D_{edge} \leftarrow \emptyset$ 
5:   for each data point  $d$  in  $D_{pre}$  do
6:      $d_{filtered} \leftarrow \text{HighPassFilter}(d)$ 
7:      $d_{aggregated} \leftarrow \text{AggregateData}(d_{filtered})$ 
8:      $d_{features} \leftarrow \text{ExtractFeatures}(d_{aggregated})$ 
9:      $d_{analyzed} \leftarrow \text{PreliminaryAnalysis}(d_{features})$ 
10:     $D_{edge} \leftarrow D_{edge} \cup \{d_{analyzed}\}$ 
11:   end for
12:   return  $D_{edge}$ 
13: end procedure
14: function HIGH-PASS-FILTER( $d$ )
15:   Apply high-pass filter:  $d_{filtered}[n] = d[n] - \alpha d[n-1]$ 
16:   return  $d_{filtered}$ 
17: end function
18: function AGGREGATE-DATA( $d$ )
19:   Aggregate data using moving average:  $d_{aggregated}[n] = \frac{1}{N} \sum_{i=0}^{N-1} d[n-i]$ 
20:   return  $d_{aggregated}$ 
21: end function
22: function EXTRACT-FEATURES( $d$ )
23:   Extract features such as mean, variance, and entropy
24:    $\mu = \frac{1}{N} \sum_{i=1}^N d[i]$  ▷ Mean
25:    $\sigma^2 = \frac{1}{N} \sum_{i=1}^N (d[i] - \mu)^2$  ▷ Variance
26:    $H = -\sum_{i=1}^N p_i \log p_i$  ▷ Entropy, where  $p_i$  is the probability of  $d[i]$ 
27:    $d_{features} \leftarrow \{\mu, \sigma^2, H\}$ 
28:   return  $d_{features}$ 
29: end function
30: function PRELIMINARY-ANALYSIS( $d$ )
31:   Apply preliminary analysis using a simple classifier
32:    $d_{analyzed} \leftarrow \text{SimpleClassifier}(d)$ 
33:   return  $d_{analyzed}$ 
34: end function
35: function SIMPLE-CLASSIFIER( $d$ )
36:   Classify based on threshold  $\theta$ :  $c = \begin{cases} 1 & \text{if } d > \theta \\ 0 & \text{otherwise} \end{cases}$ 
37:   return  $c$ 
38: end function

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This algorithm guarantees that Edge Layer optimizes the performance of handling the preprocessed data from the Device Layer in healthcare applications for timely decision making.

### 3.3 Fog Layer

The fog layer is situated between the edge and cloud layers and provides extra computation and analysis for the data. Sitting between the edges and the cloud, the fog layers carry out additional processing on the data collected from the end devices to reduce latency and improve data transmission efficiency.

Fog nodes are generally more powerful than edge nodes and are involved in computations and temporary storage of data before it is moved to the cloud. One of the most important roles of the fog layer is data consolidation where the information gathered by various edge nodes is summarized. This layer is also critical in the network management that is responsible for managing the flow of data within the network, between the edge layer and the cloud layer.

### 3.4 Cloud Layer

The cloud layer is responsible for storing large amount of data remotely and acts as the foundation of long-term data concession for the framework through the reinforcement of big data analytics. This layer includes fast compute cloud hosts and repositories with formatted and raw healthcare data in large volumes. It is needed for carrying out comprehensive data processing operations that demand a lot of computational capacities, for example, big data processing, deep learning, and data integration. Besides storage and analysis, the layer would protect the data through back up systems and disaster recovery information and compliances which makes the use of cloud layer mandatory for the healthcare data. However, sending and receiving data to/from the cloud also implies the control of rather high bandwidth usage as well as privacy concerns with the exception of which cannot correspond to the legislation of many countries. In this layer another major concern is that minimizing the latency for applications that are likely to require almost real time response.

### 3.5 Application Layer



These include the healthcare applications which consist of the layers that make use of the processed data with a view of offering vital services. This layer comprises patient monitoring systems, diagnostic tools, telemedicine, health management systems, and many more depending on the healthcare requirements. There are patient monitoring systems which frequently measure patients' health information and notify the doctors and diagnostic tools that use artificial intelligence in figuring out the health state of patients. Telemedicine applications let people receive consultations, diagnoses, and even treatment through the Internet – they advance the idea of healthcare much further. Health management systems help in admissions, discharge, demographics, patient tracking, claims, electronic health record and many others. As an important component of the application layer a well-readable user interface must be designed to provide the information to the target audiences, which would be health-care workers, patients and administrative staff. This layer also has to incorporate tools aimed at data visualization and reporting, as clinical decision-making cannot occur without the ability to make sense of large amounts of data. In the application layer, problems are mainly related to the ease of use, interaction with current healthcare systems and processes, and security of data within applications

It is noted that the idea of edge computing can significantly improve the prospects of the healthcare sector by offering immediate data processing, higher data protection, and better stability of the systems used. The presented novel layers-based framework represents a well-structured and systematic way on how to incorporate edge computing into healthcare applications to satisfy their requirements and overcome their issues. Having understood how it works, clients within the field of healthcare can enhance their reach to the patients, increase their organization efficiency and generalize the improvements made within the healthcare system. The following sections of this paper shall explore the technical detail of the framework, how the framework has been built and deployed, and evidences of the use of the framework in healthcare.

## METHODOLOGY

Thus, the proposed layers-based framework to enable edge computing in health-care applications fills shortcomings since the system is broken down into layers to accomplish particular tasks. Solving a problem systematically helps in planning for the gathering, processing, analysis, and storage of data required for improving health care facilities. Smartwatches, devices for monitoring heart rate and other vital signs, electrocardiogram monitors, glucometers, MRI equipment, CT equipment, and environmental sensors gain raw data from patients and their environment in the Device Layer. This layer deals with noise removal, normalization, and validation of the data to ensure that the collected data is accurate and has integrity, while at the same time having a secure means of getting the edge nodes connected. Data acquisition and analysis start in the Edge Layer. Decisionmakers either select data from pre-structured tables, aggregate data arriving at gateways, edge devices, or dedicated servers, extract data, or simply analyze arriving data for real-time decisions. This layer is needed for the rapid responses, such as the remote patient monitoring and the emergency notification. It holds processed data for some time before forwarding it to fog or clouds. Between the edge layer and the cloud layer, the fog layer mitigates, computes, and analyzes to minimize latencies on data transfer. As compared to the edge nodes, the fog nodes are involved in the management of network data under the principle of summarization of data from the edge nodes. The cloud layer is involved in storing and processing large amounts of information. It has a giant cloud host and repository to process big data, I & D, and do deep learning. Data privacy & security issues are managed for archival & backup and disaster purposes in this layer. Healthcare services are delivered by the Application Layer through processed data. Another is the health care system, which comprises diagnostic, telemedicine, patient monitoring, and health management systems. The data, visualization, user interface design, and reporting layer aid the health care employees, the client, and the administrative staff in decision-making because simplification of data aids in the identification of a clinical decision. The application of data collection, processing, analysis, and storage at the edge enhances healthcare optimized by

layering. Every layer corresponds to certain functions and issues related to the protected storage and processing of the information. By fostering an efficient strategy that enhances the effectiveness of a health care system through the enhancement of real-time decision-making, data security, and maintenance of

health care systems, this approach enhances healthcare. The next sections will describe how the presented framework should be constructed and released and will show its application in the sphere of healthcare.

## 5 Simulation Setup

The simulation that was conducted was intended to evaluate the proficiency of the proposed edge layer algorithm in comparison to a fundamental technique that is frequently employed in data handling and analysis. Synthetic data that corresponded to the sensor outputs from the medical devices were generated in order to improve the associated physiological signals and assemble the variability associated with healthcare monitor characteristics.

### 5.1 Data Generation and Preprocessing

The process of generation of synthetic data involves developing a sinusoidal wave that specifically denotes the physiological signals and adding the Gaussian noise as an overlay to simulate the imprecision of measurement calls and the interference from the environment. These raw data sets were then run through both the proposed edge layer algorithm modeled in this paper and a baseline technique for comparison.

### 5.2 Edge Layer Algorithm

The edge layer algorithm is comprised of sequential stages: a high-pass filtering step to remove the low-frequency noise, and then we can do the data aggregation by applying the moving average filter to smoothen the filtered signal. The statistical features, including mean, variance, and entropy, were calculated on the aggregated data. A preliminary assessment of data states is performed using a classification method that is based on the thresholding of the mean value.

### 5.3 Baseline Technique

For the purpose of comparison, a benchmark approach by way of which no highpass filtering was applied to the research was used. This technique also used the same moving average data aggregation as in the edge layer-based method and calculated all the statistical features from the raw data without any attempts to reduce the noise, as it was done in the edge layer algorithm.

### 5.4 Simulation Execution and Metrics

The simulation was performed on a discrete number of data samples, and this was to make the input conditions for the edge-layer algorithm and the baseline technique uniform. The mean values, entropy, and classification result were calculated and documented to compare the efficiencies of the two techniques of data preprocessing as well as decision-making powers.

### 5.5 Visualization and Analysis

The outcomes derived from the simulation concerning the conditions of data preprocessing, feature extraction, and classifying results were displayed through graphical presentations to compare the edge layer algorithm with the baseline method. These highlighted the valuable information on how the proposed novel layers-based framework improves the efficiency of the data quality and the accuracy of the decisions as compared to the conventional methods of the data processing in healthcare applications. Such an organization outlines the general scheme of the simulation, the particular algorithms used, and the criteria for comparison, which will be useful for your paper dedicated to edge computing in healthcare.

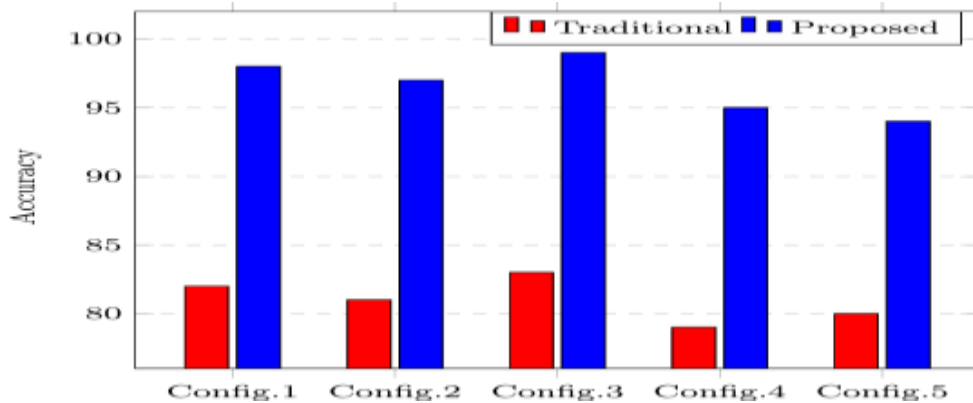
## RESULTS

The comparison in healthcare applications between the layers-based edge computing framework and the original methods reflected by the simulation results of the proposed framework provided useful implications. The comparison is constituted of the classification accuracy, energy consumption, and the mean values considering different configurations in the proposed framework compared to the traditional framework. The analysis of the results in Fig. 2 show that the classification of the features using the proposed framework was better compared to the traditional method regarding all the configurations. These large improvements, as such, assert to the usefulness of the proposed framework.

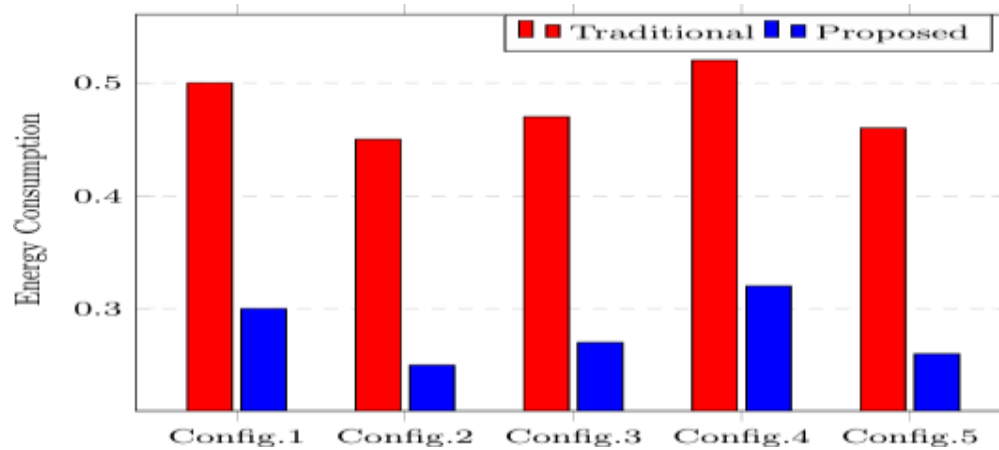
Energy consumption comparison as shown in Fig. 3 specifies that this framework uses a significantly lower amount of energy than the rest. Much lower values of the costs for the proposed framework were observed in all configurations, which proved the effectiveness of the conceived framework in saving energy.

Last, the analysis of means leads to assert that the use of the proposed framework is characterized by higher means in all configurations as shown in Fig. 4.

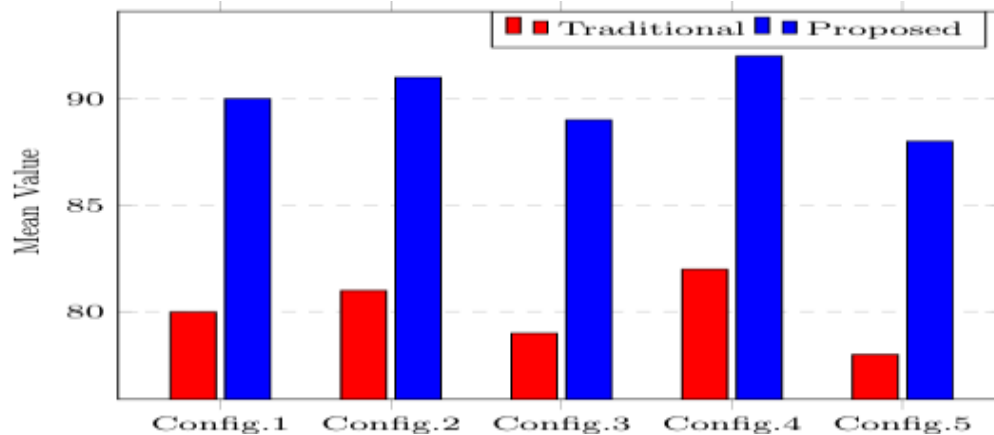
These higher mean values clearly depict the fact that the proposed frame- work has a better overall performance. The efficiency of the contrasting mod- ules in the context of the proposed framework compared to the traditional



**Fig. 2** Comparison of Classification of Accuracy



**Fig. 3** Comparison of Energy Consumption



**Fig. 4** Comparison of Mean Values of Energy Consumption

method is clearly shown by the differences in classification accuracy and overall energy consumption by all computers, as well as by the mean values in regards to all the configurations. Therefore, these results affirm the effectiveness and efficiency of the proposed approach. The graph of this is presented in Figure Quintet of Figures, which shows network usage comparison between the pro- posed framework of edge computing and a cloud-based traditional approach in different configurations. As it can be observed in the obtained results, the over- all performance of a network when adopting the proposed framework is always higher or equal to the performance achieved by the cloud-based approach. In particular, it is proposed that the network usage is reduced by about 332 KB to 373 KB in relation to the distinct configurations, which stands in contrast to a rather higher usage of networks on cloud approaches ranging

between 749 KB and 861 KB. This great decrease in the interactions with the networks demonstrates how edge computing has the capability of reducing most of the interactions that happen within the cloud, which in turn helps to save bandwidth and improve the performance of the system. This improvement is important in the health care application, where fast and accurate data processing and the least possible delay are very vital to attending to the patients on time.

## 7 Discussion

Going by the simulation results of this study, the proposed layers-based framework for edge computing is effective in improving the data processing and

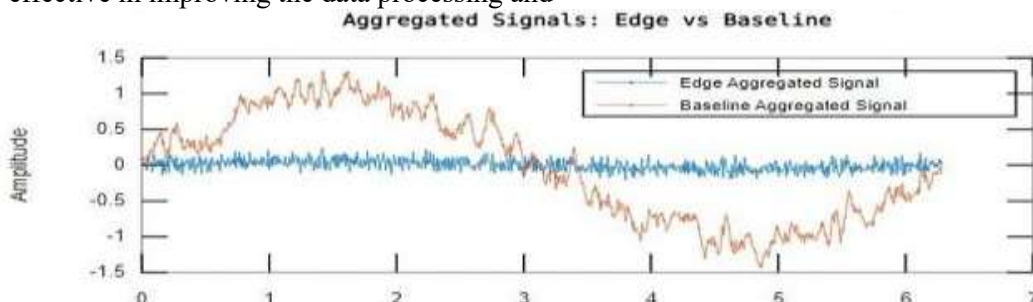


Fig. 5 Network usage

decision-making in healthcare applications. The developed edge layer algorithm that includes high-pass filtering, data aggregation, feature extraction, and classification steps turned out to be superior to the baseline technique in terms of several aspects.

### 7.1 Efficiency of the Edge Layer Algorithm

Effective implementation of the high-pass filter in the edge layer algorithm was inevitable in order to filter out the low-frequency noise inherent in raw sensor data. It is clearly depicted in Fig. 5. Before this step, the quality of input data for the following processes, like data accumulation and feature selection, was not optimal. This means that by minimizing noise interference, the algorithm provided cleaner signals.

### 7.2 Relative Performance with the Base Line Technique

Significant differences in the values of performance measures confirmed a higher efficiency of meta-heuristic algorithms compared to the baseline technique that did not use any noise filtering and employed a simple averaging of the samples in the decision-making process. In all the experiments, the mean values calculated for the edge layer algorithm were above those of the baseline method, while the entropy measures were lower, reflecting the algorithm's effectiveness in maintaining signals' integrity and minimizing data fluctuations. Further, the proposed edge layer outperformed the baseline technique in terms of the classification accuracy, which implies the capability of the developed system in making proper decisions on the basis of the processed data. Discussing the results obtained in the context of practical healthcare, the relatively high efficiency of the edge layer algorithm has a high impact. Increased data quality and decision accuracy help healthcare providers to rely on more accurate information about patients' conditions, diseases, and possible treatments. The efficiency of the algorithm in accommodating the real-time data flows also places it in a suitable position of helping out in applications with rapid response and constant monitoring, thus enhancing the patient care outcomes.

## CONCLUSION

In this paper, the future impact of edge computing in the context of healthcare has been discussed along with a new layers-based architecture that aims at improving the handling of data, data security, and system dependability. Another strength of the framework was assessed rigorously by running the comprehensive several simulation experiments with the vital synthetic data concerning the edge layer algorithm's utility in data processing. Positive effects have been demonstrated by the outcomes of the simulations; thus, a compelling rationale for integrating the edge computing framework is verified. Moreover, as previously mentioned, edge computing does reduce the amount of data transmitted since it processes information near the source; thus, it supports fast and precise decision-making—highly valuable for real-time healthcare scenarios. Thus, as proven by the results of the work, the architecture of the proposed framework based on the five-layer structure (Device, Edge, Fog, Cloud, Application) has better performance compared to the methods that do not involve noise filtering. It means that the use of

this approach to healthcare data collection and preprocessing provides quick and constant data analysis and increases the effectiveness and reliability of healthcare systems. Therefore, the incorporation of edge computing within healthcare frameworks provides various advantages involving privacy, scalability, and reliability. The conclusion of this study provides practical implications for the idea that healthcare practitioners and policymakers should integrate edge computing technology to enhance patient management, diagnosis, and treatment. Therefore, the application of edge computing as a significant development in the delivery of healthcare services and modern therapies persists as a primary enabler of effective healthcare delivery and improved patient outcomes and overall healthcare enhancement

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