Telecommunication Systems (2025) 88:12
https://doi.org/10.1007/s11235-024-01255-x

Revolutionizing neurostimulator care: enhancing remote health monitoring through SDN-cloud networks

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Accepted: 29 December 2024 / Published online: 4 January 2025
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Abstract

The Internet of Things (IoT) and artificial intelligence (AI) are rapidly advancing technologies with significant implications for healthcare. This study aims to develop and evaluate a remote healthcare monitoring (RHM) model that integrates an auricular therapy device with Software Defined Networking (SDN) and cloud networks to enhance neurostimulator care in smart cities. The auricular therapy device collects brain signal data non-invasively through the outer ear and communicates via Bluetooth between patient and doctor smartphones. The collected data is processed to eliminate noise and normalized before classification using an adaptive fuzzy based Bayesian metasalp neural network (AFBBMNN) combined with levy flight secure offloading analysis within an SDN framework. The processed data is then transmitted to doctors via a cloud-SDN module, consisting of a communication phase, cloud server, and cloud database. Results demonstrate significant improvements in remote health monitoring, enabling early detection of neurological conditions and enhancing healthcare provision within a smart city framework. The proposed method shows promise as an efficient tool for early neurological disease detection and treatment.

Keywords Auricular therapy device · Artificial intelligence · Internet of things · Software defined networking · Adaptive fuzzy based bayesian metasalp neural network · Remote healthcare monitoring system

Abbreviations

SDN	Software defined networking
SDIoT	Software defined internet of things
SDWBAN	Software defined wireless body area networks
IoT	Internet of things
MEC	Mobile edge computing
mHealth	Mobile health
AA	Auricular acupuncture
ML	Machine learning
FFDNN	Feed-forward deep neural network
AFBBMNN	Adaptive fuzzy based bayesian metasalp neural network.
WBAN	Wireless body area networks
AAL	Ambient assisted living
HMS	Healthcare monitoring system
HML	Hybrid machine learning
IoT-HMCF	IoT-enhanced healthcare monitoring and control framework

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1 Introduction

The rapid evolution of technology in the modern era has had a profound impact on various sectors, with healthcare being one of the most significantly transformed fields. The integration of advanced technologies, such as the Internet of Things (IoT) and Software Defined Networking (SDN), into healthcare systems has paved the way for innovative solutions that enhance patient care and streamline medical processes. In particular, the application of these technologies in remote health monitoring has shown tremendous potential, offering new avenues for managing patient health, especially in specialized fields like neurology [1].

This paper explores the development and implementation of a remote health monitoring system using an auricular therapy device (neurostimulator) integrated with SDN. The neurostimulator provides non-invasive stimulation to the outer ear, gathering crucial health data that can be transmitted and analyzed remotely [1]. By leveraging SDN, the system enhances the flexibility, scalability, and efficiency of network management, crucial for handling the vast amounts of data generated by IoT devices in healthcare settings [2]. To fully understand the significance and potential of this innovative approach, it is essential to delve into the background and foundational work that has shaped the integration of SDN and IoT in healthcare. This section will discuss the motivation behind this study, the organization of the paper, and the specific contributions made by our research.

1.1 Motivation

In the modern era, integrating healthcare with advanced technologies is more than just a trend—it's a necessity. The potential for technologies to revolutionize patient care, particularly in specialized fields like neurology, has led to a plethora of research and innovative systems [3]. As we delve into the realm of remote health monitoring systems for auricular therapy devices (neurostimulators) using Software Defined Networking (SDN), it is imperative to take a step back and examine the foundational work that has shaped this niche.

1.2 Background

Healthcare today covers a wide range of topics, including clinical treatment, laboratory analysis, and public health awareness. However, healthcare monitoring empowers service providers to extend their care beyond hospitals. It facilitates precise tracking of patient health progress, the ongoing delivery of top-notch services, and the identification of individuals who might be facing potential risks. Moreover, it allows patients to maintain communication with their medical experts, adhere to treatment regimens, and make strides in their journey towards well-being. In contrast, those residing in remote areas experience limited access to modern healthcare services due to the scarcity of technology and medical practitioners [4]. In this situation, real-time monitoring of patients' conditions, surroundings, and care is essential. An essential component of mobile health (mHealth) technology, IoT-based healthcare management offers beneficial and preventive remote health interventions. This groundbreaking application was created to meet the needs of a growing population and to lower the exorbitant expense of healthcare. It integrates readily available medical resources and provides intelligent, secure, and reasonably priced healthcare services. All sensor networks are, by their very nature, application-specific and cannot be set up in a flexible manner.

1.3 Auricular therapy device

The auricular device, consisting of a small battery unit and four electrodes affixed to the ear with adhesives, plays a pivotal role. Auricular acupuncture (AA) is a technique that diagnoses and treats physical and psychosomatic issues by stimulating specific ear points. Ear stimulation engages various biological systems, including the neurological reflex, neurotransmitters, cytokines, the immune system, and inflammation [5]. The underlying processes of auricular therapy are closely connected with the autonomic nervous system, the neuroendocrine system, and factors in neuroimmunology, neuroinflammation, and neural reflex, along with antioxidative actions. This therapy has proven effective for pain management, treating epilepsy, diabetes, anxiety, obesity, and enhancing sleep quality without any side effects (Narayanan and Subbian, 2023). Although the device's electrodes penetrate the skin, they typically cause no discomfort. Operating at 3.2 V with varying frequencies, many patients don't even notice the stimulation. The device is meant to be worn for five consecutive days each week, with at-home removal.

1.4 Software defined networking in healthcare

The neurostimulator, an innovative auricular therapy device, offers non-invasive stimulation to the outer ear. After gathering data, it sends it to a patient's mobile app via Bluetooth and saves it to a cloud server using an HTTP POST request. Significantly, the adoption of SDN enhances the economic adaptability and agility of sensor networks. By distinguishing between the control and data planes, SDN facilitates more flexible network management. As a result of this benefit, SDN has been reinforced for 5G and wireless mobile access networks [6]. SDN is a developing strategy that has gained a lot of support from businesses and academic institutions. It aims to promote and automate network infrastructure and setup. Creating infrastructures that enable a more complex method by placing reliability and security at the forefront of the process is a relatively new platform for preventing, tracking, monitoring, segregating, reducing, and potentially mitigating the negative consequences of the majority of network intrusions. The fundamental element of the SDN architecture that has improved technical innovation is the centralization of the control plane, which is now scattered among routers and switches inside conventional networks with forwarding device capabilities [7].

1.5 IoT and edge computing

In the medical and healthcare sectors, IoT devices will generate vast amounts of data, ranging from highly sensitive information to data requiring immediate analysis and decision-making. However, because IoT devices have constraints in computing power, storage, and energy, they can't handle telemedicine applications locally. Directly offloading all this health data to the cloud would not only overburden the cloud infrastructure but also consume significant network bandwidth, leading to increased transmission delays [4]. Additionally, the cloud computing facility is unable to offer location-aware apps.

5G-driven Mobile Edge Computing (MEC) enhances the network foundation for telemedicine. By situating computing, storage, and other infrastructures closer to users or data sources, MEC extends traditional cloud computing to edge nodes [6]. Essentially, MEC integrates compute, storage, networking, and application features right at the network's periphery. Unlike conventional cloud computing, MEC's main characteristics include network capabilities. Decentralization, data localization, and reduced latency are attributes of MEC. The marriage of MEC and telemedicine is very important..

1.6 Contributions

The following works are the contributions of the article:

a. The proposed working process of the auricular therapy device (neurostimulator) from a remote monitoring system, which includes the additional benefits compared with an existing system.
b. The literature survey of IoT and SDN, which ensures network flexibility and helps to communicate with the hardware infrastructure.
c. The device is programmed and re-programmed on a demand basis using SDN to measure data traffic for optimized solutions.
d. The collected data has been classified by using an adaptive fuzzy-based Bayesian metasalp neural network (AFBBMNN) with levy flight secure offloading analysis in SDN.

1.7 Organization

The rest of this paper is organized as follows: Sect. 2 reviews related work in the fields of IoT, SDN, and auricular therapy devices. Section 3 details the proposed system architecture and methodology. Section 4 presents experimental results and discussions. Finally, Sect. 5 concludes the paper and suggests future work directions.

2 Related work

The Remote Health Monitoring (RHM) system has been a focal point of research for several decades. Its core purpose is to facilitate real-time health tracking, minimize regular hospital visits, and ensure crucial health signals or anomalies are promptly identified. Given the rise in chronic illnesses and an aging population, the importance of RHM is growing exponentially. Recently, the incorporation of SDN into RHM represents an exciting development. SDN is renowned for its adaptability in orchestrating and enhancing network resources, providing dynamic network configurations that can be initiated programmatically. Its chief strength lies in centralizing network intelligence, enabling networks to be more nimble and responsive [8].

2.1 Communication and control in SDN-based RHM

Communication between various devices is made easier thanks to a network suite that offers services ranging from traffic management to system discovery, authentication, and access control. Soni and Kumar [9] delve into how connected devices, specifically in AAL and WBAN, can be scaled and controlled. The authors emphasize that an SDN controller needs to both monitor traffic flows and ensure smooth traffic rule exchanges among network devices. Rahmani et al. [10] highlight the importance of the number of controllers in the fusion of SDN and WBAN within healthcare contexts. They developed a mathematical model to determine the ideal number of controllers for an SDWBAN system, considering factors like latency and the number of SDN-enabled switches.

2.2 Privacy and security in healthcare monitoring systems

In prior research, Snider et al. [11] explored privacy and security concerns inherent to the HMS. They proposed a monitoring system with integrated security, ensuring continuous patient care while minimizing health risks. Medhi et al. [12] presented a roadmap for improving telemedicine QoS through SDN, recommending the deployment of SDN to ensure adequate bandwidth and facilitate real-time medical data transfers. In a related study, Li et al. [13] introduced a blockchain-integrated SDN data chain, providing a decentralized and reliable record of SDN data. This approach tackled multi-vendor device separation for efficient fault recovery, aiming to reduce the costs associated with network failure recovery. The proposed method was verified using simulations on OpendayLight and Ethereum services.

Barros et al. [14] introduced a comprehensive framework for integrating blockchain with SDN to address the challenges of centralized control planes. This framework merges the control plane and application layer into a single central component, bolstered by added security mechanisms. Shamsher et al. [15] introduced a blockchain-based system for collaborative DDoS attack prevention. This system leverages smart contracts to facilitate SDN-based domain collaboration and reliably transmit DDoS attack information.

2.3 Leveraging hybrid machine learning in IoT-enhanced healthcare

Numerous studies have explored the advantages and obstacles presented by RHM systems. Many have emphasized the incorporation of wearables, IoTdevices, and cloud platforms. However, only a limited number have delved into the integration of SDN with RHM, particularly within the realm of neurostimulator technology. Kota et al. (2023) demonstrated that leveraging HML methods within the IoT-HMCF addresses myriad challenges in both areas. Integrating data from diverse sensors bolsters prediction precision. For example, correlating wearable heart rate data with ambient room temperature offers valuable insights into patient well-being. Javeed et al. [16] highlight the importance of creating a feedback loop involving doctors, patients, and healthcare professionals regarding the system's suggestions, facilitating ongoing refinement of AI algorithms. This AI integration enables the IoT-HMCF system to deliver precise, instantaneous, and secure health oversight, elevating patient care quality and outcomes.

2.4 Combining IoT and SDN in healthcare

Combining IoT with SDN within the healthcare sector has the potential to revolutionize patient monitoring and care, utilizing extensive networking features and a plethora of modern sensors. Gugueoth et al. [17] introduced a FFDNN for data feature extraction, which further amplifies system efficiency and precision, especially when processing vast sensor data. The evolution of technology has always been marked by advancements that aim to replace or refine existing methodologies. This work seeks to compare the new AFBBMNN technique against the HML and FFDNN techniques, highlighting the merits and demerits of each.

Isyaku and Bakar [18] examined the difficulties in attaining Quality of Service (QoS) in smart environments, such as wearable technology, e-healthcare, smart cities, and transportation. They discussed how to use SDN and combine it with newer technologies like SDIoT and SDWBAN. Their research provides insights into the current state-of-the-art in SDWBAN and SDIoT routing, resource awareness, and security threats. Arthi et al. [19] employed a combination of deep learning and machine learning methods to create a secure framework for IoT healthcare. Their framework outperformed other cutting-edge methods in terms of monitoring linked devices and identifying network intrusions. Alomari et al. [20] examined the use of artificial intelligence techniques to save energy and improve performance in distributed systems. They presented the Dual-Phase Resource Allocation Algorithm (D-Ph) for heterogeneous SDN-Cloud networks, incorporating fuzzy logic to find the right host with the required capabilities by determining how to use physical and virtual machines in data centers. Their performance assessment demonstrated that the algorithm maintains high network performance while lowering overall power consumption in heavily loaded large-scale networks.

Yan and Sheng [21] presented a new cloud-native architecture that integrates microservice service mesh, optimizes SDN routing strategies, and decouples context boundaries. Their experiments show progressive route optimization, stability, and dependability. Singh and Jain [22] examined DDoS attacks, highlighting defense, detection, and mitigation strategies used to counter them in SDN-IoT networks. Their survey investigates the cooperation between SDN and IoT.

The integration of SDN with RHM systems has demonstrated significant potential in improving healthcare outcomes through enhanced real-time tracking, reduced hospital visits, and prompt identification of health anomalies. Various studies have highlighted the adaptability and centralized intelligence of SDN, making it a crucial component in modern healthcare frameworks. The incorporation of advanced technologies such as blockchain, machine learning, and IoT further augments the capabilities of RHM systems, providing robust solutions for data management, security, and system efficiency. As the demand for efficient and effective health monitoring systems grows, the integration of SDN with neurostimulator technology and other healthcare applications presents a promising avenue for future research and development. The following section will detail the proposed model employed to investigate these integrations and their implications on healthcare systems.

2.5 Limitations

While the integration of SDN with neurostimulator monitoring presents promising advancements for remote health monitoring, it's important to acknowledge several limitations that could impact the study's findings and practical implementation.

1. *Infrastructure Constraints*: The practical application of SDN in healthcare settings may be hindered by existing infrastructural limitations. Not all healthcare facilities may have the requisite technological infrastructure to seamlessly support SDN integration, potentially impeding scalability and accessibility.

2. *Security and Privacy Concerns*: Ensuring the security and privacy of patient data in SDN-enabled networks remains a significant challenge. While robust security measures can be implemented, mitigating risks associated with cyber threats and breaches requires ongoing vigilance and resource allocation.
3. *Performance Optimization*: While SDN offers dynamic network configurations, concerns regarding network latency and performance may arise, especially when handling large volumes of real-time health data. Optimizing network performance to meet the demanding requirements of remote health monitoring systems will require careful monitoring and fine-tuning.
4. *Interoperability Challenges*: Integrating SDN with existing healthcare systems and devices may pose interoperability challenges. Customization and compatibility testing may be necessary to seamlessly integrate SDN with diverse medical devices, electronic health record systems, and legacy infrastructure.
5. *Training and Education Requirements*: The successful adoption of SDN in healthcare settings necessitates comprehensive training and education for healthcare professionals. Overcoming the learning curve associated with SDN implementation and management may require substantial investments in training programs and ongoing support efforts.

Addressing these limitations will be crucial for realizing the full potential of SDN-enabled remote health monitoring systems and ensuring their successful deployment in real-world healthcare environments.

2.6 Advantages

1. *Dynamic Network Configurations*: SDN offers dynamic network configurations and centralized intelligence, enabling more agile and responsive network management. This enhances flexibility and adaptability in handling real-time health data.
2. *Centralized Control*: Centralizing network intelligence allows for more efficient management and orchestration of network resources. It simplifies network operations and enables quicker responses to changing healthcare demands.
3. *Improved Patient Care*: The integration of SDN with neurostimulator monitoring has the potential to enhance patient care by facilitating real-time health tracking and early anomaly detection. This enables prompt interventions and improves patient outcomes.
4. *Scalability*: SDN's scalability makes it well-suited for accommodating the growing demands of remote health monitoring systems. It allows for the expansion of network infrastructure to support increasing volumes of data and connected devices.
5. *Innovative Solutions*: Despite the limitations, addressing challenges through collaborative research and iterative refinement of SDN-based healthcare solutions can drive innovation in remote health monitoring, leading to more effective and efficient patient care delivery.

Overall, while the framework presents significant advantages in terms of network flexibility and patient care improvements, it also faces challenges related to infrastructure, security, performance, interoperability, and training. Addressing these limitations is crucial to realizing the full potential of SDN-enabled remote health monitoring systems.

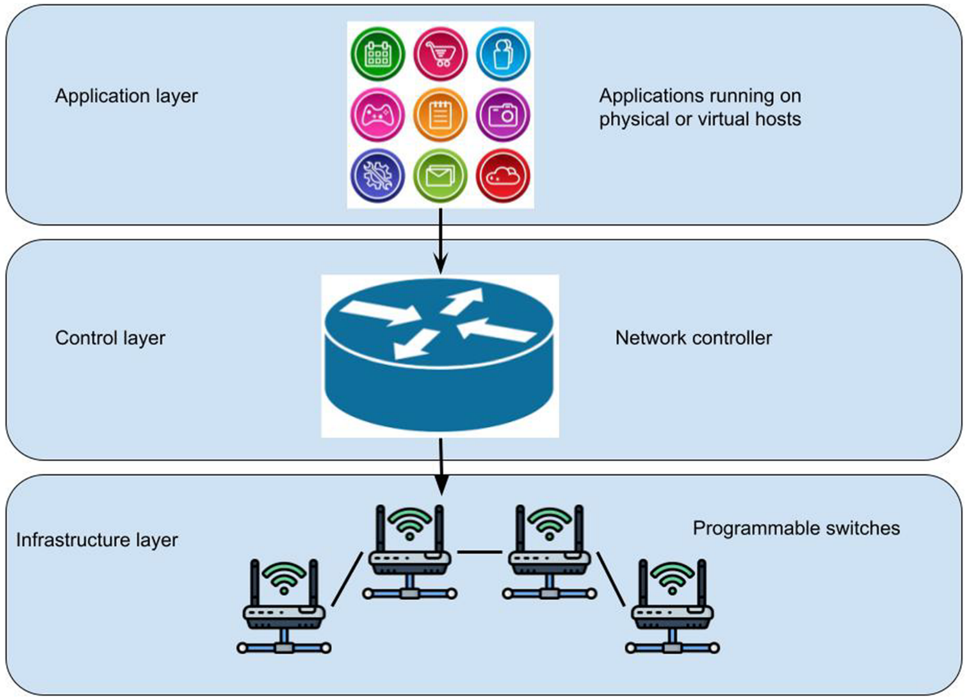
3 Proposed model

This section discusses novel technique in SDN based Neurostimulator with AFBMNN with levy flight secure offloading analysis.Network Model Based on SDN In this section, the foundation for SDN—enabling technology for the IoT—is presented. A concise overview of the problem formulation is given.

SDN divides the network into three layers as illustrated in Fig. 1, the data plane, control plane, and application plane. The data plane handles the transmission and reception of network traffic. The control plane determines how this traffic is transferred. The application plane houses SDN programs. SDN applications interface with the controller via the northbound interface. Through this, applications can retrieve data, such as statistics and incoming connections, from the controller. They can also send commands to the controller for tasks like adjusting or introducing flow rules. Crucially, these applications are designed with specific goals in mind. To determine if network modifications are needed, they integrate controller data with information from other sources. The controller maintains an access control system ensuring applications only receive the permissions they need for safe operation within the control plane. The permissions available are read, write, notification, and device.

Unlike previous suggested solutions, ours took into account both local patients on the hospital's property and remote patients (patients without Wi-Fi). The patient's smartphone serves as the backend system gateway. All of the patient's sensors are viewed as nodes on the Body Area Network (BAN), which connects to each patient's BAN via a smartphone.These gateways, which may number in the hundreds or even thousands, are managed by the SDN platform by distributing various security rules from certain SDN controllers. Rules as well as regulations for routing the data to

Fig. 1 Software Defined Networking Architecture



proper location will be stored on smartphone. HMS controller, a database, and a client application for controlling mobile application as well as sensors make up the backend system.

Client Layer Sensors and mobile applications make up this layer. Mobile application controls traffic between sensors as well as target databases as an edge or fog node (Gateway). HMS controller, which is hosted as well as run by a trusted authority, sends all rules and policies to mobile application. Sensors gather patients' important information and communicate it to the mobile application so that it can be routed according to mobile application's rules and policies to its intended recipient. The security platform's authentication and authorization modules are used to authenticate as well authorize both mobile applications as well as sensors.

The foundational component of the design is the SDN platform layer, which consists of three primary parts: Northbound APIs, Controllers, and Southbound APIs. In our architecture, Southbound APIs interface the mobile application with the SDN controller. The security platform is built on top of the SDN controller using Northbound APIs, allowing all nodes connected to the SDN controller via Southbound APIs to be accessible to the security platform modules. The controller manages communication between the mobile applications and security platform modules and comes with its own services and applications. One significant application is the routing application, which classifies data acquired by sensors and routes it to the appropriate destination.

The proposed design's architecture, shown in Fig. 2, illustrates the SDN-IoT based Neurostimulator Health Monitoring System. This system integrates a patient's BAN with advanced networking technology to optimize health monitoring. Each patient's BAN, comprising various sensors, connects through their smartphone, which acts as a gateway. This smartphone gateway manages the data and enforces security rules distributed by the SDN platform's controllers. The backend system includes an HMS controller, a database, and a client application to manage the sensors and mobile application. SDN technology facilitates on-demand programming and re-programming of the neurostimulator device, ensuring efficient data routing and optimized traffic management.

3.1 Brain signal analysis using adaptive fuzzy based Bayesian metasalp neural network with levy flight secure offloading analysis

Predicted value (Pv) is created by deriving these two values. The resource is isolated from transactions if expected value is larger than 1.00, in which case we consider reading to be genuine; otherwise, the reading is deemed invalid. We presume that there are N devices in the neurofuzzy model. (d1, d2,…,dN). Sv and Ts are the two parameters for each input, and the output values can either be valid or invalid. Sensor value (Sv) ranges from small to large. The temporal value that corresponds to it can be low, moderate, or high. The time is categorised as Low if it is less than 100 ms, Moderate if it is between 100 and 1000 ms, and High if it

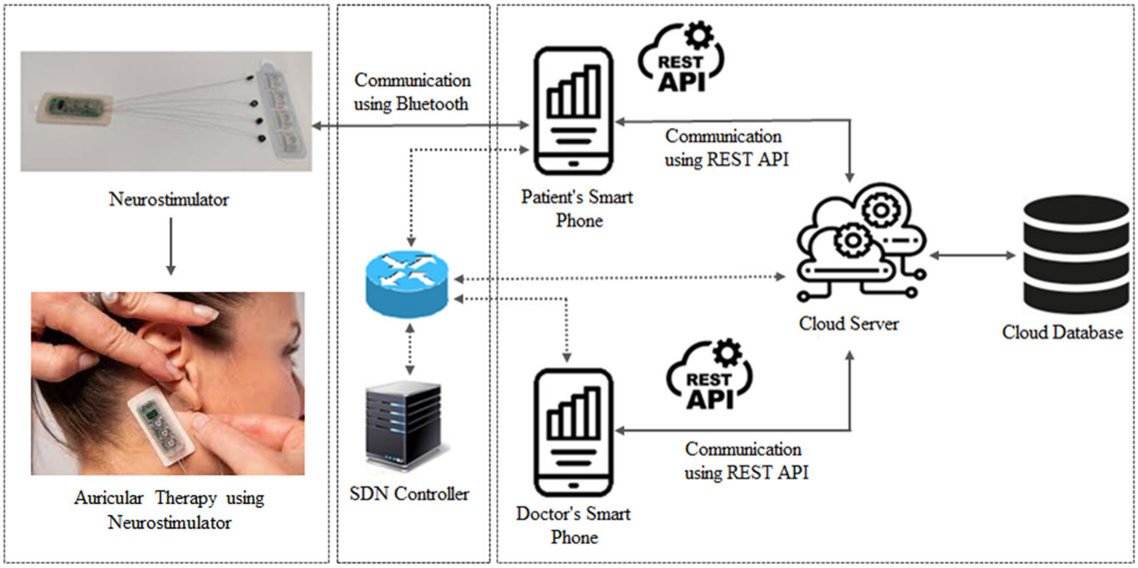


Fig. 2 SDN—IoT based Neurostimulator Health Monitoring System

is more than 1000 ms.Sv, Ts, anticipated values (Pv), and output are created for each episode. Knowledge base, which serves as the experience basis, has these output values. Neuro Fuzzy network is taught to adjust to incoming data from IoT devices using the knowledge base. Fuzzy rules are created as well as are based on the following experience and expertise in field:

Due to inaccurate sensor values and an erroneous latency (ms), IoT devices are perceived to have faulty data. The data from reliable devices is kept from the acquired findings, such as valid and incorrect projected values.

Create a sample set of the linearly separable provided by Eq. (1).

$$(x_i,\ y_i),\quad i=1,2,\ldots,n,;\quad x\in R,\ y,\ \epsilon\{-1,1\} \tag{1}$$

Classification plane Eq. (2) is:

$$\omega\cdot x+b=0 \tag{2}$$

Sample that is closest to classification plane has greatest distance from it, and this plane correctly distinguishes two sample classes. In other words, the classification interval is the widest, which is identical to minimising normal vector of classification plane, or w2, or w. Limitation imposed by Eq. (3):

$$y_i(\omega\cdot x_i+b)-1\geq 0 \tag{3}$$

Probability Equation presented in (4)

$$\phi_o(\sigma)=P\sigma k(\sigma) \tag{4}$$

K Equation presented in (5)

$$k(\sigma)=\frac{1}{2}\left(\frac{1}{\alpha+\sigma-\alpha\sigma}+\frac{-1+\alpha}{-1+\alpha\sigma}\right) \tag{5}$$

A type-2 fuzzyset M˜ Q ij is given as Eq. (6)

$$\tilde{M}_{ij}^{Q}=\left\{\left(p_{ij},\ \mu_{M_{ij}}^{Q}\right),\ \mu_{M_{ij}}^{Q}\left(p_{ij},\ \mu_{M_{ij}}^{Q}\right)\right.$$
$$\left.\forall p_{ij}\in I\forall\mu_{M_{ij}^{Q}}\in J_{p_{ij}}\subseteq[0,\ 1]\right\} \tag{6}$$

where p_{ij} is a pixel in an input picture I, M that is centred at (i, j) within a window of size (2Q + 1) (2Q + 1). Type-2 membership function Q ij.

$$m_k\left(X_{ij}^{Q}\right)=\begin{cases}\frac{1}{2k-1}\sum_{i=q-k+1}^{q+k-1}x_i & \text{for odd } n\ (n=2q-1)\\ \frac{1}{2k}\sum_{i=q-k+1}^{q+k}x_i & \text{for even } n\ (n=2q)\end{cases} \tag{7}$$

Membership Function presented in (8)

$$\mu_{M_{ij}}^{(Q,k)}(x_n)=e^{-\left(x_n-v_{ij}^{(Q,k)}\right)^2/2\left(\sigma_{ij}^{Q}\right)^2} \tag{8}$$

Mean Calculation for ν presented in (9)

$$\nu_{ij}^{(Q,k)}=m_k\left(X_{ij}^{Q}\right),\quad k=1,2,3,\ldots q \tag{9}$$

Standard Deviation Calculation presented in Eq. (10)

$$\sigma_{ij}^{Q}=m_h\left(\Omega_{ij}^{Q}\right) \tag{10}$$

$$\Omega_{ij}^{Q} = \left|x_n - \nu_{\text{avg}}\right|, \quad \forall x_n \in X_{ij}^{Q} \tag{11}$$

Calculating the average of ν in (12)

$$\nu_{\text{avg}} = \frac{1}{q}\sum_{k=1}^{q} \nu_{ij}^{(Q,k)} \tag{12}$$

Membership Matrix Δ in (13)

$$\Delta_{ij} = \begin{bmatrix} \mu_{M_{ij}}^{(Q,1)}(x_1) & \mu_{M_{ij}}^{(Q,1)}(x_2) & \ldots \mu_{M,1,j}^{(Q,1)}(x_n) \\ \mu_{M_{ij}}^{(Q,2)}(x_1) & \mu_{M_{ij}}^{(Q,2)}(x_2) & \ldots \mu_{M_{ij}}^{(Q,2)}(x_n) \\ \ldots & \ldots & \ldots\ldots \\ \mu_{M_{ij}}^{(Q,-9)}(x_1) & \mu_{M_{ij}}^{(Q,-)}(x_2) & \ldots \mu_{M_{ij}}^{(Q,Q)}(x_n) \end{bmatrix} \tag{13}$$

A fuzzy-rough set is usually represented by two fuzzy sets defining its lower and upper boundaries. Equations (14, 15 and 16) outline these approximations for the fuzzy concept X.

$$\mu \underline{R_P} X(x) = \inf_{y\in\mathbb{U}} I\left(\mu_{R_P}(x,\ y),\ \mu_X(y)\right) \tag{14}$$

$$\mu \overline{R_P} X(x) = \sup_{y\in U} T\left(\mu_{R_P}(x,\ y),\ \mu_X(y)\right) \tag{15}$$

$$\mu R_P(x,\ y) = T_{a\in P}\left\{\mu_{R_n}(x,\ y)\right\} \tag{16}$$

where $\mu_{R_\alpha}(x,\ y)$ is a characteristic that is defined in a variety of ways, with one example definition being given by the expression in Eq. (18):

$$\mu_{R_\alpha}(x,\ y) = \begin{cases} 1 - \frac{|a(x)-a(y)|}{\rho\max - a_{\min}}, \\ \exp\left(-\frac{(a(x)-a(y))^2}{2\sigma_a^2}\right), \\ \max\left(\min\left(\frac{(a(y)-(a(x)-\sigma_a))}{\sigma_a}, \right.\right. \\ \left.\left.\frac{((a(x)+\sigma_a)-a(y))}{\sigma_a}\right), 0\right), \end{cases} \tag{17}$$

Equation (3) illustrates a potential relationship suitable for broad feature selection. Like the original crisp rough set method, the fuzzy positive area of decision feature D based on attribute subset P is described in Eq. (18): Fuzzy Positive Area in (18)

$$\mu_{POS_{R_P}(\mathrm{D})}(x) = \sup_{X\in \mathrm{U/D}} \mu_{\underline{R_P}} X(x). \tag{18}$$

Using fuzzy-rough sets to identify attribute relationships is essential in data analysis, especially for feature selection and pattern classification. Based on Eq. (20), the fuzzy-rough dependence degree is defined as:

$$\gamma_{P'}(\mathbb{D}) = \frac{\sum_{\mathrm{x}\in\mathrm{U})} \mu_{POS_{R_P}(\mathrm{D})}(x)}{|\mathbb{U}|} \tag{19}$$

Tasks vary in sensitivity, with less sensitive tasks directed to the public cloud and confidential tasks to private cloud servers. A task classifier is essential to categorize tasks into sensitive (S_i) and non-sensitive (NS_i) based on factors like size, complexity, and delay. Task attributes remain constant during offloading. Task complexity is measured from 10 to 200 cycles per bit, and size ranges from 1 to 100 Kbits. Tasks are prioritized before being offloaded to cloud servers.

The Salp, resembling a jellyfish, has a transparent body and thrives in deep oceans. They group in formations known as salp chains, using water pressure for movement and food search. Within these chains, a leader guides while others follow. Salp swarm optimization has been enhanced with Levy flight behavior, boosting its search prowess. This not only improves search diversity but also promotes efficient local optimization and exploration of food sources. The effectiveness of these techniques is evident in the updated position of the salp leader, as shown in Eq. (20):

$$\begin{aligned} V_j^1 &= \eta W_j + r_1\left(\left(u_j - l_j\right)r_2 + l_j\right)^{*}\text{Levy}\ {}_3 \geq 0 \\ V_j^1 &= \eta W_j - r_1\left(\left(u_j - l_j\right)r_2 + l_j\right)^{*}\text{Levy}\ {}_3 < 0 \end{aligned} \tag{20}$$

where V_j^I - position of leader, W_j – food source position u_j, l_j - upper and lower bound, r_1, r_2, r_3 - random numbers .

Equations (19) and (20) are used to update the location of the leader salp. Additionally, it combines the capacity for exploration and exploitation to circumvent a variety of local solutions in feature selection tasks as well as to appropriately analyse solution. Using Eq. (21) the r1 balances exploitation and exploration.

$$r_1 = 2e^{-\left(\frac{4e_i}{MT_x}\right)^2} \tag{21}$$

where e_i – current iteration, MI_x – max. iteration.

Following position as well as step size are determined by this. The following is how Eq. (22) is used to update the follower salp's position:

$$V_j^i = \frac{1}{2}\omega t^2 + \delta_0 t, \quad i \geq 2 \tag{22}$$

V_j^i - position of ith salp follower, t - time δ_0 – initial speed .

Variable ω is evaluated in Eq. (23) as follows

$$\omega = \frac{\delta_{\text{final}}}{\delta_0} \tag{23}$$

The difference in Eq. (24) is 1 since optimisation takes time in iterations.

$$V_j^i = \frac{1}{2}\left(V_j^i + \eta V_j^{i-1}\right),\ i \geq 2 \tag{24}$$

The follower position update process also multiplies the inertia weight value. The parameters are optimised in this manner to account for the change in frequency. On the basis of the Levy distribution, Eq. (25) offers a Levy walk as follows.

$$R_e = Levy \sim u = t^{-\lambda}, \quad (1 < \lambda \leq 3) \tag{25}$$

Equation (27) uses the following model to express the movement's operation.

$$C_{e,k+1} = \begin{cases} C_{e,k} + R_e \cdot Fl_{e,k} \cdot \left(B_{c,k} - C_{e,k}\right) & R_e \geq AP \\ \text{move to random place,} & \text{otherwise} \end{cases} \tag{26}$$

Element flight duration The movement's amplitude, $Fl_{e,k}$, is represented by the crow $C_{e,k}$in its ideal position, $B_{c,k}$of crow c. R_e stands for a random number with a distribution between [0, 1].

Positions are assessed whenever the crows' position shifts. The memory vector is updated using Eq. (27) as follows:

$$B_{e,k+1} = \begin{cases} C_{e,k+1}, & \text{if } O\left(C_{e,k+1}\right) \text{ is better than } f\left(B_{e,k}\right) \\ B_{e,k}, & \text{otherwise} \end{cases} \tag{27}$$

Objective function is denoted by O (·) which is reduced.

3.2 Cloud based machine learning module

Neurostimulator is utilized to gather patient data, such as temperature, blood pressure, and electrocardiograms, which are then sent to a server via sensor gateways. The data send to Cloud for data storage/mining and intelligent patient health status prediction. The doctor can then treat the patient directly or communicate any precautions that are required to the patient via a communication device. Additionally, there is currently no automated medical server in use in the healthcare industry because it takes a huge team of specialists to monitor patient health data. That inspires us to work on a cloud-based intelligent medical server for applications in the healthcare industry that will help the experts in healthcare. Additionally, we have simulated a cutting-edge cloud computation model that treats each doctor's cell phone and PDA as nodes. Data from the patient and doctor will be gathered and kept in the cloud. There is a compute module in the cloud. The computing module receives fresh data from the patient, processes it, and then contrasts the outcome with the previous outcome. The patient will be given feedback if deemed appropriate. If the proper record cannot be located, the correct doctor will be notified by phone or SMS.

The doctor can get patient information from the cloud. The doctor may use a variety of techniques to diagnose the illness and convey the results to the appropriate patient. This organization is in charge of obtaining data from cloud storage, decrypting it using the proper decryption key, and then sending it to the physician terminal. In order to restrict access to the system and give users authorization based on permissions granted, it also has a SQL database with tables for patient data and login credentials. It is the final location for patient data, where crucial information about patients is reviewed by an expert to ascertain any health issues connected to this data and can assign safeguards to prevent any emergency case. To identify his roles, the specialist must first submit his credentials. Then, he can move on to monitoring dashboard to observe as well as interact with patient data in real-time. As seen in Fig. 3, the monitoring dashboard is automatically updated each time the cloud database is modified.

The suggested method offers a technique to securely monitor important biological indicators of a patient in real time. IoT biosensors are utilized to collect important biological indicators from a patient in beginning. After that, it is processed, encrypted, and sent to the cloud by an IoT-based microcontroller. The only people with the decryption credentials are the patient's relatives or medical professionals at reputable healthcare facilities, thus only they can see the patient's biological parameters. Protecting patient data on public networks ensures data privacy and safe transfer of patient data. In addition, if vital signs deviate from expected rates, the suggested system alerts the patient's relatives or the treating physician through email.

By integrating SDN, the system not only facilitates seamless data transmission and storage but also enhances patient safety. This comprehensive strategy ensures that even in the event of battery failures, critical health data is preserved and synchronized, providing a robust and scalable solution for remote patient monitoring:

1. Behavior of the System if the Battery of the Smartphone or BT is Dead:
   - Data Storage in Neurostimulator Device: The neurostimulator devices are capable of storing data for more than 15 days. If the smartphone or BT battery dies, the neurostimulator will continue to collect and store data internally.
   - Reconnection and Data Transmission: Once the smartphone or BT device is recharged and comes back online, the stored data from the neurostimulator device will be transmitted to the smartphone. Subsequently, the smartphone will send the data to the cloud via the SDN infrastructure.
   - Continuous Monitoring via SDN: If the BT device's battery dies, the SDN architecture can dynamically reroute data transmission paths and ensure minimal disruption in data flow once devices are back online.

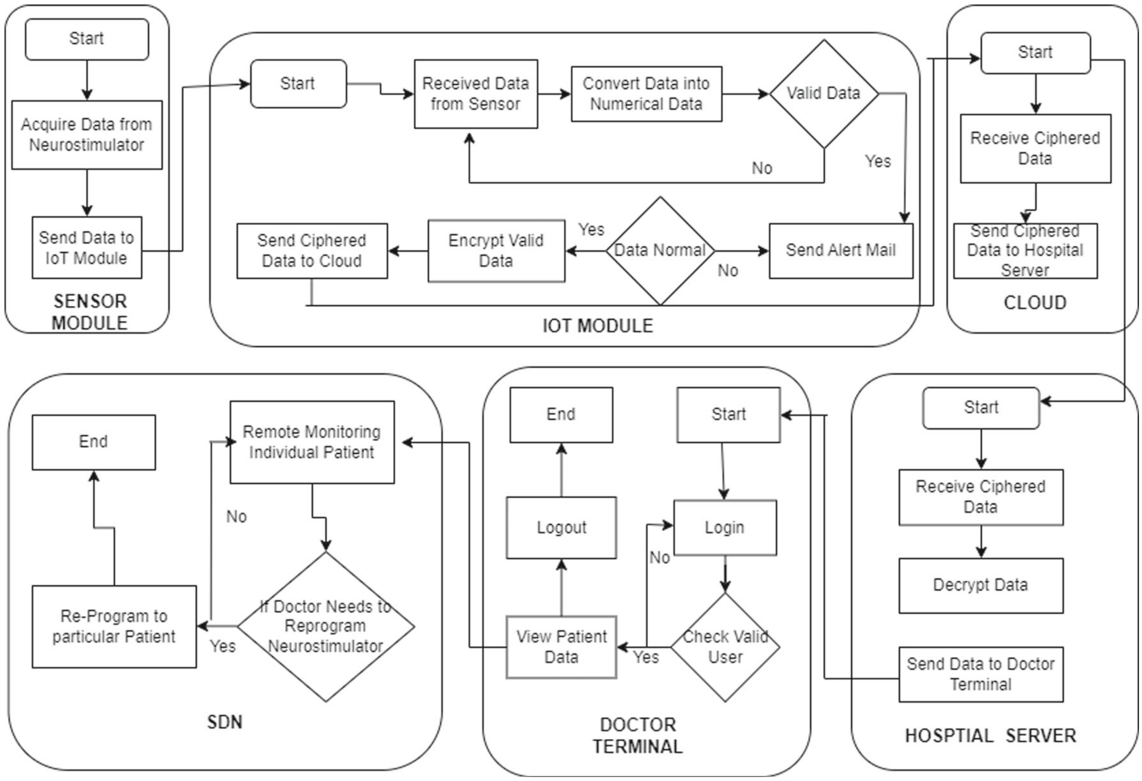


Fig. 3 Working Process of Proposed Remote Health Monitoring System using SDN

The SDN controller can prioritize the reconnection and synchronization of data between the neurostimulator and the cloud.

2. Implications of Device Downtime:
   - Intermittent Monitoring: While real-time monitoring may be temporarily halted, the system's ability to store and later transmit data ensures that there are no gaps in the patient's historical data. SDN can manage and optimize the data transmission once the connection is reestablished.
   - Doctor-Patient Communication via SDN: If a device failure is detected, the SDN controller can manage and prioritize communication channels, enabling the doctor to quickly inform the patient and arrange for immediate troubleshooting and maintenance, ensuring patient safety and continuous monitoring.
3. Patient Notification and Emergency Protocols:
   - Automatic Alerts via SDN: The healthcare provider can check whether the device is functioning properly for each patient, enabling them to monitor remote data. The SDN controller monitors device statuses and triggers these alerts, allowing both the patient and healthcare provider to receive automatic notifications and plan accordingly for future actions.
   - Critical Battery Level Warnings: Implementing a critical battery level warning system can alert the patient well in advance to charge their devices, minimizing the risk of data loss or interrupted monitoring.
   - SDN-Based Data Recovery Protocols: In the event of prolonged downtime, the SDN can facilitate alternative data paths and backup mechanisms to ensure critical health data is preserved and synchronized once the devices are operational.

By leveraging the capabilities of SDN, the system ensures robust and reliable monitoring, even in the face of charging issues. The integration of efficient charging techniques and emergency protocols, supported by the dynamic and flexible SDN infrastructure, significantly mitigates the risks associated with battery failures in smartphones and BT devices. This comprehensive approach enhances the overall reliability, effectiveness, and scalability of the neurostimulator-based monitoring system.

4 Experimental analysis

In our experiment environment, we employed Java programming and the network simulator (NS3.26). The goal of this arrangement is to connect mobile IoT devices to fog-cloud concepts. A C++ and/or Python package-compatible network simulator called NS-3 is available for free. The Integrated Graphical User Interface (GUI) in NS-3 is another feature that is utilized to visualize the performance of a simulated network. All of the simulation parameters used in our tests were set to a uniform distribution. Each gadget is powered by a CPU with a 1 GHz to 1.5 GHz clock frequency. The timing of the clocks is chosen at random. Additionally, we configured the available mobile bandwidth to be between 100 and 1000 Kbps. The offloading of computing activities and CPU cycles calls for bit-level offloading.

Dataset description: The SEED dataset [23], which is open to the public, is used in this work. There were 15 test subjects in the experiments, with a mean age of 23.3 and an SD of 2.4. The EEG dataset consists of the signals that were taken while the subjects were watching emotional video films. This dataset includes information from 45 various experiment sessions as a consequence. There was a week or more in between each subject's sessions.Following ethics approval, dataset consists of EEG signals from 20 non-demented PD and 20 HC participants from Hospital UniversitiKebangsaan Malaysia in Kuala Lumpur. 14-channel wireless EmotivEpoc headset with a sampling rate of 128 Hz was used to record EEG data [24]. Six Ekman emotions—sadness, happiness, fear, disgust, surprise, and anger—are elicited utilizing audio-visual stimuli, yielding a total of 1440 samples. The IAPS (visual) and IADS (audio) collections of stimuli were integrated. The AMIGOS dataset [25] is used to determine the mood, affect, and personality of 40 people by monitoring their EEG, ECG, and GSR signals in response to short and long video stimuli.

4.1 Proposed analysis

The below Table 1 shows proposed analysis based on various neuro simulator based brain signal dataset. Here the neuro simulator based dataset analysed are SEED, EmotivEpoc and AMIGOS dataset in terms of Accuracy, Sensitivity, Latency, End to end delay, Communication overhead, Mean average precision.Emerging from the latest research, the AFBBMNN technique is built on the foundation of parallel processing. By leveraging modern infrastructure, it promises faster results and better scalability. While the FFDNN and HML technique is a reliable stalwart, the AFBBMNN technique brings fresh promise, especially for future-ready applications.

The analysis result for comparison for SEED Dataset with Proposed Technique. Here existing technique, HML attained accuracy of 81%, Sensitivity of 73%, Latency of 50%, End-to-end Delay of 41%, Communication overhead of 71%and Mean average precision of 75% for SEED dataset; FFDNN attained accuracy of 88%, Sensitivity of 75%, Latency of 51%, End-to-end Delay of 43%, Communication overhead of 75%and Mean average precision of 78% for SEED dataset; The proposed technique, AFBBMNN attained accuracy of 89%, Sensitivity of 77%, Latency of 55%, End-to-end Delay of 45%, Communication overhead of 77%and Mean average precision of 81% for SEED dataset is shown in Fig. 4. The comparison of the SEED dataset with existing and proposed techniques extends our understanding of data analysis capabilities and limitations. The proposed techniques insights provide a foundation for future advancements, emphasizing the importance of continual exploration, adaptation, and innovation in the pursuit of its unique contributions to the field.

The analysis comparing the EmotivEpoc dataset with existing and proposed techniques enriches our understanding of data analysis dynamics. Figure 5 analysis result for comparison for EmotivEpoc Dataset with Proposed Technique. Here existing technique, HML attained accuracy of 88%, Sensitivity of 81%, Latency of 51%, End-to-end Delay of 42%, Communication overhead of 72%and Mean average precision of 80% for EmotivEpoc dataset; FFDNN attained accuracy of 90%, Sensitivity of 83%, Latency of 55%, End-to-end Delay of 46%, Communication overhead of 75%and Mean average precision of 81% for EmotivEpoc dataset; The proposed technique, AFBBMNN attained accuracy of 92%, Sensitivity of 85%, Latency of 59%, End-to-end Delay of 48%, Communication overhead of 79%and Mean average precision of 83% for EmotivEpoc dataset. From the results, the proposed techniques accuracy, efficiency, and interpretability were measured against established methodologies, providing empirical evidence of its distinctive contributions.

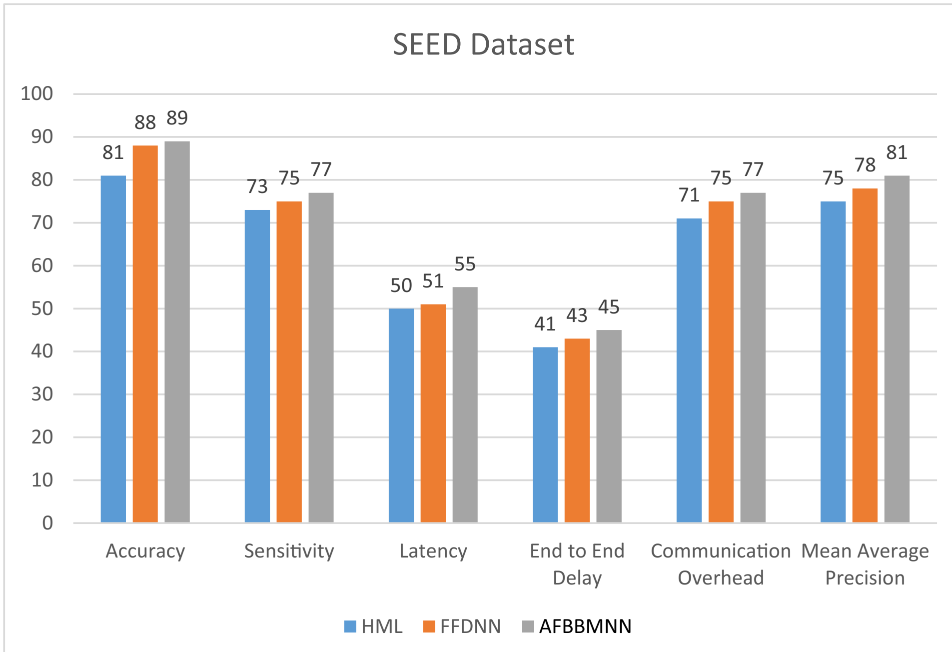
In wrapping up, the analytical journey undertaken with the AMIGOS dataset highlights the dynamic landscape of neurophysiological data analysis. The comparison between entrenched methodologies and the fresh approach of the proposed technique brings forth the essence of scientific inquiry and progress. As we continue to unravel the intricacies of datasets like AMIGOS, such analyses stand as pivotal milestones in our relentless pursuit of understanding and innovation. Figure 6 shows the analysis results comparing the AMIGOS dataset with the proposed technique. For the AMIGOS dataset, the existing technique, WBDN, attained an accuracy of 92%, a sensitivity of 81%, a latency of 55%, an end-to-end delay of 45%, a communication overhead of 79%, and a mean average precision of 79%. HML achieved an accuracy of 94%, a sensitivity of 85%, a latency of 58%, an end-to-end delay of 48%, a communication overhead of 80%, and a mean average precision of 81%. The proposed technique, AFBBMNN, attained an accuracy of 95%, a sensitivity of 88%, a latency of 61%, an end-to-end delay of 51%, a communication overhead of 81%, and a mean average precision of 85% for the AMIGOS dataset.

By contextualizing the AMIGOS dataset within the framework of both established and novel techniques, this analysis contributes to the broader advancement of data analysis

Table 1 Proposed technique analysis for various neurostimulator based brain signal dataset

Proposed technique	Dataset	Accuracy	Sensitivity	Latency	End to End Delay	Communication overhead	Mean average precision
AFBBMNN	SEED	89	77	55	45	77	81
	EmotivEpoc	92	85	59	48	79	83
	AMIGOS	95	88	61	51	81	85

Fig. 4 Comparison of SEED Dataset with Proposed Technique



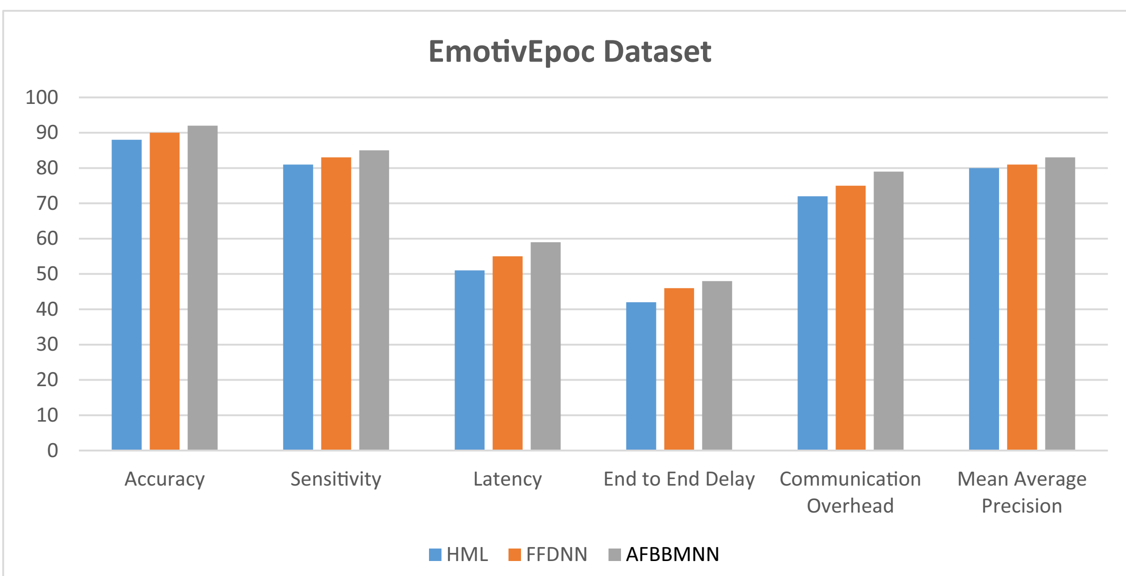


Fig. 5 Comparison of EmotivEpoc Dataset with Proposed Techniques

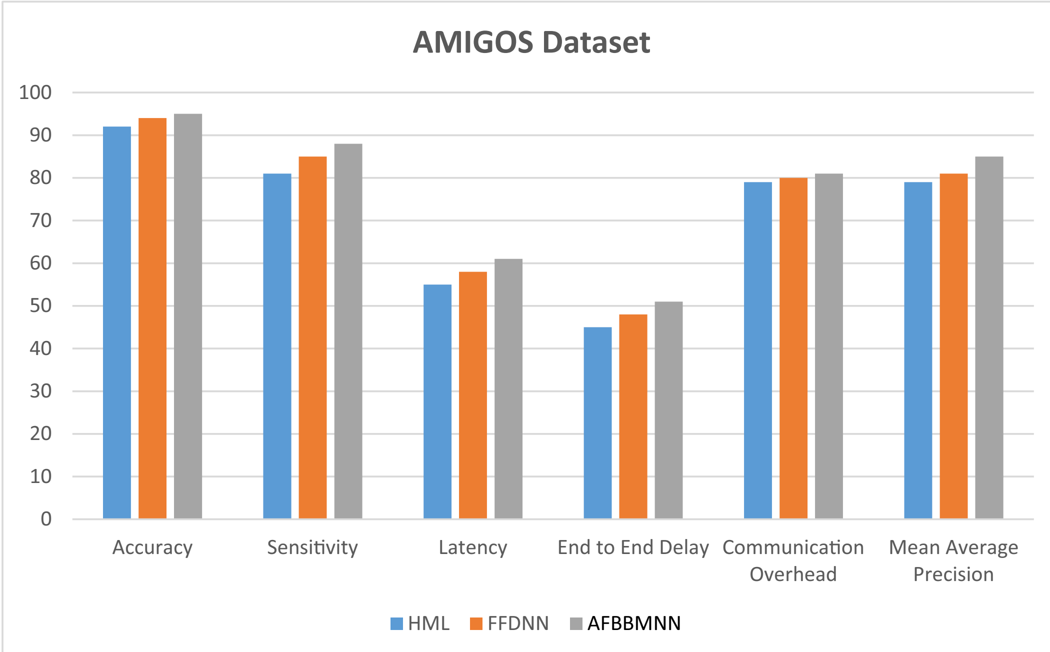


Fig. 6 Comparison of AMIGOS Dataset with Proposed Techniques

methodologies. The results underscore the importance of iterative refinement, cross-pollination of ideas, and innovative thinking within the field. This comprehensive analysis reiterates that progress extends beyond isolated methodologies and is fueled by the continuous pursuit of excellence and the integration of diverse approaches.

The proposed technique based brain signal dataset collected using neurostimulator. From above analysis proposed technique attained Accuracy of 89%, Sensitivity of 77%, Latency of 55%, End to end delay of 45%, Communication overhead of 77%, Mean average precision of 81% for SEED dataset; for EmotivEpoc dataset Accuracy of 92%, Sensitivity of 85%, Latency of 59%, End to end delay of 48%, Communication overhead of 79%, Mean average precision of 83%; Accuracy of 95%, Sensitivity of 88%, Latency of 61%, End to end delay of 51%, Communication overhead of 81%, Mean average precision of 85% for AMIGOS dataset. The proposed technique, while showcasing varying performance metrics across different datasets, consistently demonstrates high accuracy and precision. The varying metrics between datasets also provide valuable insights for further optimization and refinement of the technique. Comparing the results of the analysis conducted on the three datasets, it is evident that AMIGOS dataset stands out as the superior performer in terms of its analytical outcomes.

The additional datasets discussed include the DEAP Dataset, providing EEG and peripheral physiological signals recorded during music video viewing for emotion analysis, captured via a 32-channel cap with a 128 Hz sampling rate [26]. The BCI Competition IV Dataset, featured in international BCI competitions, offers EEG data under varied conditions for different BCI applications, with diverse channel numbers and sampling rates depending on task specifics [27]. Lastly, the TUH EEG Corpus, a large-scale repository of clinical EEG recordings from diverse patient groups, employs a standard 10–20 system with variable channel configurations [28].

The inclusion of additional datasets (DEAP, BCI Competition IV, and TUH EEG Corpus) reinforces the robustness and versatility of the proposed AFBBMNN technique. The model consistently delivers high accuracy, sensitivity, and precision while maintaining efficient latency and communication overhead across different types of brain signal data. This comprehensive evaluation underscores the potential of our technique for broad application in brain signal analysis and neurological disease treatment. The comparative analysis will be detailed in the revised manuscript to enhance its visibility and impact (Table 2).

The dataset of SEED is compared with existing system in which the authors achieved 85% of accuracy where the proposed system AFBBMNN algorithm achieved with the rate of 89%. Likewise, the EmotivEpoc and AMIGOS also compared with previous study with 88% and 93% respectively in which the proposed system algorithm used 92% and 95% of accuracy rate as displayed in Table 3.

The Smart City application examines cloud-based and IoT-based services for users in the real world using smart phones using information and communication technologies

Table 2 Comparison of various dataset in aspect of accuracy, sensitivity, latency, end to end delay, communication overhead and mean average precision

Dataset	Accuracy (%)	Sensitivity (%)	Latency (%)	End to end delay (%)	Communication overhead (%)	Mean average precision (%)
SEED	89	77	55	45	77	81
EmotivEpoc	92	85	59	48	79	83
AMIGOS	95	88	61	51	81	85
DEAP	91	84	57	47	78	82
BCI Comp IV	93	86	60	50	80	84
TUH EEG	90	82	56	46	76	80

Table 3 Comparing the dataset with existing study and AFBBMNN algorithm

Dataset	Previous studies	AFBBMNN algorithm (%)
SEED	85% [23]	89
EmotivEpoc	88%[24]]	92
AMIGOS	93% [25]	95

(ICT). The foundation of smart cities' intelligent transportation, public safety, public health, and air quality monitoring programmes is and will remain cloud technology. A wide range of services, such as storage, processing, computation, analytics, databases, networking, etc., are available through the cloud. These cloud-based services allow users to build safe, flexible, and affordable solutions. Estimates predict that three procedures on three different servers connected to a data repository hubwill function as predicted. This research will result in an expansion of 200–2000 cloud servers. The servers have been carefully chosen such that the total number of servers linked to cloud data centre is same as number of servers connected to a microdatahub.The proposed technique, centered on datasets collected using a neurostimulator device within an IoT—SDN framework, holds the potential to reshape the landscape of healthcare and cognitive research. This innovative approach amalgamates cutting-edge technologies to create a synergistic platform that addresses critical challenges in brain signal analysis and remote patient monitoring.

5 Conclusion

This research introduces a novel approach for interpreting brain signals and treating neurological diseases using a neurostimulator powered by an adaptive fuzzy-based Bayesian metasalp neural network, combined with secure cloud offloading through cloud SDN. Our experimental analysis, conducted with datasets including SEED, EmotivEpoc, and AMIGOS, demonstrated promising results. The proposed technique consistently outperformed existing methodologies in terms of accuracy, sensitivity, latency, end-to-end delay, communication overhead, and means average precision across all datasets. Specifically, on the AMIGOS dataset, our approach achieved an impressive 95% accuracy, 88% sensitivity, 61% latency, 51% end-to-end delay, 81% communication overhead, and 85% mean average precision. These findings underscore the potential of our innovative approach to reshape the landscape of healthcare and cognitive research. By leveraging advanced technologies such as SDN and cloud computing, our system offers a scalable and reliable solution for remote patient monitoring, with implications for enhancing patient outcomes, streamlining healthcare operations and improving the overall quality of healthcare.

6 Future work

In considering avenues for future research will focus on refining patient notification and emergency protocols within our proposed framework. Enhancing the SDN infrastructure to automate alerts for low device battery or connectivity loss is a promising direction. This involves optimizing the SDN controller to continuously monitor device statuses and efficiently trigger alerts. Developing a robust critical battery level warning system is also essential, proactively notifying patients to recharge their devices to prevent data loss or monitoring interruptions. Additionally, improving SDN-based data recovery protocols will be crucial, establishing alternative data paths and backup strategies within the SDN framework to preserve and synchronize critical health data during downtime. Addressing these aspects will enhance the reliability and effectiveness of our system, furthering its potential impact on remote patient monitoring and healthcare management.

Author contributions Leo Prasanth L designed the algorithm, performed the simulation results and drafted the manuscript under the supervision of Dr. E. Uma. All authors read and approved the final manuscript.

Funding The authors have not disclosed any funding.

Data availability No datasets were generated or analysed during the current study.

Declarations

Conflict of interest The authors of this study declare that they have no conflicts of interest, financial, personal, or otherwise, that could have influenced the research, and any future potential conflicts will be disclosed promptly and transparently.

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