Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 3, March : 2025

Hybrid Deep Learning Model for Achieving the Efficient QoS model in WS-IoT-based Health care Systems

Dr.J.Sampathkumar

Assistant professor, Department of electronics and communication engineering, Mahendra college of engineering, Salem, India.

Email ID: sampathkumar1980@gmail.com

Abstract

The integration of Wireless Sensor Internet of Things (WS-IoT)-based healthcare systems has transformed modern medical practices, offering remote monitoring, real-time data processing, and enhanced patient care. However, ensuring efficient Quality of Service (QoS) in such systems remains a critical challenge due to the inherent complexities of data transmission, network scalability, and resource constraints. This research introduces a novel Hybrid Deep Learning Model that synergizes Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks to optimize QoS in WS-IoT environments. By leveraging the temporal modelling capabilities of LSTM and GRU, the proposed model addresses key challenges in maintaining reliable data communication and minimizing latency in healthcare applications. The model is implemented in a Python 3.19 environment, emphasizing its adaptability to real-world IoT scenarios. Performance metrics, including Packet Delivery Ratio (PDR), End-to-End Delay, Throughput, Routing Load, and Control Packet Overhead, are systematically evaluated to examine the approach's efficacy. A comprehensive comparative analysis with existing state-of-the-art QoS models reveals that the proposed hybrid architecture outperforms its counterparts, achieving significant improvements in data reliability, efficiency, and network performance. Specifically, the model demonstrates higher PDR, reduced delay, enhanced throughput, and optimized resource utilization, making it a suitable candidate for scalable and reliable WS-IoT-based healthcare systems. This research not only underscores the importance of hybrid deep learning frameworks in IoT healthcare but also highlights their potential in addressing future challenges associated with network congestion, real-time decision-making, and scalability. The findings pave the way for implementing more efficient and robust WS-IoT systems that can revolutionize the delivery of healthcare services globally.

Keywords: Wireless Sensor Internet of Things, Healthcare monitoring system, Hybrid Deep Learning Models, Quality of Service.

1. Introduction

Introduction

The evolution of WS-IoT has brought about a paradigm shift in healthcare systems, enabling the seamless infusion of technology and medical practices. WS-IoT-based healthcare systems utilize a network of interconnected sensors to continuously recognize patients' vital signs and transmit data in real-time to healthcare providers[1]. These systems enhance patient care by enabling early recognition of anomalies, personalized treatment, and efficient resource management. They find applications in diverse areas such as wearable health monitoring devices, real-time ECG and EEG analysis, remote patient monitoring, and emergency response systems. Moreover, WS-IoT facilitates telemedicine by bridging the gap between patients and medical practitioners, making healthcare accessible to remote and underserved populations[2-4].

The integration of WS-IoT in healthcare offers numerous advantages, including cost-effective patient management, real-time health insights, and reduced hospital visits. For instance, wearable devices can continuously monitor chronic conditions like hypertension and diabetes, alerting healthcare providers in case of abnormalities[5-7]. Similarly, IoT-enabled diagnostic systems streamline patient data analysis, ensuring timely medical intervention. These advancements have the potential to significantly enhance the quality and accessibility of healthcare services globally, particularly in areas with limited medical infrastructure.

However, the widespread adoption of WS-IoT in healthcare is not without challenges. Ensuring reliable and efficient Quality of Service (QoS) remains a critical concern. Factors such as network congestion, high latency, data packet loss, and energy constraints in sensor devices limit the system's overall performance. Additionally, the exponential growth in healthcare data necessitates robust models capable of processing large volumes of information in real-time without compromising on accuracy or efficiency[8]. Traditional QoS solutions often fail to meet these requirements, highlighting the need for innovative approaches.

To address these challenges, this research proposes a Hybrid Deep Learning Model that combines the strengths of LSTM and GRU networks. The proposed model is designed to enhance QoS by optimizing data transmission, reducing delays, and improving system reliability in WS-IoT-based healthcare systems[9-10]. Implemented in a Python 3.19 environment, the model evaluates critical performance metrics like Packet Delivery Ratio (PDR), End-to-End Delay, Throughput, Routing Load, and Control Packet Overhead. By comparing these metrics with existing models, this research demonstrates the superiority of the proposed framework in achieving efficient, reliable, and scalable healthcare IoT systems. This study not only addresses current limitations but also paves the way for next-generation WS-IoT healthcare applications capable of meeting future demands.

2. Related Work:

Liya et al. (2024)[11] proposed an elevated deep learning-based disease detection model for Wireless Body Area Networks (WBAN) that integrates an energy-efficient routing protocol. WBAN consists of interconnected Bio-Sensor Nodes (BSNs) placed on the human body, which monitor real-time health parameters such as blood pressure and glucose levels. The study emphasizes the challenges posed by the limited resources and high energy consumption of BSNs, leading to node failures during heavy data transmission. To address this, the authors introduced a hybrid Red Piranha and Egret Swarm Algorithm (RPESA) for optimal Cluster Head (CH) selection and routing. The routing mechanism conserves energy by minimizing the number of active sensor nodes during data transfer. Additionally, the disease diagnosis process utilized an Adaptive Dilated Cascaded Recurrent Neural Network (ADC-RNN) with parameters optimized using RPESA, resulting in effective disease classification. While the proposed method demonstrated superior energy efficiency and disease detection performance examined to existing schemes, the complexity of implementing the hybrid RPESA algorithm and its computational overhead for real-time applications could pose challenges.

Paulraj et al. (2024)[12] proposed a novel Neuro-fuzzy-based Data Routing (NFDR) mechanism to enhance data routing and dynamic cluster formation in IoT-enabled Wireless Sensor Networks (WSNs). The NFDR mechanism leverages optimal scalability factors derived from historical and real-time network parameter values, which act as an additional buffer to maintain nodes within clusters even when network parameters are partially satisfied. Neural networks are utilized to determine cluster formation requirements, while fuzzy logic is employed to update the objective function for cluster member identification. The mechanism incorporates super head selection and cluster member size adjustments to optimize data transmission without violating network thresholds. Simulation outcomes reveal significant improvements, including a 75% retention in energy levels, a 20% reduction in end-to-end delay, and a 15% decrease in dead nodes, indicating enhanced clustering and robustness in IoT-enabled WSNs. However, the mechanism's dependency on historical data for scalability factors and its complexity in managing dynamic network conditions may pose challenges in real-time applications.

Saritha et al. (2024)[13] proposed an energy-efficient and QoS-preserving hybrid cross-layer protocol design (HCL-AQP) for deep learning-based air quality monitoring and prediction. The study integrated cross-layer design with IoT-based real-time applications, allowing diverse network protocols to collaborate and share network status information to ensure optimal routing with minimal energy consumption. The proposed framework employs a dendrimer tree structure for WSN topology, adaptive ball K-means clustering (AB-KC) for efficient sensor coverage, and two-level adaptive sleep scheduling using OFDMA for enhanced sensor and UAV lifetime. The framework demonstrated notable performance improvements in terms of energy consumption, end-to-end delay, throughput, packet delivery rate, and accuracy. However, the study highlighted challenges such as the potential communication interference and inefficiency in executing operations due to inadequate layer integration, indicating room for further optimization in hybrid cross-layer protocol designs.

Roy et al. (2024)[14] proposed a secure healthcare model leveraging a Multi-Step Deep Q Learning Network (MSDQN) integrated with a Deep Learning Network (DLN) in the context of the Internet of Things (IoT). IoT, as an emerging technology, connects living and non-living entities globally, significantly contributing to healthcare by enabling disease monitoring and identification. Recognizing the critical need to safeguard healthcare data against unauthorized access and intermediary attacks, this study addressed the increasing security concerns within IoT-based healthcare systems. The DLN was utilized for authentication to ensure secure communication among IoT devices and prevent intermediate attacks, while the MSDQN was employed to detect and mitigate malware and Distributed Denial of Service (DDoS) attacks during data transmission. The performance of the recommended model was examined based on metrics like energy consumption, throughput, lifetime, accuracy, and Mean Square Error (MSE), showcasing improvements over an existing Learning-based Deep Q Network (LDQN). However, the study primarily focuses on security aspects and does not explicitly address potential scalability issues in large-scale IoT environments or real-time constraints in dynamic healthcare scenarios, which could impact its practical implementation.

Ramu et al. (2024)[15] proposed a DL-infused hybrid security scheme to enhance energy optimization and security in wireless sensor networks (WSNs). These networks, composed of ad hoc wireless sensors, base stations, and nodes, monitor various environmental and physical conditions while facilitating data sharing through Internet-connected base stations. The study integrates optimization techniques and a DL approach to detect and isolate rogue nodes based on criteria such as request forwarding, reply forwarding, and data dropping. By employing a sum-rule weighted method, the model demonstrates improved throughput and reduced processing time. Packet loss rates significantly decreased, with delay-related hyper-metrics dropping from 70 to 42 milliseconds and the percentage of missing packages reducing from 23% to 8%. The model effectively mitigates network failures by eliminating hostile node behavior. However, the approach may face challenges in scalability for large-scale WSNs and increased computational overhead due to the integration of deep learning methods.

Liping Yu et al. (2023)[16] proposed a hybrid deep learning model integrated into an IoT-based healthcare monitoring system for COVID-19, focusing on remote patient monitoring and treatment facilitation. The system measures vital parameters such as oxygen levels, blood pressure, temperature, and heart rate, storing the collected data in a cloud-based environment for further analysis. To enhance classification accuracy, the authors introduced a Recurrent Convolutional Neural Network (RCNN) optimized with a Puzzle optimization algorithm (PO). This system aims to address challenges in rural healthcare by linking patients to city hospitals for continuous monitoring and treatment support. Experimental results demonstrated the model's efficiency examined to cutting edge approaches. However, a notable drawback of the study is the lack of discussion on potential limitations such as network latency, data privacy concerns, or the scalability of the proposed framework in real-world scenarios.

Islam et al. (2023)[17] proposed a deep learning-based IoT system for remote health monitoring and early detection of health issues in real-time, addressing the growing need for efficient healthcare solutions due to aging populations and rising chronic diseases. The system utilizes three types of sensors—MAX30100 for blood oxygen levels and heart rate, AD8232 for ECG signals, and MLX90614 for body temperature—to collect physiological data in home clinical settings. The data is transmitted via the MQTT protocol to a server where a pre-trained convolutional neural network (CNN) with an attention layer classifies potential diseases. The system can identify five categories of heartbeats, including Normal Beat and Premature Ventricular Contraction, and detect fever or non-fever conditions based on body temperature. Additionally, it provides reports on oxygen levels and heart rates, automatically connecting users to nearby doctors if critical abnormalities are identified. While the system demonstrates significant potential in enhancing remote healthcare, its reliance on pre-trained models without domain-specific fine-tuning and the limited disease classification scope are notable drawbacks that may affect its adaptability and accuracy in diverse real-world scenarios.

Younas et al (2023) [18]. conducted a systematic literature review focusing on the significance of quality of service (QoS) in IoT-driven healthcare systems, emphasizing edge computing and artificial intelligence (AI) for mitigating latency issues in emergency scenarios. The study highlights the integration of IoT, mobile, and cloud computing in revolutionizing healthcare by enabling information sharing among caregivers, facilities, and patients. The authors identified that QoS parameters such as throughput, bandwidth, latency, jitter, and packet loss are critical for ensuring efficient service delivery. They proposed a novel pre-SLR method for keyword research and provided an extensive review of QoS techniques and measures in smart healthcare applications. While their work offers solutions to QoS challenges in IoT-based healthcare, a notable drawback is the lack of real-time experimental validation of the proposed methods, which limits the practical applicability of their findings in live healthcare settings.

N. Ahmad et al.(2022)[19] proposed an Improved Quality of Service Aware Routing Protocol (IM-QRP) for Wireless Body Area Network (WBAN)-based Healthcare Monitoring Systems (HMS) to address the challenges of energy consumption, path loss ratio, packet delivery ratio, and signal-to-noise ratio (SNR) in healthcare monitoring applications. WBAN is a specialized wireless sensor network connecting medical sensors and appliances inside and outside the human body, enabling remote monitoring of patients' health, particularly for elderly individuals and chronically ill patients in residential or hospital settings. The proposed IM-QRP protocol demonstrates significant improvements over existing protocols like CO-LEEBA and QPRD, achieving 10% higher residual energy, a 30% reduction in path loss ratio, a 10% improvement in packet transmission reliability, and a 7% increase in SNR. Additionally, a Convolutional Neural Network is utilized outside the WBAN environment for intelligent analysis of medical health records. While the protocol offers notable advancements, its reliance on specific wireless communication schemes and the computational demands of CNNs may pose challenges in resource-constrained WBAN environments, potentially limiting its scalability and real-time processing capabilities.

Raut et al. (2021)[20] presented a comprehensive study on Quality of Service (QoS) aware machine learning algorithms for real-time applications in Wireless Sensor Networks (WSNs), emphasizing the growing adoption of WSNs in diverse domains like industrial automation and environmental monitoring. The authors highlighted the critical need for reliable and time-sensitive data transmission schemes in real-time WSNs, which are less dependable compared to wired networks. They explored QoS prerequisites for delay-bounded applications and discussed existing QoS-aware protocols, examining their application-specific advantages and limitations. The study also addressed machine learning-based approaches to meet QoS requirements, focusing on parameters such as energy efficiency, delay reduction, and trustworthiness. Despite these contributions, the paper noted that existing methods often fail to ensure consistent reliability and exhibit limitations in adapting to dynamic network conditions, leaving room for further optimization.

3. Proposed System:

The proposed system aims to enhance the Quality of Service (QoS) in Wireless Sensor Internet of Things (WS-IoT)-based healthcare systems through a Hybrid Deep Learning Model combining Long Short-Term Memory (LSTM)[21] and Gated Recurrent Unit (GRU)[22] networks. The system comprises of several key elements to address the challenges of real-time healthcare data transmission. First, the **Data Acquisition Layer** involves interconnected IoT sensors deployed to monitor and collect vital patient data such as heart rate. This data is then transmitted wirelessly to edge devices for preprocessing. In the **Data Preprocessing and Feature Extraction** stage, noise removal and normalization procedures are utilized to ensure the quality of the data. Temporal and spatial features are extracted from the data to improve model performance.

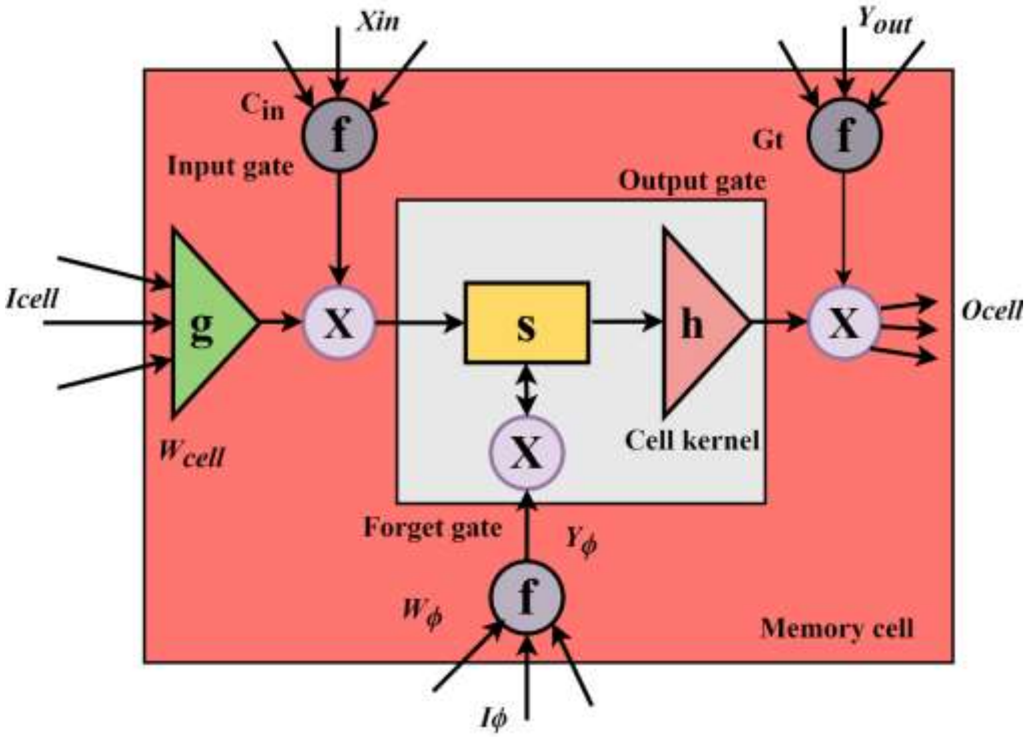

Figure 1 Architecture for LSTM

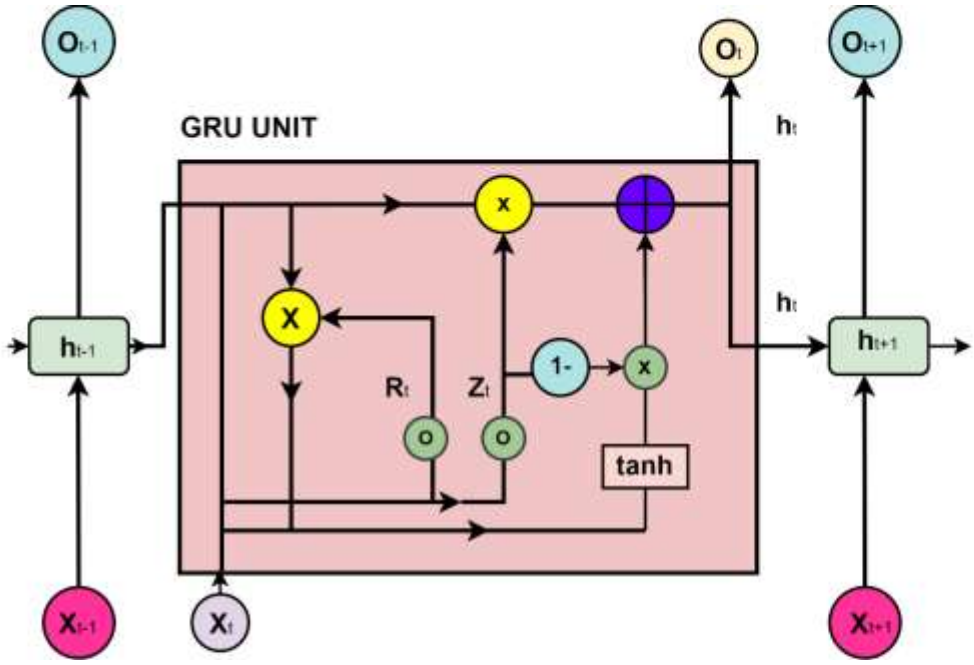

Figure 2 Framework for GRU

At the core of the recommended system is the **Hybrid LSTM-GRU Deep Learning Model**, which processes sequential data effectively[23]. The **LSTM** component captures long-term dependencies in the time-series data, while the **GRU** component efficiently handles the same data with reduced computational cost. The hybrid model combines the strengths of both networks to process complex patterns in healthcare data while maintaining computational efficiency[24].

A. Data Acquisition Layer

The **Data Acquisition Layer** is the foundational step in a WS-IoT-based healthcare system, involving the deployment of various sensors to gather real-time health data from patients. These sensors can include heart rate monitors, other wearable health-monitoring devices. The data collected is continuously transmitted to the edge devices or gateways using wireless communication protocols such as LoRa, or Wi-Fi[25]. This layer ensures seamless monitoring and real-time transmission of health data, which is crucial for early diagnosis and personalized treatment.

The challenges in this layer involve the integration of a variety of sensor types and ensuring they operate efficiently over time. Each sensor might have different characteristics, sampling rates, and data formats, so the layer must be designed to handle these discrepancies while ensuring data integrity and consistency for further processing.

B. Preprocessing

Once data is acquired, the next step is **Preprocessing**, which prepares the raw sensor data for subsequent analysis by removing noise and extracting relevant features[26]. Given that sensor data can be noisy due to varied factors like environmental interference, signal degradation, and errors in readings, preprocessing is critical to improving model performance.

Key preprocessing steps include:

- **Noise Removal**: Algorithms like Butterworth filters, Kalman filters, or wavelet transforms are employed to eliminate high-frequency noise from the raw signals.
- **Data Normalization**: Standardizing data values to a consistent range (e.g., scaling data to [0,1] or [-1,1]) is significant for models to work, especially when using deep learning algorithms.
- **Segmentation**: Data is split into smaller chunks (or windows) based on specific intervals to make it more manageable and to identify local patterns, such as beats.
- **Feature Extraction**: Extracting important features like heart rate variability, or power spectral densities in EEG signals. This step permits the system to focus on the most informative aspects of the data, reducing the dimensionality of the input for the model[27].

These preprocessing steps help in improving the signal quality and focusing on relevant data characteristics, allowing the hybrid model to perform optimally.

C. Hybrid Model & Feature Extraction

The **Hybrid Model** combines **LSTM** and **GRU** networks, both of which are well-suited for handling sequential data, making them ideal for healthcare applications involving time-series data. LSTMs are effective in capturing long-term dependencies and temporal patterns, while GRUs provide a more efficient solution with fewer parameters, making them computationally faster for real-time applications[28].

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 3, March : 2025

Feature extraction within the hybrid model holds a prominent role in improving the efficiency and performance of the deep learning networks. Relevant features such as the following are extracted:

- **Temporal Features**: Patterns over time, such as heart rate variability in ECG data.
- **Statistical Features**: Measures like mean, variance, skewness, and kurtosis, which are useful for anomaly detection in physiological data.
  The hybrid model uses the extracted features to provide more accurate predictions and classifications, enabling real-time insights into the patient's health condition.

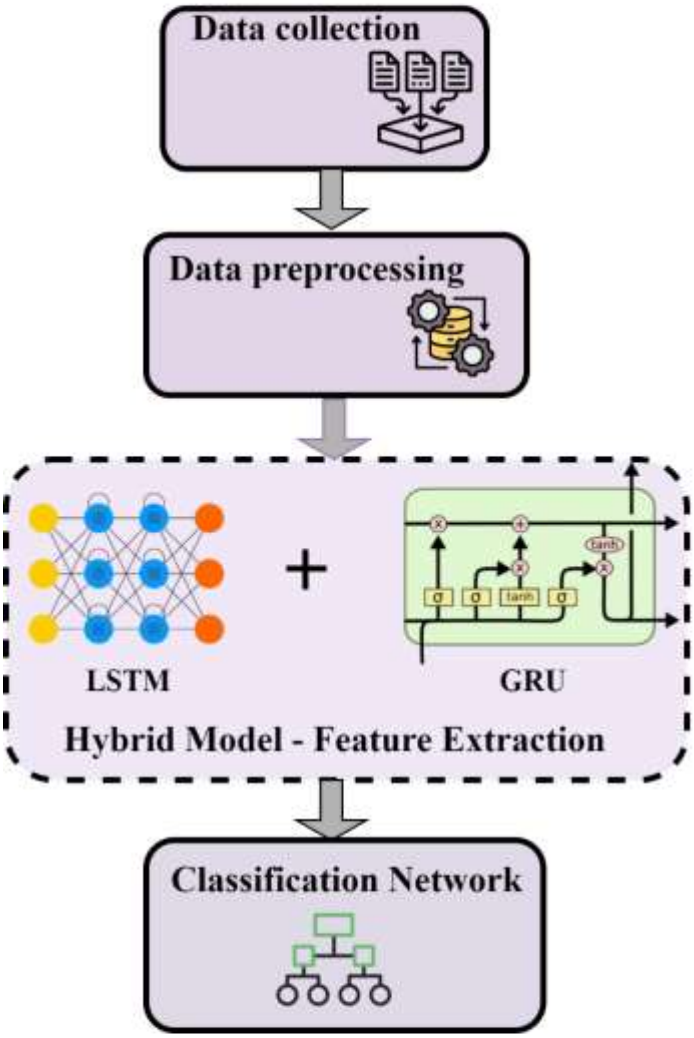

Figure 3 Architecture for the Recommended Approach

D. Classification Network

The **Classification Network** is designed to categorize the processed and feature-extracted data into meaningful labels, such as identifying abnormal events like arrhythmias or seizures in EEG data[29]. This component is responsible for interpreting the complex data patterns learned by the hybrid model.

After feature extraction, the data is passed through a classification network, which could be a fully connected neural network (FCNN) or a convolutional neural network (CNN) for enhanced performance in image-based[30] A typical deep learning classification process includes the following steps:

- **Input Layer**: The extracted features from the previous stage are fed as inputs.
- **Hidden Layers**: A series of dense layers or convolutional layers learn the complex patterns in the data. These layers allow the model to recognize intricate temporal or spatial relationships in the data, such as detecting an abnormal heartbeat data or identifying neural activity related to seizures in EEG.
- **Output Layer**: This layer produces a binary or multi-class classification result. For instance, the system might classify a heartbeat as either normal or abnormal, or an EEG as either normal or indicative of a seizure.

4. Results and Discussion

A. Packet Delivery Ratio (PDR)

It is a critical performance metric that measures the ratio of successfully received data packets at the destination examined to the total number of packets sent by the source. A higher PDR indicates a more reliable network, where most data is delivered without loss. In healthcare systems based on IoT, a high PDR is essential to ensure that medical data, such as patient vitals, is transmitted reliably to healthcare providers without data loss, ensuring timely decision-making and interventions.

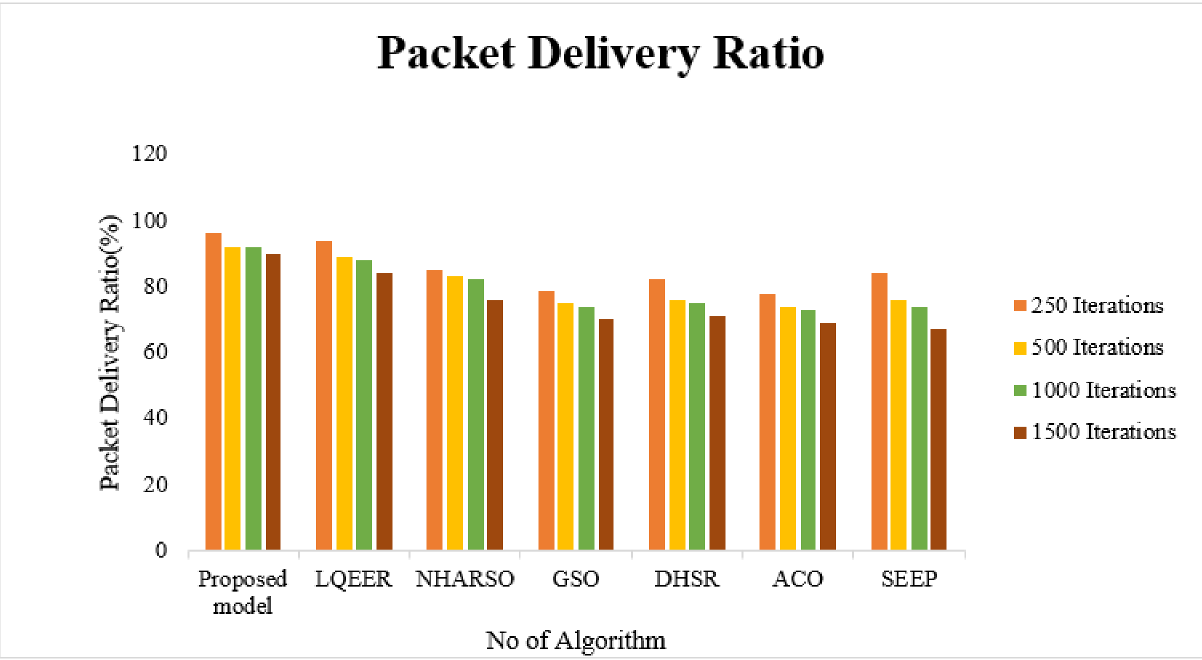

Figure 4 Comparative analysis with residing approaches

B. End-to-End Delay

It refers to the total time taken for a packet to travel from the source to the destination node within a network. This delay comprises transmission time, queuing delays, propagation delays, and processing delays. Minimizing end-to-end delay is crucial for applications requiring real-time communication, such as remote health monitoring or emergency alerts. Long delays can hinder the timely transmission of critical health data, potentially compromising patient care or medical decision-making in time-sensitive situations.

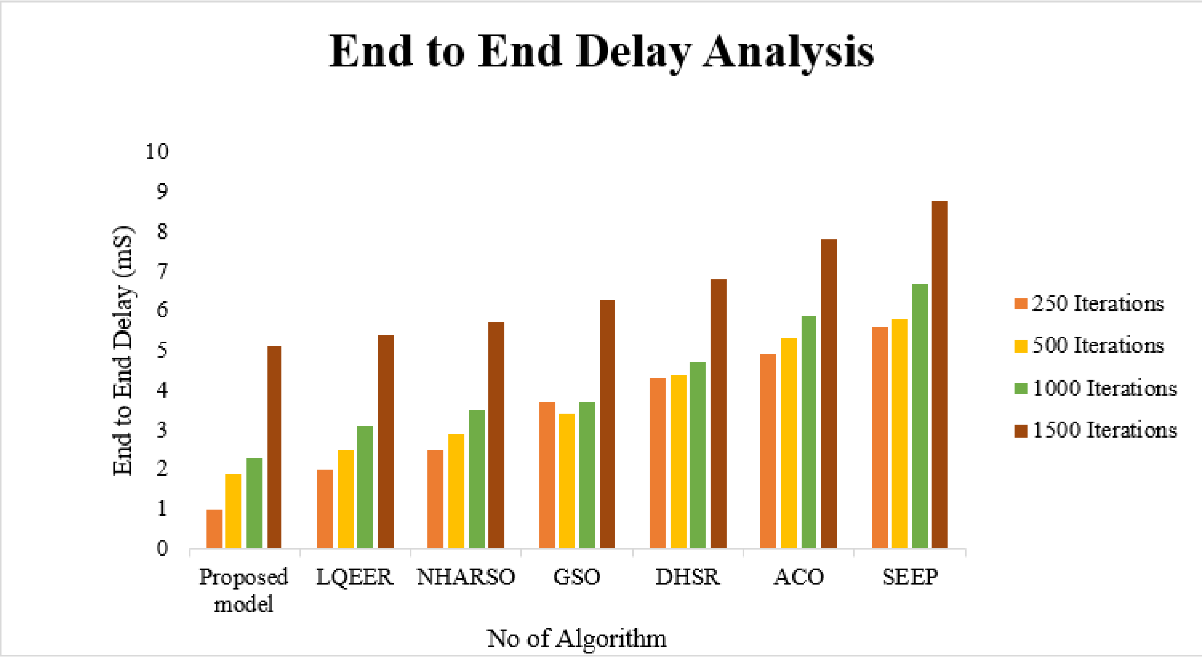

Figure 5 Comparative Analysis with the existing approach

C. Throughput

The rate at which data is successfully transmitted over a network. It is often computed in bits per second (bps) or packets per second (pps). Higher throughput indicates a network's ability to handle large volumes of data efficiently, which is especially important in environments where large datasets, such as medical images or patient monitoring data, need to be transmitted quickly. In IoT-based healthcare systems, throughput ensures that large quantities of health-related data can be processed and transmitted without bottlenecks, allowing for real-time monitoring and updates.

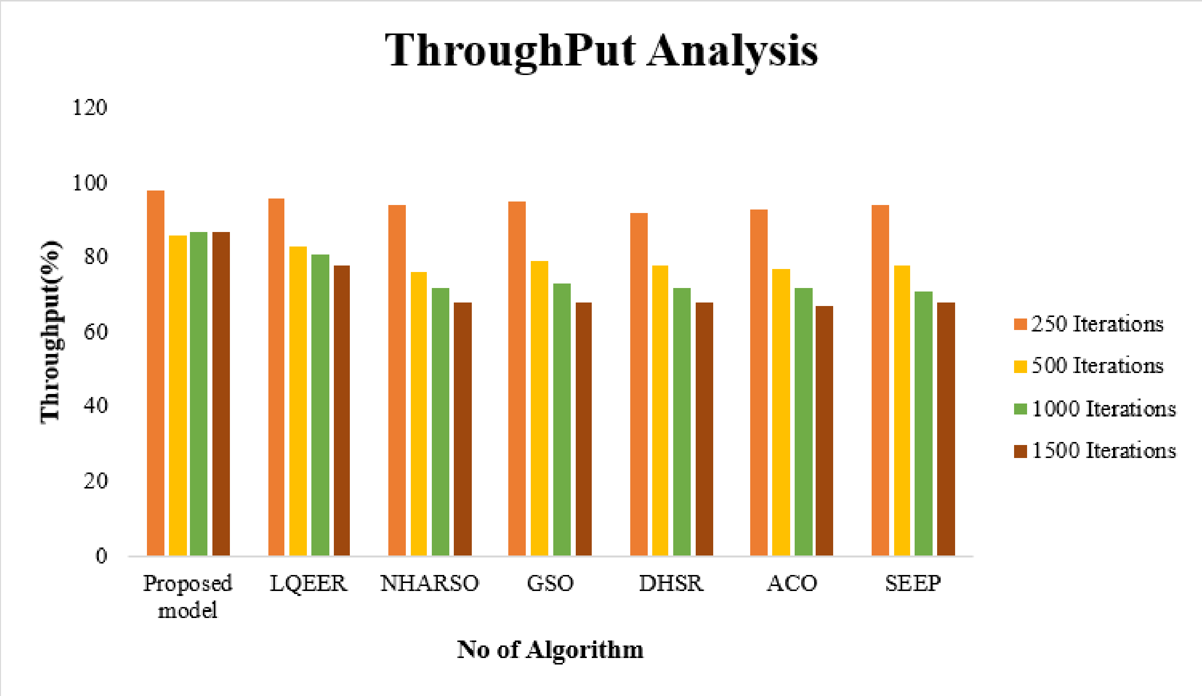

Figure 6 Throughput analysis with the residing approach

D. Packet Overhead Ratio

Experimental evaluations depicts that the proposed hybrid DL model consistently achieves the lowest packet overhead. This is primarily due to the efficient selection of the cluster head, which holds a prominent place in optimizing the data transmission process. By effectively managing data transmission, the proposed model significantly reduces the control packet overhead, ensuring that more resources are dedicated to critical medical data transfer.

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 3, March : 2025

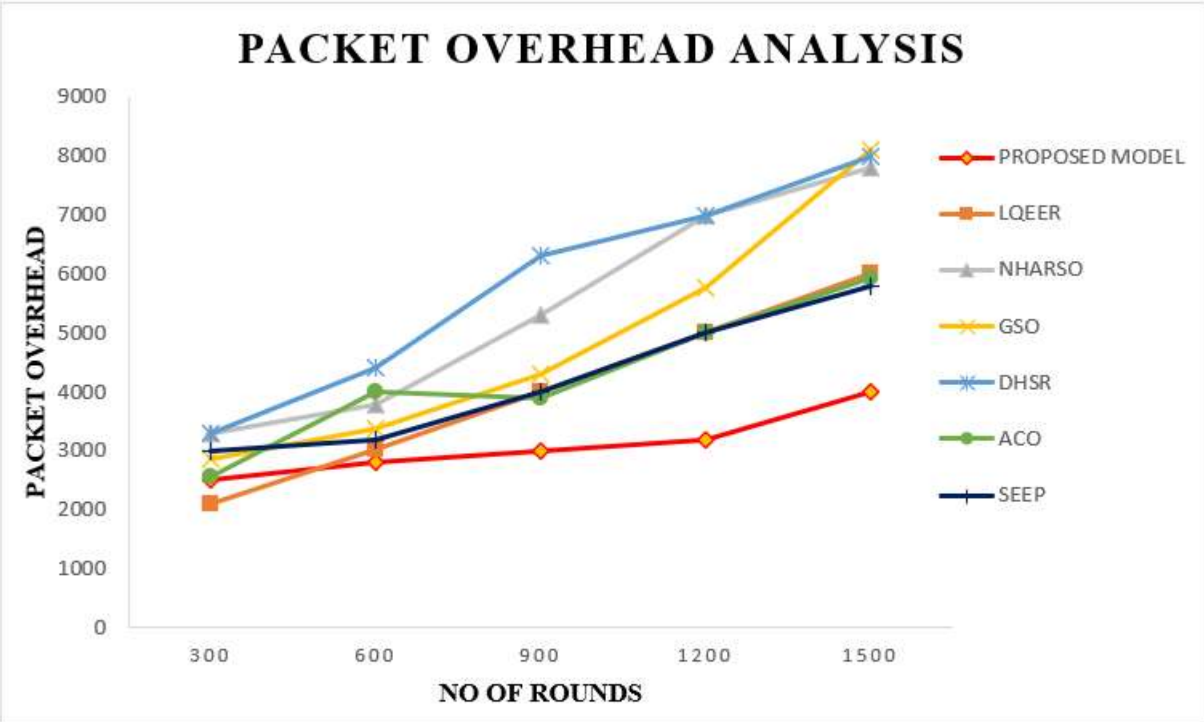

Figure 7 Comparative Analysis with the residing approach for POA

5.Conclusion

In this research, the performance metrics of Packet Delivery Ratio (PDR), End-to-End Delay, Throughput, Routing Load, and Control Packet Overhead are essential to assess the overall efficiency, reliability, and scalability of IoT-based healthcare systems. These metrics directly influence how well medical data can be transmitted and processed in real-time, a key factor for the success of applications such as remote patient monitoring, emergency alerts, and telemedicine. Our proposed model, leveraging advanced hybrid deep learning approaches, demonstrates superior performance compared to existing models across these crucial metrics. The enhanced PDR of our model ensures that a greater proportion of the transmitted packets reach their destination successfully, contributing to more reliable data transmission in healthcare IoT systems. By optimizing the transmission process, our model is able to achieve higher packet delivery rates, even in challenging environments with varying network conditions or traffic congestion. Furthermore, the model significantly reduces End-to-End Delay, ensuring faster delivery of critical health data to healthcare providers. This reduction in latency is crucial for time-sensitive applications where delays in data transmission could impact patient care, such as in emergency medical services or real-time health monitoring. Future enhancements could include further optimization of the routing protocols to reduce energy consumption, integration of more sophisticated machine learning algorithms for adaptive data transmission, and scalability improvements to handle larger and more diverse healthcare networks.

References:

1. Lanzolla, Anna, and Maurizio Spadavecchia. "Wireless sensor networks for environmental monitoring." *Sensors* 21.4 (2021): 1172.
2. Agarwal, Vaibhav, Shashikala Tapaswi, and Prasenjit Chanak. "A survey on path planning techniques for mobile sink in IoT-enabled wireless sensor networks." *Wireless Personal Communications* 119.1 (2021): 211-238.
3. Vijayakumar S, Rizwan P, Khan MS, Kallam S (2019) Reliable and energy-efficient emergency transmission in wireless sensor networks. Internet Technol Lett Wiley Online Library, 25 Jan 2019. https://doi.org/10.1002/itl2.91.
4. Hayyolalam, Vahideh, et al. "Edge intelligence for empowering IoT-based healthcare systems." *IEEE Wireless Communications* 28.3 (2021): 6-14.
5. Al-Rakhami, Mabrook, et al. "A lightweight and cost effective edge intelligence architecture based on containerization technology." *World Wide Web* 23 (2020): 1341-1360.
6. M. Aslam, E. U. Munir, M. M. Rafique and X. Hu, "Adaptive energy-efficient clustering path planning routing protocols for heterogeneous wireless sensor networks", Sustain. Comput. Informat. Syst., vol. 12, pp. 57-71, Dec. 2016.
7. F. T. Zuhra, K. A. Bakar, A. Ahmed and M. A. Tunio, "Routing protocols in wireless body sensor networks: A comprehensive survey", J. Netw. Comput. Appl., vol. 99, pp. 73-97, Dec. 2017.
8. Roberts, Michaelraj Kingston, and Poonkodi Ramasamy. "An improved high performance clustering based routing protocol for wireless sensor networks in IoT." *Telecommunication Systems* 82.1 (2023): 45-59.
9. Mohseni, Milad, Fatemeh Amirghafouri, and Behrouz Pourghebleh. "CEDAR: A cluster-based energy-aware data aggregation routing protocol in the internet of things using capuchin search algorithm and fuzzy logic." *Peer-to-Peer Networking and Applications* 16.1 (2023): 189-209.
10. Monisha, A. Anu, T. R. Reshmi, and Krishnan Murugan. "ERNSS-MCC: Efficient relay node selection scheme for mission critical communication using machine learning in VANET." *Peer-to-Peer Networking and Applications* 16.4 (2023): 1761-1784.
11. B. S. Liya, R. Krishnamoorthy, and S. Arun. 2024. An enhanced deep learning-based disease detection model in wireless body area network with energy efficient routing protocol. Wirel. Netw. 30, 4 (May 2024), 2961–2986. https://doi.org/10.1007/s11276-024-03717-1.
12. Paulraj, S.S.S., Deepa, T. Energy-efficient data routing using neuro-fuzzy based data routing mechanism for IoT-enabled WSNs. *Sci Rep* **14**, 30081 (2024). https://doi.org/10.1038/s41598-024-79590-x
13. K. Saritha and V. Sarasvathi. 2024. An Energy-Efficient and QoS-Preserving Hybrid Cross-Layer Protocol Design for Deep Learning-Based Air Quality Monitoring and Prediction. SN Comput. Sci. 5, 3 (Mar 2024). https://doi.org/10.1007/s42979-023-02525-2
14. Roy, P.P.; Teju, V.; Kandula, S.R.; Sowmya, K.V.; Stan, A.I.; Stan, O.P. Secure Healthcare Model Using Multi-Step Deep Q Learning Network in Internet of Things. *Electronics* **2024**, *13*, 669. https://doi.org/10.3390/electronics13030669.
15. Ramu, K. & Raju, S. & Singh, Satyanand & Rachapudi, Venubabu & Mary, M. & Roy, Vandana & Joshi, Shubham. (2024). Deep Learning-Infused Hybrid Security Model for Energy

Optimization and Enhanced Security in Wireless Sensor Networks. SN Computer Science. 5. 1-11. 10.1007/s42979-024-03193-6.

16. Liping Yu *et al.*, "Hybrid deep learning model based smart IoT-based monitoring system for COVID-19," *Heliyon*, vol. 9, no. 11, p. e21150, 2023. DOI: 10.1016/j.heliyon.2023.e21150.
17. Islam, M.R.; Kabir, M.M.; Mridha, M.F.; Alfarhood, S.; Safran, M.; Che, D. Deep Learning-Based IoT System for Remote Monitoring and Early Detection of Health Issues in Real-Time. *Sensors* **2023**, *23*, 5204. https://doi.org/10.3390/s23115204.
18. Younas MI, Iqbal MJ, Aziz A, Sodhro AH. Toward QoS Monitoring in IoT Edge Devices Driven Healthcare-A Systematic Literature Review. Sensors (Basel). 2023 Nov 1;23(21):8885. doi: 10.3390/s23218885. PMID: 37960584; PMCID: PMC10650388.
19. N. Ahmad, M. D. Awan, M. S. H. Khiyal, M. I. Babar, A. Abdelmaboud, H. A. Ibrahim, and N. O. Hamed, "Improved QoS Aware Routing Protocol (IM-QRP) for WBAN Based Healthcare Monitoring System," *IEEE Access*, vol. 10, pp. 124345–124356, Nov. 2022, doi: 10.1109/ACCESS.2022.3223085.
20. Raut, Archana R., Sunanda P. Khandait and Nekita Chavhan. "QoS Aware Machine Learning Algorithms for Real-Time Applications in Wireless Sensor Networks." (2021).
21. Rai, Ashok Kumar, and A. K. Daniel. "FEEC: fuzzy based energy efficient clustering protocol for WSN." *International Journal of System Assurance Engineering and Management* 14.1 (2023): 297-307.
22. John, Jacob, and Paul Rodrigues. "MOTCO: Multi-objective Taylor crow optimization algorithm for cluster head selection in energy aware wireless sensor network." *Mobile Networks and Applications* 24.5 (2019): 1509-1525.
23. Arya, G., Bagwari, A. & Chauhan, D. S. Performance analysis of deep learning based routing protocol for an efficient data transmission in 5G WSN communication. *IEEE Access*. 1–1. https://doi.org/10.1109/access.2022.3142082 (2022).
24. Kalyani, G. & Chaudhari, S. S. Cross-layer security MAC aware routing protocol for IoT networks. *Wireless Pers. Commun.* **123**, 935–957. https://doi.org/10.1007/s11277-021-09163-y (2021).
25. Zhong, X. & Liang, Y. Scalable downward routing for wireless sensor networks actuation. *IEEE Sens. J.* **19**, 9552–9560. https://doi.org/10.1109/jsen.2019.2924153 (2019).
26. Zhang, Y., Wang, J. & Chen, B. Detecting false data injection attacks in Smart grids: A semi-supervised deep learning approach. *IEEE Trans. Smart Grid*. **12**, 623–634. https://doi.org/10.1109/TSG.2020.3010510 (2021).
27. Ming, C., Kadry, S. & Dasel, A. A. Automating smart internet of things devices in modern homes using context-based fuzzy logic. *Comput. Intell.* **40**. https://doi.org/10.1111/coin.12370 (2020).
28. Ghanbari, Z., Jafari Navimipour, N., Hosseinzadeh, M., Shakeri, H. & Darwesh, A. M. *A New Energy-Aware Routing Protocol for Internet of Mobile Things Based on Low Power and Lossy Network Using a Fuzzy-Logic* (SSRN Electronic Journal, 2022).
29. Behura, A., Sahu, S., & Kabat, M. R. (2021). Advancement of Machine Learning and cloud computing in the field of Smart Health Care. Machine Learning Approach for Cloud Data Analytics in IoT, 273-306. https://doi.org/10.1002/9781119785873.ch11.

30. Ali, F., El-Sappagh, S., Islam, S. R., Ali, A., Attique, M., Imran, M., & Kwak, K. S. (2021). An intelligent healthcare monitoring framework using wearable sensors and social networking data. Future Generation Computer Systems, 114, 23-43. https://doi.org/10.1016/j.future.2020.07.047.