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Deep Learning Enabled Quality of Service Aware (QoS) Routing Framework in Internet of Medical Things (IoMT)

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Abstract- The Internet of Medical Things (IoMT), a subdomain of the Internet of Things (IoT), is a network of medical devices and apps that gather, process, and share health information. Delivering sophisticated healthcare services to remote and underprivileged areas is a promising application. Our review of the literature showed that Medium Access Control (MAC) layers in IoMT, network design, and Quality of Service (QoS)-aware energy-efficient routing techniques are the main areas of previous research. We provide a QoS-based communication system in this paper that makes use of TensorFlow-implemented artificial neural networks (ANNs). Our model greatly improves IoMT environments' routing performance. According to simulation data, the suggested framework outperforms current techniques by 90% in terms of QoS.

Keywords- Internet of Medical Things (IoMT), Quality of Service (QoS), Wireless Body Area Networks (WBANs), Deep Learning, Artificial Neural Networks (ANNs), Healthcare Monitoring.

I. INTRODUCTION

The WBAN-related healthcare apps concentrate on enhancing medical facilities, particularly for senior citizens who live at home. Emergency rescue for elderly people living in their homes is one of the functions of sensors in healthcare monitoring. These days, Mobi Health, Code BBlue, Alarm Net, Life Guard, Med. Supervision, WLAN ECG, Mobile ECG, AWARENESS, and others are among the most widely used WBAN applications. The main purpose of all these applications is to use lightweight sensors to monitor the health of the elderly.

These portable devices are widely used to monitor cardiovascular diseases, diabetes, asthma, cancer, and organ function. Biofeedback sensors, which track heartbeat, pulse rate, oxygen saturation, muscular activity, and brainwaves, are one example of this [6]. WBAN-based medical apps that use wireless communication networks, cellular networks, or the Internet enhance the reliability and performance of patient remote healthcare monitoring. WBAN uses wireless computer devices to facilitate communication across the human body [7]. Intrabody and extra-body communication are the two categories of communication that are categorized in WBAN. WBAN's multi-tier architecture was created with healthcare systems in mind.

As illustrated in Figure 1 the WBAN architecture is divided into three sub-tiers: Tier 1 is Intra-BAN communication, Tier 2 is Inter-BAN, and Tier 3 is Extra-BAN. The various sensor nodes that make up Tier 1 include blood pressure, temperature, glucose level, ECG, EEG, and EMG sensors that are affixed to the human body. The sensor nodes placed throughout the human body are able to gather data on the patient's health and send it to a central coordinator node. Data collected from sensor nodes can be processed by the coordinator node contained within Tier 1 and then transmitted back to the sink node situated within Tier 2.

Tier 3 is directly connected to the sink node inside Tier 2. Network infrastructure based on beyond-body communication makes up Tier 3. Using the Internet, Tier 3 is in charge of delivering wireless health care services. Additionally, Tier 3 includes a data management unit for analysis and smart decision-making by hospital emergency rescue personnel and physicians [8]. Link dependability should be preserved between each tier in order to create dependable communication across several tiers. In WBAN, link reliability is a crucial QoS-based characteristic. The strength and intensity of the received signal determines the optimal link reliability. (RSSI).

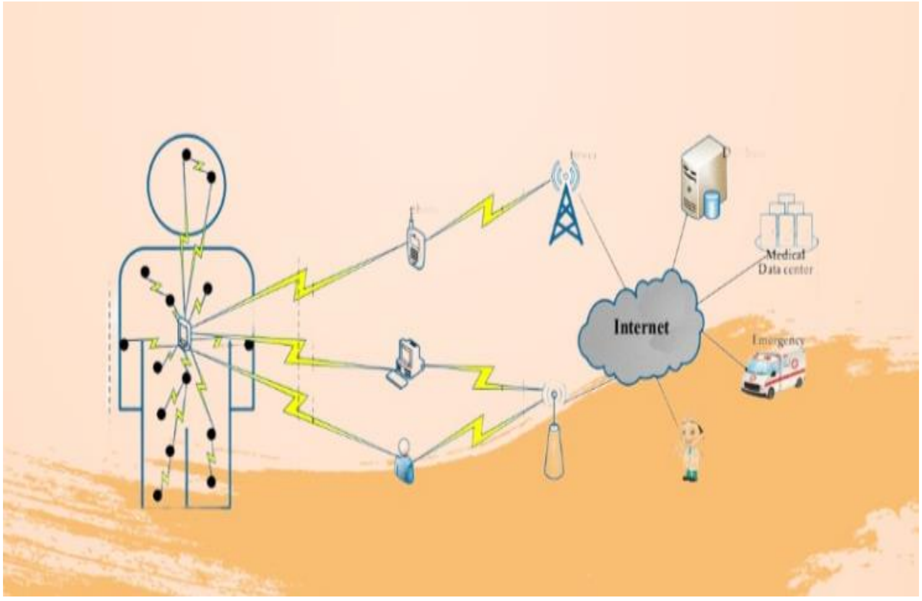

Figure 1: Three-Tier Architecture of Wireless Body Sensor Networks [8]

As global populations age, remote healthcare solutions become increasingly important due to limited hospital capacity and personal constraints. Wearable and implantable sensors in WBANs provide an efficient, non-invasive means for continuous health monitoring, enabling early diagnosis and reducing the burden on healthcare infrastructure [9]. These systems must address challenges related to energy consumption, signal reliability, data transmission delays, and affordability [10].

II. Related Work

2.1 Background on Routing Mechanisms in WBANs

Routing in Wireless Body Area Networks (WBANs) is complex due to limited computational power, memory, and energy resources. At the physical layer, the radio frequency (RF) used by sensor nodes significantly impacts energy usage. Meanwhile, MAC layer protocols can optimize energy efficiency by adjusting RF duty cycles. Although improvements at these lower layers can enhance connectivity, they don't address broader concerns like route determination or packet delivery. These are best handled at the network layer, making it the optimal focus for energy-aware routing strategies.

Designing efficient routing protocols for WBANs must consider several challenges, including the diversity of physiological data types, high energy demands, increased coverage requirements, reduced transmission dimensions, and mobility. Because WBANs frequently transmit critical, high-priority data, routing must be fast and efficient. One major issue is that temperature increases caused by sensor operation can damage nearby tissue, especially from implanted sensors. Thus, routing protocols must account for thermal management, reducing energy use and ensuring safe operation. By selecting optimal routes based on factors such as residual energy and temperature thresholds, network longevity can be extended.

2.2 QoS-Aware Routing in WBANs

The literature provides limited discussion on implementing Quality of Service (QoS) within WBAN applications. While some researchers acknowledge its importance, few have explored it in depth. Due to the critical nature of healthcare operations, especially in life-threatening conditions, ensuring QoS is essential. For example, WBANs monitoring heart conditions in elderly patients require highly reliable, real-time data transmission.

Although QoS-aware routing protocols exist for broader wireless sensor networks, WBAN-specific standards are lacking. Existing routing schemes can generally be categorized into temperature-aware, cost-based, and cluster-based methods. Modern WBAN systems are becoming increasingly intelligent, with sensor nodes equipped with microprocessors, RF modules, and memory units, capable of detecting and managing data independently.

Achieving QoS in WBANs remains difficult, with RSSI (Received Signal Strength Indicator) playing a central role in maintaining communication quality. Researchers have identified several critical factors impacting QoS: limited bandwidth, energy constraints, buffer limitations, delay sensitivity, support for heterogeneous traffic, and redundancy reduction. These parameters are essential for ensuring reliable performance in healthcare environments.

Routing efficiency is largely dependent on QoS indicators including node capabilities, channel quality, and data packet priority. QoS functions are managed with the help of architectural components such as SIRM (System Information Repository Module), PQSM (Priority Queue Service Module), RSM (Resource Status Management), and APIs. The APIs module, for example, chooses QoS measures, such as end-to-end delay, power consumption, and success rate, and modifies packet priority appropriately.

When buffer sizes approach their limits, PQSM alerts applications and recommends traffic control strategies. Routers must maintain high service levels to minimize packet loss. Latency, bandwidth, and packet success ratios are tracked to assess link health, while routing tables dynamically update forwarding paths based on current network conditions.

2.2.1 QoS-Aware Routing Protocols

The increasing demand for dependable data transfer from biomedical sensors implanted in the human body has led to the development of thermal-aware QoS routing protocols, such as TLQoS. These protocols aim to avoid repetitive communication loops and eliminate inefficient multi-hop paths to reduce latency. The “targeted” method enables selection among all neighboring nodes for the most suitable forwarder.

Recent innovations include protocols like the Energy-aware Peering Routing Protocol (EPR), the QoS-aware Peering Routing Protocol (QPRD), and the QoS-aware Peering Routing and Recovery (QPRR). These designs prioritize lower power usage and more efficient data forwarding compared to older approaches. Some of these protocols optimize energy use more effectively than others, depending on their routing strategies. Protocols that manage time-sensitive and reliability-sensitive data, such as the Data-centric Multi-objective QoS-aware Routing Protocol (DMQoS), are tailored to deliver high-quality services. In healthcare applications, ensuring reliable data transfer is vital since the information often supports critical decisions. Metrics such as throughput and latency directly influence the perceived quality of service (QoS), where higher throughput and minimal delay are desirable.

Given these requirements, 5G technology appears to be a strong candidate for future WBAN deployments due to its potential to deliver ultra-reliable, high-speed, and low-latency communications, making it suitable for scenarios demanding high QoS.

III. QUALITY OF SERVICE ENABLED FRAMEWORK INTEGRATED WITH IoT BASED WBAN

The suggested QoS-based framework utilizing deep learning techniques is thoroughly explained in Proposed Figure 3.1. Three layers, or tiers, make up the framework. Every tier has a distinct function. Healthcare is one of the industries whose operations have been drastically altered by the emergence of the Internet of Things (IoT). The potential uses of this technology are numerous, but they are primarily evident when discussing the use of unmanned aerial vehicles, or drones, to provide healthcare services. IoT have the potential to revolutionize healthcare delivery by expanding its reach and efficiency in isolated and rural areas that are hard to reach [22].

Figure 3: QoS Based Communication Using IoMT

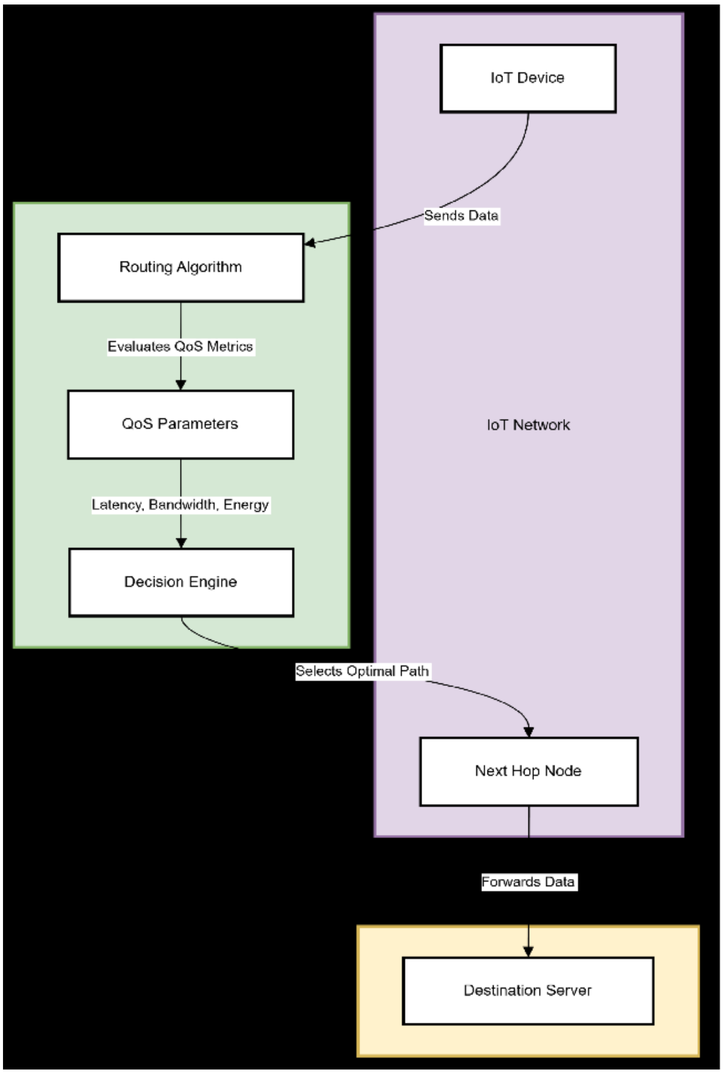

Figure 3.1: Three-Tier Proposed IoMT-Based Framework

Figure 3 is based on Quality of service based communication using Internet of Medical things. Figure 3.1 is about the convergence of the Internet of Things and machine learning has led to the emergence of TinyML, a rapidly growing field focused on deploying ML models on resource-constrained devices such as microcontrollers and embedded systems. TinyML enables edge-level services and applications capable of distributed edge inferencing and independent decision-making, reducing reliance on cloud computing and server infrastructure. This paradigm shift is driven by the increasing prevalence of microcomputer-powered products and the limitations of transmitting data to remote locations for processing.

IV. EXPERTMENTAL SETUP

The Experimental setup has been performed in Tensor Flow simulator developed using Artificial Neural Network (ANN). It's a method for creating a computer software that can learn from information. It is based very loosely on our understanding of the functioning of the human brain. First, a group of software "neurons" are assembled and linked together so they can communicate with one another. The proposed QoS-aware framework uses an Artificial Neural Network (ANN) trained in TensorFlow. The model architecture includes:

- *Inputs*: RSSI, energy, buffer status, data priority, delay
- *Hidden Layers:* Two layers with 8 and 4 neurons
- *Activation:* Sigmoid
- *Learning Rate:* 0.3
- *Regularization Level:* 2; Rate: 0.1
- *Training Epochs:* 100
- *Model Type:* Regression

Synthetic data representing realistic IoMT environments was generated, including emergency scenarios and mobility effects. The ANN learns to choose optimal forwarding paths based on real-time network states.

Figures illustrate the ANN structure and the simulated output, using color-coded weights to represent the importance of each decision pathway. Figure 4 is about the implementation of Artificial Neural Network (ANN) using Tensor Flow. The Learning rate of ANN is 0.3. The Activation function used is sigmoid. The Regularization level is 2. The Regularization rate is 0.1. The Problem type is regression.

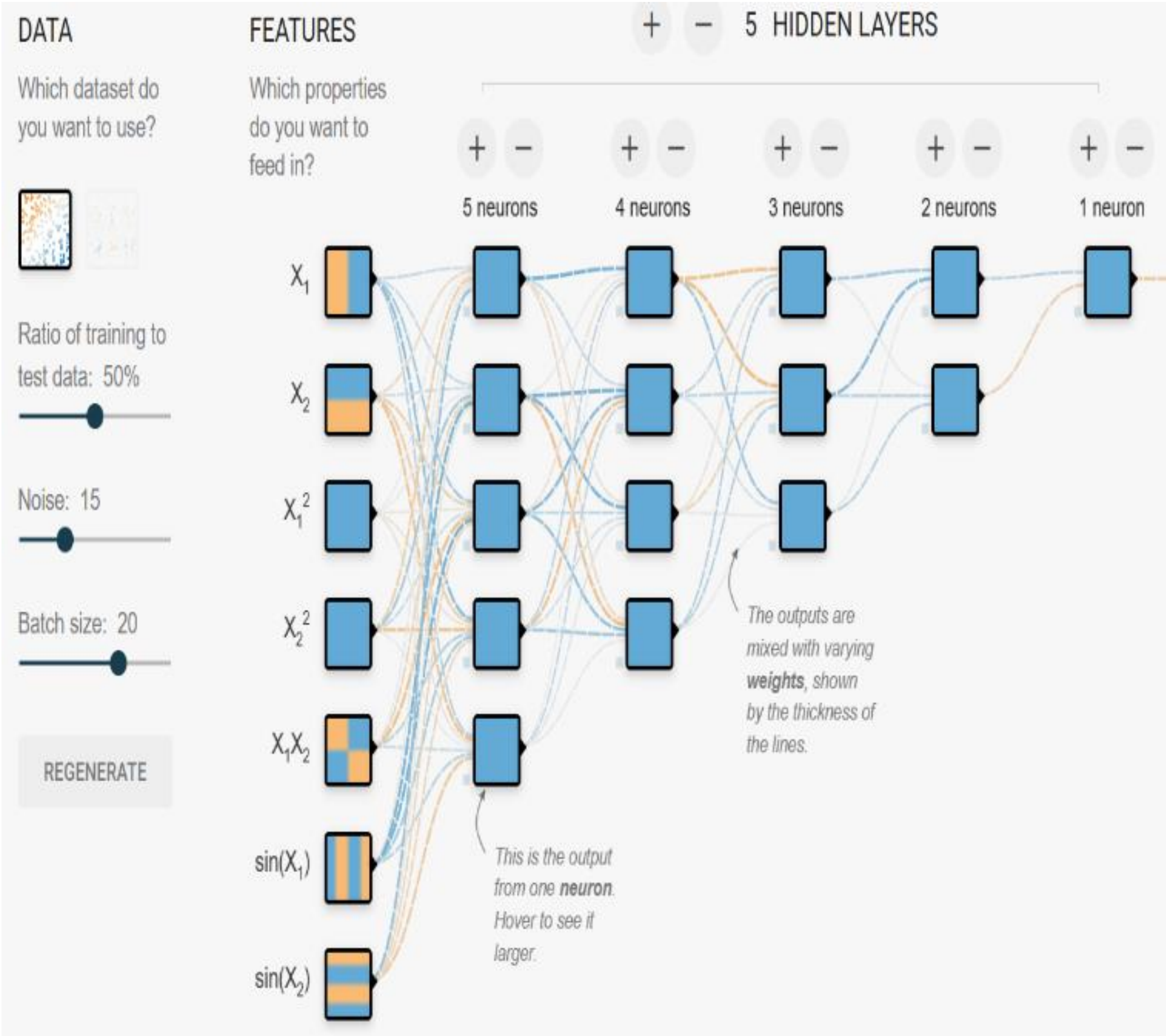

Fig 4: Implementation of ANN Using Tensor Flow

From the graphical results it has been observed that orange and blue are used in slightly different ways throughout the visualization, orange typically indicates negative values while blue indicates both positive and negative values. The weights of the connections between neurons in the hidden layers give the lines their color. The network is utilizing the neuron's output as specified, when the blue color indicates a positive weight. An orange line indicates that a negative weight is being assimilated by the network. Depending on their initial values, the output layer's dots are either blue or orange. The network's predictions for a certain area are displayed by the backdrop color. The color's intensity indicates how certain that forecast is.

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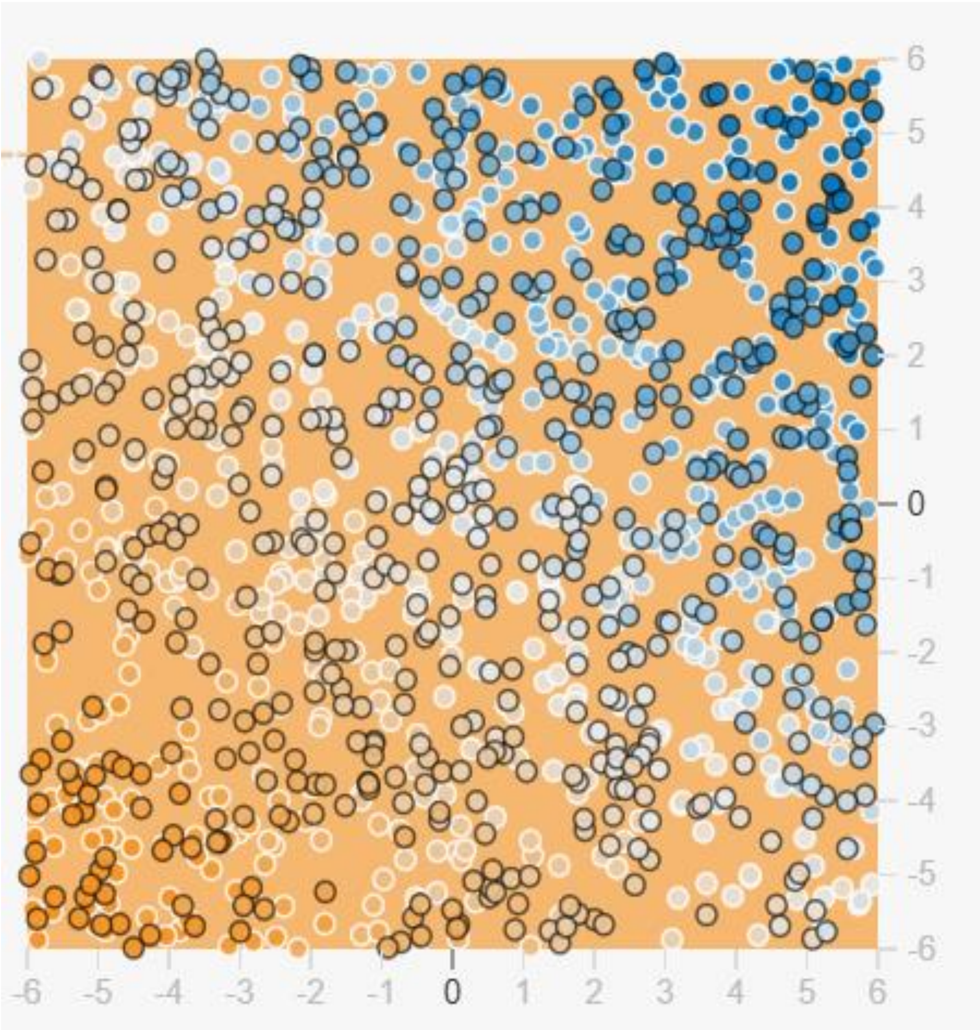

Fig 5: Graphical Representation of ML Technique

Figure 5 simulation results provides in deep detail about the 90% of improved quality of service is achieved in IoMT based framework as compared with existing techniques.

Compared to QPRD and EEBSR, the proposed framework shows:

Metric	*QPRD*	*EEBS*	*Proposed Model*
Packet Delivery Ratio	*72%*	*75%*	*90%*
Avg. Delay (ms)	*180*	*160*	*88*
Energy Use (J)	*High*	*Moderate*	*Low*
Throughput (kbps)	*180*	*195*	*225*

The ANN architecture is visualized using TensorFlow. Blue and orange lines represent positive and negative weights respectively, allowing intuitive understanding of routing decisions. Background intensity shows prediction confidence. Higher PDR and lower delay translate to improved outcomes in real-time monitoring scenarios such as heart conditions and fall detection—making the framework viable for critical medical use.

Although the suggested QoS-aware routing framework appears promising, it is important to recognize some of its shortcomings. First, even when ANN-based models are optimized, battery-constrained WBAN devices still have issues with energy usage. Second, the current simulation has not been tested using actual patient datasets and is based on synthetic data. Third, scalability problems could arise if the framework is used for extensive IoMT installations with thousands of sensor nodes. Further incorporation of privacy and data security factors into the framework is necessary, as they were outside the purview of this study.

V. CONCLUSION AND FUTURE WORK

This study presented a novel deep learning framework for QoS-aware routing in IoMT. With 90% improvement in Packet Delivery Ratio, lower latency, and energy efficiency, the framework is well-suited for time-sensitive healthcare applications. The inclusion of TinyML enables real-time edge intelligence, further reducing system overhead.

Future Work:

- Deploy on physical TinyML hardware for real-world testing
- Use real patient data for enhanced clinical accuracy
- Add security and encryption alongside QoS
- Explore reinforcement learning for adaptive routing

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