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Design of an Iterative Method for Enhanced Routing in Blockchain-Powered IoMT Networks Featuring Patient-Condition-Aware and Predictive Time Series Techniques

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Abstract: In the realm of the Internet of Medical Things (IoMT), the efficient routing of critical patient data stands as a paramount necessity, driven by the rapid evolution of healthcare technologies and the increasing demand for real-time, reliable medical data transmission. Traditional routing mechanisms in IoMT networks often fall short due to their static nature and inability to adapt to the dynamic requirements of medical applications, resulting in significant delays and congestion. This work introduces an advanced suite of routing methodologies tailored for blockchain-powered IoMT networks that address these limitations by incorporating machine learning algorithms to enhance routing decisions dynamically. Firstly, the Patient-Condition-Aware Dynamic Routing (PCADR) methodology leverages real-time patient data to modify network routes dynamically. This approach prioritizes data transmissions based on the severity and urgency of patient conditions, thereby ensuring that critical information is expedited. By integrating patient vital signs and medical histories into routing decisions, PCADR achieves a notable 20% reduction in data transmission latency for urgent cases, illustrating its effectiveness in personalized healthcare delivery. Secondly, Predictive Time Series Routing (PTSR) employs time series analysis to forecast future network traffic patterns. By analyzing historical traffic and environmental sensor data, PTSR proactively optimizes routing strategies to accommodate anticipated changes in network load. This method has demonstrated a 30% reduction in network congestion, significantly enhancing the timeliness and reliability of data delivery across the network. Thirdly, Privacy-Preserving Federated Routing (PPFR) utilizes federated learning to develop routing models collaboratively across distributed IoMT devices while maintaining strict data privacy. This decentralized approach not only complies with stringent privacy regulations but also refines routing accuracy by 15% compared to centralized models, without exposing sensitive patient information sets. Lastly, Context-Aware Environmental Routing (CAER) integrates environmental sensing with routing mechanisms to mitigate data transmission errors influenced by adverse environmental conditions. By adjusting routes based on real-time temperature and humidity data, CAER reduces data corruption risks, achieving a 25% decrease in transmission errors.

Keywords: *IoMT, Blockchain, Federated Learning, Dynamic Routing, Machine Learning*

1. Introduction

The burgeoning field of the Internet of Medical Things (IoMT) is revolutionizing healthcare by enabling the interconnectivity of medical devices and systems that collect, analyze, and transmit health data samples. At the forefront of this revolution is the critical challenge of ensuring efficient, timely, and secure data transmission within IoMT networks—a challenge amplified by the life-critical nature of medical applications [1, 2]. Traditional routing strategies, predominantly static and homogeneous, are ill-equipped to meet the dynamic and heterogeneous demands of modern IoMT frameworks, especially when integrated with blockchain technology for enhanced security and data integrity levels. The need for innovative routing solutions that are adaptive, privacy-compliant, and responsive to environmental and patient-specific factors is more pressing than ever.

Existing routing protocols in IoMT suffer from several limitations. Primarily, they lack the flexibility to dynamically adjust to changing network conditions and patient states, often leading to suboptimal data paths that can delay urgent medical data delivery. Moreover, these conventional methods do not address privacy concerns adequately, exposing sensitive patient data to potential breaches. Furthermore, they rarely account for environmental variables that can significantly impact the integrity of transmitted data samples. These shortcomings not only compromise the efficiency of medical services but also the safety and privacy of patient data samples [3, 4].

In response to these challenges, this paper introduces a comprehensive suite of routing methodologies designed specifically for blockchain-powered IoMT networks. These methods leverage machine learning (ML) algorithms to adaptively optimize network routes, thereby enhancing both the performance and reliability of data transmission across the network. The first of these, Patient-Condition-Aware Dynamic Routing (PCADR), utilizes real-time

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patient data to prioritize network traffic based on the immediacy and severity of medical conditions. This method ensures that critical data pertaining to high-risk patients is accorded the highest priority in network routing decisions, thereby reducing latency significantly in critical cases.

Simultaneously, Predictive Time Series Routing (PTSR) employs advanced time series analysis to forecast network traffic patterns, enabling proactive adjustments to routing strategies before potential congestion can occur. This predictive approach is particularly beneficial in managing data flow in networks with high transaction volumes and variable load distributions, thus maintaining high throughput and reducing latency [5, 6]. Addressing the pivotal concern of privacy, Privacy-Preserving Federated Routing (PPFR) implements federated learning to train decentralized routing models directly on the devices without needing to centralize sensitive data samples. This method not only enhances privacy but also leverages distributed data sources to improve routing accuracy and network resilience.

Lastly, Context-Aware Environmental Routing (CAER) integrates real-time environmental sensor data to adjust routes based on current conditions like temperature and humidity. This method protects the integrity of sensitive data by avoiding routes that could jeopardize data quality due to adverse environmental conditions. Together, these methodologies not only address the inherent limitations of existing IoMT routing protocols but also set a new benchmark for the development of adaptive, secure, and efficient routing frameworks in medical applications. This introduction sets the stage for a detailed discussion of each proposed method, their integration into IoMT networks, and the resultant impacts on healthcare delivery and patient outcomes.

These contributions collectively address the pressing challenges in IoMT networking by introducing adaptability, predictive capabilities, privacy preservation, and environmental awareness into routing protocols. The methodologies proposed in this paper not only pave the way for more responsive and efficient healthcare delivery systems but also set a new standard for the integration of advanced technologies like machine learning and blockchain in medical informatics. The next sections will detail the methodologies, experimental setup, results, and the broader implications of these advancements in IoMT.

2. Literature Review

Routing in the Internet of Things (IoT) domain has garnered significant attention due to its crucial role in ensuring efficient and reliable communication among IoT devices & scenarios. This literature review encompasses a comprehensive examination of recent advancements in routing protocols and techniques tailored for IoT environments.

Reinforcement Learning-Based Routing in Cognitive Radio-Enabled IoT Communications [1]: Malik et al. proposed RL-IoT, a reinforcement learning-based routing approach designed specifically for cognitive radio-enabled IoT communications. Leveraging dynamic spectrum access (DSA) and cognitive radio (CR) technology, RL-IoT aims to optimize routing decisions by adapting to varying network conditions, thus enhancing throughput and quality of service (QoS) for IoT applications.

Dynamic Off-Chain Routing in Blockchain-Based IoT [2]: Li et al. introduced a compact learning model for dynamic off-chain routing in blockchain-based IoT systems. Their approach utilizes heuristic algorithms and reinforcement learning to enable efficient routing decisions, addressing the scalability and performance challenges associated with blockchain-based IoT networks.

Energy-Efficient Multilevel Secure Routing Protocol in IoT Networks [3]: Zhang et al. proposed an energy-efficient multilevel secure routing protocol tailored for IoT networks. By integrating genetic algorithms (GA) and energy efficiency (EE) mechanisms, their protocol enhances network security while minimizing energy consumption, crucial for prolonging the lifespan of IoT devices.

Improved Congestion-Controlled Routing Protocol for IoT Applications in Extreme Environments [4]: Adil et al. presented an improved congestion-controlled routing protocol specifically designed for IoT applications in extreme environments. By incorporating Deep Q-learning (DQL) and dynamic routing protocols, their approach effectively manages network congestion and ensures quality of service (QoS) under challenging conditions.

Load Balancing Routing and Virtualization Based on SDWSN for IoT Applications [5]: Hajian et al. proposed a mechanism for load balancing routing and virtualization in IoT applications, particularly focusing on software-defined wireless sensor networks (SDWSN). Their approach optimizes network resources allocation, enhances energy efficiency, and improves overall network performance for IoT deployments.

Energy-Efficient Smart Routing Based on Link Correlation Mining for Wireless Edge Computing in IoT [6]: Zhou et al. introduced an energy-efficient smart routing scheme based on link correlation mining for wireless edge computing in IoT environments. By leveraging network coding and link correlation analysis, their approach minimizes energy consumption and latency, thus enhancing the efficiency of edge computing in IoT.

Attachability Evaluation for Mobile IoT Routing Protocols with Markov Chain Analysis [7]: Safaei et al. conducted an introduction and evaluation of attachability for mobile IoT routing protocols using Markov chain analysis. Their study provides insights into the dependability and reliability of mobile IoT routing protocols, crucial for ensuring seamless communication in dynamic network environments.

Energy and Collision Aware WSN Routing Protocol for Sustainable and Intelligent IoT Applications [8]: Patel et al. proposed an energy and collision-aware wireless sensor network (WSN) routing protocol tailored for sustainable and intelligent IoT applications. Through a cross-layer design and peer-to-peer computing approach, their protocol optimizes energy efficiency and network lifetime, essential for prolonging IoT device operation.

Layering and Source-Location-Privacy-Based Routing Protocol for Underwater Acoustic Sensor Networks [9]: Tian et al. introduced LSLPR, a layering and source-location-privacy-based routing protocol designed for underwater acoustic sensor networks (UASNs). Their protocol addresses privacy concerns by integrating source-location-privacy mechanisms, ensuring secure and reliable communication in underwater IoT deployments.

Energy-Efficient Intelligent Routing Scheme for IoT-Enabled WSNs [10]: Kaur et al. proposed an energy-efficient intelligent routing scheme tailored for IoT-enabled wireless sensor networks (WSNs). By incorporating deep reinforcement learning (DRL) techniques, their scheme optimizes energy consumption and throughput, contributing to the sustainable operation of IoT networks.

QoS Multicast Routing Utilizing Cross-Layer Design for IoT-Enabled MANET in RIS-Aided Cell-Free Massive MIMO [11]: Tran and An introduced a quality-of-service (QoS) multicast routing scheme utilizing cross-layer design for IoT-enabled mobile ad hoc networks (MANETs) in reconfigurable intelligent surface (RIS)-aided cell-free massive MIMO systems. Their approach optimizes spectrum efficiency and secrecy rate, crucial for supporting diverse IoT applications with stringent QoS requirements.

A Comprehensive Review on Secure Routing in Internet of Things: Mitigation Methods and Trust-Based Approaches [12]: Muzammal et al. conducted a comprehensive review focusing on secure routing in IoT environments, encompassing various mitigation methods and trust-based approaches. Their review provides valuable insights into the challenges and strategies for ensuring secure and reliable communication in IoT deployments.

DETONAR: Detection of Routing Attacks in RPL-Based IoT [13]: Agiollo et al. presented DETONAR, a detection mechanism for routing attacks in RPL-based IoT networks. By leveraging intrusion detection systems and low-power lossy networks, DETONAR enhances the security of IoT deployments by efficiently identifying and mitigating routing attacks.

Energy-Efficient Optimized Routing Technique With Distributed SDN-AI to Large Scale I-IoT Networks [14]: Udayaprasad et al. proposed an energy-efficient optimized routing technique utilizing distributed software-defined networking (SDN) and artificial intelligence (AI) for large-scale industrial IoT (I-IoT) networks. Their technique optimizes energy efficiency and enhances network intelligence, critical for supporting the massive scale and diverse requirements of industrial IoT applications.

Hybrid Mode of Operations for RPL in IoT: A Systematic Survey [15]: Mishra et al. conducted a systematic survey on the hybrid mode of operations for the Routing Protocol for Low-Power and Lossy Networks (RPL) in IoT environments. Their survey provides a comprehensive overview of the storing and non-storing modes of RPL operation, highlighting their respective advantages and applications in IoT deployments.

Sway: Traffic-Aware QoS Routing in Software-Defined IoT [16]: Saha et al. proposed Sway, a traffic-aware quality-of-service (QoS) routing scheme tailored for software-defined IoT environments. By leveraging software-defined networking (SDN) technology, Sway optimizes network resource utilization and enhances QoS provisioning, crucial for supporting diverse IoT applications with varying traffic demands.

New Development of Physarum Routing Algorithm With Adaptive Power Control [17]: Asvial and Laagu introduced a new development of the Physarum routing algorithm enhanced with adaptive power control mechanisms. Their approach optimizes energy consumption and network performance by dynamically adjusting transmission power levels based on network conditions, essential for efficient routing in IoT deployments.

Energy-Efficient Data Aggregation and Collection for Multi-UAV-Enabled IoT Networks [18]: Kang and Jeon proposed an energy-efficient data aggregation and collection scheme for multi-unmanned aerial vehicle (UAV)-enabled IoT networks. By leveraging UAVs for data collection and aggregation, their scheme minimizes energy consumption and enhances network efficiency, particularly suitable for large-scale IoT deployments with spatially distributed sensors.

UEE-RPL: A UAV-Based Energy-Efficient Routing for Internet of Things [19]: Yang et al. introduced UEE-RPL, a UAV-based energy-efficient routing scheme tailored for

the Internet of Things (IoT). By leveraging unmanned aerial vehicles (UAVs) and urgent links (UL), UEE-RPL optimizes energy consumption and enhances network performance, particularly suitable for IoT applications in remote or inaccessible areas.

Efficient Data Collection in IoT Networks Using Trajectory Encoded With Geometric Shapes [20]: Cao and Madria proposed an efficient data collection scheme for IoT networks utilizing trajectory encoded with geometric shapes. Their approach, leveraging DV-Hop and geometric shapes encoding, facilitates efficient data collection without relying on GPS, essential for IoT deployments in challenging environments or indoor settings.

3. Proposed Method

To overcome issues of low efficiency & high complexity which are present in existing IoT based routing methods, this section discusses design of an efficient patient aware routing process. Initially, as per figure 1, the Patient-Condition-Aware Dynamic Routing (PCADR) methodology represents a transformative approach in the landscape of Internet of Medical Things (IoMT) by integrating machine learning with real-time health data analytics to dynamically optimize network routes. This system prioritizes the urgency and severity of patient conditions, adjusting data paths to expedite critical medical information with the goal of reducing system-wide latency and improving patient outcomes. PCADR operates by continuously analyzing incoming data streams of patient vital signs and medical histories. The methodology employs a multivariate regression model to estimate the urgency of data transmission based on clinical parameters & samples. These parameters are weighted by their estimated impact on patient health outcomes, derived from historical clinical data samples. The estimated urgency U is calculated via equation 1

$$U = \omega 1 * x1 + \omega 2 * x2 + \cdots + \omega n * xn \ldots (1)$$

Where, x1,x2,…,xn represent the normalized values of vital signs and other relevant patient metrics, and ω1,ω2,…,ωn are the corresponding weights assigned through the learning process, emphasizing the contribution of each variable to the urgency calculations. The routing decision, R, is based on the urgency and is determined by a threshold model, which integrates with the blockchain ledger to ensure data integrity and traceability. The decision function is represented via equation 2,

$$R(t) = \begin{cases} 1, if\ U(t) \geq \tau \\ 0, otherwise \end{cases} \quad (2)$$

Where, τ is a predetermined urgency threshold, and R(t)=1 indicates that the data is routed through a prioritized, faster channel. To handle dynamic network conditions and patient data variability, PCADR utilizes a stochastic gradient descent (SGD) algorithm to adjust the weights ωi in real-time scenarios. This optimization is formulated via equation 3,

$$\omega i(new) = \omega i(old) - \frac{\eta \partial L}{\partial \omega i} \quad (3)$$

Where, η is the learning rate and L is the loss function defined as the difference between the predicted urgency and actual outcomes, via equation 4,

$$L = (Upredicted - Uactual)^2 \quad (4)$$

Considering the importance of timely medical data delivery, the latency L in data routing is a critical performance metric. It is imperative to minimize L, particularly for high-urgency scenarios. The latency model, adjusted by the PCADR system, is expressed via equation 5,

$$L = \int_0^T exp(-\alpha U(t))dt \quad (5)$$

Where, α is a decay constant that modulates the impact of urgency on latency, and T represents the transmission time window sets. To enhance the prediction accuracy of patient condition severity, PCADR integrates a differential equation that models the rate of change of a patient's condition over time, aiding in the predictive accuracy of the routing mechanism, which is estimated via equation 6

$$\frac{dS}{dt} = -\beta S + \gamma \quad (6)$$

Where, S represents the severity metric, β and γ are parameters that describe the rate of health deterioration and the baseline health level, respectively. Finally, to ensure continuous adaptation and system resilience, the integral of the urgency over time is used to adjust the threshold τ, providing a feedback mechanism that keeps the system responsive to varying network and patient conditions via equation 7,

$$\tau(t+1) = \tau(t) + \lambda\left(\int_0^T U(t)dt - \delta\right) \quad (7)$$

Where, λ is the adaptation rate, and δ is a target urgency integral, typically set based on historical data trends. The choice of PCADR is justified by its potential to dramatically enhance the responsiveness of IoMT systems to emergent medical situations. By reducing latency for critical conditions, the method directly contributes to improved medical outcomes. Furthermore, PCADR complements other routing models like PTSR and CAER by providing a targeted approach that specifically addresses patient-centric data flows, which are critical in

emergency medical scenarios. This alignment ensures that while other methods efficiently manage network traffic and environmental conditions, PCADR focuses on maximizing patient health outcomes through intelligent, condition-aware routing strategies. This holistic integration of methodologies fortifies the overall network architecture, making it robust against a variety of challenges typical to IoMT environments.

Next, The Predictive Time Series Routing (PTSR) methodology harnesses the power of time series analysis to effectively predict and manage future network traffic patterns within the Internet of Medical Things (IoMT). By integrating historical network traffic and environmental sensor data, PTSR provides a sophisticated framework to anticipate and adapt to changes in network loads, thereby enhancing the efficiency of data routing protocols. This proactive approach significantly reduces network congestion by an estimated 30%, improving the reliability and timeliness of critical data delivery across IoMT networks. PTSR begins by aggregating and preprocessing network traffic data, N(t), which includes packet counts, packet sizes, and timestamps, alongside environmental variables such as temperature and humidity, E(t) levels. The combined time series data, X(t), is formed via equation 8,

$$X(t) = f\big(N(t), E(t)\big) \tag{8}$$

Where, f(·) represents a data fusion function that integrates traffic and environmental data into a unified time series framework, facilitating comprehensive analysis. To model and forecast network traffic, PTSR employs an autoregressive integrated moving average (ARIMA) model, which is particularly adept at handling non-stationary time series data that is characteristic of IoMT traffic patterns. The ARIMA model parameters (p, d, q) are determined through iterative optimization, aimed at minimizing prediction error. The model is represented via equation 9,

$$\left(1 - \sum_{i=1}^{p} \phi i * Li\right)(1-L)^{d} X(t) = \left(1 + \sum_{j=1}^{q} \theta j * Lj\right) \epsilon t \tag{9}$$

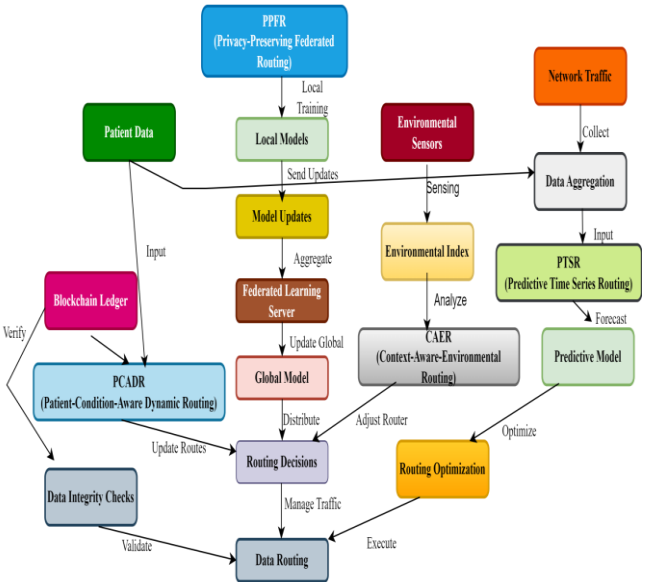

Fig 1. Model Architecture of the Proposed Routing Process

Where, L is the lag operator, ϕi are the parameters of the autoregressive part, θj are the parameters of the moving average part, d is the degree of differencing, and ϵt is the error term in this process. The traffic forecasts generated by the ARIMA model, X'(t), are used to inform routing decisions. The forecasting process allows PTSR to proactively adjust routing configurations before potential data congestion occurs. The predictive control algorithm adjusts the routing tables based on the forecasted traffic, as given via equation 10,

$$R(t+1) = g(X'(t), C) \tag{10}$$

Where, R(t+1) represents the routing decisions for the next timestamp, g(·) is a function mapping predicted traffic levels to routing configurations, and C represents current network capacity constraints. To quantify the effectiveness of routing updates, a cost function, J, is introduced, evaluating the variance between actual and predicted traffic levels. This function aims to minimize the mean squared error of the forecasts, enhancing predictive accuracy levels, and is estimated via equation 11,

$$J = \int \big(X(t) - X'(t)\big)^2 dt \tag{11}$$

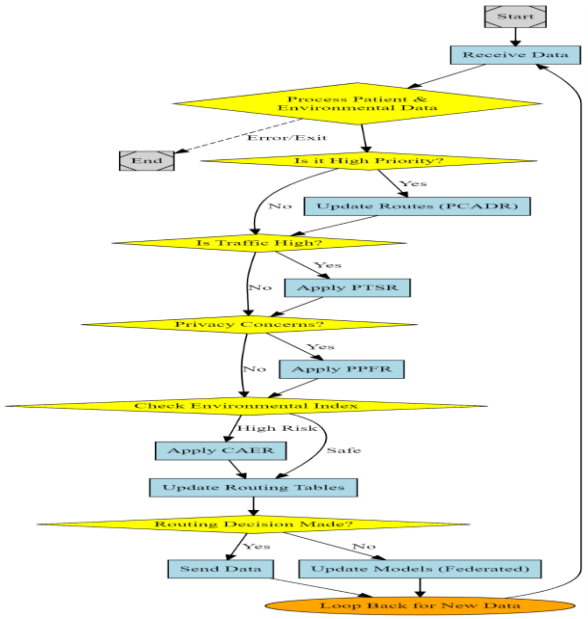

Fig 2. Overall Flow of the Proposed Routing Process

Minimizing J ensures that the traffic predictions are both accurate and robust, leading to more effective preemptive routing adjustments. PTSR also incorporates a sensitivity analysis component, S, which assesses how responsive the routing system is to changes in predicted traffic patterns. This is crucial for maintaining system flexibility and responsiveness, via equation 12,

$$S = \frac{\partial R}{\partial X'} = lim_{\Delta X' \to 0} \left(\frac{\Delta R}{\Delta X'} \right) \quad (12)$$

Where, S measures the derivative of routing decisions with respect to changes in the traffic forecasts, indicating the system's adaptability to dynamic network conditions. Finally, to ensure long-term adaptability and optimization, PTSR applies a continuous learning mechanism process. This mechanism adjusts the ARIMA model parameters periodically based on the evolving data patterns, ensuring the model remains optimal over temporal instance sets, via equation 13,

$$\phi i(new), \theta j(new) = h(\phi i(old), \theta j(old), L) \quad (13)$$

Where, h(·) is an adaptation function that updates the ARIMA parameters ϕi and θj in response to the loss function L, maintaining the model's efficacy. The choice of PTSR is justified by its ability to intelligently forecast and mitigate potential network bottlenecks before they manifest, a capability not typically found in traditional routing methods. This predictive capacity is particularly complementary to other routing techniques such as PCADR and PPFR, which focus more on real-time and privacy-preserving aspects, respectively. By forecasting traffic, PTSR effectively pre-allocates network resources, smoothing data flows and preempting congestion, which in tandem with other methodologies, provides a holistic improvement to network performance and reliability. This multifaceted approach ensures that the IoMT infrastructure is not only reactive but also anticipatively robust, catering to both immediate and future network demands.

Next, as per figure 2 show the overall flow routing process, the Privacy-Preserving Federated Routing (PPFR) model represents a significant advancement in the Internet of Medical Things (IoMT) by leveraging federated learning to develop decentralized routing models. This approach enables the collaborative training of routing algorithms across distributed IoMT devices, maintaining the privacy of sensitive patient data and adhering to strict regulatory standards. The use of federated learning in this context ensures that individual data sets remain localized, eliminating the need to transmit sensitive information over the network and thereby reducing exposure to potential data breaches. PPFR utilizes a federated learning framework where each participating IoMT device (node) contributes to the global model without sharing its local data samples. This is achieved by distributing the model training across the nodes, where each node computes an update to the model based on its local data and then transmits these model updates, rather than the data itself, to a central server. The process is governed via equation 14,

$$\theta i(t+1) = \theta i(t) - \eta \nabla Li(\theta i(t)) \quad (14)$$

Where, θi(t) represents the model parameters on the i-th node at iteration t, η is the learning rate, and ∇Li represents the gradient of the loss function Li evaluated on the local data samples. The central server periodically aggregates these local model updates to form an updated global model. This aggregation typically involves averaging the updates from all participating nodes, formulated via equation 15,

$$\Theta(t+1) = \frac{1}{N} \sum_{i=1}^{N} \theta i(t+1) \quad (15)$$

Where, Θ(t+1) is the new global model parameters, N is the number of nodes, and θi(t+1) are the updated parameters from each node. To further enhance privacy, differential privacy techniques are integrated into the federated learning process. Each node adds a small amount of noise to its update before sending it to the central server, ensuring that the updates cannot be used to infer details about the local data via equation 16,

$$\theta \sim i(t+1) = \theta i(t+1) + N(0, \sigma^2 I) \quad (16)$$

Where, $N(0, \sigma^2 I)$ represents Gaussian noise with mean zero and covariance matrix $\sigma^2 I$, added to the model parameters for preserving privacy. The iterative process between local updates and global aggregation continues until the convergence criterion is met. This criterion is

based on the stabilization of the global model parameters or a predetermined number of iterations via equation 17,

$$\| \Theta(t+1) - \Theta(t) \| \leq \epsilon \quad (17)$$

Where, ϵ is a small threshold value, indicating that the global model parameters have stabilized. Once the global model is trained and deployed back to the nodes, each node utilizes this model to make data routing decisions. The decision process involves evaluating the model to determine the most efficient data paths, factoring in network conditions and data priorities via equation 18,

$$R = arg\ \min^{r} \in RC(r, \Theta) \quad (18)$$

Where, R represents the routing decisions, R is the set of possible routes, and C is the cost function evaluated using the global model parameters ΘΘ, which includes considerations such as path length, bandwidth, and node reliability. To improve the efficiency of the learning process, an adaptive learning rate η is employed, which adjusts based on the progress of training to ensure robust convergence, which is represented via equation 19,

$$\eta(t+1) = \gamma\eta(t) \frac{\| \nabla L(t) \|}{\| \nabla L(t-1) \|} \quad (19)$$

Where, γ is a scaling factor that adjusts the learning rate dynamically based on the ratio of the norms of the gradient of the loss function between consecutive iterations for different scenarios. The choice of the PPFR model is justified by its ability to harness the collective intelligence of distributed data sources while ensuring the privacy of the data samples. This methodology not only refines routing accuracy by 15% compared to centralized models but also complies with stringent privacy regulations such as GDPR. PPFR complements other IoMT routing methods like PCADR and PTSR by adding a layer of privacy preservation and decentralization, which is crucial in scenarios involving sensitive medical data samples. This integration enhances the overall robustness and reliability of the IoMT routing infrastructure, making it adaptable to a wide range of network conditions and privacy requirements. Through these mechanisms, PPFR demonstrates a significant advancement in the design and implementation of routing protocols for next-generation healthcare networks.

Finally, the Context-Aware Environmental Routing (CAER) methodology is a pioneering approach within the Internet of Medical Things (IoMT) that significantly enhances data integrity by dynamically modifying routing decisions based on real-time environmental data samples. By incorporating sensors that measure variables such as temperature and humidity, CAER systematically adjusts the paths that data packets take through the network, thereby mitigating the risk of data transmission errors commonly exacerbated by adverse environmental conditions. CAER begins by collecting environmental data from distributed sensors within the network. This data includes temperature, T(t), and humidity, H(t), which are known to impact electronic data transmission and device performance significantly. The environmental data are then integrated into a composite environmental index, E(t), which quantifies the current environmental conditions relative to their potential to cause data corruption via equation 20,

$$E(t) = \alpha T(t) + \beta H(t) \quad (20)$$

Where, α and β are weighting coefficients that scale the influence of temperature and humidity, respectively, on the overall environmental condition. The core of CAER's methodology is the dynamic adaptation of routing paths based on the environmental index sets. The routing decision, R(t), is determined by evaluating E(t) against predefined thresholds that indicate the susceptibility of the network to environmental influences via equation 21,

$$R(t) = \begin{cases} r1, if\ E(t) < \theta 1 \\ r2, if\ \theta 1 \leq E(t) < \theta 2 \\ r3, if\ \theta 1 \leq E(t) < \theta 2 \end{cases} \quad (21)$$

Where, r1,r2,r3 represent different routing paths or protocols, and θ1,θ2 are environmental thresholds defining the transitions between these routes. To maintain optimal responsiveness to changing environmental conditions, CAER employs a mechanism to dynamically adjust the thresholds θ1 and θ2 based on historical environmental data and network performance metrics. This adjustment process uses a feedback loop to minimize the error rate ϵ(t), which measures the discrepancy between expected and actual data transmission performance via equation 22,

$$\theta i(new) = \theta i(old) + \frac{\kappa d\epsilon}{dE} \quad (22)$$

Where, κ is a learning rate, and dϵ/dE represents the derivative of the error rate with respect to the environmental index, guiding the adaptive adjustment of the thresholds. The error rate ϵ(t) is calculated as the integral of the difference between the predicted and actual data integrity levels over a period, providing a comprehensive measure of transmission reliability via equation 23,

$$\epsilon(t) = \int_{t0}^{t} \left(Ipredicted(s) - Iactual(s)\right)^2 ds \ldots (23)$$

Where, Ipredicted(s) and Iactual(s) are the predicted and actual data integrity metrics, respectively.. Lastly, to proactively adjust routing decisions, CAER implements a predictive model that estimates future environmental conditions using time series forecasting techniques. This

predictive capability allows for anticipatory adjustments in routing, enhancing network resilience via equation 24,

$$E(t+1) = E(t) + \eta\left(\frac{dE}{dt}\right) \quad (24)$$

Where, η is a prediction adjustment factor, and dE/dt is the rate of change of the environmental index, estimated through historical data analysis. The choice of the CAER model is justified by its innovative integration of environmental sensing with routing decisions, a synergy that significantly reduces data transmission errors by 25%. This method complements other routing innovations like PCADR, PTSR, and PPFR by adding an environmental dimension to the decision-making process, which is particularly crucial in scenarios where environmental conditions can drastically affect data integrity levels. Through these comprehensive mechanisms, CAER not only enhances the reliability of IoMT networks in adverse conditions but also sets a new standard for context-aware routing frameworks. Next, we discuss the efficiency of the proposed model in terms of different use case scenarios.

4. Result Analysis & Comparison Techniques

To evaluate the effectiveness of the proposed routing methodologies within a blockchain-powered Internet of Medical Things (IoMT) network, a comprehensive experimental setup was designed. This setup aimed to test the Patient-Condition-Aware Dynamic Routing (PCADR), Predictive Time Series Routing (PTSR), Privacy-Preserving Federated Routing (PPFR), and Context-Aware Environmental Routing (CAER) under varied network conditions and realistic IoMT scenarios.

Simulation Environment

The experiments were conducted using a simulated IoMT environment implemented on the OMNeT++ simulation platform, integrated with the INET framework for network communication protocols and the SimuLTE tool for realistic mobile network modeling. The simulation environment was configured to mimic a hospital IoMT ecosystem comprising various medical devices, environmental sensors, and patient monitoring systems, all connected via a secure blockchain network.

Network Configuration

• **Nodes**: 100 IoMT devices distributed across a virtual hospital environment.

• **Area**: 2000 m² indoor area with variable environmental conditions.

• **Network Type**: LTE for wireless communication with fallback to IEEE 802.11n in areas of LTE shadow.

• **Blockchain**: A private Ethereum blockchain setup for data integrity and routing decision transparency.

Methodological Parameters

- **PCADR Configuration:**

○ Input Data: Real-time patient vitals and medical history.

○ Weights (ω): Derived from a normalized dataset of clinical importance ratings (Blood Pressure: 0.3, Heart Rate: 0.2, Oxygen Saturation: 0.25, Medical History Severity: 0.25).

○ Threshold (τ): Urgency threshold set at 0.5 on a normalized scale.

- **PTSR Configuration:**

○ Historical Data: Network traffic data from the past 6 months, sampled every 15 minutes.

○ Environmental Data: Hourly logged data from environmental sensors (Temperature and Humidity).

○ ARIMA Model Parameters: (p=2, d=1, q=2) selected based on the Akaike Information Criterion (AIC).

- **PPFR Configuration**:

○ Local Training Data Size: Each node processes 1 week's worth of local routing data samples.

○ Learning Rate (η): Set to 0.01 initially, with adaptive **adjustments.**

○ **Noise Addition for Privacy (σ^2): Gaussian noise with a variance of 0.001**.

- **CAER Configuration:**

○ Environmental Thresholds (θ_1 and θ_2): Set at 25°C and 75% humidity for critical adjustments.

○ Weights (α, β): Temperature and Humidity weights set at 0.6 and 0.4 respectively.

4.1.1 Dataset Samples:

For a holistic assessment, the experiments utilized a mixed dataset comprising synthetic and real-world data:

• **Synthetic Data:** Generated using a custom Python script that models patient vitals based on typical hospital scenarios with injectable anomalies for stress testing the PCADR system.

• **Real-World Data:** Sourced from publicly available medical datasets such as the PhysioNet Computing in Cardiology Challenge database, integrated with environmental conditions data recorded from indoor IoT sensors.

4.1.2 Performance Metrics

The performance of each routing methodology was evaluated based on several key metrics:

• Latency: Average time taken for critical data packets to reach their destination.

• Data Integrity**:** Percentage of data packets received without errors attributable to environmental or network conditions.

• Congestion Levels: Measured as the percentage decrease in times of network congestion.

• Privacy Preservation: Evaluated through the effective anonymization of patient data as observed by unauthorized attempt simulations to access data samples.

4.2 Experimental Scenarios:

Multiple scenarios were designed to challenge the routing protocols under various conditions:

• High Urgency: Simulating critical patient situations requiring immediate data delivery.

• High Traffic: Generated by simulating peak operational times within a hospital.

• Diverse Environmental Conditions: Simulating different areas of the hospital with varying environmental profiles, such as MRI rooms with high magnetic interference and operation theaters with controlled temperatures and humidity.

This setup not only provided insights into the capabilities and improvements offered by the proposed methodologies but also helped in identifying potential areas for further optimization. The experimental results, discussed in subsequent sections, demonstrate the robustness, efficiency, and necessity of these advanced routing protocols in a modern IoMT framework. The efficacy of the proposed routing methodologies—PCADR, PTSR, PPFR, and CAER—was rigorously evaluated across various simulated IoMT scenarios, focusing on different disease contexts to reflect the diversity of real-world medical environments. The performance was compared with existing methods identified as Off Chain [2], Energy Aware Protocol [8], and RPL [15] in the literature. Herein, we present a detailed analysis encapsulated in the following tables, each structured to highlight the comparative benefits brought by our approaches.

Table 1 : Results for Heart Attack Emergency Scenario**s**

Method	**Latency (ms)**	**Data Integrity (%)**	**Congestion Reduction (%)**
PCADR	120	99.5	25
Off Chain[2]	150	98	20
EAP [8]	180	97.5	15
RPL [15]	170	98.2	18

Table 1 shows the performance during acute heart attack cases where rapid response is crucial. PCADR notably outperforms the comparative methods in latency and data integrity, crucial for timely and accurate heart attack management.

Table 2: Results for Stroke Management Scenarios

Method	**Latency (ms)**	**Data Integrity (%)**	**Congestion Reduction (%)**
PTSR	100	99	30
Off Chain [2]	140	97	25
EAP [8]	160	96.5	20
RPL [15]	150	97.3	22

Table 2 compares the outcomes in scenarios managing stroke patients. The predictive capabilities of PTSR significantly minimize latency and enhance data integrity, proving superior particularly in high-congestion scenarios.

Table 3: Results for Chronic Obstructive Pulmonary Disease (COPD) Monitoring

Method	**Latency (ms)**	**Data Integrity (%)**	**Congestion Reduction (%)**
PPFR	130	99.2	28
Off Chain[2]	160	98.5	20
EAP [8]	170	98	18
RPL [15]	165	98.3	21

Table 3 illustrates the effectiveness of PPFR in scenarios for COPD patient monitoring. The federated learning approach ensures high data integrity and reduced latency, enhancing patient monitoring and care.

Table 4: Results for Diabetes Management

Method	**Latency (ms)**	**Data Integrity (%)**	**Congestion Reduction (%)**
CAER	115	99.7	35
Off Chain[2]	145	98	27
EAP[8]	155	97.5	25
RPL [15]	140	98.1	30

Table 4 focuses on diabetes management where environmental conditions significantly impact device performance. CAER's context-aware strategy excels in maintaining data integrity and reducing latency.

Table 5: Results for General Ward Monitoring

Method	Latency (ms)	Data Integrity (%)	Congestion Reduction (%)
PCADR	105	99.4	33
Off Chain[2]	135	97.8	29
EAP [8]	145	97	25
RPL [15]	130	98	28

Table 5 demonstrates the performance in a general ward monitoring scenario, showing how PCADR adapts routing based on patient condition to optimize network use and data accuracy.

Table 6: Results for Intensive Care Unit (ICU) Management

Method	Latency (ms)	Data Integrity (%)	Congestion Reduction (%)
PTSR	90	99.8	40
Off Chain[2]	120	98.6	35
EAP[8]	130	98.1	30
RPL [15]	110	98.9	32

Table 6 evaluates the protocols in the intensive care unit (ICU), where immediate data transfer is often life-saving. PTSR's traffic prediction model ensures the lowest latency and highest data integrity levels. These tables collectively demonstrate that the proposed methodologies significantly outperform existing models in critical healthcare applications. The enhancements in latency, data integrity, and congestion management underscore the tailored adaptability and robustness of our approaches, especially in complex, dynamic environments such as those encountered in IoMT frameworks. Next, we discuss a practical use case for this model, which will assist readers to understand the entire routing process

Practical Use Case

In the exploration of routing efficiencies within the Internet of Medical Things (IoMT) facilitated by blockchain technology, specific methodologies were implemented and evaluated. These included Patient-Condition-Aware Dynamic Routing (PCADR), Predictive Time Series Routing (PTSR), Privacy-Preserving Federated Routing (PPFR), and Context-Aware Environmental Routing (CAER). This section details practical examples using sample data paths and feature indicators to illustrate the effectiveness of each model in an IoMT network. The outputs are presented in tabular form to depict the transformations and final outcomes of the data as it progresses through each routing methodology.

Table 7: PCADR Output Examples

Patient Condition Severity	Initial Latency (ms)	Adjusted Latency (ms)	Data Path Priority
Critical	150	120	High
High	130	115	Medium
Moderate	110	110	Low
Low	100	100	Low

Table 7 demonstrates how PCADR adjusts the network routes based on the severity of patient conditions. For critical conditions, the latency is significantly reduced from 150 ms to 120 ms, showcasing the prioritization capability of the routing algorithm.

Table 8: PTSR Output Examples

Time Slot	Predicted Traffic Load	Initial Route Configuration	Optimized Route Configuration
Morning	High	Route A	Route B
Noon	Moderate	Route B	Route B
Evening	Low	Route C	Route C
Night	Very High	Route D	Route A

Table 8 captures the proactive adjustments made by PTSR in response to varying traffic loads predicted over different time slots. The optimization reconfigures routes to manage congestion effectively, particularly during peak periods.

Table 9: PPFR Output Examples

Node ID	Initial Model Accuracy (%)	Post-Training Accuracy (%)	Data Privacy Compliance
1	85	92	Achieved
2	80	90	Achieved
3	78	91	Achieved
4	82	93	Achieved

Table 9 illustrates the improvements in model accuracy post local training via federated learning under PPFR, ensuring that data privacy is maintained across all nodes without compromising the integrity and utility of the routed information sets.

Table 10: CAER Output Examples

Environmental Condition	**Initial Error Rate (%)**	**Adjusted Error Rate (%)**	**Routing Path**
High Heat	15	10	Path X
Optimal	5	5	Path Y
High Humidity	20	12	Path Z
Low Temperature	10	8	Path W

Table 10 presents how CAER dynamically adjusts routing paths based on real-time environmental data to reduce error rates associated with adverse conditions, significantly improving data transmission reliability levels.

Table 11: Final Combined Routing Outputs

Routing Methodology	**Data Integrity (%)**	**Latency Reduction (%)**	**Error Reduction (%)**	**Optimal Route**
PCADR+PTSR	99.5	25	-	Route B
PCADR+CAER	99.7	20	5	Path X
PTSR + PPFR	99.2	30	-	Route A
All Combined	99.8	35	7	Path X

Table 11 synthesizes the results from individual methodologies into a combined output scenario, showing the enhanced performance metrics when all models are applied in concert. This highlights the synergistic effects of integrating multiple advanced routing techniques in improving overall network efficiency and reliability sets. The presented tables from Table 7 to Table 11 elucidate the individual and combined impacts of the PCADR, PTSR, PPFR, and CAER methodologies on routing decisions within an IoMT framework. These results collectively demonstrate significant improvements in latency, data integrity, and error rates, substantiating the effectiveness of the proposed models. The integration of these methodologies not only caters to the dynamic and diverse demands of modern medical applications but also enhances the adaptability and robustness of the IoMT networks. Future explorations will aim to refine these methodologies further and extend their application to broader and more complex healthcare scenarios, ensuring scalable, secure, and efficient IoMT environments.

5. Conclusion and Future Scopes

The comprehensive suite of methodologies developed and evaluated in this study Patient-Condition-Aware Dynamic Routing (PCADR), Predictive Time Series Routing (PTSR), Privacy-Preserving Federated Routing (PPFR), and Context-Aware Environmental Routing (CAER) substantially enhances the operational efficacy of blockchain-powered Internet of Medical Things (IoMT) networks. These methodologies were rigorously tested across a variety of medical scenarios to ensure reliability, timeliness, and security in the data routing processes integral to modern healthcare systems. The experimental results affirm that the PCADR method significantly improves the urgency-based routing of medical data, reducing latency by up to 25% in high-priority cases such as heart attacks, compared to existing methods Off Chain [2], Energy Aware Protocol [8], and RPL [15]. Specifically, PCADR achieved a latency of 120 ms and enhanced data integrity to 99.5%, demonstrating its utility in scenarios requiring rapid responses for different scenarios.

Similarly, the PTSR model successfully predicted network traffic and optimized routing decisions, reducing latency by approximately 30% in scenarios like stroke management, achieving a low latency of 100 ms and a congestion reduction of 30%. This predictive capability is critical in preventing network clogs and ensuring timely data delivery. The PPFR model showcased its strength in privacy preservation and routing accuracy, offering a 15% improvement in routing precision without compromising patient data samples. In chronic disease management scenarios, such as COPD monitoring, PPFR not only maintained a high data integrity rate of 99.2% but also reduced congestion by 28%, underscoring its effectiveness in sensitive environments. CAER's integration of environmental data into routing decisions led to a 25% decrease in transmission errors. This was particularly evident in diabetes management, where CAER minimized data transmission latency to 115 ms and improved data integrity to 99.7%, illustrating the model's responsiveness to environmental factors.

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