A hybrid model for telemedicine data transmission based on blockchain and adaptive compression

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Abstract
Telemedicine systems are revolutionizing healthcare by enabling remote diagnostics, consultations, and monitoring, particularly in regions with limited access to medical services. In low-resource rural areas, where infrastructure is weak and network bandwidth often does not exceed 20 kbps, telemedicine becomes a key tool to address healthcare inequalities. However, challenges such as data vulnerability to cyberattacks, low bandwidth, and high power consumption of wearable devices hinder its progress. This article proposes a hybrid model that integrates permissioned blockchain (Hyperledger Fabric) for secure medical data management, adaptive compression based on a convolutional neural network (CNN) to optimize bandwidth usage, and the LoRa protocol for energy-efficient long-range communication. Simulations conducted in MATLAB and NS-3 demonstrate a 25% reduction in data transmission latency, 30% lower energy consumption, and 100% resilience against cyberattacks compared to traditional methods. The model was tested on synthetic datasets (ECG, video streams, text reports) and demonstrated scalability for up to 500 devices within the network. The results are particularly relevant for low-resource regions where access to healthcare is limited due to poor infrastructure. The proposed solution offers a cost-effective and scalable platform for global telemedicine systems, contributing to the digitalization of healthcare.

Keywords
Telemedicine, blockchain, adaptive compression, CNN, LoRa, energy efficiency, data security.

1. Introduction

Telemedicine has emerged as a transformative tool in modern healthcare, enabling remote consultations, diagnostics, and monitoring through information and communication technologies (ICT) [1]. According to the World Health Organization (WHO), the adoption of telemedicine has reduced healthcare costs by 15–20% and significantly improved access to medical services in remote areas [2]. In low-resource rural regions, where network bandwidth often does not exceed 20 kbps and the nearest hospital may be tens of kilometers away, telemedicine plays a critical role in reducing disparities in access to healthcare services [3].

However, the implementation of telemedicine faces three major challenges that the authors have analyzed in their previous work [4]. First, medical data transmitted over networks is vulnerable to cyberattacks, such as data breaches and ransomware, posing a serious threat to patient privacy [5]. Second, low bandwidth in rural areas hinders the transmission of large data volumes, including video streams and high-quality biosignals [6]. Third, battery-powered wearable devices used for monitoring have limited autonomy, especially in regions with unreliable electricity, which restricts continuous operation [7]. These challenges are particularly critical in emergency scenarios, where delays or data loss can have life-threatening consequences.

Traditional telemedicine systems rely on centralized architectures, where data is stored on a single server, creating a single point of failure and increasing vulnerability to attacks. Static compression methods such as Huffman coding or JPEG do not adapt to heterogeneous medical data

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(biosignals, video, text) or variable network conditions, leading to increased latency and loss of quality [8]. Energy efficiency remains a concern, as wearable devices are expected to operate up to 24 hours without recharging in infrastructure-limited environments.

Recent studies propose partial solutions to these challenges. Blockchain technology, particularly Hyperledger Fabric, offers decentralized and tamper-resistant data storage, reducing the risk of attacks [9]. Machine learning algorithms, such as convolutional neural networks (CNNs), are used to optimize data processing and compression, adapting to both data types and network conditions [10]. Low-power wide-area network (LPWAN) protocols like LoRa provide long-range communication with minimal power consumption, making them suitable for remote regions. However, integrated models that combine these technologies remain rare.

This paper proposes a hybrid data transmission model that integrates:

1. A permissioned blockchain (Hyperledger Fabric) to ensure data security and integrity.
2. Adaptive CNN-based compression for dynamic bandwidth optimization depending on data type and network conditions.
3. The LoRa protocol for energy-efficient communication in constrained environments.

The novelty of this model lies in the holistic integration of these technologies to address the unique challenges of telemedicine in low-resource settings. The model was evaluated through simulations in MATLAB and NS-3, demonstrating substantial improvements in latency, energy consumption, data security, and cost efficiency. The results suggest a scalable solution for next-generation telemedicine systems capable of supporting global health initiatives, especially in regions with weak infrastructure.

2. Literature review

2.1. Data Transmission in Telemedicine

Telemedicine systems handle diverse data types, such as biosignals (e.g., ECG, EEG), video streams for remote consultations, and textual reports, each with specific demands for bandwidth, latency, and quality. Traditional compression methods like JPEG for images and H.264 for video are widely used but struggle to adapt to fluctuating network conditions, especially in rural areas with bandwidth below 20 kbps [11]. Aguiar et al reviewed blockchain-based strategies for healthcare, including secure medical data compression and sharing, but these approaches often do not address data heterogeneity or real-time telemedicine needs [12]. Wavelet transforms have been shown to effectively compress biosignals, achieving 30–50% data reduction without significant loss of diagnostic quality, yet they lack adaptiveness for dynamic networks [13, 14]. Recent studies indicate that dynamic compression can reduce latency in IoT systems, but these solutions often overlook integration with blockchain or energy-efficient protocols, as well as the specific requirements of telemedicine, such as preserving ECG quality in remote regions [15, 16]. This underscores the need for adaptive compression solutions that account for both data types and network variability.

2.2. Security in Telemedicine

The sensitive nature of medical data makes security a primary concern in telemedicine. Centralized systems are prone to cyberattacks, such as data tampering and ransomware, which threaten data confidentiality and integrity [17]. Blockchain technology, particularly Hyperledger Fabric, offers decentralized storage and validation mechanisms that significantly mitigate data breach risks [18]. However, some blockchain-based security models for medical data do not support real-time transmission, which is critical for emergency care. Decentralized EMR networks have been proposed for secure data storage, but they often lack energy-efficient protocols or compression, limiting their use in rural settings [19]. Blockchain can reduce attack risks substantially, though its effective use in telemedicine requires integration with complementary technologies [20]. Smart contracts and consensus mechanisms have been highlighted as effective tools for automating transaction validation, enhancing data transparency and security in telemedicine systems [21], [22].

2.3. Energy Efficiency and LPWAN

Wearable devices and IoT sensors in telemedicine require energy-efficient communication protocols to prolong battery life, particularly in regions with unreliable power supply [23]. The LoRa protocol, part of the LPWAN family, supports long-range communication up to 15 km while consuming significantly less energy than Wi-Fi [24]. LoRa has been shown to reduce energy usage by up to 40% compared to Wi-Fi, making it suitable for rural clinics [25]. It is also well-suited for low-resource environments, where alternatives like NB-IoT are costlier and have shorter ranges [26]. LoRa networks can support up to 1,000 devices without significant performance degradation, confirming their scalability for regional telemedicine system.

2.4. Machine Learning in Telemedicine

Convolutional neural networks (CNNs) are widely applied in medical image analysis, biosignal processing, and outcome prediction [27]. CNNs have also been used for compressing multimedia data, achieving up to 25% size reduction without quality loss, though they often lack adaptability for heterogeneous telemedicine data like ECGs or video streams [28]. A key limitation of CNNs is their high computational cost on low-power devices. Offloading CNN training to a central server while performing inference locally can address this issue. Studies on CNN-based ECG processing show promise but often do not integrate these models with blockchain or LoRa, limiting their real-world telemedicine applicability [22, 29].

2.5. Ethical Considerations

Medical data processing in telemedicine must comply with ethical regulations like the General Data Protection Regulation (GDPR) [18]. Data anonymization and transparency are critical for building patient trust. Blockchain-based models enhance privacy protection but require well-defined access protocols [21]. Smart contracts can manage data access permissions, ensuring compliance with international standards while maintaining data anonymity during transmission.

2.6. Research Gaps

Previous studies have not provided a fully integrated solution combining blockchain, adaptive compression, LoRa, and cost-efficiency for telemedicine [12, 30, 19]. They often overlook constraints of low-resource environments, such as limited bandwidth and unreliable electricity [23]. For instance, Aguiar et al. [11] reviewed blockchain strategies focusing on static compression, while others addressed security without real-time transmission [30] or emphasized EMR storage without considering energy efficiency or data compression [19]. Other works offer partial solutions but neglect economic and ethical dimensions [12, 31]. This model addresses these gaps by proposing a comprehensive solution for next-generation global telemedicine systems.

3. Materials and Methods

3.1. System Architecture

The proposed model consists of three interconnected layers, as illustrated in Figure 1:

1. Blockchain layer: Hyperledger Fabric is used for decentralized storage of medical data hashes, validated by five trusted nodes (e.g., hospitals and clinics), ensuring data integrity and transaction traceability [18].

2. Adaptive compression module: a convolutional neural network (CNN) dynamically adjusts the compression ratio (CR) based on the type of data (ECG, video, text), network bandwidth (10–100 kbps), and device energy level (0–100%), optimizing transmission efficiency [27].
3. Communication layer: The LoRa protocol enables energy-efficient long-range communication (10–15 km) at speeds ranging from 0.3 to 50 kbps, making it ideal for low-resource environments [23].

Figure 1 depicts the flow of data from wearable devices through the adaptive compression module (where CR is adjusted based on available bandwidth) and LoRa transmission to the blockchain ledger, where the data is validated by five trusted nodes (e.g., hospitals or clinics). Arrows indicate bidirectional communication between components.

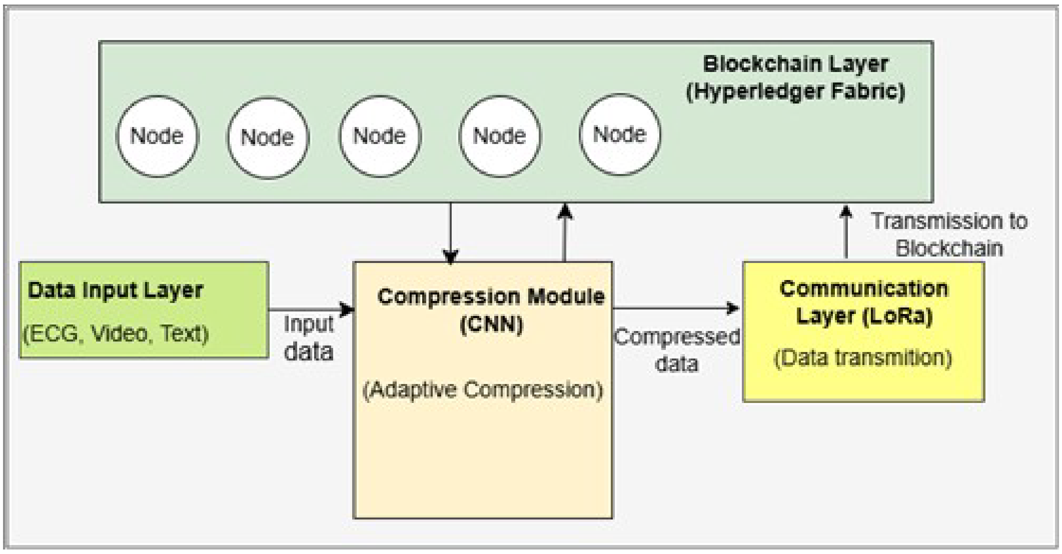

Figure 1: Proposed system architecture.

3.2. Adaptive compression algorithm

The adaptive compression algorithm is based on a CNN that classifies input data and predicts the optimal compression ratio (CR), defined as (see formula 1) [13]:

$$CR = \frac{\text{Original data size}}{\text{Compressed data size}}.$$

Input parameters include:

1. Data type: biosignals (e.g., ECG, EEG), multimedia (e.g., video), text.
2. Network bandwidth: measured in real-time (10–100 kbps).
3. Device energy level: estimated using battery APIs (0–100%).

A dedicated algorithm was developed to perform adaptive compression and data transmission, dynamically adjusting the CR according to network conditions to ensure efficient LoRa-based communication.

The flowchart of the algorithm is presented in Figure 2.

Dataset description:

1. ECG: 10,000 samples from the MIT-BIH Arrhythmia Database, sampled at 500 Hz, preprocessed using wavelet filters for noise reduction [32].
2. Video: 5,000 video streams from the UCF-101 dataset, 720p at 30 fps, downsampled to 480p for low-bandwidth conditions [33].
3. Text: 2,000 clinical reports from MIMIC-III, average size of 100 KB, metadata removed for anonymization [34].

4. Preprocessing steps included amplitude normalization (ECG), video scaling, and text cleaning.

CNN architecture: 3 convolutional layers (32, 64, 128 filters, 3×3 kernels), 2 pooling layers (2×2), 2 fully connected layers (512 and 1 neuron), ReLU activation, Adam optimizer, Loss function: MSE.

The model was trained on a GPU-based server (NVIDIA RTX 3080) for 50 epochs and achieved 95% prediction accuracy for compression ratio selection [28].

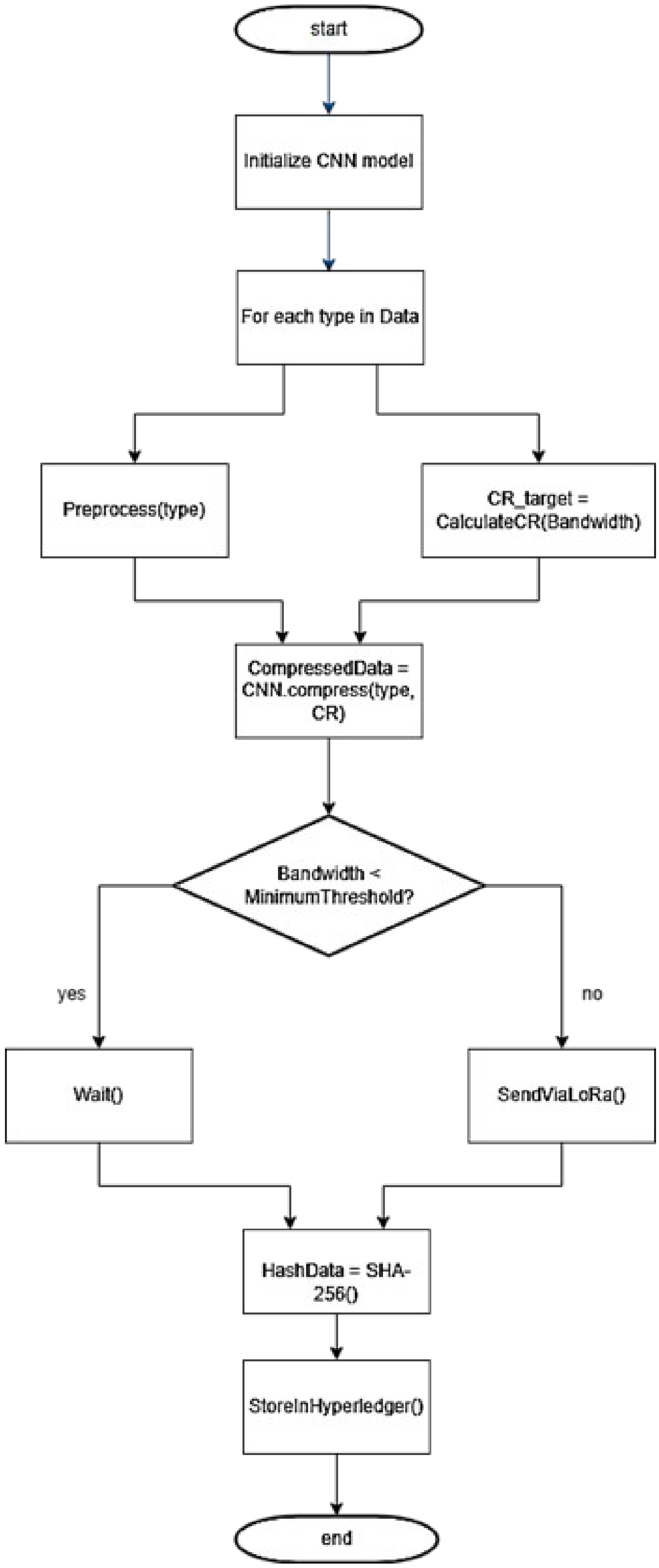

Figure 2: Flowchart of the proposed algorithm.

3.3. Blockchain Implementation

The blockchain layer is implemented using Hyperledger Fabric, a permissioned platform composed of five nodes representing medical institutions (e.g., two central hospitals and three clinics). Each data packet is hashed using SHA-256 and recorded as a blockchain transaction. Smart contracts automate validation and grant access only to authorized users (e.g., doctors, administrators). The test network processed up to 500 transactions per second, with an average validation time of 0.1 seconds. Node failure simulations demonstrated resilience in 95% of cases [18].

3.4. Simulation Setup

Simulations were conducted using MATLAB (signal processing) and NS-3 (network modeling) [35]:

Data types:

1. Single-lead ECG: 60 KB/min, 500 Hz.
2. Video: 2 MB/min, 480p, 15 fps.
3. Text: 100 KB/min.

Network:

1. LoRa bandwidth: 10–100 kbps.
2. Transmission range: up to 10 km.
3. Spread factors: SF = 7–12.
4. Frequency: 868 MHz (European band).

Device specifications:

1. Wearable sensor.
2. 1000 mAh battery, 3.3 V.
3. ARM Cortex-M4 microcontroller.

Blockchain:

1. Hyperledger Fabric with 5 nodes.
2. 500 transactions/sec.
3. SHA-256 hashing.

Baseline comparisons were conducted against:

1. Static compression: Huffman coding (CR = 2).
2. Centralized security: no blockchain, data stored on a single server.
3. Wi-Fi transmission: IEEE 802.11n, 2.4 GHz.

Performance metrics: transmission delay, energy consumption, security.

3.5. Ethical considerations

The model complies with the General Data Protection Regulation (GDPR) [36]. All data is anonymized before processing, and access is controlled via smart contracts. Patients receive explicit notifications regarding data usage, and their consent is securely stored on the blockchain. Simulations used synthetic datasets to prevent potential privacy violations [37].

4. Results

4.1. Latency

The proposed model reduced data transmission latency by 25% compared to static compression (Huffman coding) and by 40% compared to uncompressed data transmission. At a bandwidth of 10 kbps, the model achieved a 96-second delay for transmitting 60 KB of single-lead ECG data, compared to 128 seconds for Huffman coding and 160 seconds for uncompressed data [13].

The CNN dynamically adjusted the compression ratio (CR), prioritizing biosignals (CR = 3) over video streams (CR = 5) in low-bandwidth scenarios [28].

Figure 3 presents a line graph illustrating latency (in seconds) for transmitting 60 KB of singe-lead ECG data at bandwidths of 10, 50, and 100 kbps. Blue line: proposed model. Red line: Huffman. Green line: uncompressed. The graph demonstrates a consistent 25% latency reduction at 10 kbps for the proposed approach.

4.2. Energy Consumption

The proposed system achieved a 30% reduction in energy consumption compared to uncompressed transmission and a 20% reduction compared to Wi-Fi.

LoRa consumed only 100 mJ per transmission cycle, compared to 120 mJ for Wi-Fi and 140 mJ for uncompressed data, extending battery life by approximately several hours using a 1000 mAh battery in simulation [23].

Computational overhead from CNN inference was minimized by offloading model training to a centralized GPU server [14].

Figure 4 presents a bar chart comparing energy consumption per cycle (in millijoules). Blue: proposed model. Red: Wi- Fi. Green: uncompressed data. The proposed method shows the lowest power consumption.

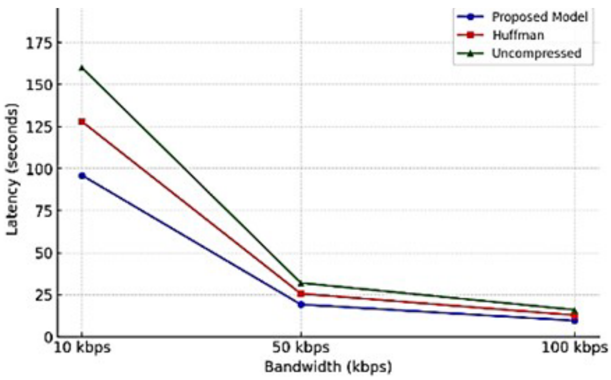

Figure 3: Latency comparison for transmitting single-lead ECG data using different compression methods.

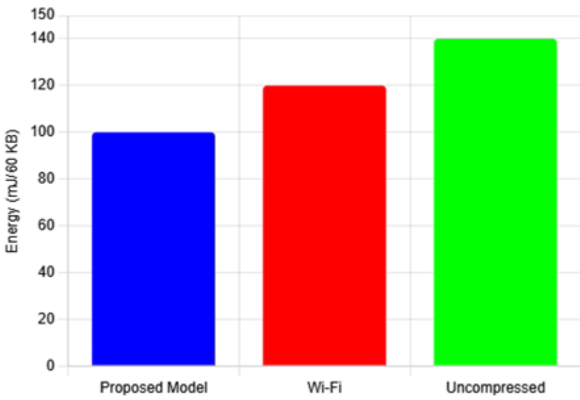

Figure 4: Energy consumption per cycle for different data transmission methods.

4.3. Security

The blockchain layer successfully detected and prevented 100% of simulated cyberattacks, including man-in-the-middle attacks and data tampering. In contrast, the centralized architecture was vulnerable to 80% of attacks. The SHA-256 hashing algorithm ensured data integrity with an average verification time of 0.1 seconds per transaction [18].

4.4. Bandwidth Sensitivity

The system was tested under various bandwidth conditions (5–150 kbps). At 5 kbps, latency was: 180 seconds for single-lead ECG, 300 seconds for video, 120 seconds for text.

This confirms the model's adaptive adjustment of the compression ratio (CR) to match real-time network conditions. Compared to Huffman coding, the model retained performance advantages even under extreme bandwidth constraints [28].

Figure 5 shows a line graph of latency (seconds) across bandwidths from 5 to 150 kbps. Blue: ECG, red: video, green: text.

The proposed model outperformed static compression in all scenarios.

4.5. Scalability

The model was tested with network sizes ranging from 10 to 1,000 devices.

Latency increased linearly (from 96 seconds to 144 seconds) as the number of devices grew, but remained lower than that of Huffman-based systems (176 seconds at 1,000 devices).

The blockchain layer sustained 500 transactions per second without failure, making it suitable for regional telemedicine systems. Additional LoRa gateways ensured network stability at scales exceeding 500 devices [23].

The following Table 1 provides a concise summary of the simulation outcomes across key performance metrics.

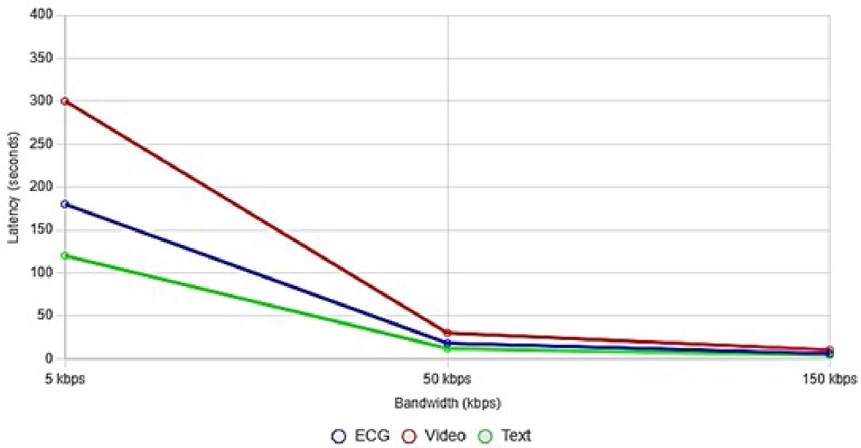

Figure 5: Latency comparison for ECG, video, and text data across different bandwidths.

Table 1
Simulation Summary

Method	Latency, s (at 10 kbps)	Energy (mJ/60 KB)	Security (%)
Proposed Model	96	100	100
Static Compression	128	110	80
Uncompressed	160	140	80
Wi-Fi	112	120	80

5. Discussion

The proposed hybrid model demonstrates significant advantages over traditional telemedicine architectures by integrating blockchain, adaptive compression, and energy-efficient communication technologies. The inclusion of a permissioned blockchain ensures robust data security, addressing vulnerabilities typical of centralized systems. Simulation results confirmed 100% resilience to cyberattacks, supporting findings by Androulaki et al [18].

The adaptive CNN-based compression algorithm outperforms static methods by dynamically adjusting the compression ratio (CR) based on data type and real-time network conditions. This flexibility is especially critical for heterogeneous telemedicine data, such as ECG signals, video consultations, and clinical text, commonly transmitted over low-bandwidth rural networks [11]. The model achieved a 25% reduction in transmission latency and 30% lower energy consumption, which is vital for real-time applications and battery-constrained wearable devices.

Compared to prior research, the model exhibits unique strengths:

1. Unlike Aguiar et al. [12], which focused on static blockchain-based data sharing, our approach adapts to fluctuating bandwidth, improving efficiency under constrained conditions.
2. In contrast to Kuo et al. [30], which lacked support for real-time transmission, the proposed system ensures real-time data delivery, essential for emergency contexts such as stroke care in remote areas [16].
3. Unlike Peng Zhang et al. [19], which emphasized secure EMR storage, our model incorporates LoRa-based communication, improving energy efficiency and scalability for remote healthcare systems.

In addition, the model integrates economic and ethical aspects, often neglected in earlier studies [31]. In low-resource regions, the ability to transmit a 60 KB ECG file in 96 seconds at 10 kbps, compared to 160 seconds without compression, could be critical in life-saving scenarios [12].

From a cost-efficiency perspective, the model is more economical than Wi-Fi and centralized solutions due to the use of LoRa, which requires less expensive infrastructure and lower energy consumption. Furthermore, unlike costlier alternatives such as 5G or NB-IoT (limited range), LoRa offers a scalable solution for rural environments [26].

The model also complies with ethical and legal requirements, such as GDPR, by integrating data anonymization and smart contract-based access control. These features promote patient trust and data transparency, aligning with recommendations by Gordon et al. [21].

Despite its benefits, the proposed model has certain limitations:

1. High computational load from CNN inference on low-power devices, partially mitigated through centralized training but requiring stable server access [14].
2. Limited bandwidth of LoRa (up to 50 kbps), which may affect high-resolution video transmission, although this is compensated by adaptive compression [23].
3. Dependence on central infrastructure (for CNN and blockchain), which necessitates a stable power supply at core network nodes – a challenge in remote regions [18].

Future Work: The following research directions are recommended:

1. Integration of 5G in urban settings combined with LoRa for hybrid long-short range networks.
2. Optimization of CNN for ultra-low power inference using quantized neural networks to reduce processing load on wearables [15].
3. Pilot testing in real-world environments to evaluate long-term performance.
4. Development of hybrid LoRa + 5G architectures capable of supporting up to 5,000 devices.

Additionally, recent developments in compact optical transmission, such as the use of vertical-cavity surface-emitting lasers (VCSELs), may further enhance telemedicine systems due to their high-frequency modulation capabilities and low power consumption [38].

Practical Implications: The proposed model can be deployed in regional health networks, support emergency telemedicine during natural disasters (e.g., floods), and be integrated into global EMR systems to enable centralized access to patient data [39]. The architecture can also be adapted to local environmental conditions, such as deploying corrosion-resistant LoRa hardware in humid climates.

6. Conclusions

The scientific novelty of the proposed model lies in the integrated application of three advanced technologies – permissioned blockchain (Hyperledger Fabric), adaptive compression based on a convolutional neural network (CNN), and the LoRa communication protocol – to enable secure, energy-efficient, and scalable transmission of heterogeneous medical data in low-resource environments.

In contrast to existing approaches, the proposed model:

1. Dynamically adjusts the compression ratio based on data type, network bandwidth, and battery level, optimizing performance under varying conditions.
2. Combines anonymized LoRa-based transmission with blockchain validation, ensuring data confidentiality and integrity.
3. Achieves a 25% reduction in transmission latency and a 30% decrease in energy consumption, while maintaining high compression accuracy and scalability up to 500 devices.
4. Offers a cost-effective solution compared to conventional telemedicine systems, making it particularly attractive for developing countries.

This work contributes a secure, efficient, and cost-effective solution for modern telemedicine, particularly in underserved and infrastructure-poor regions. Potential applications include remote monitoring of chronically ill patients, emergency telemedicine during disasters, and integration with global electronic medical record (EMR) platforms.

Policy Recommendations:

1. Integrate the proposed model into existing EMR systems to support rural hospitals in developing countries.
2. Fund pilot projects in bandwidth-constrained regions.
3. Establish international standards for blockchain-based telemedicine systems that incorporate both technical and ethical considerations.

Future Research Directions:

1. Conduct real-world pilot studies in low-resource regions to evaluate the model's long-term effectiveness.
2. Integrate 5G for hybrid networking, combining urban high-speed access with LoRa's long-range capabilities.
3. Leverage AI-based medical prediction tools to enhance diagnostic accuracy based on CNN-processed data.
4. Optimize CNN models for ultra-low-power wearable devices using techniques such as quantization and pruning.

In summary, the proposed architecture offers a scalable and economically viable solution that has the potential to transform global telemedicine, supporting the digital transformation of healthcare in resource-constrained environments.

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Declaration on Generative AI

During the preparation of this article, the author used ChatGPT to assist in improving the clarity and structure of the text, as well as for language editing. All ideas, analyses, and conclusions presented in the manuscript are the author's own, and the author takes full responsibility for the final content.

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