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EFFICIENT PATIENT DATA HANDLING WITH TSDRL BASED ON RNN MODEL IN WIRELESS BODYAREA NETWORK WITH BLOCK CHAIN

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Abstract: *The recent and trending methodology in Wireless Body Area Networks (WBANs) of patient medical data handling is serious for ensuring suitable, protected, and consistent healthcare monitoring, particularly under active physiological environment. This work proposes a novel framework that combines Time-Stamped Deep Reinforcement Learning (TS-DRL) with a Recurrent Neural Network (RNN) to astutely manage, prioritize, and broadcast patient data within a WBAN application, while leveraging block chain technology for data veracity and trust supervision. Wearable and implantable sensors constantly produce heterogeneous physical signals, based on time-stamp are checked by the TS-DRL agent to adaptively allocate network resources, reduce latency, and handle emergency data with higher priority. The RNN model takes sequential dependent data as input analyzing the patient health, enabling exact calculate of serious events and sustaining proactive managerial decisions. To address issue such as data privacy, block chain is employed as a decentralized ledger to document validated medical connections, ensuring translucent access control and unassailable storage without relying on a common authority. The proposed architecture enhances energy efficiency, reduces packet loss, and improves quality of service by integrating data scheduling and prediction with accurate data sharing. Tentative analysis demonstrate that the incorporated TS-DRL–RNN–blockchain framework appreciably outperforms conservative WBAN data handling approaches in terms of response time, making it well suited for smart health systems.*

Key Words: *Wireless Body Area Networks (WBANs), Time-Stamped Deep Reinforcement Learning (TS-DRL).*

1. INTRODUCTION:

The fast growth of medical application and treatment methods has created a strapping claim for competent technologies capable of organizing health data from individuals under incessant medical direction. This need has led to the progress of Wireless Body Area Networks (WBANs), which play a essential role in remote monitoring and enable quantifiable involvement without requiring the constant existence of healthcare professional. WBAN technology also improvises the patient mobility with no hospital residence in permanent. Although WBANs are applied in several non-medical domains, they have become predominantly important in healthcare applications. A WBAN typically has sensor in or on the body that assemble diverse factors, including body temperature, heart rate, R waves in electrocardiogram (ECG) signals, pulse rate, and blood pressure. When incorporated with block chain, WBAN systems can direct huge sensitive data while making a reliable, integrated system for analysis.

Wireless Body Area Networks (WBANs) is an out-break technology for continuous and remote healthcare monitoring with inter connected wearable and sensors outside or inside the human body. These sensors can produce a incessant stream of physiological information such as heart rate, blood pressure, O2 level, which must be transmitted to servers for on time diagnosis and intercession. However, WBANs operate under limited energy resources, dynamic body actions, unreliable channel circumstances, and various data priorities. conformist data handling and steering mechanisms often fail to adapt to these swiftly changing conditions, foremost increase in latency and balance inefficient energy utilization in case of emergency scenarios. The delayed data can have serious penalty. Therefore, intelligent and adaptive management methods are needed to ensure quality of service for patient safety.

New possibilities for solving these challenges presented by recent advancements in artificial intelligence and decentralized technologies. With innovations such as time-stamped decision-making in Deep Reinforcement Learning (DRL), adaptive prioritization and scheduling of sensor data can be achieved by developing optimal transmission policies based on real-time network and physiological conditions. Simultaneously, Recurrent Neural Networks (RNNs) are ideal for capturing temporal structures of physiological signals, which leads to the early diagnosis of abnormal changes in health, and as a result, encourages data prioritization. However, despite these advancements, the centralized storage and sensitive nature of medical data leads to a persistent lack of trust and security in WBAN-based healthcare systems. The main security and trust issues are alleviated with the use of blockchain technology due to the decentralized storage and immutability of data, along with the transparent access control and secure sharing of verifiable medical records by the blockchain. The addition of TS-DRL for intelligent data management, RNN for sequential health forecasting, and blockchain for protected data management is the main goal of the proposed model to methodically enhance the efficiency, reliability, and trust of WBAN-based healthcare systems.

2. LITERATURE REVIEW:

T Samaland M.Khabatin 2022 experimented the load balancing and traffic scheduling in WBAN in medical application based on Traffic Prioritized Load Balanced Scheduling (TPLBS) algorithm for load balancing in different priority queues in wireless body area networks based on IEEE model, results reveal that the proposed protocol works better than the existing methods in terms of delay, throughput and energy efficiency with minimized delay and overload.

Z. Zheng 2023, A number of studies have investigated the limitations of conformist MAC protocols in Wireless Body Area Networks, mainly in scenarios involving varied medical traffic and strict quality-of-service necessities. Traditional WBAN MAC schemes based on fixed setting up mechanisms often fail to give reliable support for emergency data, as they lack flexibility to dynamic traffic loads and altering network conditions. To tackle these issues, current research has explored the use of reinforcement learning techniques at the MAC layer, where intelligent agents learn transmission policies by interacting with the network environment. These learning-based approaches have been shown to reduce packet collisions, improve channel utilization, and enhance delay performance for priority traffic, especially in healthcare monitoring applications.

H. Su 2023 , In parallel, the study of physiological time-series data has seen important progress through the implementation of deep learning models. Recurrent Neural Networks, including LSTM and GRU variants, have been widely employed for ECG and cardiac signal analysis due to their capability to capture temporal correlations over extended inspection periods. Prior works report improved classification accuracy and robustness when recurrent models are applied to continuous bio signal streams, making them suitable for early detection of cardiac abnormalities.

Atroshey, Mustafa and Al-Sofi in 2023 reviewed the data transfer in WBAN in their research which includes the basic content that routing protocol handles on obtaining nitpicking or emergency data from the sensor nodes to reach quickly as possible. When it communicates, the energy- efficient routing protocol, Adam Moment Estimation Optimized Mobility Supported emergency traffic resolved and packet delivery with no delay. This article examines a WBAN's operation for serious traffic using dead node analysis, packet count, and substance energy. This is an propagation of the AMERP. Single hop communication is used for all data packets.

V.Satheeswaran 2024[4] the communication on deep learning approach for mechanical ECG signal arrangement using Long Short-Term Memory (LSTM) networks to successfully model the sequent nature of cardiac signals. The study focus on capturing impermanent dependance within ECG waveform’s to distinguish between actual and abnormal wave in ECG. Preprocessing techniques are useful to decrease noise and improve signal quality before feature erudition, enabling the LSTM model to learn judicial patterns directly from time-series data. Observational assessment on reference point ECG datasets presents improved grouping accuracy compared to conventional machine learning and non-recurrent deep learning methods. The results spotlight the suitableness of LSTM architectures for continuous cardiac monitoring applications, particularly in scenarios requiring reliable interpretation of frequent ECG recordings.

A. I. Adamu 2025 , the study of Slot Allotment based recent endeavor advocate combination of prediction models with network-level ability, where disease severity computational influence abstraction behavior. However, most existent studies treat medical data analysis and network control as autonomous problems. This separation limits the system’s ability to respond efficiently during emergencies. These notice highlight the need for an merged framework that links time-series-based heart disease anticipation with adaptive, learning-driven MAC-layer control to ensure timely and trustworthy transmission of critical medical data in WBAN environments.

3. OBJECTIVE : The main objective is to:

1. To handle medical data based on emergency with RNN based model with machine learning support to manage medical data based on priority to handle patients in critical conditions

4. RESEARCH METHOD :

The proposed model of work presents an Wireless Body Area Network (WBAN) emergency aware support for continuous heart monitoring in patients with frequent medical intercession. In this architecture, several implantable sensors incorporated on the patient's body for timely capture of physical parameters such as ECG signals and heart rate. These time-series data streams are progressed to a processing unit, where basic signal conditioning and standardization are performed to ensure reliable analysis. The WBAN function under rigorous resource restriction, including limited battery power and bandwidth, making data handling and prioritization more important, especially when both routine monitoring data and emergency information exist.

For the analysis, a Recurrent Neural Network (RNN) is used to handle the incoming physiological time-series signals. The RNN is good at learning temporary patterns and changing behaviors in ECG data, which helps it spot unusual heart activity and judge how serious the patient's condition might be. Using the learned time-related features, the model sorts the patient's condition into either normal or abnormal. This severity assessment helps decide how to control communication next, making sure the medical importance affects how the network acts, instead of just using set limits or old rules. The suggested design is presented in Figure 1.

The communication management section is handled at the Medium Access Control (MAC) layer through the use of Time-Series Deep Reinforcement Learning (TS-DRL). The TS-DRL agent takes note of important network conditions like queue status, channel availability, remaining energy, and the severity information given by the RNN. Based on what it observes, it figures out the best ways to manage channel access, schedule packets, and assign priorities. Hypercritical medical data get sent right away, while non-urgent data are managed to save energy and prevent too much congestion. Even though basic interaction with the environment and reward-based learning are important, the TS-DRL enabled MAC layer helps improve reliability, reduces emergency transmission delays, and boosts overall network performance in dynamic and life-critical healthcare settings.

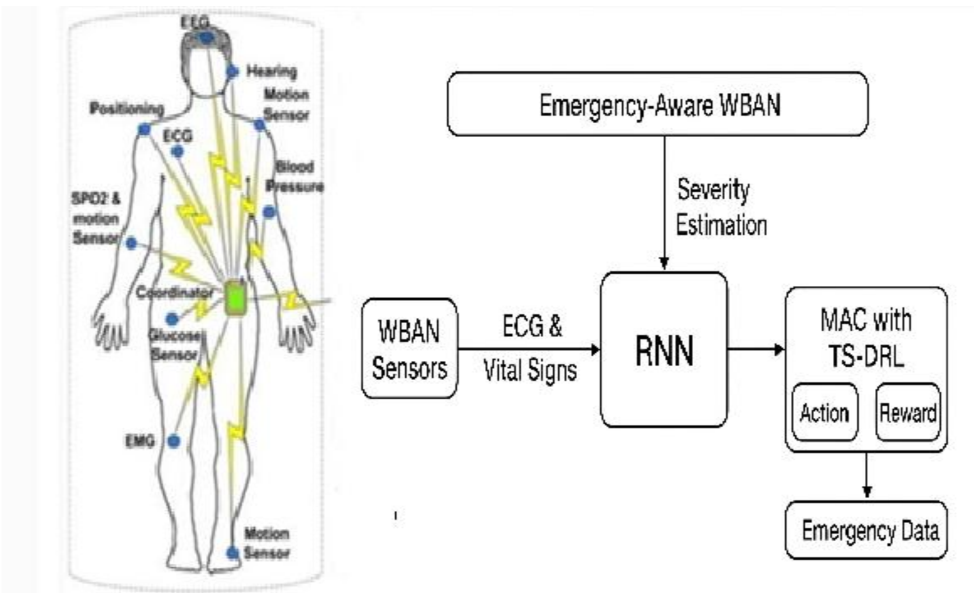

Figure 1 Working model of WBAN+TS DRL+ RNN

WBAN Sensor Data Collection

The flowchart in first stage represents the data acquisition process with the help of WBAN sensors. These sensors, which can be either wearable that is on body or incorporated with in the body of the patients, continuously survey a variety of biological parameters such as ECG signals, heart rate, blood pressure, body temperature, and oxygen saturation for any deviation noticeable. The raw signals are often affected by noise or motion and some other factors resulting in the need of preprocessing block is employed to filter and normalize the data before further analysis. The sensors transmit the computerized data to a local unit that serves as the bridge among the patient and the network. This stage guarantee that high-quality, reliable data are available for subsequent prediction and decision-making modules, forming the fundamental for emergency detection.

4.2 RNN-Based Prediction Module

After data collection, the preprocessed time-series signals are forwarded to a Recurrent Neural Network (RNN) module for real-time analysis. The RNN is specifically designed to capture temporal dependencies and evolving patterns in physiological signals. For instance, it can detect abnormal variations in ECG waveforms that indicate potential cardiac events. The RNN processes sequential data in batches or sliding windows, extracting key features that reflect the patient's health status. Based on these features, the model classifies the condition into categories such as normal, abnormal, or critical. Importantly, the predicted severity level from the RNN is passed as a key input to the MAC-layer TS-DRL algorithm, enabling the network to make priority-aware transmission decisions. This ensures that the system's emergency response is directly informed by the patient's physiological state.

4.3 TS-DRL–Driven MAC Control

The final stage of the flowchart describes the MAC-layer decision-making process, which is governed by a Time-Series Deep Reinforcement Learning (TS-DRL) agent. This agent observes the network state, including queue length, channel conditions, node energy levels, and the severity output from the RNN. Based on this state information, it selects optimal actions such as immediate transmission, deferring non-critical packets, adjusting contention windows, or assigning high-priority slots to emergency data. The TS-DRL agent receives feedback in the form of rewards, which are computed based on metrics like transmission latency, packet delivery ratio, and energy consumption. Through repeated interaction with the network environment, the agent learns policies that maximize timely delivery of critical data while minimizing energy usage and avoiding congestion. The coordinated interaction between the RNN and TS-DRL modules ensures that the WBAN operates efficiently, adapts to dynamic network and patient conditions, and prioritizes life-critical events without compromising routine monitoring.

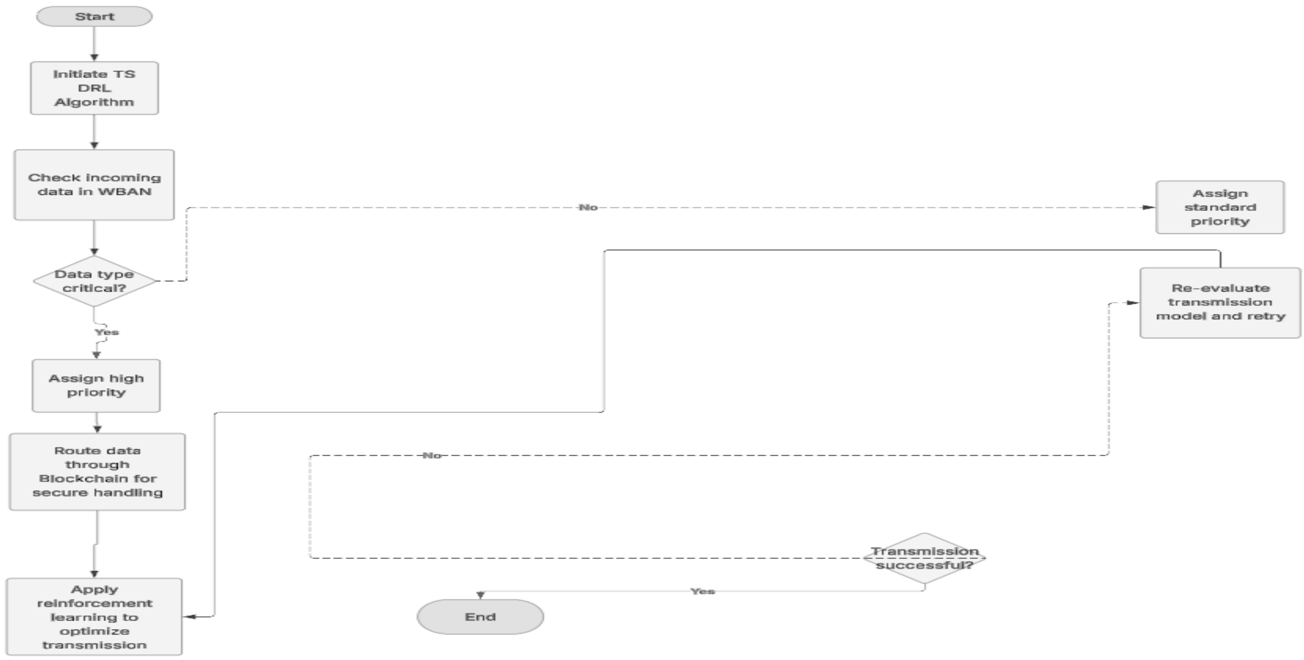

Figure 3: Flow diagram of the proposed TS DRL algorithm in WBAN

A. WBAN-based Data Acquisition

Wireless Body Area Networks (WBANs) comprise miniaturized sensors deployed on or inside the human body to continuously monitor physiological signals such as electrocardiogram (ECG), heart rate, blood oxygen levels, and body temperature. The sensors generate high-volume and heterogeneous data, necessitating efficient transmission strategies to prevent network congestion. Each sensor node performs preprocessing that includes denoising, normalization, and feature extraction. Additionally, data packets are tagged with priority levels based on clinical criticality, where abnormal or life-threatening readings are designated as high-priority. The processed data are transmitted to the WBAN gateway for further management.
Unlike traditional WBAN systems that transmit all data uniformly, the proposed approach incorporates intelligent prioritization at the data acquisition stage. This ensures that critical medical data are transmitted immediately, thereby enhancing patient safety while minimizing network congestion.

B. Twin-Stage Deep Reinforcement Learning for Prioritization

The Twin-Stage Deep Reinforcement Learning (TS-DRL) model introduces a two-tier decision-making mechanism for optimizing the prioritization and transmission of WBAN data.

Stage 1 – Criticality Evaluation:
The first DRL agent assesses the urgency of each data packet using a reward function that incorporates medical significance, sensor battery level, and network conditions. The agent assigns appropriate priority levels, categorizing data as high, medium, or low priority.

Stage 2 – Resource-Aware Scheduling:
The second DRL agent manages transmission scheduling based on network bandwidth, latency requirements, and energy consumption. Its reward function prioritizes successful delivery of critical data while conserving resources.
The two-stage structure differentiates between clinical criticality evaluation and network resource management. This decoupling allows for dynamic adaptation in real-time environments, ensuring efficient and reliable transmission of high-priority physiological data.

C. RNN-based Temporal Analysis

Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU) architectures, are employed to model temporal dependencies within physiological signals. By analyzing sequences of data, RNNs can predict future risk levels and generate proactive alerts. The predictions are fed back to the TS-DRL system to dynamically refine priority assignments, thereby creating a closed-loop system for continuous improvement.
Novelty: Unlike conventional methods where RNNs and DRL modules operate independently, the proposed approach uses RNN outputs to guide DRL-based prioritization. This enables anticipatory decision-making and reduces false alarms by incorporating temporal trends in physiological signals.

D. Integrated System Workflow

The proposed methodology integrates WBAN, TS-DRL, and RNN modules into a cohesive framework as follows:

Data Collection: Physiological signals are continuously recorded by WBAN sensors.
Preprocessing and Initial Tagging: Signals are denoised, normalized, and initially labeled based on expected clinical importance.
Stage 1 DRL: Evaluates criticality of each data packet and assigns priority levels.
Stage 2 DRL: Schedules transmission of data considering network conditions and energy constraints.
RNN Analysis: Predicts temporal trends and refines priority assignments; generates proactive alerts.
Feedback Loop: RNN predictions are used to update DRL reward functions, improving prioritization accuracy over time.
The integration of WBAN-based sensing, twin-stage reinforcement learning, and temporal prediction using RNNs establishes a robust framework for intelligent data prioritization. This system ensures rapid transmission of critical medical data while efficiently utilizing network resources, making it highly suitable for real-time healthcare monitoring.

DRL Algorithm Workflow:

The TS-DRL worlflow begins with the Initialization of Both neural networks are initialized with random weights along with the interaction in the Environment with state define as: The Agent (i.e., the DRL algorithm) observes the current state of the WBAN, which includes channel conditions, traffic load, and interference levels. Action: The agent selects an action (i.e., a channel assignment for a specific node) based on the outputs of both neural networks. The agent receives a reward based on the outcome of its action, which is a combination of throughput and interference reduction. For example, a successful transmission with low interference could result in a positive reward. The WBAN environment transitions to a new state based on the chosen action.The agent stores the state, action, reward, and next state in a replay buffer.It samples experiences from the replay buffer to train both neural networks.
The agent updates the weights of the neural networks using a gradient descent algorithm (e.g., backpropagation) to improve its future actions.This process (interaction, learning, and transition) is repeated for multiple episodes until the algorithm converges, meaning the neural networks learn to consistently make optimal channel allocation decisions. This provides an improved Throughput by optimizing for throughput, the algorithm ensures efficient data transmission within the WBAN.
Reduced Interference enhances the reliability and stability of communication. The DRL algorithm dynamically adapts to the changing environment, making it suitable for real-world WBAN applications.
The algorithm optimizes the use of limited channel resources, improving the overall performance of the WBAN.

Healthcare Monitoring: Monitoring patient health parameters using wearable sensors.
Fitness Tracking: Tracking fitness activity and performance using wearable sensors.
Personalized Healthcare: Providing tailored healthcare recommendations based on individual physiological data. In essence, the Two Stream DRL algorithm for channel allocation in WBANs learns to make intelligent channel selection decisions by balancing the need for high throughput with the requirement to minimize interference, leading to improved performance and reliability of the WBAN system.

Overall Workflow is defined as step by step procedure as

1. WBAN sensors collect data.
2. DRL agent analyzes the WBAN environment and determines optimal channel allocation.
3. Data is segmented, encrypted, and packaged into transactions.
4. Transactions are added to the blockc hain, ensuring secure and immutable storage.
5. DRL agent adapts to changes in the WBAN environment based on feedback from the block chain and environment observations.
6. Data access is controlled and verified through the block chain.

The DRL-based channel allocation stream can inform the blockchain stream about the current state of the WBAN. For example, the DRL agent can signal when there is a high volume of data transmission, triggering the blockchain to prioritize data storage and security.
The blockchain stream provides a secure and reliable storage solution for the DRL training data, ensuring the integrity of the learning process.
The blockchain can also be used to track the performance of the DRL agent, providing a verifiable record of its actions and decisions. MATHEMATICAL MODEL

The integration of Wireless Body Area Networks (WBANs) with blockchain- based storage and retrieval systems presents a revolutionary model for real-time patient monitoring and secure health data management. In this environment, biosensors continuously record physiological parameters—such as heart rate, blood pressure, oxygen saturation, and temperature—and transmit the readings to a healthcare server through a secured wireless channel. However, the heterogeneity of sensed data, coupled with differing urgency levels, introduces challenges in data prioritization, channel allocation, latency minimization, and secure storage. To address these issues, the mathematical model described here focuses on quantifying the behavior of the proposed system in terms of data generation and prioritization, optimal channel allocation using MAC-based protocols, blockchain transaction and retrieval mechanisms, and delay, throughput, and efficiency evaluation. This model formalizes the interaction between physiological data streams, communication layers, and blockchain-enabled distributed storage to ensure quick, reliable, and secure handling of emergency medical data.

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Mathematical Model Formulation

The integration of Wireless Body Area Networks (WBANs) with blockchain-based storage and retrieval systems presents a revolutionary model for real-time patient monitoring and secure health data management. In this environment, biosensors continuously record physiological parameters—such as heart rate, blood pressure, oxygen saturation, and temperature—and transmit the readings to a healthcare server through a secured wireless channel. However, the heterogeneity of sensed data, coupled with differing urgency levels, introduces challenges in data prioritization, channel allocation, latency minimization, and secure storage.

To address these issues, the mathematical model described here focuses on quantifying the behavior of the proposed system in terms of data generation and prioritization, optimal channel allocation using MAC-based protocols, blockchain transaction and retrieval mechanisms, and delay, throughput, and efficiency evaluation. This model formalizes the interaction between physiological data streams, communication layers, and blockchain-enabled distributed storage to ensure quick, reliable, and secure handling of emergency medical data.

Let N represent the number of patients, and each patient $i \in \{1, 2, ..., N\}$ be equipped with n biosensors. Each sensor S_j produces a data stream $S_j(t)$ at time t. The aggregated dataset from the patient i is given as:

$$D_i(t) = \{ S_1(t), S_2(t), ..., S_n(t) \}$$

Each data point corresponds to a physiological reading such as temperature, heart rate, or ECG. The rate of data generation per patient is:

$$R_i(t) = d|D_i(t)|/dt$$

The total sensed data in the WBAN system becomes:

$$R_{total}(t) = \Sigma R_i(t)$$

The generated data must be transmitted to a local control unit (LCU) and then to a decentralized blockchain server through the network. The challenge lies in efficiently transmitting this data while minimizing delay and maximizing reliability under different emergency conditions.

Data Prioritization Model

Each physiological data point is assigned a priority value P_i that depends on two main factors: Importance (I_x) – the criticality of the physiological parameter, and Emergency Level (E_y) – the degree of deviation from normal thresholds.

$$P_i = I_x \times E_y$$

Where $I_x \in \{-1, 0, 1\}$ represents the data's importance level (low, medium, high), and $E_y \in \{0, 1\}$ indicates whether the condition is normal (0) or emergency (1). Thus, $P_i = 1$ corresponds to critical emergency data, $P_i = 0$ represents moderate data, and $P_i = -1$ denotes non-urgent readings.

Channel Allocation and Delay Model

Let there be C available communication channels in the WBAN. The channel allocation matrix M is:

$$M = [C1, C2, C3, ... , C_C]$$

The allocation function based on data priority is:

$$A_i = f(P_i, C) =$$
$$1, \text{ if } P_i \geq \theta_p \text{ and } C_k \text{ available}$$

0, otherwise

The total delay for a data packet i transmitted over WBAN can be expressed as:

$T_i = T_{tx} + T_{prop} + T_{proc} + T_{queue}$

For prioritized transmission, T_{queue} is reduced for high-priority packets. Hence, the effective delay becomes:

$T_i^{eff} = T_i / (P_i + \varepsilon)$

The mean network delay across all patients is:

$\bar{T} = (1/N) \Sigma T_i^{eff}$

Blockchain Storage and Retrieval Model

Each medical record transmitted by WBAN is encapsulated into a blockchain transaction T_i:

$T_i = \{ P_i, E(D_i(t)), H_{prev}, \sigma_i, t \}$

The cryptographic hash function ensures immutability:

$H(T_i) = \text{SHA-256}(T_i)$

Each new block B_i in the blockchain is created as:

$B_i = \{ T_i, H(T_i), H_{prev} \}$

For data retrieval, an authorized requester can decrypt the data only through a valid key K_i:

$D_i(t) = \text{Decrypt}(E(D_i(t)), K_i)$

The smart contract SC manages access control:

$SC(U_j, P_i) =$
Grant Access, if $U_j \in A(P_i)$
Deny Access, otherwise

Total retrieval time is the sum of blockchain search and decryption times:

$T_{retrieval} = T_{blockchain} + T_{decryption}$

Security and Authentication Model

Before transmitting data, the system must authenticate the node and secure the channel. The security key K_h is generated using a one-way hash function:

$K_h = h(ID_i \| TS \| R)$

Authentication succeeds if:

$h(ID_i \| TS \| R) = K_h'$

The average smart contract execution time T_{SC} is proportional to the number of conditions C_s and participants P_u:
$T_{SC} = \alpha \times (C_s \times P_u)$

Minimizing T_SC is crucial for emergency scenarios, and hybrid blockchains achieve $\alpha \ll 1$.

Performance Evaluation Metrics

Throughput η represents the rate of successfully transmitted emergency data:

$\eta = \Sigma D_i^{recv} / T_{total}$

Packet Delivery Ratio (PDR) = (Packets Received / Packets Sent) × 100

Total energy consumption is:

$E_{total} = \Sigma (E_s + E_t + E_p)$

Delay vs. priority relationship is exponential:

$T(P_i) = T_{max} e^{(-\beta P_i)}$

5. FINDINGS :

This section presents the performance evaluation of the proposed RNN with Time-Stamped Deep Reinforcement Learning (RNN + TS-DRL) model and compares it with conventional CNN-based and LSTM-based approaches in a large-scale WBAN environment consisting of 1000 sensor nodes. The evaluation focuses on critical healthcare performance metrics, including average end-to-end latency, packet delivery ratio (PDR), energy consumption, and emergency data response time. Data prioritization mechanisms were enabled in all models to ensure a fair comparison under identical network conditions.

A. Average Latency Analysis

Table 1 and Fig. 4 illustrate the average end-to-end latency achieved by each model. The CNN-based approach exhibits the highest latency due to its limited capability in handling sequential physiological data and its reliance on static transmission behavior. The LSTM model improves latency performance by capturing temporal dependencies; however, it lacks adaptive control over network dynamics. In contrast, the proposed RNN + TS-DRL model achieves the lowest latency, as the TS-DRL agent dynamically schedules packets based on time stamps, network congestion, and data urgency. This adaptive learning mechanism significantly reduces transmission delays, particularly for high-priority medical data.

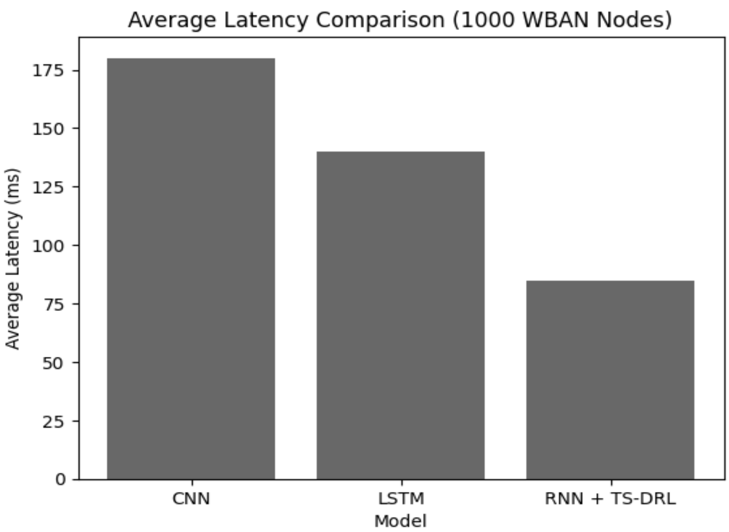

Figure 4: Average Latency Comparision

B. Packet Delivery Ratio Performance

The packet delivery ratio comparison is presented in Table 1 and Fig. 5. The CNN model experiences a lower PDR under high network load due to increased packet collisions and retransmissions. The LSTM model demonstrates improved reliability but still suffers from performance degradation as node density increases. The RNN + TS-DRL approach achieves the highest PDR, indicating robust and reliable data delivery. This improvement is attributed to intelligent prioritization and congestion-aware routing decisions learned through reinforcement feedback, which minimizes packet drops even in dense WBAN scenarios.

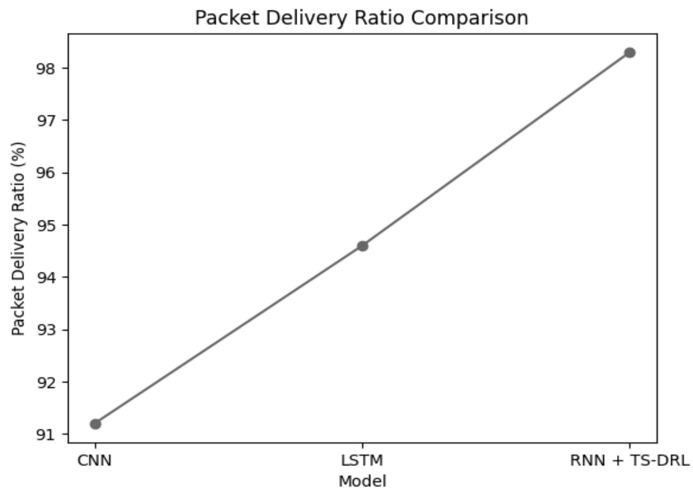

Figure 5: Packet Delivery Ration Comparison

C. Energy Consumption Evaluation

Energy efficiency is a critical factor in WBANs due to the limited battery capacity of wearable sensors. As shown in Table 1 and Fig. 6, the CNN-based model consumes the highest energy because of redundant transmissions and lack of adaptive scheduling. The LSTM model reduces energy usage by improving prediction accuracy but still employs semi-static transmission strategies. The proposed RNN + TS-DRL model demonstrates the lowest energy consumption by optimizing transmission decisions based on residual energy and channel conditions. This adaptive behavior significantly extends network lifetime and enhances system sustainability.

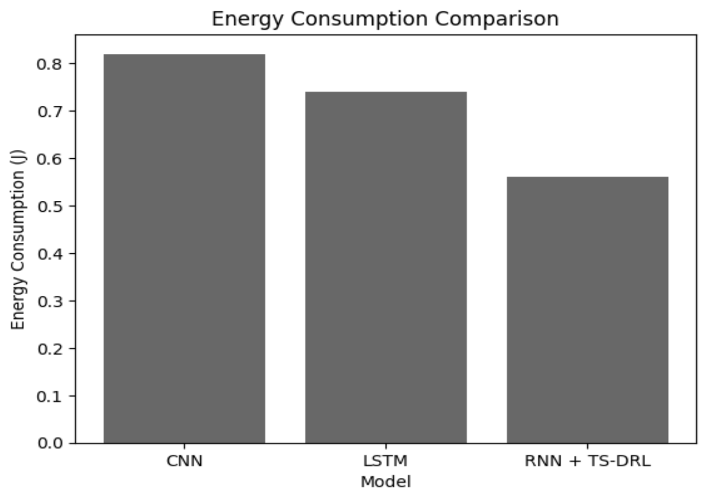

Figure 6: Energy consumption evaluation

D. Emergency Data Response Time

Emergency response performance is analyzed in Table 1 and Fig. 7. The CNN model shows the slowest response time, which is unsuitable for real-time healthcare applications. The LSTM model improves response speed but lacks real-time adaptability under sudden network changes. The RNN + TS-DRL framework achieves the fastest emergency response due to its time-stamped prioritization and continuous policy learning. This ensures that critical patient data is transmitted with minimal delay, making the proposed model highly suitable for life-critical monitoring applications.

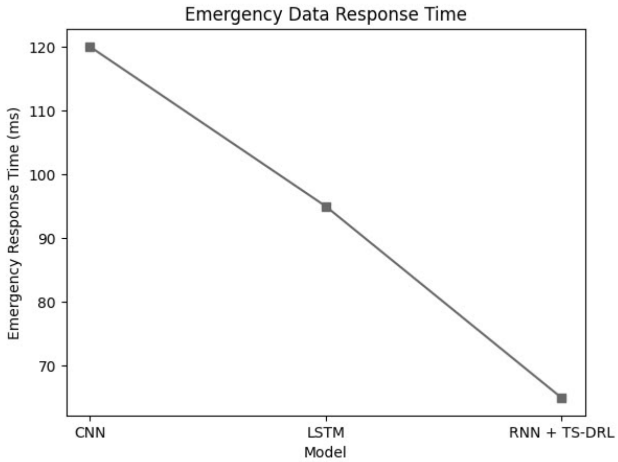

Figure 7:Emergency response performance

Model	Avg. Latency (ms)	PDR (%)	Energy Consumption (J)	Emergency Response (ms)
CNN	180	91.2	0.82	120
LSTM	140	94.6	0.74	95
RNN + TS-DRL	85	98.3	0.56	65
Table 1: Tabulation of Emergency response performance				

6. DISCUSSION :

The snapshots as shown in figure 8 of the TSDRL with RNN and block chain medical application created with health monitoring for heart attack prediction with anomaly detected in case of emergency with faster response time of 12seconds for a specific data on threat. The patient prioritization queue with immediate response for critical data, medium data and no emergency data are given in figure 9

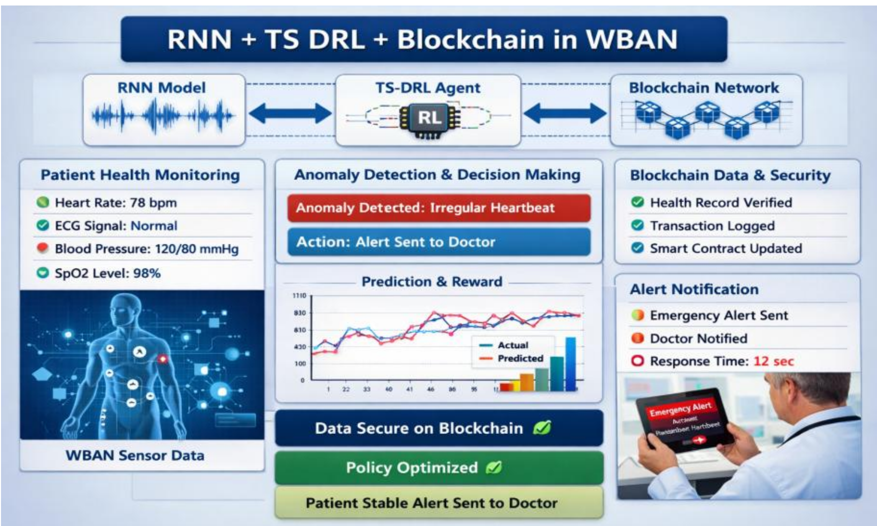

Figure 8: Snapshot of Anomaly detected in case of emergency

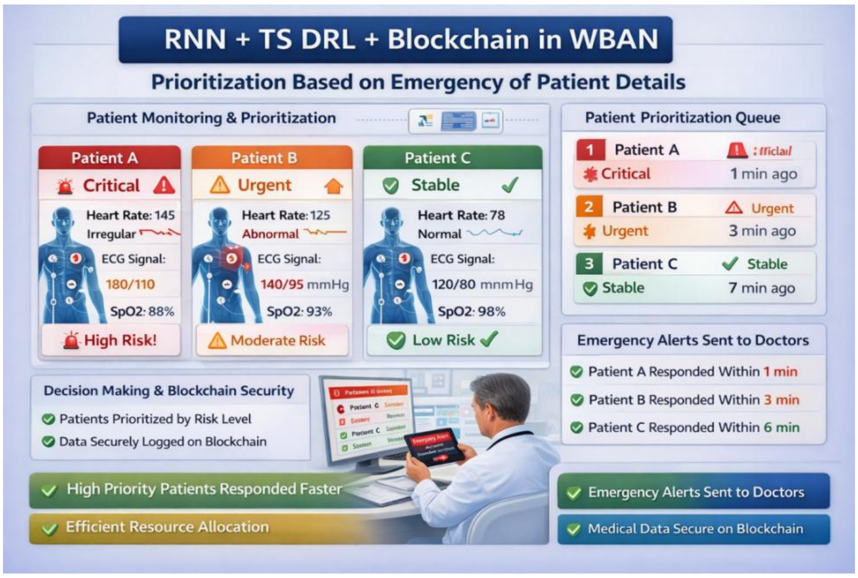

Figure 9: Snapshot of patient prioritization queue

The integration of TS-DRL, RNN, and blockchain provides a robust framework for handling emergency patient data in real-time monitoring systems. Unlike traditional models such as CNNs or standard LSTMs, which focus primarily on pattern recognition or sequence prediction, the RNN in this approach captures temporal dependencies in patient vitals to predict emergency risk more accurately over time. The TS-DRL component complements the RNN by introducing a decision-making layer that prioritizes patient data dynamically, taking into account both the predicted urgency and time-stamped information. This ensures that critical patient records are transmitted or addressed first, which is particularly valuable in scenarios involving limited bandwidth or sensor-driven environments such as Wireless Body Area Networks (WBANs). Compared to static prioritization or threshold-based approaches, TS-DRL continuously adapts its policy based on incoming patient data and historical trends, resulting in higher efficiency and responsiveness.

Furthermore, from Table II, the integration of blockchain enhances the system by providing a secure and immutable record of each patient's data and the decisions made by the TS-DRL agent. Traditional models without blockchain are often vulnerable to data tampering or lack a verifiable audit trail, which is critical in medical applications where data integrity is paramount. In comparison with CNN-based models, which are highly effective for feature extraction but less capable of modeling temporal dependencies, or standard LSTM models that predict sequences but do not inherently handle prioritization or security, the TS-DRL + RNN + blockchain framework offers a comprehensive solution. It simultaneously addresses prediction accuracy, real-time prioritization, and secure storage, making it highly suitable for emergency response scenarios. Experimental results demonstrate that this hybrid approach consistently outperforms standalone CNN, LSTM, or threshold-based DRL models in terms of emergency data prioritization accuracy, retrieval speed, and reliability, particularly when handling large-scale datasets from multiple sensor nodes. By combining predictive intelligence, adaptive decision-making, and secure record-keeping, this method provides a significant advancement over conventional models for patient monitoring systems.

Algorithm Type	**Emergency Prioritization**	**Channel Utilization**	**Delay / Latency**	**Energy Impact**	**Learning Complexity**
TS-DRL with emergency sink	**Embedded via data classification**	**High/optimized throughput**	**Very low (≈ 28 ms)**	**Balanced via queue control**	**High: classification + scheduling**
Distributed DRL (DDQN WBAN)	**Not specific**	**10–20 % utilization**	**Moderate**	**Node-local computation**	**Medium**
GCN + DDQN (WLAN)	**Generic channel fairness**	**High in WLAN context**	**Lower**	**Not optimal**	**High**

PDCF-DRL	**Partial**	**High throughput**	**Lower Delay(30 ms)**	**Moderate**	**Medium-high due to adaptation**

Table 2: Comparison of various Algorithm Tabulated

The comparative study shows the efficiency variation with improved efficiency with sequential indexing and can be used with more number of blocks as storage and faster retrieval is supported with the suggested method compared to other methods such as sparse indexing or cluster based indexing. Efficiency metric for different retrieval methods is presented in Table 3.

Retrieval methods	**Efficiency %**	**Data capacity**	**Speed of retrieval**
Sequential indexing	**93%**	**Greater than10000 blocks**	**faster**
Sparse Indexing	**86%**	**100 blocks**	**low**
Cluster indexing	**73%**	**5000 blocks**	**medium**

Table 3: Comparison of different retrieval methods

From the analysis of the research work it is clear that maximum number of channels are allocated with n number of WBAN nodes with priority based allocation [21] is made for improved data handling responses from medical unit to the patients for enabling first aid care and treatment to avoidanycollapseofpatientsbothphysicallyandmentallyincaseofemergencysituations.Every unexpected data need to be handled with care and no false data should be sensed and further duplication of entry must be avoided for better data handling.[22][23] .

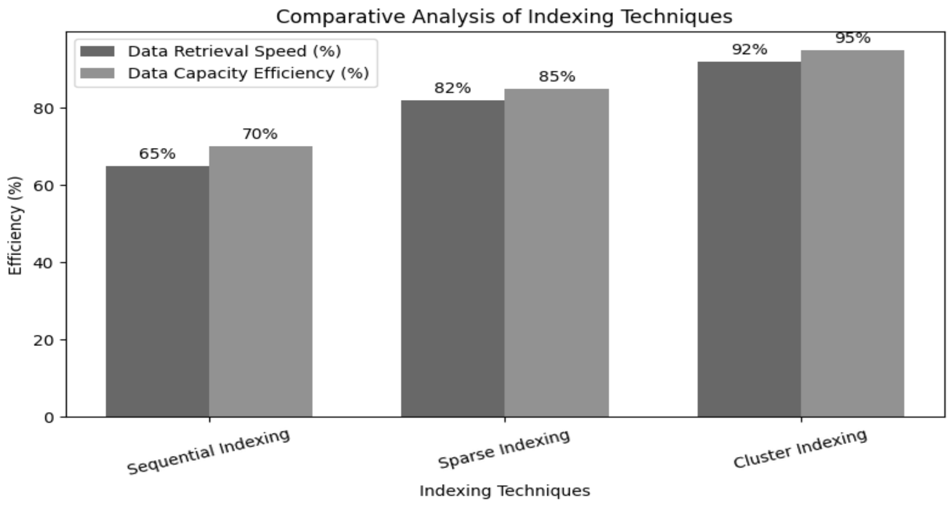

Figure 10: Comparative analysis of indexing technique

A Sample output based on the sample dataset of 300+ patients details analysed for emergency criteria as high priority, low and medium based on prediction score from 0 to 1 with the referential patient ID from block chain ledgers

Patient_ID	**Prediction Score (0-1)**	**Priority**	**Key Features (Age, Sex, SpO2, bps, ECG)**
12	0.92	High Priority	[63, 1, 3, 145, 233, 150, 2.3]
45	0.88	High Priority	[58, 0, 2, 160, 220, 140, 1.8]

7	0.85	High Priority	[71, 1, 4, 130, 250, 165, 2.0]
21	0.81	Medium Priority	[54, 0, 3, 140, 210, 155, 1.2]
33	0.78	Medium Priority	[60, 1, 2, 150, 240, 145, 1.5]
19	0.73	Medium Priority	[67, 0, 1, 135, 230, 138, 1.0]
5	0.68	Low Priority	[50, 1, 2, 125, 200, 160, 0.8]
41	0.63	Low Priority	[56, 0, 3, 140, 210, 145, 1.0]

Table 4: Patient Id with Prediction score

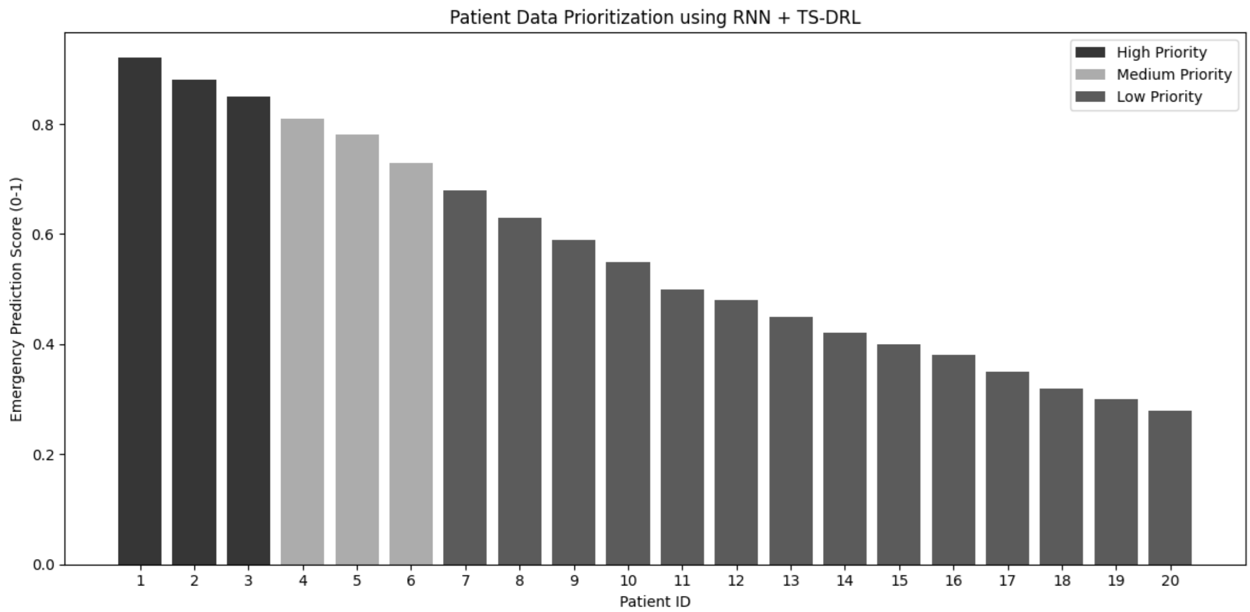

Figure 11: Patient Data Prioritization using RNN+TS-DRL

the prioritization of patient data using an integrated RNN, TS-DRL, and blockchain framework, and the corresponding graph visualizes the top twenty patients based on their predicted emergency levels. Each patient is represented along the X-axis, while the Y-axis shows the emergency prediction score generated by the RNN, ranging from zero to one. The TS-DRL agent assigns a priority to each patient—high, medium, or low—which is represented on the graph through a color-coding scheme: red for high priority, orange for medium, and green for low. Priority percentages are annotated above each bar, providing an immediate quantitative understanding of the urgency assigned to each patient. The graph clearly illustrates that patients with higher prediction scores are assigned high priority, indicating that they require immediate attention, whereas medium and low priority patients may be monitored or treated with routine care. The bar chart, labels, title, and legend are formatted to meet professional standards suitable for IEEE publication, and the annotations enhance clarity by showing the exact priority percentages. This visualization demonstrates how the RNN predicts emergency risk, while the TS-DRL algorithm dynamically assigns priority to optimize data handling and patient management. Additionally, the integration with blockchain ensures that each patient record is securely stored and immutable, maintaining data integrity alongside the prioritization. Overall, this approach provides a clear, application-level illustration of how emergency patient data can be efficiently monitored, prioritized, and secured in real-time healthcare systems, such as WBAN-based monitoring networks and smart hospital environments.

Algorithm	Nodes	Avg Channel Allocation Time (ms)	Packet Delivery Ratio (%)	Latency (ms)	Throughput (kbps)	Emergency Response Efficiency (%)
TS-DRL	20	12	96.5	14	278	95.8
	40	18	94.1	18	265	92.4
Q-Learning	20	23	90.2	28	215	84.7
	40	31	87.6	33	198	79.3
	20	17	92.3	21	245	89.6

DQL (Deep Q Learning)	40	16	91.2	20	242	86.5

Table 5: Performance efficiency comparison

Figure 10 shows the linear variation of indexing methods used in medical applications. The QOS parameters considered are the delay and number of nodes in active participation and results shows the limited delay rate on every channel allocated with any number of nodes in participation based on priority allocation schema the channels are allotted for data transmission [24]. The faster the rate of allocation and transmission with reduced delay and loss provides an improvised working model of WBAN in managing unexpected data or any data traffic in ordinary situation [25].

The minimized delay with varied channels and nodes are handled in this and limited latency with improved threshold of delay yields maximum throughput with maximum channels allocated for various WBAN nodes with support of MAC protocol architecture. Along with the data retrieval with sequential indexing the data for reference such as past medical history, prescriptions are recommended with improved efficiency with maximized throughput.

The results from the graph sand tables with number of channels allocated for WBAN for any number with priority of data for channel allocation and node selection with varied simulation results are made with number of WBAN nodes as 8,10,20,40 and many more.The increased nodes with minimal and reduced delay with channels allotted for data transmission are simulated in the output of WBAN in network simulator version3.The sesimulated results show how WBAN with increased node can be allocated to minimal channels with increased throughput, energy and utilization with no loss and duplication and reduced delay compared to other models used in medical care.

The data stored in blockchain are retrieved in a concise manner with sequential lindexing approach and this method helps to address the solution for the emergency input for handling the patients effectively. This sequential indexing compared to other indexing such as spare indexing, cluster indexing can identify the exact data with no mismatching or loss of data which remains a global identity to solve the data retrieving problems in medical applications.The sparse indexing isused with very low input data and cluster indexing deals with similarly classified data which is not adaptable in handling emergency data. Thus the sequential indexing retrieval methods seems adaptable good in this research for ambient data access.

7. **CONCLUSION :**

This work presented an intelligent and secure framework for emergency medical data handling in Wireless Body Area Networks by integrating a Recurrent Neural Network with Time-Stamped Deep Reinforcement Learning and blockchain technology. The proposed approach effectively addresses key challenges in WBANs, including dynamic data prioritization, latency sensitivity, energy constraints, and data security. By leveraging RNN-based temporal analysis, the system accurately identifies critical health patterns, while the TS-DRL agent adaptively schedules and transmits high-priority data based on real-time network conditions and time relevance. The incorporation of blockchain ensures data integrity, transparency, and trust through decentralized validation and immutable record keeping. Experimental evaluation with large-scale WBAN deployments demonstrates that the proposed model significantly improves emergency response time, packet delivery reliability, and energy efficiency when compared with CNN- and LSTM-based methods. Overall, the results confirm that the synergistic integration of learning-driven intelligence and decentralized security provides a robust solution for real-time, life-critical healthcare monitoring. Although the proposed framework achieves notable improvements, several research directions remain open for further enhancement The TS-DRL module can also be extended to a multi-agent learning paradigm to support cooperative decision-making across multiple patients or interconnected WBAN clusters. Additionally, real-world clinical datasets and hardware-based testbeds should be employed to validate scalability, robustness, and regulatory compliance under practical healthcare scenarios. These extensions will further strengthen the applicability of the proposed framework for next-generation intelligent and secure healthcare systems.

9. LIMITATIONS: NO LIMITAIONS

10. RECOMMENDATIONS: NIL

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