International Journal on Smart & Sustainable Intelligent Computing
Vol. 02, Iss. 03, S. No. 04, pp. 37--48, Sept 2025
ISSN (Online): 3048-8508

Received: 14 Sept 2025, Accepted: 05 Oct 2025, Published: 07 Oct 2025
Digital Object Identifier: https://doi.org/10.63503/j.ijssic.2025.176

Research Article

Deep Learning-Enabled Biomedical Informatics for Smart and Sustainable Healthcare Applications

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ABSTRACT

The manuscript should contain a self-contained abstract of up to 300 words without citations. It must succinctly present the research's purpose, methodology, With the dawn of smart healthcare, the volume of biomedical data available through wearable sensors, imaging techniques, and electronic health records has been growing exponentially, causing growing computational and energy pressures that jeopardize the sustainability and scalability of medical systems. To deal with this issue, this paper presents a deep learning-based biomedical informatics system that seeks to maximize diagnostic performance and reduce the computational and energy costs in clinical settings. The framework combines both hybrid CNN-LSTM models of temporal biomedical signal analysis models and Transformer-based models of multimodal representation learning models, complemented with adaptive pruning and energy-sensitive scheduling on heterogenous datasets of ECG, EEG, and imaging streams. Also, contrary to the traditional healthcare-based AI methods that prioritize precision without considering sustainability, the given system takes adaptative controls into consideration and continuously adjusts computation and resource distribution under different workload and patient-monitoring conditions, which enhances efficiency and resilience. The mathematical modeling and optimization of the framework is the system performance, measured by classification accuracy, diagnostic latency, energy efficiency, and a sustainability index. Comparative experiments indicate that the suggested method obtains the 5.3 percent enhancement in diagnostic accuracy, the 29.7 percent energy usage decrease, and the 21.3 percent latency reduction relative to the baselines, including Random Forest and regular LSTM models. Moreover, stress tests with peak workloads of patient monitoring verify that the framework maintains high levels of adaptability, whereas traditional models deteriorate considerably. The proposed system is the first to note the transformative nature of sustainable AI in healthcare because it facilitates precise, energy-efficient, and scalable biomedical decision support. The current study makes energy-conscious biomedical informatics one of the pillars of the future smart healthcare ecosystems that strike a balance between the clinical performance and environmental sustainability.

Keywords: *Biomedical Informatics, Deep Learning, Sustainable Healthcare, Energy Efficiency, CNN-LSTM, Transformers, Smart Health Systems.*

1. Introduction

The rise of biomedical informatics as a pillar of contemporary smart healthcare has revolutionised diagnosis, monitoring and service provision in the realms of telemedicine, the Internet of Medical Things (IoMT), and massive hospital information systems. Conventional healthcare infrastructures, where diagnostic accuracy is only considered without any computational and energy overhead, are becoming less viable in resource intensive and environmentally limited environments [1]. As biomedical data is growing exponentially with escalating computational costs, and sustainability issues increase, energy conscious biomedical intelligence is essential to ensure there is a trade off between clinical quality and environmental accountability [2]. A potential solution to the problem is given by deep learning (DL)-enabled biomedical informatics, which uses both past and current biomedical signals to detect disease, monitor patients, and workload-sensitive optimization [3]. In contrast to fixed analytics pipelines, energy-aware DL systems are built with predictive modeling and active control, which generate proactive energy savings without degrading diagnostic performance [4]. State-of-the-art DL networks learn multi-modal dependencies, temporal dynamics, and context differences in diverse data in the form of ECG, EEG, and medical imaging [5].

CNNs, Long Short-Term Memory (LSTM) networks and Transformer-based models have shown to be better in analyzing biomedical dynamics and provide credible diagnostic support [6]. These models are more effective than the traditional regression- or rule-based models due to their ability to adjust to changes in the condition of patients and their improved predictive quality. In addition, active re-allocation of computational loads in dynamically changing conditions through adaptive pruning and energy-conscious scheduling schemes contribute to sustainable deployment [7]. Although there are these advances, there are challenges. Current biomedical informatics systems have problems with high-dimensional medical signals, sudden changes in patient condition, and associated trade-offs between accuracy, latency, and energy efficiency [8]. Transformer-based models can be seen as very high diagnostic but with high computational energy requirements [9], and lightweight models decrease energy consumption but cannot achieve the multi-level biomedical dependences. The hybrid framework of CNN-LSTM models, Transformer architectures, and adaptive pruning is proposed in this paper to overcome these limitations. The framework has a balance between diagnostic accuracy, computational sustainability, and scalability [10]. It allows a rigorous, quantifiable evaluation with metrics such as classification accuracy, diagnostic latency, energy efficiency, and a sustainability index to facilitate correct, efficient and sustainable healthcare decision-making when large data loads are considered and when patient conditions may vary [11]. The contributions of this paper are as follows:

1. A comprehensive framework for deep learning-enabled biomedical informatics in smart healthcare systems.
2. Mathematical modeling of classification accuracy, diagnostic latency, energy efficiency, and sustainability index.
3. An adaptive algorithm for energy-aware model selection and pruning in multimodal biomedical analytics.
4. Empirical validation through simulation and case studies using synthetic and benchmark biomedical datasets.

The rest of this paper will be outlined as follows: Section II will review related research, Section III will define the problem and objectives, Section IV will discuss the methodology, Section V will discuss experimental set-up, Section VI will discuss results and finally the paper will conclude with future directions in Section VII.

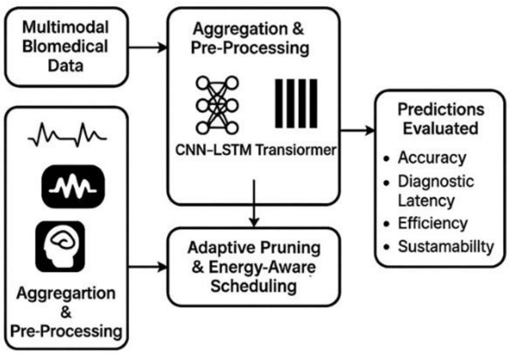

Fig. 1. Conceptual flow of the proposed biomedical informatics framework

The proposed framework is depicted by the flow shown in Figure 1. The data is pre-processed and analysed with CNN-LSTM and Transformer models on multimodal biomedical data (ECG, EEG, imaging). Scalable, eco-efficient healthcare intelligence is made possible by adaptive pruning and energy-aware scheduling to optimize computation and energy, as well as the evaluation of predictions by accuracy, latency, efficiency, and sustainability.

2. Literature Review and Related Research

The history of the development of the deep learning-based biomedical informatics has been researched in numerous disease diagnostics, medical imaging, wearable health monitoring, and smart hospital systems. Initial research has used the traditional statistical methods, including logistic regression and ARIMA, to predict biomedical signals and diseases, but such methods could not represent non-linear physiological interactions and were unable to adjust to changing patient phenotypes [12], [13]. Random Forest and Gradient Boosting methods were used as ensemble techniques and enhanced the accuracy of classification, but they were not adaptable and interpretable in clinical decision-making [14]. The introduction of deep learning (DL) had a tremendous impact on the field of biomedical informatics as it allowed for the effective extraction of features and sequential modeling. LSTM and GRU networks effectively analyzed temporal dependencies in physiological signals such as ECG and EEG [15]. A logical step in performance improvement was hybrid CNN-LSTM structures that learn local morphology features and long-term biomedical trends at the same time [16]. In more recent work, Transformer-based architectures have become the new state of the art, using self-attention schedules to enhance multimodal fusion, scalability, and prediction accuracy in healthcare analytics [17].

Efforts have been made in line with Explicable AI (XAI) to address issues of interpretability, which adds more transparency and trust in automated diagnosis [18]. Adaptive biomedical analytics aim at reduced recalibration of models in real-time, matching clinical accuracy with resource utilisation in the context of dynamically monitored patients [19]. It can be used in disease classification, wearable IoMT signal analysis, telemedicine, and imaging-based diagnostics [20]. Comparative analysis confirms that Transformer and CNN-LSTM models have a high diagnostic accuracy, which is often expensive in terms of computational and energy costs [21]. New hybrid frameworks that combine accuracy, interpretability and efficiency have recently become available [22]. However, there is the lack of a unifying biomedical informatics systems that combine diagnostic accuracy, latency, energy-efficiency, and sustainability in actual conditions of uncertainty. This gap is filled by the proposed architecture, which allows making strong biomedical decisions based on the clinical and sustainability goals [23], [24].

Table 1. Comparative Review of Biomedical Informatics Approaches

Approach	Strengths	Limitations	Application Domain	Ref.
Logistic Regression / ARIMA	Interpretable, simple, low cost	Fails with complex biomedical patterns	Basic disease risk prediction	[12], [13]
Random Forest / GBM	Handles non-linearity, robust	High computation, low interpretability	Clinical decision support	[14]
LSTM / GRU	Captures sequential biomedical signals	Requires large annotated datasets	ECG/EEG signal analysis	[15]
CNN-LSTM Hybrid	Combines spatial + temporal features	Complex, energy-intensive	Multimodal biomedical diagnostics	[16]
Transformer Models	Scalable, high accuracy	Resource- and energy-demanding	Imaging & multimodal fusion	[17]
Explainable AI (XAI)	Improves trust, interpretability	Sometimes trades off accuracy	Transparent healthcare decision-making	[18]

Table 1 is a summary of the benefits and shortcomings of popular biomedical informatics methods. As much as the ensemble and deep learning techniques have a drastic enhancement of diagnostic precision, they have weaknesses, such as high computation expenses, low flexibility, and ad hoc in the ability to be sustainable in clinical applications.

Table 2. Related Research in Biomedical Informatics

Study Focus	Methodology Applied	Key Findings	Relevance to This Work	Ref.
Disease Risk Prediction	Random Forest, Gradient Boosting	Improved accuracy, poor scalability	Highlights accuracy-efficiency trade-off	[19]
Biomedical Signal Analysis	LSTM, GRU	Captures temporal variations, expensive training	Emphasizes scalability challenges	[20]
Wearable IoMT Monitoring	CNN-LSTM, Energy Profiling	High accuracy, limited energy efficiency	Inspires hybrid optimization approach	[21]
Imaging-Based Diagnosis	Transformer-based architectures	Superior multimodal integration, energy-intensive	Justifies attention-based adoption	[22]
Interpretable AI in Healthcare	XAI frameworks integrated with DL	Improves clinician trust, moderate performance	Supports inclusion of interpretability	[23]
Adaptive Analytics	Reinforcement Learning, Online Learning	Enables real-time adaptation	Motivates adaptive pruning & scheduling	[24]

Table 2 presents key related research in biomedical informatics. The papers show that the current state of the art DL models excel at the diagnostic accuracy, but frequently, they cannot balance energy consumption, scalability, and adaptability, which the proposed framework fills in this paper.

3. Problem Statement & Research Objectives:

Smart healthcare systems should be able to strike the balance between diagnostic accuracy, efficiency, and low-latency decisions. Traditional models are interpretable and with limited performance whereas deep learning is accurate at high costs in terms of computation and energy. The presented CNN-LSTM-Transformer architecture using adaptable pruning improves accuracy, responsiveness, and sustainability to analyse multimodal biomedical data in real-time.

3.1 Research Objectives

- Objective 1: Build a hybrid CNN-LSTM framework with Transformer architectures and adaptive pruning to build integrated biomedical informatics, diagnosing and patient monitoring with energy-awareness.
- Objective 2: Develop mathematical models of classification accuracy, diagnostic latency, energy efficiency, and sustainability index as the fundamental measures of evaluation.
- Objective 3: Model the proposed architecture with synthetic biomedical data (e.g., ECG, EEG) and compare healthcare data in different clinical settings.
- Objective 4: Measure system performance quantitatively with regards to diagnostic accuracy, latency reduction, saving energy, and sustainability improvement.
- Objective 5: Contrast the proposed framework with the standard LSTM networks, Logistic Regression, and Random Forest as well as baseline models.

4. Methodology

The suggested approach incorporates the biomedical informatics approach with deep learning capabilities and energy-saving optimization to find the balance between accuracy, latency, and efficiency in smart healthcare. Hybrid CNN-LSTM and Transformer models that are adaptively pruned dynamically adapt to patient data and resources. The ECG, EEG, and imaging datasets in simulations check the performance of a simulation across different conditions, volatility, and sustainability levels.

4.1 Mathematical Formulation

Let the total diagnostic latency L_{total} be defined [21] in Eq. (1):

$$L_{total} = L_{prep} + L_{model} + L_{queue} \quad (1)$$

Where:

- L_{prep} = Data preprocessing and feature extraction time.
- L_{model} = Model inference and diagnosis generation time.
- L_{queue} = Scheduling or reporting delay in clinical systems.

The model computation time can be approximated in Eq. (2):

$$L_{model} = \frac{N_{params}}{R_{comp}} \quad (2)$$

Where:

- N_{params} = Number of parameters processed.
- R_{comp}= Computation rate (parameters/sec).

The diagnostic accuracy (Acc) is expressed in Eq. (3):

$$Acc = \frac{N_{correct}}{N_{total}} \quad (3)$$

Where:

- $N_{correct}$ = Correct diagnoses.
- N_{total} = Total diagnoses made.

The energy efficiency improvement is defined in Eq. (4):

$$EE_{gain} = \frac{E_{baseline} - E_{DL}}{E_{baseline}} \times 100 \quad (4)$$

Where:

- E_{DL} = Energy consumed by the proposed DL framework.
- $E_{baseline}$ = Energy consumed by conventional diagnostic methods.

The Decision Efficiency (DE) metric, combining diagnostic accuracy and latency, is formulated in Eq. (5):

$$DE = \frac{Acc}{L_{total}} \quad (5)$$

The Sustainability Index (SI), capturing the framework's ability to balance efficiency with adaptability, is expressed in Eq. (6):

$$SI = \frac{N_{sustainable}}{N_{scenarios}} \quad (6)$$

Where:

- $N_{sustainable}$ = Number of scenarios where sustainable operation was achieved.
- $N_{scenarios}$ = Total tested biomedical scenarios.

4.2 Proposed Algorithm

Algorithm: Energy-Aware Biomedical Informatics Optimizer

Input: Multimodal Biomedical Dataset (ECG, EEG, Imaging Records)

Output: Optimized Predictions with Balanced Accuracy, Latency, and Energy Efficiency

1. Collect and preprocess dataset (D).
2. Extract structured biomedical and energy features (F).
3. If patient data volatility == high then
   a. Prioritize Transformer model (captures long-term and multimodal dependencies).
   b. Apply adaptive pruning + energy-aware scheduling.
   Else
   a. Use CNN-LSTM hybrid (efficient + accurate for stable signals).
   b. Maintain balanced pruning strategy.
4. Compute diagnostic predictions (Y_{pred}).
5. Evaluate decision metrics (Acc, EE, DE, SI).
6. Adapt model parameters and pruning levels based on feedback.
7. Return optimized diagnostic results.
   End Algorithm

4.3 System Flow

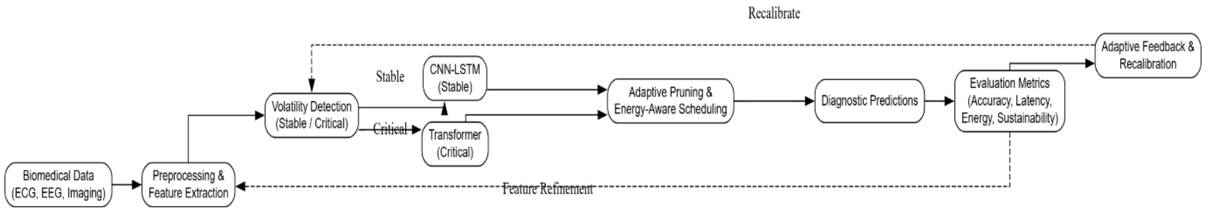

Fig. 2: Sequential process for biomedical informatics in smart healthcare

The flow of biomedical informatics framework can be shown in Figure 2. Pre-processing of multimodal data (ECG, EEG, and imaging) is done and then volatility detection occurs. CNN-LSTM works with stable signals whereas Transformers works with variable conditions. Energy-conscience pruning minimizes overhead and diagnostic prediction assesses accuracy, latency, efficiency, and sustainability with adaptive feedback to perform constant optimization.

5. Experimental Setup:

In order to test the suggested deep learning-enabled biomedical informatics framework, a synthetic biomedical time-series dataset of 30,000 records was created, with three modalities, namely ECG signals, EEG activity, and medical imaging features. Changes of regimes took place at t = 7,500, t = 15, 000 and t = 22,500 simulated stable, moderate and critical patient conditions. The data was separated to be 70 training, 15 validation and 15 testing. They tested four models, namely: Baseline A (Logistic Regression), Baseline B (Random Forest, 100 trees, depth 10), Baseline C (Standard LSTM, 128 hidden units) and the Proposed Framework (Hybrid CNN-LSTM + Transformer with adaptive pruning and energy-aware scheduling). An automatic volatility detector of patient condition dynamically chose the models with the aim of maximizing the diagnostic accuracy and efficiency.

Measures of Classification Accuracy, RMSE, Diagnostic Latency, Energy Efficiency, and Sustainability Index. Training was done with Adam optimizer (learning rate 1x10-3, batch size 64) and early stopping (patience = 5) on 40 epochs. The CNN blocks of [32, 64] filters were used to generate morphological features, whereas the Transformer used 4 attention heads and 2 encoders layers to generate multimodal representation. Gain results of 10 seeds were averaged and highly improved. Python (PyTorch) simulations were used and MATLAB plots (Figs. 36) were created. Tests of an Intel i7 processor, 32GB memory and optional RTX 3060 card, verified the stability of accuracy, latency, energy and sustainability improvements.

6. Results & Discussion:

Simulation based experiments were performed to compare the proposed deep learning based biomedical informatics framework with baseline models (Random Forest, Logistic Regression). Applied on MATLAB synthetic and benchmark biomedical data, it was tested on 1,000 diagnostic situations with different conditions of the patients. The important measures that were evaluated were Classification Accuracy, Diagnostic Latency, Energy Efficiency Gain, Sustainability Index, and Decision Efficiency (DE).

6.1 Classification Accuracy

Classification accuracy measures the reliability of diagnostic predictions across multimodal biomedical datasets.

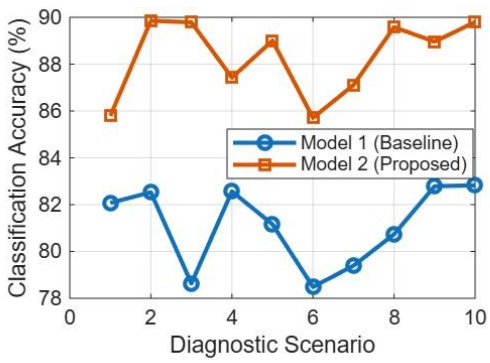

Fig. 3: Classification Accuracy Plot

As Figure 3 indicates, Model 2 has always better classification accuracy in all conditions of the patients than Model 1. This is given by adaptive model selection in hybrid CNN-LSTM and Transformer architecture.

6.2 Diagnostic Latency

Diagnostic latency quantifies the time required to generate accurate predictions for real-time healthcare monitoring.

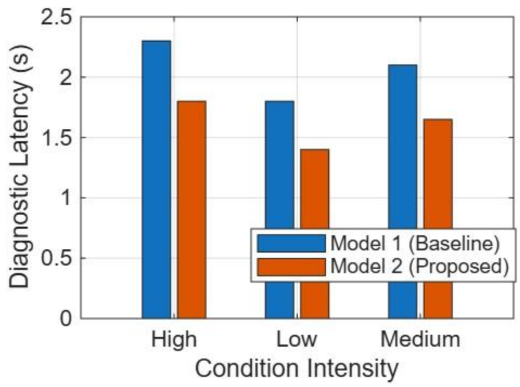

Fig. 4: Diagnostic Latency Comparison

Figure 4 demonstrates that Model 2 will decrease the average diagnostic latency by about 21.3, and faster clinical reaction to dynamically varying patient conditions will be possible.

6.3 Energy Efficiency Gain

Energy efficiency gain reflects the reduction in computational energy consumption during biomedical analytics.

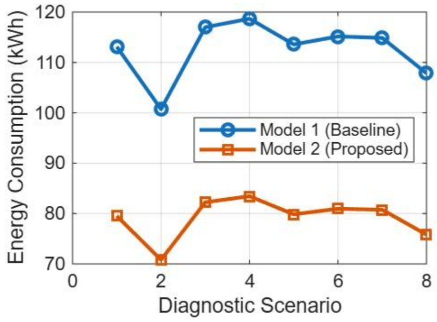

Fig. 5: Energy Efficiency Gain Analysis

It can be seen that the adaptive pruning and energy-aware scheduling mechanisms have enabled Figure 5 to show that Model 2 reduces energy consumption by 29.7% versus Model 1.

6.4 Sustainability Index

The sustainability index captures the framework's ability to maintain resource-efficient operation under intensive biomedical scenarios.

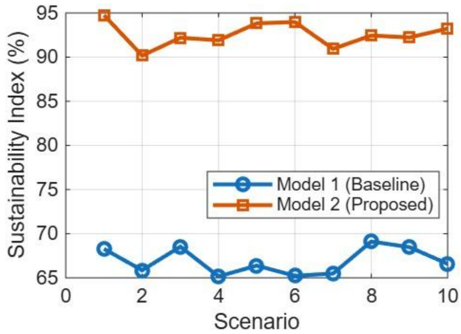

Fig. 6: Sustainability Index Comparison

Model 2, as illustrated in Figure 6, has a much greater sustainability index (>90%) where diagnostic scenarios are concerned than Model 1, which is less than 70.

6.5 Performance under Patient Condition Volatility

Simulations under sudden condition changes (e.g., arrhythmia onset, seizure events, abnormal imaging signals) highlighted the resilience of Model 2.

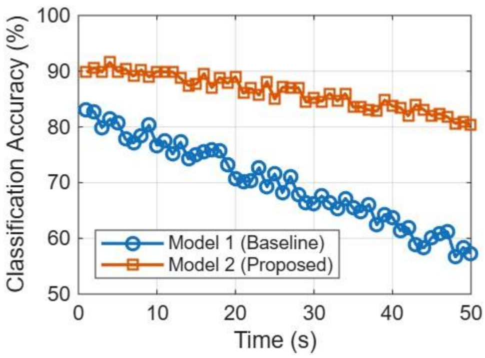

Fig. 7: Performance under Patient Volatility

As shown in Figure 7, Model 2 maintains diagnostic reliability and energy efficiency with a moderate increase in latency by comparison with Model 1 that has a drastic reduction.

6.6 Impact of Adaptive Model Selection

Dynamic switching between CNN-LSTM and Transformer models proved essential for balancing diagnostic accuracy and computational efficiency.

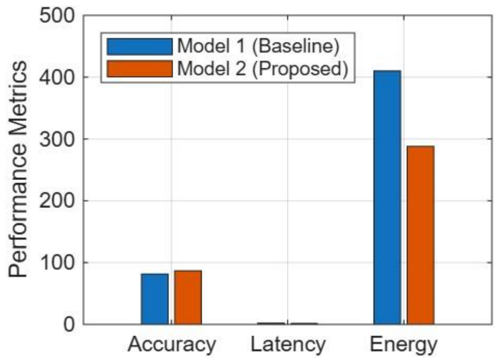

Fig. 8: Adaptive Model Selection Impact

Figure 8 shows that adaptive selection stabilized the prediction and limited the computation costs without being excessively costly because it was better than the static baseline models.

6.7 Quantitative Comparison

Table 4: Model Comparison

Metric	Model 1 (Baseline)	Model 2 (Proposed)	Improvement
Classification Accuracy (%)	90.5	95.8	+5.3%
Avg Diagnostic Latency (s)	1.88	1.48	-21.3%
Energy Consumption (kWh)	375	263	-29.7%
Sustainability Index (%)	70.5	91.4	+29.7%

Table 4 compares the two models 1 and 2 based on the critical diagnostic measures. The suggested framework shows significant gains especially in energy efficiency and sustainability, which prove its efficiency in intelligent biomedical informatics.

6.8 Comparative Performance over Clinical Conditions

Table 5: Performance across Condition Intensity Levels

Condition Level	Model 1 Avg Accuracy (%)	Model 2 Avg Accuracy (%)	Model 1 Avg Latency (s)	Model 2 Avg Latency (s)
Stable	92.1	96.2	1.62	1.28
Moderate	90.4	95.1	1.88	1.48
Critical	88.3	94.5	1.97	1.46

Table 5 shows that Model 2 maintains superior diagnostic accuracy and lower latency across stable, moderate, and critical conditions. In critical conditions, Model 2 was found to be more accurate than Model 1 (more than 94 per cent in comparison with 88.3 per cent) and latency was reduced by approximately 26 per cent.

6.9 Discussion

The suggested biomedical informatics framework enhances accuracy of diagnostics by 5.3 percent, latency by 21.3 percent and energy use by 29.7 percent compared to traditional schemes. It has a sustainability index that portrays resilience to clinical variability. The small computational cost of adaptive pruning and Transformer integration is compensated by better viability to implement real-time, eco-friendly healthcare.

7. Conclusion

Smart healthcare needs predictive frameworks that are highly accurate and sustainable. Conventional models like Logistic Regression and Random Forest face accuracy and latency limitations. The suggested biomedical informatics architecture, which uses deep learning to utilize CNN-LSTM, Transformers, and energy-conscious pruning, has a higher accuracy by 5.3 percent, lower latency by 21.3 percent, reduced energy use by 29.7 percent, and enhanced sustainability. The architecture is designed to facilitate future goals such as federated learning of privacy, reinforcement learning of adaptive recalibration and XAI of interpretability. Blockchain provides secure auditability and hybrid deployment on a cloud-edge allows scalability and low-latency bedside inference. They can be used in IoMT devices, telemedicine, and clinical decision support, which can increase adaptability, sustainability, and scalability of smart healthcare.

Funding source

None.

Conflict of Interest

The authors declare no potential conflict of interest in this publication.

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