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# REINFORCED ADAPTIVE HYBRID LSTM AUTOENCODER WITH SELF-HEALING INTELLIGENT REMEDATION ENGINE FOR AUTOMATED DATA QUALITY MANAGEMENT IN HEALTHCARE IIOT SYSTEMS

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## SUMMARY

**Background:** Healthcare Industrial Internet of Things (IIoT) application majorly focuses on clinical decision support, remote healthcare services, intelligent medical data management and patient monitoring to save the life of patients. The existing techniques of anomaly detection have issues of temporal misalignment, noisy physiological signals and poor handling of missing values. **Objectives:** To design an adaptive healthcare IIoT framework for accurately identifying the anomalies, predicting data degradation risks, improving the data quality and ensures efficient healthcare analytics within the intelligent edge-cloud. **Proposed Methodology:** Initially, the healthcare data were collected and processed using Synthetic Quality Degradation Injection where, missing values, timestamp misalignment, Gaussian noise, sensor drift, packet loss, and outliers were introduced to simulate IIoT sensing and communication failures. Adaptive Context-Aware Data Ingestion (ACADI) prioritized and synchronized data, while Dynamic Residual Quality Normalization (DRQN) performed missing-value estimation, denoising, error correction, normalization, and outlier removal. These pre-processed data were given to the Temporal Multi-Scale Healthcare Feature Fusion (TMHFF) for extracting and fusing the short-term, long-term, and frequency-domain healthcare features. Then, the fused features are fed into the Reinforced Adaptive Hybrid Long Short-Term Memory Autoencoder (RAHLA) model for detecting the anomalies with the help of Bidirectional LSTM, Sparse Autoencoder Reconstruction, and Reinforcement Learning-based threshold optimization. Predictive Evolutionary Quality Estimator (PEQE) evaluates the quality degradation risks of healthcare data and Self-Healing Intelligent Remediation Engine (SHIRE) reconstructs the degraded healthcare streams. Finally, Meta-Adaptive Feedback Optimization (MAFO) optimized model parameters, and Latency-Aware Adaptive Edge Orchestration (LAAEO) enabled efficient latency aware cloud-edge task orchestration. **Result:** The proposed framework achieved an Accuracy value of 98.37%, Precision of 99.17% and Latency of 1.79s, which describes better enhancement of healthcare data quality and the performance of anomaly detection. **Conclusion:** The proposed framework provides scalable, reliable and intelligent healthcare IIoT data quality management for healthcare analytics and monitoring applications.

Key words: *healthcare, IIoT, adaptive context-aware data ingestion, anomaly detection, predictive evolutionary quality estimator, latency-aware adaptive edge orchestration.*

## INTRODUCTION

Industrial Internet of Things (IIoT) has revolutionized the healthcare sector by connecting wearable sensors, smart medical devices, cloud systems, and edge servers to facilitate real-time patient monitoring and automated healthcare management [1]. Healthcare IIoT systems collect massive amounts of healthcare data from ECG sensors, glucose monitoring devices, blood pressure sensors, oxygen monitoring systems and electronic health records that are always flowing and constantly produced in a heterogeneous format. The systems are used for enhanced disease diagnosis, remote health care, emergency response, and clinical decision-making processes. Hence, automated data quality management is crucial in healthcare IIoT environments to provide reliable data monitoring and intelligent healthcare analysis. Recently, machine learning and deep learning approaches have been increasingly utilized for healthcare data validation, anomaly detection, feature extraction, and error correction. Additionally, adaptive task offloading mechanisms between cloud and edge environments can minimize latency, optimize resource usage, save energy, and aid in making real-time healthcare decisions in dynamic healthcare environments [2].

Several existing techniques were introduced for healthcare IIoT data quality management and task offloading. Decision Tree (DT) techniques showed better performance in classification in health care but their accuracy is reduced in heterogeneous health care data. Random Forest (RF) methods improved the performance of anomaly detection while the more computational cost impacted real-time processing [3]. Convolutional and Long Short-Term Memory (LSTM) methods proved to be suitable for sequential healthcare monitoring but negatively impacted continuous processing precision due to higher training times [4]. While Graph Neural Network (GNN) frameworks are believed to improve relational healthcare data analysis, scalability challenges decrease performance in large healthcare IIoT networks. Optimized workload distribution with Particle Swarm Optimization (PSO) is contrasted by the decreased adaptability of premature convergence. Genetic Algorithm (GA) based offloading enhanced the efficiency of resource allocation, but it had a more complex optimization due to slower convergence [5]. In order to address these challenges, proposed a Hybrid Deep learning-based model for anomaly detection and latency aware model for task offloading in cloud-edge environments.

Major contribution of the work is given below,

- A unified Adaptive hybrid deep learning models for Automated Data Quality Management in Healthcare IIoT Systems.
- Synthetic Quality Degradation Injection is used to stimulate real-world communication failures and sensing using missing values, Gaussian noise, packet loss, timestamp misalignment, sensor drift, and outliers.
- An ACADI and DRQN performs adaptive packet prioritization, intelligent healthcare data synchronization, congestion-aware stream management and enhancing the data quality.
- RAHLA performs the adaptive real-time healthcare anomaly detection and PEQE predicts the quality of degradation risks.
- SHIRE reconstructs the degraded healthcare streams and LAAEO ensures intelligent workload balancing in edge-cloud healthcare environments.

The manuscript sections are organized as follows: A number of research articles methods for anomaly detection and latency aware model for task allocation, which are included in Section 2. In Section 3, the proposed technique is explained and Section 4, the outcomes and performance criteria are examined. Section 5 describes the conclusion for the entire work.

## LITERATURE SURVEY

Several techniques were used for anomaly detection and task allocation in cloud-edge environments, some of the most recent detection methods are illustrated below.

The Classwise Wasserstein Distance-based Logistic Regression with Particle Swarm Optimization (CWD-LR-PSO) technique for detecting the anomalous in Internet of Medical Things (IoMT) environment. This model achieved an overall F1-score of 94.23% and F1-score of attack-category was 96.08% [6]. To analyzed a Machine Learning-based anomaly detection framework within the healthcare systems. This framework utilizes the Local Outlier Factor (LOF) and Random Forest (RF) algorithms for detecting the heart rate anomalies, and achieved the hit rate of 92.5% for the anomaly dataset within the heart rate range of 60–100bpm [7]. To developed the Isolation Forest (iForest) and Simple Isolation score using Nearest Neighbor Ensemble (SiNNE) based anomaly detection framework for healthcare data analysis. The detected anomalies achieved an average AUC value of 0.78 and a runtime of 0.19sec for the heart disease dataset [8].

Non-dominated Sorting Genetic Algorithm II-Sequence-to-Sequence (NSGA-II-Seq2Seq) algorithm for task-load aware and predictive-based workflow scheduling in cloud-edge collaborative environments. The model adopted predictive ranging from 0.5W to 1.0W for the transmission power and from 15MHz to 25MHz for the datacentres bandwidth [9]. The Delay-Aware Edge-Cloud Collaboration (DECC) framework for accelerating Deep Neural Network (DNN) inference in edge-cloud environments. The average latency speedup and throughput improvement of 1.1 to 1.4 times and 1.2 to 1.5 times for DECC [10].

Recent developments in healthcare IIoT include implementation of artificial intelligence, edge computing, and deep learning strategies to optimize healthcare monitoring and decision-making in real-time. The application of edge intelligence-based healthcare architecture has shown potential to decrease communication delay and perform real-time analysis, yet computational restrictions continue to be significant barriers for scalability [11]. Deep learning methodologies based on CNN, LSTM, and autoencoder models have been widely used for detection of abnormalities and analysis of physiological signals thanks to the capability of deep learning models to recognize complex time-dependent patterns. Nonetheless, contemporary deep learning strategies still experience difficulties dealing with noisy, missing data, interpretability, and efficient deployment in the context of constrained healthcare environments [12]. The development of hybrid deep learning models has enabled better prediction and monitoring in healthcare through combination of spatial and time-dependent feature extraction capacities. Nevertheless, efficient processing of heterogeneous data in terms of its dynamics remains to be a challenging task [13][17].

Healthcare systems based on edge AI have become popular because of low dependence on cloud systems and enhanced performance of latency-dependent applications. While edge-based intelligence enhances responsiveness and local decision-making process, the limitation of resources in devices and model adaptation are still limiting the practical implementation of such systems in big healthcare IIoT networks [14]. Machine learning-based anomaly detection schemes have been widely researched in order to detect anomalous healthcare events. Existing studies show that deep learning-based algorithms outperform conventional methods in terms of detection accuracy; yet there are issues regarding real-time adaptability, robustness to environment changes and resource efficiency [15]. Adaptive edge computing solutions have researched intelligent allocation of healthcare tasks between IoT devices, edge servers, and cloud computing infrastructure. Such solutions help decrease processing delay and enhance resource efficiency; however, do not address healthcare data quality deterioration and self-recovery mechanisms [16]. Frameworks for smart healthcare driven by AI systems have made clear the need for integration of IoT, AI, and cloud-edge technologies for the effective monitoring of patients. However, the issues of data quality management, security, latencies, and autonomous decision making still pose challenges in the research field [36]. The other recent research on healthcare monitoring has brought to light the use of hybrid machine learning techniques for the purposes of anomaly detection and prediction. While these techniques boost the efficiency of health care analysis, their combined application is rather scarce [18].

## A. Research Gap

The reviewed studies indicate that existing healthcare IIoT approaches mainly address individual challenges such as anomaly detection, feature extraction, or edge-cloud optimization. Deep learning methods improve detection capability but are affected by missing data, noise, and temporal inconsistencies, whereas edge-cloud approaches focus mainly on reducing latency and improving resource allocation. Therefore, an integrated framework is required to jointly manage healthcare data quality, detect anomalies, predict degradation, recover corrupted data, and optimize cloud-edge operations. Based on these observations, the proposed RAHLA-LAAEO framework combines adaptive preprocessing, multi-scale feature fusion, reinforcement learning-based anomaly detection, self-healing mechanisms, and latency-aware edge orchestration for reliable healthcare IIoT data management.

## PROPOSED METHODOLOGY

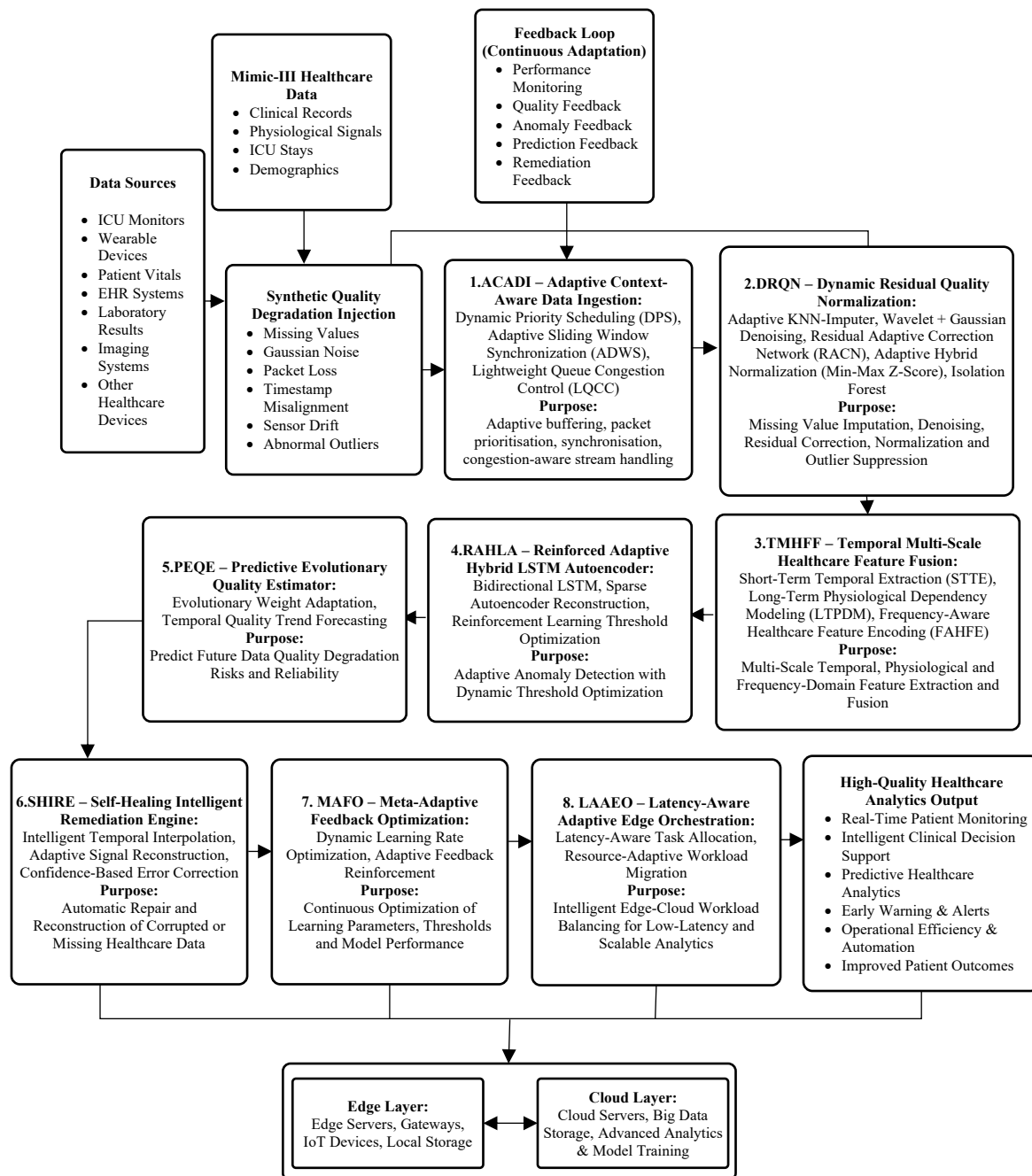


Figure 1. Unified adaptive RL architecture for automated data quality management in healthcare IIoT systems

Healthcare-based IIoT applications include smart sensors, wearable devices, and cloud-edge systems, which delivers real-time healthcare monitoring. However, the existing anomaly detection and task offloading methods suffer from low accuracy, high latency, and high computational overhead. To overcome from these issues, proposed a Reinforced Adaptive Hybrid LSTM Autoencoder framework for anomaly detection and Latency-Aware Adaptive Edge Orchestration for task offloading within the cloud-edge environments in the healthcare sector.

Figure 1 illustrates the flow diagram for the proposed model. Initially, healthcare data from MIMIC-III dataset and heterogeneous IIoT devices are collected and subjected to Synthetic Quality Degradation Injection to simulate real-world issues such as missing values, noise, packet loss, timestamp misalignment, sensor drift, and outliers. The degraded data are processed by the Adaptive Context-Aware Data Ingestion (ACADI) framework, where the Dynamic Priority Scheduling (DPS) performs adaptive healthcare packet prioritization, Adaptive Sliding Window Synchronization (ASWS) synchronizes heterogeneous healthcare streams with different timestamps, and Lightweight Queue-Based Congestion Control (LQCC) maintains adaptive buffering and communication stabilization for efficient healthcare stream handling. Subsequently, the Dynamic Residual Quality Normalization (DRQN) framework, in which KNN imputer estimates missing physiological values, Wavelet Denoising with Gaussian Filtering reduces the noise in biomedical signals, Residual Adaptive Correction Network (RACN) corrects the errors in the healthcare signals, Adaptive Min-Max Z-Score Hybrid Normalization dynamically normalizes healthcare signals, and Isolation Forest eliminates healthcare outliers. The enhanced healthcare data is then passed to the Temporal Multi-Scale Healthcare Feature Fusion (TMHFF) module, which performs the Short-Term Temporal Extraction (STTE) to extract short-term temporal fluctuations within the healthcare data, the Long-Term Physiological Dependency Modeling (LTPDM) to learn long-term healthcare temporal dependencies, and the Frequency-Aware Healthcare Feature Encoding (FAHFE) to extract the hidden frequency-domain biomedical features and produce fused multi-scale healthcare feature representations. The extracted healthcare feature representations are analysed by the Reinforced Adaptive Hybrid LSTM Autoencoder (RAHLA), which contains Bidirectional LSTM to learn forward and backward healthcare temporal sequences, Sparse Autoencoder Reconstruction to reconstruct normal healthcare patterns, and Reinforcement Learning-based Adaptive Threshold Optimization to dynamically optimize the threshold of anomaly detection in adaptive healthcare anomaly detection. The predicted quality of healthcare information is then fed into the Self-Healing Intelligent Remediation Engine (SHIRE), which includes Intelligent Temporal Interpolation to fill in missing healthcare sequences, Adaptive Signal Reconstruction to restore corrupted physiological signals, and Confidence-Based Error Correction to validate and correct reconstructed healthcare data streams. Subsequently, the Meta-Adaptive Feedback Optimization (MAFO) module optimizes model weights, adaptive thresholds, convergence parameters, optimization strategies, and feedback policies based on the behaviour of the healthcare system over time. Lastly, the Latency-Aware Adaptive Edge Orchestration (LAAEO) module intelligently orchestrates edge-cloud healthcare workloads with the integration of Latency-Aware Task Allocation and Resource-Adaptive Workload Migration algorithms, aiming to allocate latency-sensitive healthcare tasks to edge nodes and migrate computationally intensive healthcare analytics and adaptive learning operations to cloud infrastructure.

### **Step 1: Data Collection and Synthetic Degradation Injection**

Initially, the MIMIC-III data, which includes clinical records, physiological signals, ICU stay information, wearable sensor readings, patient vital signs, EHR, laboratory reports, and medical imaging data were collected from IoT devices and given to the Synthetic Quality Degradation injection for artificially degrading the missing values, Gaussian noise, packet loss, timestamp misalignment, sensor drift, and abnormal outliers to simulate real-world healthcare communication and sensing failures.

### **Step 2: Adaptive Context-Aware Data Ingestion**

DPS is used for continuously analysing incoming healthcare data packets and allocating a priority score to each packet according to clinical criticality, urgency, and relevance in real time [11]. The scheduler then dynamically sorts and queues the packets in order of priority, which allows high-priority physiological

signals, such as abnormal vitals, to be sent first. Therefore, the DPS priority score is calculated based on equation (1).

$$P_i = \alpha C_i + \beta U_i + \gamma R_i \quad (1)$$

Where,  $C_i$  denotes the clinical criticality of the packet,  $U_i$  represents the urgency level of patient data,  $R_i$  indicates the real-time relevance of the signal,  $\alpha, \beta, \gamma$  denotes the adaptive weighting coefficients and  $P_i$  represents the priority score of packet  $i$ . The ASWS approach essentially involves creating a time window that varies dynamically with incoming data samples from various healthcare sensors, grouping them according to their time stamps [12]. It continually gathers and synchronizes data points that are contained in the current sliding window so that the temporal consistency of the data in the streams is maintained. The Adaptive Sliding Window Update was derived as in equation (2).

$$W_t = W_{t-1} + \eta(\sigma_t - \mu_t) \quad (2)$$

Where,  $\mu_t$  denotes the mean inter-arrival time of healthcare packets at time,  $\eta$  represents the adaptation rate,  $\sigma_t$  indicates the variance of packet arrival delay,  $W_{t-1}$  denotes the previous window size and  $W_t$  represents the current sliding window size. LQCC is implemented by maintaining the queue length by continuously updating it according to the rate of incoming and outgoing healthcare packets [13]. It tracks the number of packets received into the buffer and the number of packets that were successfully transmitted to the remote node, thus controlling congestion in real time. Whereas, the Queue Length Dynamics were shown as in equation (3).

$$Q_t = Q_{t-1} + \lambda A_t - \mu D_t \quad (3)$$

Where,  $Q_{t-1}$  denotes the previous queue length,  $\lambda$  represents the arrival rate scaling factor,  $A_t$  represents the incoming healthcare packets at time  $t$ ,  $D_t$  indicates the processed or transmitted packets,  $\mu$  denotes the service rate factor and  $Q_t$  represents the queue length.

### Step 3: Dynamic Residual Quality Normalization

The synchronized healthcare data were given to DRQN for improving the data quality. Adaptive KNN-Imputer works by identifying healthcare samples that are most similar to the incomplete data record using distance-based similarity measurement [14]. The missing value in the healthcare dimension is then estimated by averaging or weighting the values of the selected neighbouring points. The KNN imputation is expressed in equation (4).

$$\hat{x}_m = \frac{1}{K} \sum_{i=1}^K x_i \quad (4)$$

Where,  $K$  denotes the number of nearest neighboring samples,  $x_i$  represents the value of  $i^{th}$  nearest neighboring healthcare sample,  $i$  indicates the neighbor sample index and  $\hat{x}_m$  denotes the estimated missing healthcare value. Wavelet Denoising with Gaussian Filtering is implemented by first decomposing the healthcare signal into a number of frequency components by using wavelet transformation to detect the noisy signal coefficients [15]. Important physiological patterns are retained in the signal, but the high-frequency noise components are suppressed. The reconstructed healthcare signal is then subjected to Gaussian filtering to smooth the signal and eliminate residual noise variations. However, the Gaussian Filtering was shown in equation (5).

$$G(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2}{2\sigma^2}} \quad (5)$$

Where,  $x$  denotes the signal intensity,  $e$  represents the exponential constant,  $\pi$  indicates the mathematical constant and  $G(x)$  denotes the Gaussian filtered output signal. RACN is based on the principle of learning the residual errors in preprocessed medical information, and then adaptively correcting corrupted physiological information patterns [16]. It estimates the residual distortion between the reconstructed

healthcare signal and the original input signal, which is due to noise, packet corruption, and temporal inconsistencies. The Residual Adaptive Correction were expressed in equation (6).

$$R_c = X_i + F(X_i, W) \quad (6)$$

Where,  $X_i$  denotes the input healthcare signal,  $W$  represents the adaptive network weight parameters,  $R_c$  indicates the output of corrected healthcare signal and  $F(X_i, W)$  denotes the learned residual correction function.

Adaptive Min-Max Z-Score Hybrid Normalization is a method that dynamically normalizes heterogeneous healthcare signals of different physiological ranges and statistical distributions. First, Min-Max normalization ranges healthcare features within a common range, and then Z-Score normalization sets the mean and standard deviation of the signal. The framework dynamically integrates both normalization strategies based on the characteristics of the healthcare signals in terms of their variability and temporal distribution. Multiple isolation trees are built to isolate the healthcare samples; corrupted or abnormal physiological patterns have been isolated in fewer partitioning steps than normal healthcare patterns.

#### Step 4: Temporal Multi-Scale Healthcare Feature Fusion

These quality enhanced healthcare data were given to the STTE, LTPDM and FAHFE techniques to fuse multiscale feature representations for further processing.

STTE extracts immediate changes at the physiological level of the continuous stream of healthcare signals and short-duration temporal patterns. To identify sudden changes in ECG readings, sudden change in heart rate and sudden changes in oxygen saturation, sliding temporal windows are applied to the healthcare sequences [36]. The Short-Term Temporal feature extraction was derived in equation (7).

$$F_t = \sum_{i=t-w}^t x_i \quad (7)$$

Where,  $x_i$  denotes the healthcare signal value at time instance,  $F_t$  represents the extracted short-term temporal healthcare feature at time  $t$ ,  $w$  indicates the size of the short temporal observation window and  $i$  denotes the index of healthcare signal samples under the window. LTPDM is a method for modelling long range physiological dependencies and patient behaviour from extended healthcare signal sequences [18]. The temporal healthcare digital information from the previous time intervals is continuously stored and propagated, which can track gradual physiological changes and the long-term health trend [35]. The extracted long-term healthcare dependencies are used to enhance the accuracy of adaptive anomaly detection, predictive healthcare analysis, and patient condition monitoring. The Long-Term physiological dependency is expressed as equation (8).

$$H_t = f(X_t, H_{t-1}) \quad (8)$$

Where,  $X_t$  denotes the current healthcare input signal,  $H_t$  represents the current long-term healthcare hidden state representation,  $H_{t-1}$  indicates the previous temporal healthcare hidden state and  $f$  denotes the learning function of long-term dependency. FAHFE is a technique for deriving hidden frequency domain features from physiological healthcare signals that supports multi-scale healthcare feature representation [19]. Significant physiological functions are encoded with frequency components and fused with temporal healthcare features for adaptive learning. These encoded frequency-aware healthcare features enhance the accuracy of anomaly detection and the representation quality of complex healthcare signals. The Frequency-Aware Feature Encoding were expressed as equation (9).

$$F(k) = \sum_{n=0}^{N-1} x(n) e^{-j2\pi kn/N} \quad (9)$$

Where,  $x(n)$  denotes the healthcare signal value at simple index  $n$ ,  $N$  represents the total number of healthcare signal samples,  $k$  indicates the frequency component index,  $F(k)$  denotes the frequency domain healthcare feature,  $e$  represents the exponential constant,  $j$  represents the imaginary unit and  $\pi$  indicates the mathematical constant.

**Step 5: Reinforced Adaptive Hybrid LSTM Autoencoder**

Then, these fused features were fed into the Bidirectional LSTM, Sparse Autoencoder Reconstruction, and Reinforcement Learning-based Adaptive Threshold Optimization for healthcare anomaly prediction.

Bidirectional LSTM models temporal sequences in healthcare data from both forward and backward directions, capturing the complete physiological dependency information [20]. The forward and backward hidden healthcare representations are combined to generate comprehensive temporal healthcare features for adaptive anomaly analysis. The hidden state of Bidirectional LSTM was expressed in equation (10).

$$H_t = [\overrightarrow{H_t}; \overleftarrow{H_t}] \quad (10)$$

Where,  $\overrightarrow{H_t}$  and  $\overleftarrow{H_t}$  denotes the forward and backward healthcare hidden state representations and  $H_t$  represents the combined bidirectional healthcare hidden state. Sparse Autoencoder Reconstruction learns compact representations of normal healthcare patterns by encoding and reconstructing healthcare signal features with sparse neuron activation [21]. The reconstruction difference is used to identify anomalies and improve adaptive healthcare anomaly detection performance. Therefore, the Sparse Autoencoder Reconstruction loss function is expressed in equation (11).

$$L = \|X - \hat{X}\|^2 + \lambda \sum_{j=1}^m |h_j| \quad (11)$$

Where,  $X$  denotes the original healthcare input signal,  $\hat{X}$  represents the reconstructed healthcare input signal,  $\|X - \hat{X}\|^2$  indicates the reconstruction error between original and reconstructed healthcare data,  $L$  denotes the total Sparse Autoencoder Reconstruction loss,  $h_j$  represents the Activation of hidden neuron  $j$ ,  $m$  indicates the total number of hidden neurons and  $\lambda$  denotes the coefficient of Sparsity regularization. Reinforcement Learning based Adaptive Threshold Optimization maintains anomaly detection thresholds in real-time based on reinforcement learning algorithms, which adapt to the varying conditions of a healthcare system [22]. The reinforcement learning agent is constantly monitoring the performance of the healthcare anomaly detection system and modifies the thresholds to reduce the number of false alarms and missed detections. Therefore, the Adaptive Threshold Update is derived as in equation (12).

$$T_{t+1} = T_t + \alpha(R_t - E_t) \quad (12)$$

Where,  $T_t$  denotes the threshold of current anomaly detection,  $T_{t+1}$  represents the threshold of updated anomaly detection,  $E_t$  indicates the detection error,  $\alpha$  denotes the learning rate for threshold adaptation and  $R_t$  represents the reinforcement reward value.

Figure 2 describes the architecture for the RAHLA model. It receives multi-scale healthcare features and utilizes a Bidirectional LSTM to learn temporal healthcare dependencies in both forward and backward directions. The learned features are then compacted and reconstructed using the Sparse Encoder–Decoder layers, with the resulting error signals revealing abnormal healthcare patterns and corrupted data streams. The Reinforcement Learning-based Adaptive Threshold Optimization module dynamically tunes the anomaly thresholds, allowing for the correct classification of anomalous and normal healthcare data.

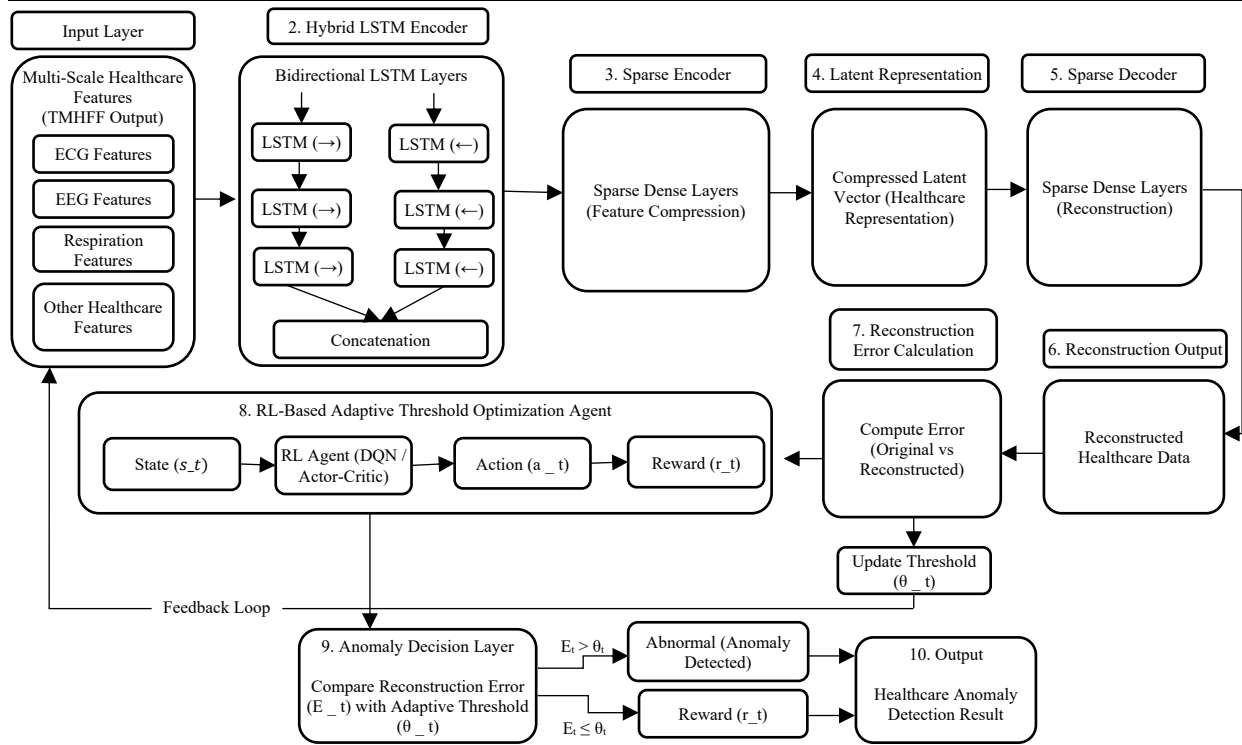


Figure 2. Architecture for the reinforced adaptive hybrid LSTM autoencoder model

### Step 6: Predictive Evolutionary Quality Estimator

Evolutionary Weight Adaptation and Temporal Quality Trend Forecasting algorithms were used to predict the risks of future healthcare data quality degradation.

EWA continually adapts the healthcare learning weights based on the current pattern of healthcare data quality and system performance. Evolutionary learning strategies are iteratively optimized to enhance the predictive accuracy of the quality estimation of the healthcare system. This adaptive optimization allows the framework to learn the changing trend of deterioration in healthcare and maintain a consistent prediction accuracy. The updated evolutionary weights were shown as in equation (13).

$$W_{t+1} = W_t + \beta \Delta W_t \quad (13)$$

Where,  $W_t$  denotes the current adaptive weight,  $\Delta W_t$  represents the weight adjustment value,  $\beta$  indicates the evolutionary adaptation rate and  $W_{t+1}$  denotes the updated adaptive weight at time  $t + 1$ . Temporal Quality Trend Forecasting is the analysis of historical healthcare data quality trends, forecasted to determine future trends in data quality degradation, including sensor drift, packet corruption, and communication instability. Healthcare quality observations are made at a number of time intervals, continuously monitored over time to detect long-term degradation behavior and quality fluctuations. The forecasted healthcare quality trends allow proactive anomaly prevention and adaptive healthcare data management in IIoT environments. The Temporal Healthcare Quality Trend Prediction were expressed as in equation (14).

$$Q_{t+1} = Q_t + \theta(Q_t - Q_{t-1}) \quad (14)$$

Where,  $Q_t$  denotes the current healthcare quality value,  $Q_{t-1}$  represents the previous healthcare quality value,  $\theta$  indicates the trend forecasting coefficient and  $Q_{t+1}$  denotes the predicted healthcare quality value.

### Step 7: Self-Healing Intelligent Remediation Engine

After the process of data quality degradation, the missing and corrupted healthcare data were reconstructed using Intelligent Temporal Interpolation, Adaptive Signal Reconstruction and Confidence-Based Error Correction techniques.

Intelligent Temporal Interpolation reconstructs the missing values of a healthcare signal by exploiting the temporal physiological pattern similarity of neighbouring signals in a continuous healthcare sequence [23]. Previous and subsequent healthcare observations are used in temporal relationships to accurately estimate missing physiological information. The reconstruction process re-establishes incomplete healthcare streams and maintains temporal consistency for accurate healthcare analysis and anomaly detection. Here, the Temporal Healthcare Signal Interpolation were expressed as in equation (15).

$$\hat{X}_t = X_{t-1} + \frac{(X_{t+1} - X_{t-1})}{2} \quad (15)$$

Where,  $X_{t-1}$  denotes the value of previous healthcare signal,  $\hat{X}_t$  represents the estimated missing healthcare signal and  $X_{t+1}$  indicates the next value of the healthcare signal. Adaptive Signal Reconstruction is designed to recover signals from physiological healthcare signals that were corrupted and learn the healthcare signal pattern from nearby temporal observations [24]. The reconstruction process keeps updating the parameters for signal correction based on the changes in healthcare signals and the level of corruption in the signal. This adaptive restoration enhances the consistency of the healthcare signal and retains the valuable physiological information. Adaptive Healthcare Signal Reconstruction is mathematically shown as in equation (16).

$$\hat{S}(t) = S(t) + \delta(t) \quad (16)$$

Where,  $S(t)$  denotes the original corrupted healthcare signal,  $\delta(t)$  represents the adaptive correction term applied to the signal and  $\hat{S}(t)$  indicates the reconstructed healthcare signal. Confidence Based Error Correction determines the validity of the recovered health care data by computing the confidence level of the corrected physiological data [25]. High confidence scores are accepted on healthcare samples directly, and low-confidence corrected signals are further refined and validated.

### Step 8: Meta-Adaptive Feedback Optimization

Then, the entire adaptive healthcare learning process is continuously optimized through the Dynamic Learning Rate Optimization and Adaptive Feedback Reinforcement techniques for further processing.

Dynamic Learning Rate Optimization tracks the performance of healthcare models in training and continuously assesses the variation in the error, during adaptive learning [26]. The learning rate is adjusted automatically based on the behavior of convergence, and the update strength stronger when the error is larger, and the unnecessary fluctuation of the weight smaller when the error is smaller. The updated Dynamic learning rate is evaluated based on equation (17).

$$\eta_{t+1} = \eta_t \times (1 - \beta E_t) \quad (17)$$

Where,  $\eta_t$  denotes the current learning rate,  $E_t$  represents the training error,  $\eta_{t+1}$  indicates the updated learning rate at time  $t + 1$  and  $\beta$  denotes the coefficient of learning rate adjustment. Adaptive Feedback Reinforcement constantly observes the performance of the healthcare system, and outputs feedback signals based on the accuracy of anomaly detection and the improvement of the quality of healthcare data [27]. Feedback information is used for continuous learning to adaptively adjust the parameters of the healthcare model, optimization policies and decision strategies.

### Step 9: Latency-Aware Adaptive Edge Orchestration

Finally, the Latency-Aware Task Allocation and Resource-Adaptive Workload Migration algorithm were used to offload the tasks in cloud-edge environments.

Latency-Aware Task Allocation is a dynamic allocation of tasks for healthcare processing to edge/ cloud nodes based on latency requirements and computational workload conditions [28]. Latency-sensitive healthcare operations such as patient monitoring and anomaly detection are allocated to nearby edge nodes for faster response. Healthcare analytics and adaptive learning tasks require more resources and are sent to cloud infrastructures to optimize resources and system efficiency. The Latency Aware Task Allocation were expressed as in equation (18).

$$T_a = \arg \min_{n \in N} (L_n + C_n) \quad (18)$$

Where,  $N$  denotes the set of available edge and cloud nodes,  $n$  represents the index of candidate edge or cloud node,  $C_n$  indicates the computational cost of node,  $T_a$  denotes the healthcare task allocation of selected node and  $L_n$  represents the communication latency. Resource-Adaptive Workload Migration continuously monitors workload distribution and available computational resources in the healthcare domain on edge and cloud infrastructures. Tasks are dynamically moved between nodes based on available resources, workload and system performance conditions in healthcare processing. This adaptive workload balancing optimizes resource utilization, decreases processing delay, and ensures a stable performance of healthcare analytics in IIoT environments.

### Section III-A Algorithmic Workflow of Proposed RAHLA-LAAEO Framework

Algorithm 1: Reinforced Adaptive Hybrid LSTM Autoencoder Based Healthcare IIoT Data Quality Management

*Algorithm 1: RAHLA – LAAEO Framework for Adaptive Healthcare IIoT Data Management*

*Input:*

*Healthcare IIoT data streams  $D$*   
*Sensor measurements  $S$*   
*MIMIC – III healthcare dataset  $M$*   
*Edge – cloud resources  $R$*   
*Initial model parameters  $\theta$*

*Output:*

*Anomaly prediction results  $A$*   
*Recovered healthcare data  $D'$*   
*Optimized task allocation decisions  $O$*

*Begin*

- 1: *Initialize RAHLA parameters, adaptive threshold  $\tau$ ,  
MAFO parameters, and edge – cloud resources*
- 2: *Collect healthcare data  $D$  from IoT sensors and MIMIC – III dataset*
- 3: *Perform Synthetic Quality Degradation Injection:*
  - Introduce missing values, Gaussian noise,*
  - packet loss, timestamp misalignment,*
  - sensor drift, and outliers*

- 4: Apply Adaptive Context – Aware Data Ingestion (ACADI)
- 5: For each incoming healthcare packet  $p \in D$  do
- 6:   Calculate packet priority using  
Dynamic Priority Scheduling (DPS)
- 7:   Synchronize healthcare streams using  
Adaptive Sliding  
Window Synchronization (ASWS)
- 8:   Update communication queue using  
Lightweight Queue – Based  
Congestion Control (LQCC)
- 9: End For
- 10: Apply Dynamic Residual Quality Normalization (DRQN)
- 11: Estimate missing healthcare values  
using Adaptive KNN Imputation
- 12: Remove signal noise using Wavelet – Gaussian Filtering
- 13: Correct residual errors using Residual  
Adaptive Correction Network
- 14: Normalize healthcare features using Hybrid Min – Max Z – score method.
- 15: Remove abnormal samples using Isolation Forest
- 16: Generate healthcare feature representation  
using TMHFF
- 17: Extract short – term temporal features using STTE
- 18: Extract long – term physiological dependencies using LTPDM
- 19: Encode frequency – domain features using FAHFE
- 20: Feed fused features into RAHLA model
- 21: Apply Bidirectional LSTM for temporal  
feature learning
- 22: Reconstruct normal healthcare patterns  
using Sparse Autoencoder
- 23: Calculate reconstruction error:  
$$E = |X - X'|$$
- 24: If  $E > \tau$  then
- 25:   Identify healthcare sample as anomaly
- 26: Else
- 27:   Identify healthcare sample as normal
- 28: End If
- 29: Optimize anomaly threshold using  
Reinforcement Learning

30: Predict future healthcare quality degradation using PEQE  
31: Estimate sensor drift, packet corruption, and communication degradation probability  
32: Apply SHIRE for degraded data recovery  
33: Perform temporal interpolation for missing samples  
34: Perform adaptive signal reconstruction  
35: Validate reconstructed data using confidence – based error correction.  
36: Update model parameters using MAFO  
37: Adjust learning rate, weights, thresholds, and feedback policies  
38: Apply LAAEO for cloud – edge task orchestration  
39: If task latency requirement < threshold then  
40:     Allocate task to edge node  
41: Else  
42:     Offload task to cloud node  
43: End If  
44: Return anomaly results A, recovered data D', and optimized allocation O  
End

### Algorithm Explanation

The proposed RAHLA-LAAEO framework handles the IIoT healthcare data with respect to adaptive preprocessing, feature extraction, anomaly detection, restoration, and task optimization. First of all, the degraded healthcare data is improved via ACADI and DRQN techniques; then multi-scale features are extracted via TMHFF. Anomalies are detected via RAHLA framework using BiLSTM and Sparse Autoencoder, where the thresholds are optimized using reinforcement learning. PEQE forecasts the future degradation of data; on the other hand, SHIRE reconstructs the corrupted data, and MAFO/LAAEO optimizes the model parameters.

### RESULT AND DISCUSSION

The proposed model incorporates RAHLA technique for the anomalous prediction in healthcare, whereas LAAEO based model were used to offload the tasks in cloud-edge environments. To evaluate the model performance, Python 3.8 is used to implement the proposed setup, which has an Intel Core i5 CPU, 16GB of RAM, and Nvidia GeForce GTX 1650 graphics.

The simulation parameters for the ACADI, DRQN, TMHFF, RAHLA, PEQE, SHIRE, MAFO and LAAEO are listed in table 1. Therefore, the parameter includes Dynamic Priority Weight, KNN Neighbors, STTE Window Size, Bi-LSTM Hidden Units, Evolutionary Population Size, Interpolation Window, Initial Learning Rate, Edge Node Count and etc.

Table 1. Simulation parameters for the proposed model

| Parameter                           | Model | Range         |
|-------------------------------------|-------|---------------|
| Dynamic Priority Weight             | ACADI | 0.6           |
| Synchronization Window Size         |       | 50 ms         |
| Queue Buffer Size                   |       | 1000 packets  |
| KNN Neighbors                       | DRQN  | 5             |
| Gaussian Filter Kernel Size         |       | $5 \times 5$  |
| Wavelet Decomposition Level         |       | 4             |
| STTE Window Size                    | TMHFF | 10 timesteps  |
| LTPDM Sequence Length               |       | 100 timesteps |
| Frequency Bins                      |       | 128           |
| Bi-LSTM Hidden Units                | RAHLA | 128           |
| Number of LSTM Layers               |       | 2             |
| Latent Dimension                    |       | 64            |
| Evolutionary Population Size        | PEQE  | 50            |
| Mutation Rate                       |       | 0.1           |
| Forecast Window                     |       | 20 timesteps  |
| Interpolation Window                | SHIRE | 5 samples     |
| Reconstruction Confidence Threshold |       | 0.90          |
| Error Correction Weight             |       | 0.8           |
| Initial Learning Rate               | MAFO  | 0.001         |
| Feedback Update Rate                |       | 0.05          |
| Reinforcement Discount Factor       |       | 0.95          |
| Edge Node Count                     | LAAEO | 10            |
| Cloud Node Count                    |       | 3             |
| Latency Threshold                   |       | 50s           |

### A. Evaluation Metrics

The performance of the proposed framework is evaluated using classification and regression-based metrics.

#### Classification Metrics

##### Accuracy

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (19)$$

##### Precision

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (20)$$

##### Recall

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (21)$$

##### F1-Score

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (22)$$

In equations (19), (20), (21) and (22), where TP, TN, FP, and FN denote True Positives, True Negatives, False Positives, and False Negatives, respectively.

**Area Under the Receiver Operating Characteristic Curve (AUC)**

$$\text{AUC} = \int_0^1 \text{TPR}(\text{FPR}) d(\text{FPR}) \quad (23)$$

In equation (23) describes TPR represents the True Positive Rate and FPR represents the False Positive Rate.

**Regression and Error Metrics****Mean Absolute Error (MAE)**

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i| \quad (24)$$

**Root Mean Squared Error (RMSE)**

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \quad (25)$$

**Coefficient of Determination ( $R^2$ )**

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2} \quad (26)$$

In equation (24), (25) and (26) describes  $N$  is the total number of samples,  $y_i$  is the actual value,  $\hat{y}_i$  is the predicted value, and  $\bar{y}$  is the mean of the actual values.

**Edge-Cloud Task Optimization Metrics****Latency**

$$\text{Latency} = T_{\text{response}} - T_{\text{request}} \quad (27)$$

In equation (27) Where  $T_{\text{response}}$  is the response time and  $T_{\text{request}}$  is the request timestamp.

**Throughput**

$$\text{Throughput} = \frac{N_{\text{completed}}}{T_{\text{execution}}} \quad (28)$$

In equation (28) describes  $N_{\text{completed}}$  denotes the total number of completed tasks and  $T_{\text{execution}}$  represents the total execution time.

**Load Balancing Index (LBI)**

$$\text{LBI} = 1 - \frac{\sigma_L}{\mu_L} \quad (29)$$

In equation (29) describes the where  $\sigma_L$  and  $\mu_L$  represent the standard deviation and mean of the workload distribution across the system, respectively.

## B. Dataset Description

The MIMIC-III dataset contains de-identified ICU patient records, including demographics, vital signs, laboratory results, medications, clinical notes, and physiological measurements, which is collected from critical care patients [29]. This MIMIC-III healthcare repository is of unstructured data with many folders. So, the data are aligned and converted into structured format and attained a total sample of 12, 268.

Table 2. Total sample splitting for training and testing

| Dataset                | MIMIC-III |      |
|------------------------|-----------|------|
| Total samples          | 12,268    |      |
| Classwise distribution | Normal    | 6134 |
|                        | Anomaly   | 6134 |
| Training               | 9814      |      |
| Testing                | 2454      |      |

Table 2 contains the total samples for anomaly detection. In this shows that, the total number of samples were 12,268. From that, 80% were used for training, and 20% for testing.

Table 3. Sample data for original, corrupted and recovered

| Original Data Samples |                                |                      |                  |                   |
|-----------------------|--------------------------------|----------------------|------------------|-------------------|
| Heart Rate (bpm)      | Respiration Rate (Breaths/Min) | SpO <sub>2</sub> (%) | Temperature (°F) |                   |
| 104                   | 25                             | 98                   | 98.1688          |                   |
| 99                    | 17                             | 98                   |                  |                   |
| 96                    | 20                             | 98                   |                  |                   |
| 95                    | 23                             | 98                   |                  |                   |
| 92                    | 91                             | 97                   |                  |                   |
| Corrupted Data        |                                |                      |                  |                   |
| Heart Rate (bpm)      | Respiration Rate (breaths/min) | SpO <sub>2</sub> (%) | Temperature (°F) | Degradation Type  |
| 104.018               | 25.017                         | 97.99                | 98.155           | Gaussian Noise    |
| NaN                   | 17.002                         | 97.982               | 98.177           | Missing Value     |
| 95.966                | 19.983                         | 0                    | 98.15            | Packet Loss       |
| 142.488               | 22.998                         | 98.042               | 98.143           | Outlier Injection |
| 92.005                | 90.98                          | 96.979               | 98.451           | Sensor Drift      |
| Recovered Samples     |                                |                      |                  |                   |
| Heart Rate (bpm)      | Respiration Rate (breaths/min) | SpO <sub>2</sub> (%) | Temperature (°F) |                   |
| 97.226                | 21.377                         | 97.984               | 98.152           |                   |
| 96.815                | 21.812                         | 97.988               | 98.152           |                   |
| 96.274                | 22.451                         | 97.998               | 98.152           |                   |
| 95.682                | 23.414                         | 98.015               | 98.153           |                   |
| 94.959                | 24.718                         | 98.044               | 98.154           |                   |

Table 3 displays the samples healthcare data of quality management. Initial rows represent the original clinical samples from MIMIC-III. For analysing the pattern of data degradation some noise injections were performed which results in corrupted. Finally in last few rows the recovered samples is provided.

Table 4. Prediction performance for healthcare normal and anomaly classes

| Class 0 (Normal)    |                   | Class 1 (Anomaly)   |                   |
|---------------------|-------------------|---------------------|-------------------|
| Correctly Predicted | Wrongly Predicted | Correctly Predicted | Wrongly Predicted |
| 1217                | 10                | 1197                | 30                |

Table 4 represents the Prediction performance of each classes. This table 4 shows the correctly and wrongly predicted values of each class accurately.

Table 5. Classwise performance report for the proposed model

| RAHLA            |           |        |          |
|------------------|-----------|--------|----------|
| Class            | Precision | Recall | F1-Score |
| 0 (Normal)       | 0.98      | 0.99   | 0.98     |
| 1 (Anomaly)      | 0.99      | 0.98   | 0.98     |
| Weighted Average | 0.98      |        |          |

Table 5 describes the classification report for the RAHLA model. It shows that the proposed model provides highly effective and balanced classification performance across all classes with strong prediction capability.

Figure 3 shows the AUC and ROC plots for the proposed model. The model ability to discriminate between classes is demonstrated by the ROC curve, which plots the True Positive Rate varies with False Positive Rate. AUC value attained for proposed model is 0.99, which shows that the model obtains improved accuracy indicated by a curve towards the upper-left corner.

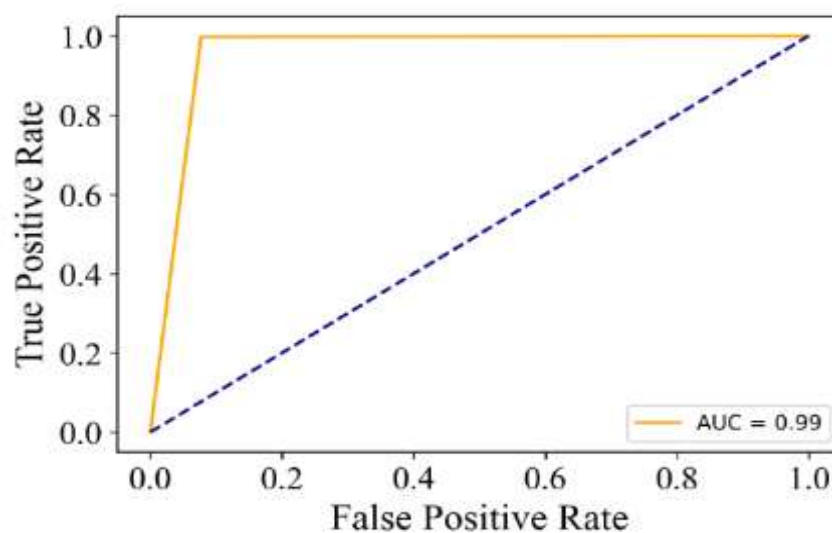


Figure 3. AUC and ROC plots for RAHLA model

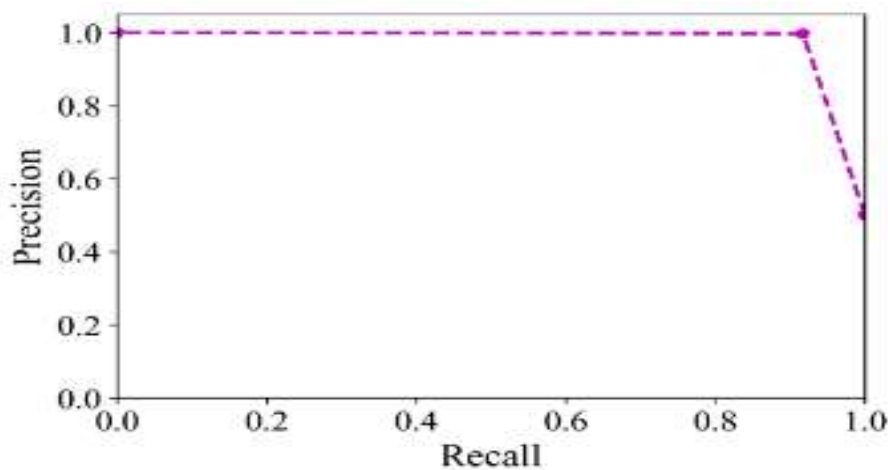


Figure 4. Precision-recall curve for the RAHLA model

Figure 4 represents a Precision Recall curve that shows the correlation between precision and recall of the classification model. The precision is near to 1.0 with a large recall range with just a few false positives and more positive samples detected. The extreme-recall sharp decline serves as a reminder of the trade-off where the model tries to overcome with all the positives, at the expense of a little in prediction reliability.

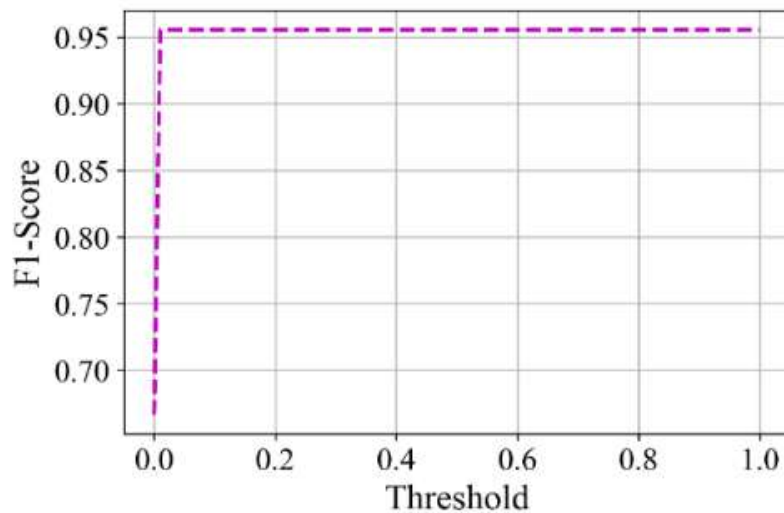


Figure 5. Threshold with F1-score value for the proposed model

Figure 5 describes the correlation of the threshold and F1-score plot. F1-score is maintained with high value which is approximately 0.96 over the entire range of threshold which is ranging between 0 and 1. The dotted line indicates a steady performance in classification, which shows that the model is well-tuned.

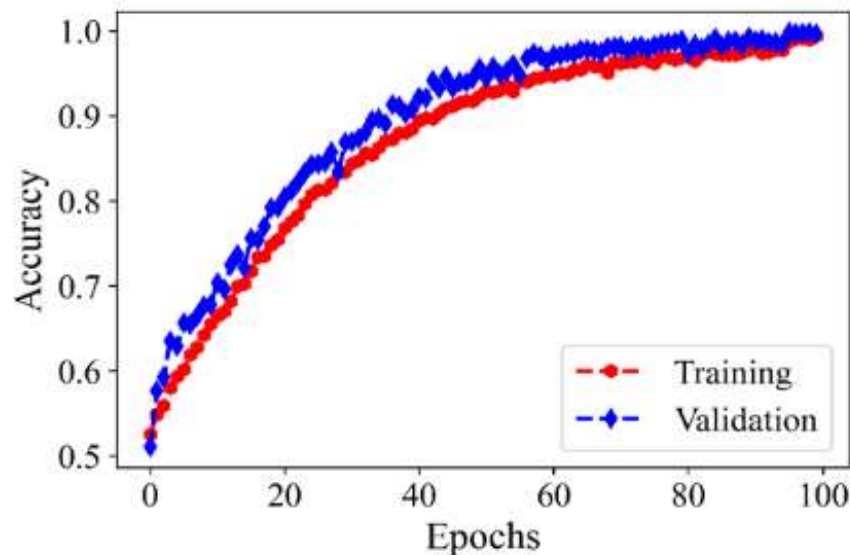


Figure 6. Training and validation accuracy for different epochs

Figure 6 describes the training and validation accuracy per epoch of the RAHLA model. The training accuracy gradually improves with each epoch from 52% to 99.2% at epoch 0 to 100, showing a successful learning of the model. Similarly, the testing accuracy improves from 51% to 99.8%, remaining slightly higher than the training accuracy and demonstrating strong generalization performance.

Figure 7 illustrates the training and validation loss per epoch of the RAHLA model. The training loss decreases significantly from 0.79 to 0.8 at epoch 0 to 100, showing continuous optimization during training. Similarly, the validation loss decreases from 0.7 to 0.2 in accordance with the training loss, demonstrating the stability and robustness of the proposed model.

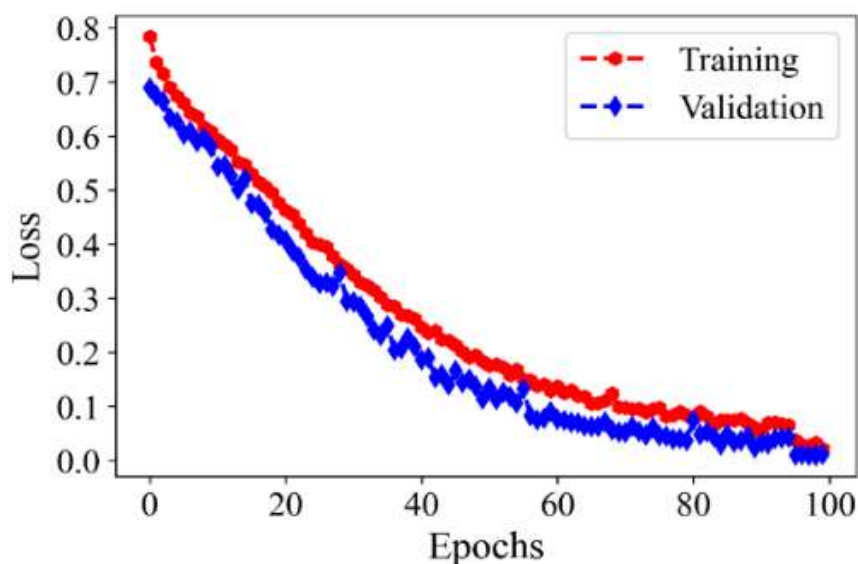


Figure 7. Training and validation loss for RAHLA model

### Comparison Analysis For Anomaly Detection

In order to evaluate the performance of a model, the proposed RAHLA model was compared with other existing techniques such as Bidirectional Gated Recurrent Unit- Temporal Convolutional Network (BiGRU-TCN), Convolutional Neural Network (CNN) and Gated Attention- Deep Neural Network (GA-DNN) [30][31].

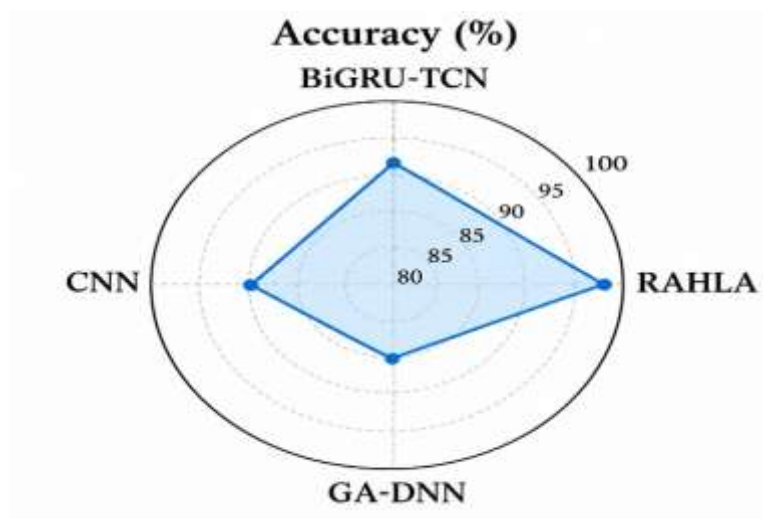


Figure 8. Comparison of RAHLA's accuracy with other contemporary methods

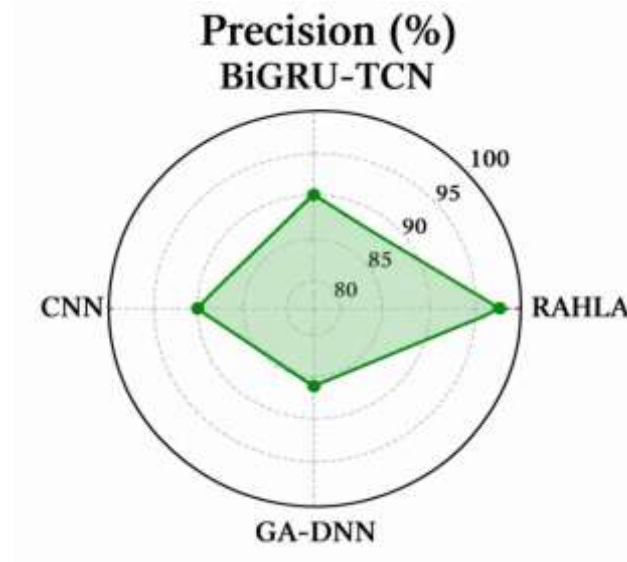


Figure 9. Comparison of precision for RAHLA with other existing techniques

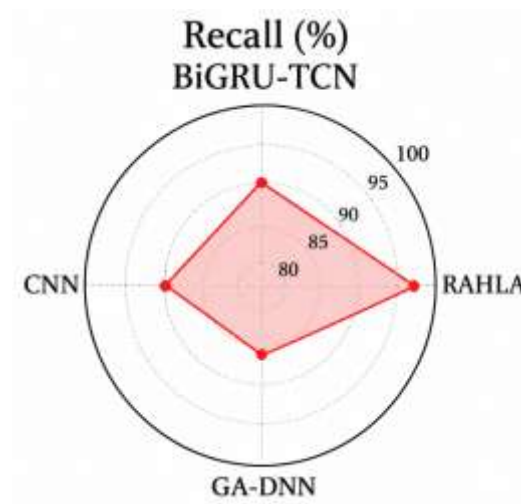


Figure 10. RAHLA's recall compares to other existing techniques

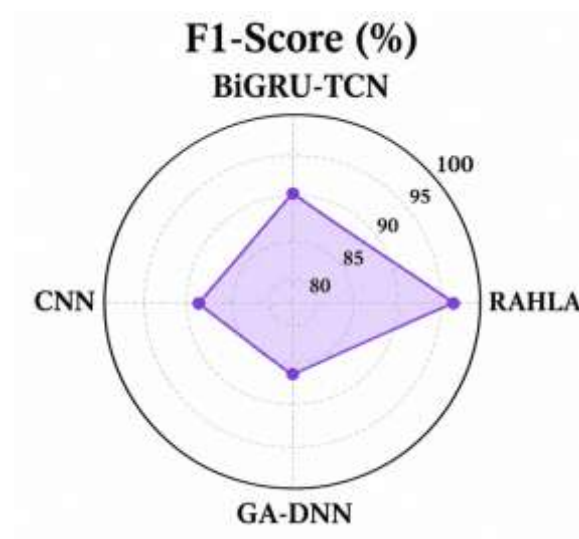


Figure 11. F1-score for RAHLA compared to other existing methods

Figures 8, 9, 10 and 11 shows the Comparison of Accuracy, Precision, Recall and F1-Score values. The proposed RAHLA model achieves the Accuracy value of 98.37% as well as the Precision value of 99.17%, Recall value of 97.5% and F1-Score value of 98.3%, which is better compared to other existing techniques. Thus, the proposed RAHLA model enhancing healthcare data anomaly analysis with high accuracy, precision, recall and F1-Score values.

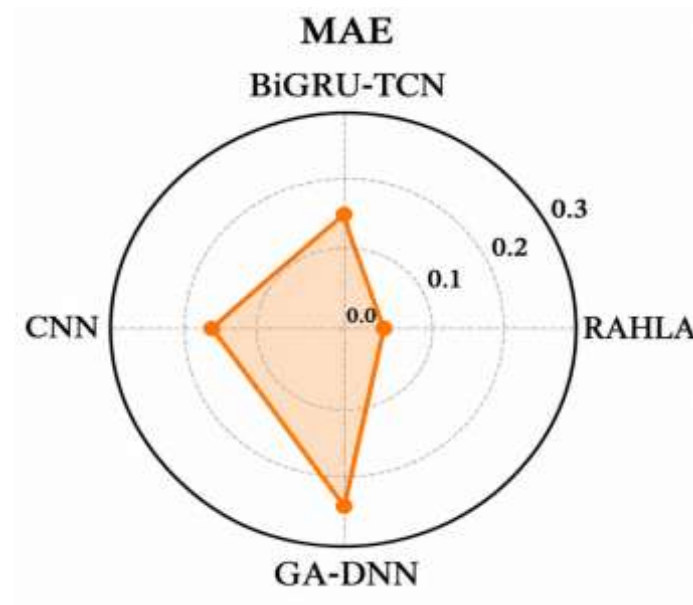


Figure 12. Comparison of RAHLA's MAE among different algorithms

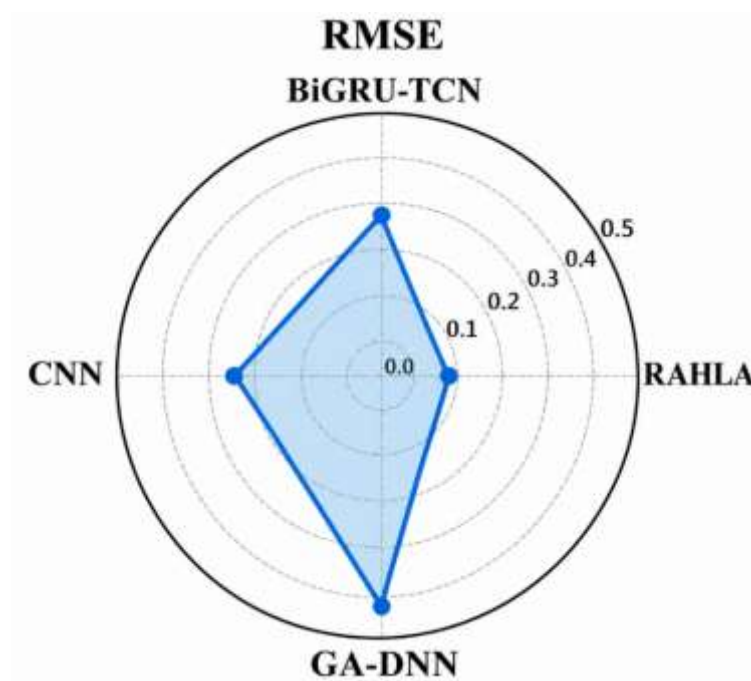


Figure 13. Validation of RMSE value for proposed RAHLA with existing models

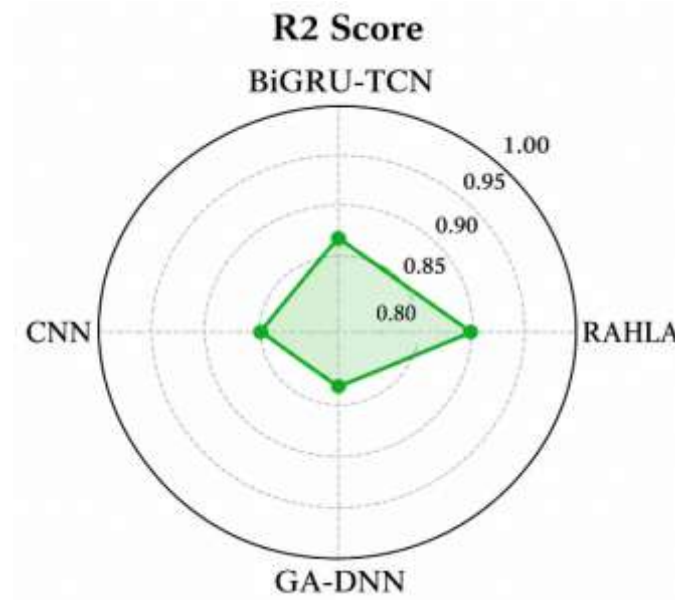


Figure 14. Comparison of R2 score for proposed RAHLA with existing models

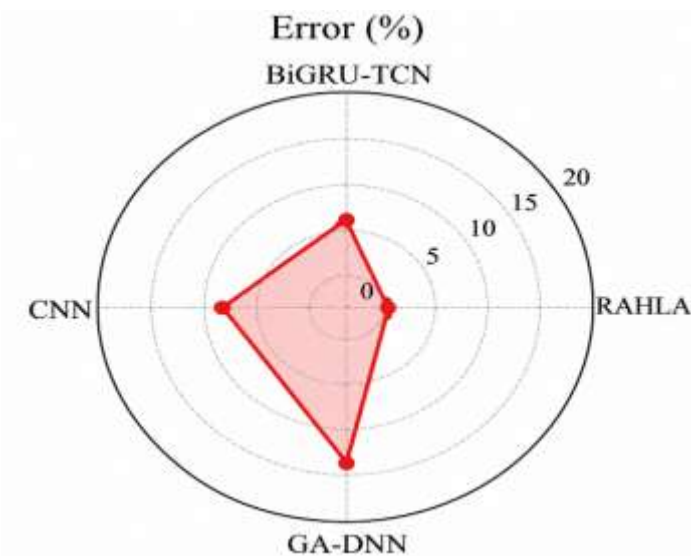


Figure 15. Error comparison for proposed RAHLA with existing methods

Figures 12, 13, 14 and 15 shows the comparison MAE, RMSE, R2 Score and Error values with other approaches. The approaches for MAE of RAHLA, BiGRU-TCN, CNN, and GA-DNN values are 0.039, 0.14, 0.17, and 0.25. The values of RMSE are 0.12, 0.28, 0.31, and 0.44, R2 Score values are 0.933, 0.89, 0.85, and 0.83, and Error values are 1.63%, 6.4%, 9.5%, 14.6% respectively. Hence, the lower error value, RMSE, and MAE and the higher R2 Score indicate that the proposed RAHLA model has better prediction accuracy and robustness than the previous models.

#### COMPARISON ANALYSIS FOR TASK OFFLOADING

The proposed LAEO is compared to a number of current algorithms, such as NSGA-II-Seq2Seq, Energy-Efficient Dynamic Task Offloading (EEDTO) and Delay-Aware Edge-Cloud Collaboration (DECC) for evaluating the performance.

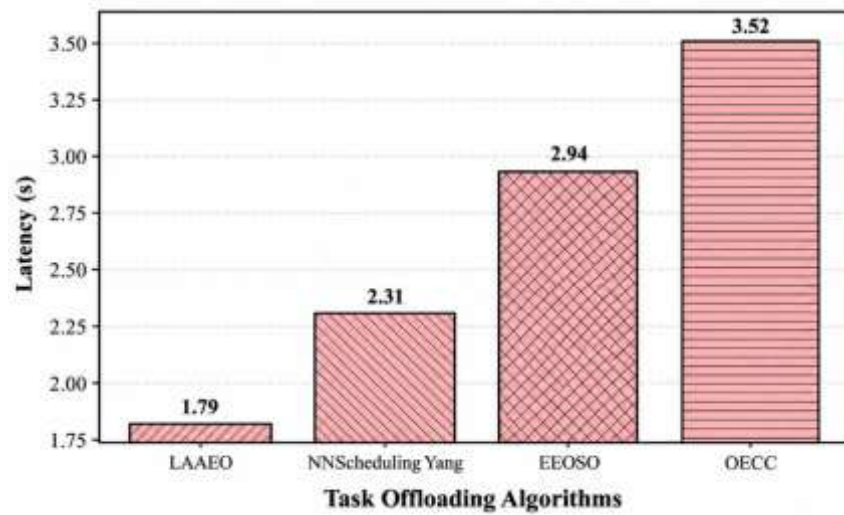


Figure 16. Latency of LAAEO compared with other existing methods

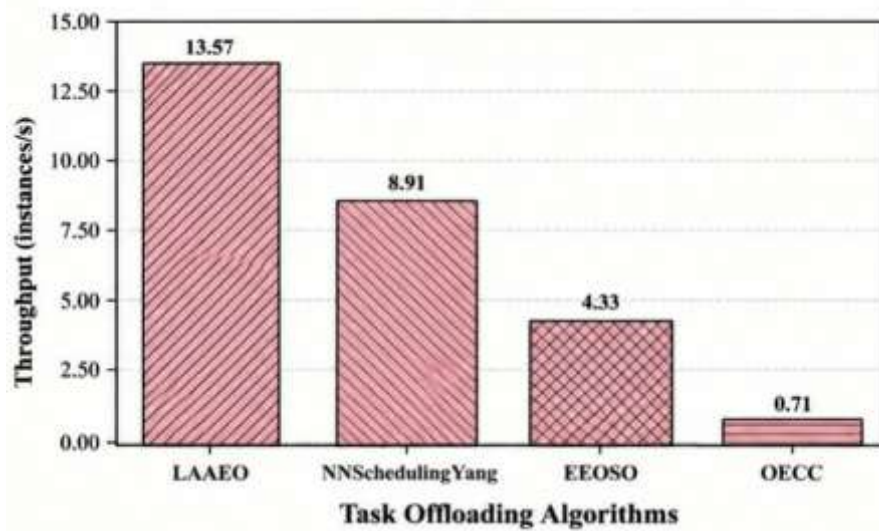


Figure 17. LAAEO's throughput value compared to other existing techniques

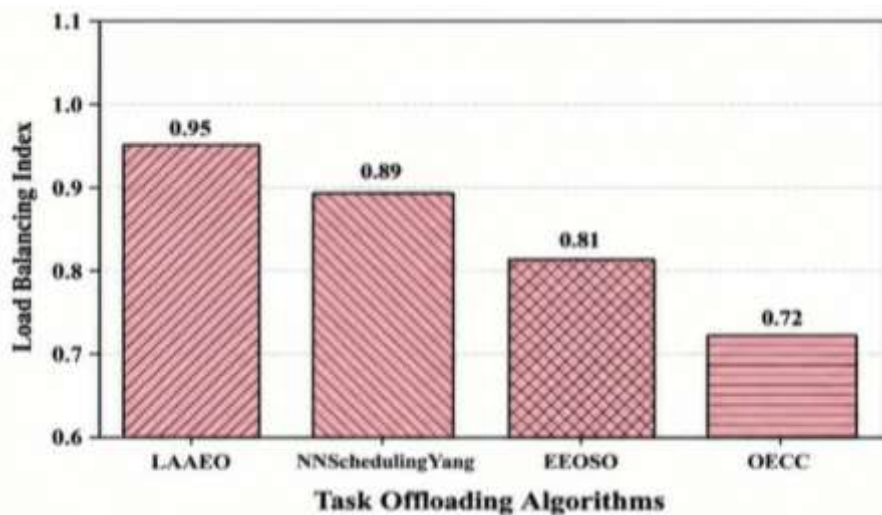


Figure 18. Evaluation of load balancing index for proposed LAAEO with existing models

Figures 16[32], 17[33] and 18[34] shows the Comparison of proposed Latency, Throughput and Load Balancing Index values with existing methods. The proposed LAAEO model achieves Latency value of 1.79s and Throughput value of 1371tasks/sec as well as the Load Balancing Index values of 0.95, which is better compared to other existing techniques. Consequently, the lower latency, higher throughput and better load balancing index indicate its efficiency and effectiveness for optimized task offloading in the cloud-edge environment based on the proposed LAAEO model.

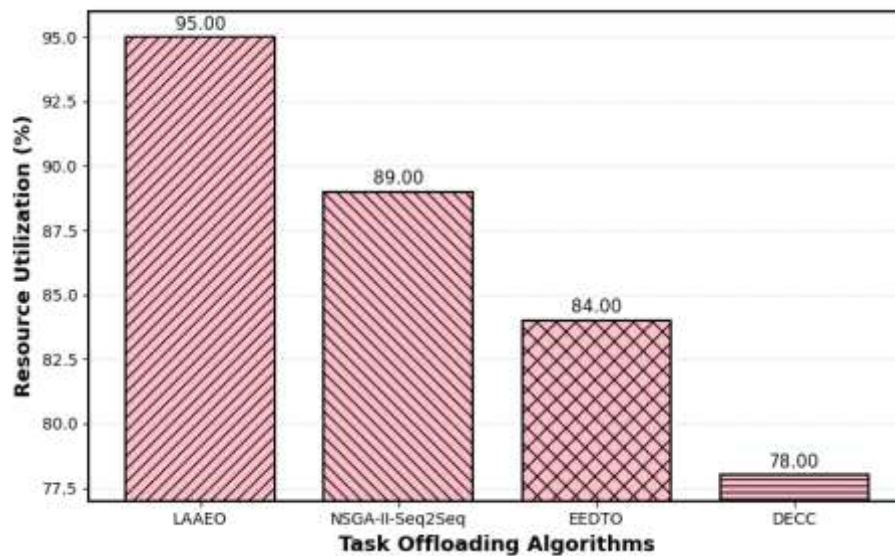


Figure 19. Comparison of LAAEO's resource utilization among different algorithms

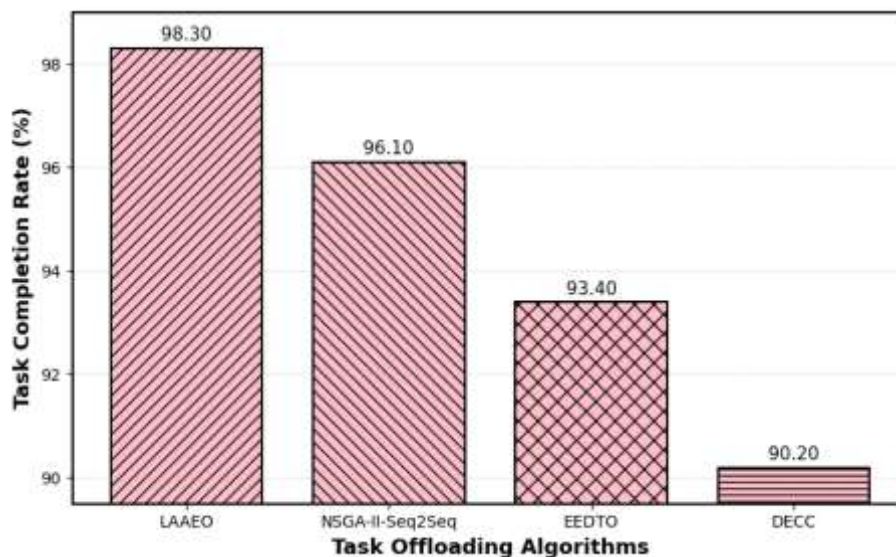


Figure 20. Task completion rate comparison for LAAEO with other existing techniques

Figures 19, 20, and 21 shows the Comparison of Resource utilization, Task Completion Rate and Response Time values for proposed with existing methods. The proposed LAAEO model achieves Resource utilization value of 95%, Task Completion Rate of 98.30%, as well as the Response Time of 0.73ms, which is better compared to other existing techniques. Overall, the results of higher resource utilization and task completion rate, and lower response time, indicate that the proposed LAAEO model performs better and manages resources better.

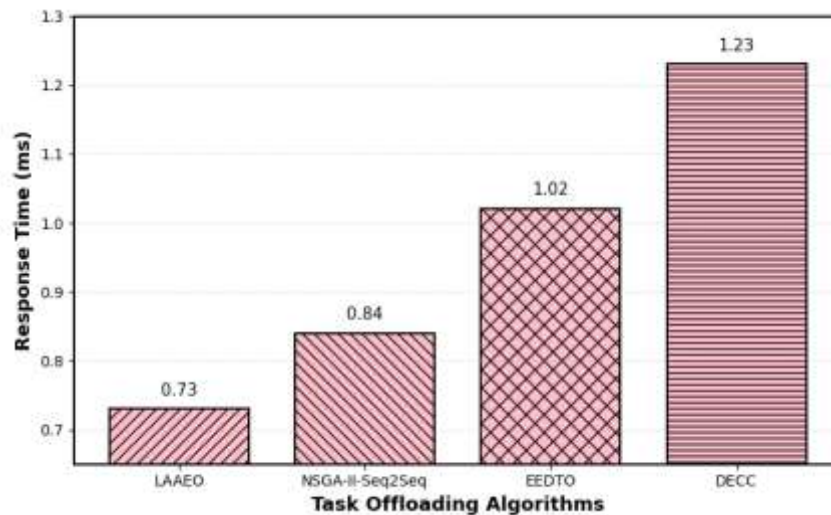


Figure 21. Evaluation of response time for LAAEO with existing models

Table 6. Ablation study for the proposed model

| Methods                                                               | Accuracy (%) | Precision (%) | Recall (%) |
|-----------------------------------------------------------------------|--------------|---------------|------------|
| Synthetic Quality Degradation Injection +ACADI+DRQN+TMHFF+RAHLA model | 98.37        | 99.17         | 97.5       |
| ACADI+DRQN+TMHFF+RAHLA model                                          | 94.20        | 95.03         | 93.02      |
| Synthetic Quality Degradation Injection + ACADI +TMHFF+RAHLA model    | 93.12        | 94.26         | 92.23      |

Table 6 presents the results of an ablation study evaluating an anomaly detection. All phases as Quality Degradation Injection, Data Ingestion, Preprocessing, Fusion and Anomaly detection model (Synthetic Quality Degradation Injection + ACADI+DRQN+TMHFF+RAHLA), without Quality Degradation Injection (ACADI+DRQN+TMHFF+RAHLA) model, without Preprocessing model (Synthetic Quality Degradation Injection + ACADI +TMHFF+RAHLA) for evaluating its effectiveness of an overall model.

Table 7. State of art methods for the proposed model

| Anomaly Detection      |                                                |          |        |
|------------------------|------------------------------------------------|----------|--------|
| Researches             | Method                                         | Accuracy | Recall |
| Proposed               | RAHLA                                          | 98.37%   | 97.5%  |
| Alkhafaji et al., [30] | Genetic Algorithms and Deep Learning (GA-DL)   | 96%      | 94%    |
| Hairab et al., [31]    | Convolutional Neural Networks with L2 (CNN-L2) | 90.75%   | -      |

Table 7 shows the comparison performance of the proposed methods with other existing techniques. These result describes that the proposed technique performs better than other techniques.

## CONCLUSION

IIoT based healthcare environments ensures the continuous patient monitoring, remote diagnosis, automated clinical decision-making and predictive healthcare analytics. Whereas, the existing anomaly detection techniques face issues of handling noisy healthcare streams, evolving healthcare data quality conditions and communication failures. In order to address these challenges, proposed an adaptive framework for data quality management and anomaly detection for secure data transmission. The proposed framework combines ACADI for adaptive healthcare data ingestion, DRQN is used to enhance the quality of healthcare data. Then, the TMHFF framework is used to extract and fuse the multi-scale healthcare features and RAHLA for adaptive anomaly detection. After anomaly detection, PEQE predicts the degradation risks of future healthcare quality and SHIRE is used to perform the intelligent data reconstruction. Then, the MAFO optimizes the learning behavior and LAAEO enables the latency-aware cloud-edge healthcare workload orchestration. In summary, the proposed model achieves the performance

within the accuracy value of 98.37%, Recall of 97.5% and Latency of 1.79s, which shows that these model has the capability of effective healthcare data quality enhancement and anomaly detection in healthcare sectors. The proposed model achieves a better performance, but its performance can degrade when the healthcare devices generate irregular, incomplete or severely corrupted data and heavily depends on availability of consistent sensor streams and communication links within the extended periods. In future, the lightweight optimization strategies, enhanced privacy-preserving mechanisms, real-time deployment and federated healthcare learning techniques were used to improve the performance and security of smart healthcare ecosystems.

## REFERENCES

- [1] Murala DK, Madhura K, Vuyyuru VA, Rao KV, Hitimana E. Trustfed a scalable privacy preserving federated AI framework for industrial IoT healthcare and finance. Discover Internet of Things. 2026 Jan 14;6(1):13. <https://doi.org/10.1007/s43926-025-00276-5>
- [2] Chaudhari DD, Basha DK, Srivastava K, Naved M, Ghosh P, Mohan CR. Blockchain-powered secure encryption for smart healthcare in industrial IoT with multi-aspect graph attention spherical convolutional neural network. Iran Journal of Computer Science. 2026 Dec;9(1):25. <https://doi.org/10.1007/s42044-025-00366-1>
- [3] Upadhyaya B, Panda AC, Mohanty SS, Pati A, Mohapatra P. QLight-IIoT: A Quantum-Resistant Lightweight Authentication and Key Agreement Scheme for Resource-Constrained IIoT Environments. IEEE Internet of Things Journal. 2026 Apr 8. <https://doi.org/10.1109/JIOT.2026.3682119>
- [4] Karthikeyan B, Kumar P, Karthikeyan P, Soufiene BO, Elngar A, Dhanaselvam PS, Kavitha K. Adaptive artificial intelligence for intelligent fault detection and correction in sensor systems. In Adaptive AI in Sensor Informatics 2026 Jan 1 (pp. 133-152). Elsevier. <https://doi.org/10.1016/B978-0-443-36412-9.00007-8>
- [5] Erfan F, Bellaiche M, Halabi T. Sybil attack defense in blockchain-based industrial IoT systems using decentralized federated learning. Internet of Things. 2026 Mar 26:101927. <https://doi.org/10.1016/j.iot.2026.101927>
- [6] Mahbub M, Riasat MT, Hamid T, Sutradhar SC, Khan MS. A minimalistic yet effective domain adaptation strategy for IoMT network intrusion detection. Discover Internet of Things. 2026 Feb 9;6(1):28. <https://doi.org/10.1007/s43926-026-00288-9>
- [7] Šabić E, Keeley D, Henderson B, Nannemann S. Healthcare and anomaly detection: using machine learning to predict anomalies in heart rate data. Ai & Society. 2021 Mar;36(1):149-58. <https://doi.org/10.1007/s00146-020-00985-1>
- [8] Samariya D, Ma J, Aryal S, Zhao X. Detection and explanation of anomalies in healthcare data. Health Information Science and Systems. 2023 Apr 6;11(1):20. <https://doi.org/10.1007/s13755-023-00221-2>
- [9] Zhang M, Yang Z, Yan J, Ali S, Ding W, Wang G. Task-load aware and predictive-based workflow scheduling in cloud-edge collaborative environment. Journal of Reliable Intelligent Environments. 2022 Mar;8(1):35-47. <https://doi.org/10.1007/s40860-022-00173-6>
- [10] Zhuang Z, Chen J, Xu W, Qi Q, Guo S, Wang J, Lu L, Yang H, Liao J. DECC: Delay-aware edge-cloud collaboration for accelerating DNN inference. IEEE Transactions on Emerging Topics in Computing. 2024 Jun 7;13(2):438-50. <https://doi.org/10.1109/TETC.2024.3404551>
- [11] Al Arafat A, Wilson K, Yang K, Guo Z. Dynamic priority scheduling of multithreaded ROS 2 executor with shared resources. IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems. 2024 Nov 6;43(11):3732-43. <https://doi.org/10.1109/TCAD.2024.3445259>
- [12] Iqbal W, Berral JL, Carrera D. Adaptive sliding windows for improved estimation of data center resource utilization. Future Generation Computer Systems. 2020 Mar 1;104:212-24. <https://doi.org/10.1016/j.future.2019.10.026>
- [13] Ma H, Xu D, Wang X. Congestion control algorithm-aware queue management. Computer Networks. 2026 Jan 7;111975. <https://doi.org/10.1016/j.comnet.2025.111975>
- [14] Altamimi A, Alarfaj AA, Umer M, Alabdulqader EA, Alsubai S, Kim TH, Ashraf I. An automated approach to predict diabetic patients using KNN imputation and effective data mining techniques. BMC Medical Research Methodology. 2024 Sep 27;24(1):221. <https://doi.org/10.1186/s12874-024-02324-0>
- [15] Das M, Sahana BC. Optimized orthogonal wavelet-based filtering method for electrocardiogram signal denoising. Journal of The Institution of Engineers (India): Series B. 2025 Jun;106(3):965-78. <https://doi.org/10.1007/s40031-022-00796-6>
- [16] Bojian CH, Changqing SH, Juanjuan SH, Lin KO, Luyang TA, Dong WA, Zhongkui ZH. Continual learning fault diagnosis: A dual-branch adaptive aggregation residual network for fault diagnosis with machine increments. Chinese Journal of Aeronautics. 2023 Jun 1;36(6):361-77. <https://doi.org/10.1016/j.cja.2022.08.019>

- [17] Bajaj A, Pradeep NS, Aarthi V. Energy-Efficient Container Orchestration for HPC Workloads using ML in Kubernetes on Cloud Platforms. In 2026 International Conference on Recent Advancement in Electrical, Computer and Communication Technologies (IECCT) 2026 Apr 10 (pp. 1-6). IEEE.  
<https://doi.org/10.1109/IECCT68664.2026.11541572>
- [18] Li Q, Shen Z, Li Q, Barratt DC, Dowrick T, Clarkson MJ, Vercauteren T, Hu Y. Long-term dependency for 3D reconstruction of freehand ultrasound without external tracker. IEEE Transactions on Biomedical Engineering. 2023 Oct 19;71(3):1033-42. <https://doi.org/10.1109/TBME.2023.3325551>
- [19] Chen L, Fu Y, Gu L, Yan C, Harada T, Huang G. Frequency-aware feature fusion for dense image prediction. IEEE transactions on pattern analysis and machine intelligence. 2024 Aug 26;46(12):10763-80.  
<https://doi.org/10.1109/TPAMI.2024.3449959>
- [20] Bi J, Chen Z, Yuan H, Zhang J. Accurate water quality prediction with attention-based bidirectional LSTM and encoder-decoder. Expert Systems with Applications. 2024 Mar 15;238: 121807.  
<https://doi.org/10.1016/j.eswa.2023.121807>
- [21] Chen X, Zhou M, Zou L, Fan L, Hu J, Geng G, Zhang H. A fast reconstruction method of the dense point-cloud model for cultural heritage artifacts based on compressed sensing and sparse auto-encoder: X. Chen et al. Optical and Quantum Electronics. 2019 Oct;51(10):322. <https://doi.org/10.1007/s11082-019-2038-y>
- [22] Choi KH, Ha JE. An adaptive threshold for the canny algorithm with deep reinforcement learning. IEEE Access. 2021 Nov 23; 9:156846-56. <https://doi.org/10.1109/ACCESS.2021.3130132>
- [23] Bäck TH, Kononova AV, van Stein B, Wang H, Antonov KA, Kalkreuth RT, de Nobel J, Vermetten D, de Winter R, Ye F. Evolutionary algorithms for parameter optimization—thirty years later. Evolutionary Computation. 2023 Jun 1;31(2):81-122. [https://doi.org/10.1162/evco\\_a\\_00325](https://doi.org/10.1162/evco_a_00325)
- [24] Di Mauro M, Galatro G, Postiglione F, Song W, Liotta A. Hybrid learning strategies for multivariate time series forecasting of network quality metrics. Computer Networks. 2024 Apr 1; 243: 110286.  
<https://doi.org/10.1016/j.comnet.2024.110286>
- [25] Meza-Pantoja A, Lawson AC, Caputo CC, Ge J, Cohen DJ, Krieger A, Saeidi H. A confidence-based shared control strategy for robotic electrosurgery. IEEE transactions on medical robotics and bionics. 2025 Apr 14;7(2):583-94. <https://doi.org/10.1109/TMRB.2025.3560400>
- [26] Yang D, Zhang W, Ye Q, Zhang C, Zhang N, Huang C, Zhang H, Shen X. DetFed: Dynamic resource scheduling for deterministic federated learning over time-sensitive networks. IEEE Transactions on Mobile Computing. 2023 Aug 7;23(5):5162-78. <https://doi.org/10.1109/TMC.2023.3303017>
- [27] Wang D, Gao N, Liu D, Li J, Lewis FL. Recent progress in reinforcement learning and adaptive dynamic programming for advanced control applications. IEEE/CAA Journal of Automatica Sinica. 2023 Nov 10;11(1):18-36. <https://doi.org/10.1109/JAS.2023.123843>
- [28] Chiaro C, Monaco D, Sacco A, Casetti C, Marchetto G. Latency-aware scheduling in the cloud-edge continuum. In NOMS 2024-2024 IEEE Network Operations and Management Symposium 2024 May 6 (pp. <https://doi.org/10.1109/NOMS59830.2024.10575183>
- [29] Asjad K. MIMIC-III - Deep reinforcement learning. Kaggle; 2022.  
<https://www.kaggle.com/datasets/asjad99/mimiciii>
- [30] Alkhafaji N, Viana T, Al-Sherbaz A. Integrated genetic algorithm and deep learning approach for effective Cyber-Attack detection and classification in industrial Internet of things (IIoT) environments. Arabian Journal for Science and Engineering. 2025 Aug;50(15):12071-95.  
<https://doi.org/10.1007/s13369-024-09663-6>
- [31] Hairab BI, Elsayed MS, Jurcut AD, Azer MA. Anomaly detection based on CNN and regularization techniques against zero-day attacks in IoT networks. IEEE Access. 2022 Sep 12; 10 :98427-40.  
<https://doi.org/10.1109/ACCESS.2022.3206367>
- [32] Yang Z, Zhang M, Li H, Ding W. A novel seq2seq-based prediction approach for workflow scheduling. Cluster Computing. 2024 Apr;27(2):1897-910. <https://doi.org/10.1007/s10586-023-04061-3>
- [33] Wang J, Hu J, Min G, Zomaya AY, Georgalas N. Fast adaptive task offloading in edge computing based on meta reinforcement learning. IEEE Transactions on Parallel and Distributed Systems. 2020 Aug 6;32(1): 242-53. <https://doi.org/10.1109/TPDS.2020.3014896>
- [34] Chen X, Jiao L, Li W, Fu X. Efficient multi-user computation offloading for mobile-edge cloud computing. IEEE/ACM transactions on networking. 2015 Oct 26;24(5):2795-808.  
<https://doi.org/10.1109/TNET.2015.2487344>
- [35] Sundareswari K. Exploring nonlinear dynamics of information flow in distributed academic and library service and information source networks. Applied Nonlinearity in Science and Technology. 2026 Jun 8;2(2):9-18.
- [36] Yuqi J, An A, Lu Z, Ping H, Xiaomei L. Short-term load forecasting based on temporal importance analysis and feature extraction. Electric Power Systems Research. 2025 Jul 1; 244:111551.  
<https://doi.org/10.1016/j.epsr.2025.111551>