Natural Resources for Human Health
eISSN: 2583-1194

Original Research
Received 27 May 2026
Revised 24 June 2026
Accepted 16 July 2026

Natural Resources for Human Health 2026, Vol. 6 (10s): 671–692

KEYWORDS:
Artificial Intelligence; Auto Encoder; Deep learning; ECG Signal Denoising; LSTM.

Development of Hybrid Deep Learning Models for Robust ECG Signal Denoising under Real time Noise Conditions

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ABSTRACT: Increasing heart diseases are a major concern in the healthcare domain, especially in the cardiac department. To predict cardiovascular disease, electrocardiogram (ECG) signals are commonly used. The disease prediction is conducted using the pattern of ECG signals. However, the ECG signal output is biased with a noise signal produced from electrode motion, electromagnetic interference, muscular artifacts, and baseline wander. The noise signals adversely impact the ECG signal and lead to wrong predictions, which badly affect the patient's life. In this regard, ECG signal denoising techniques are important for better prediction of cardiovascular diseases. In this research, ECG signal denoising is performed using deep learning (DL) models. Also, developed the hybrid DL model for enhancing the effectiveness of ECG signal denoising. In this study, the MIT-BIH Atrial Fibrillation data set is used to generate real-time probable noise signals. The general types of noise signals produced in these circumstances are Gaussian Noise, baseline wander, electrode motion artefacts, muscle artefacts, and electromagnetic interference, which are created and tested with the hybrid deep learning models. There are four deep learning models, such as Denoising Autoencoder (DAE), Long Short-Term Memory (LSTM), hybrid DAE-LSTM and CNN-BiLSTM models, which have been developed. In order to enhance the denoising performance, the addition of temporal sequence learning and spatial feature extraction is inculcated. The developed DL models underwent detailed testing with a generated noise model and were evaluated for performance accordingly. After the testing, it was found that the hybrid DAE-LSTM model outperforms other DL models in terms of the performance parameters such as signal-to-noise ratio, peak signal-to-noise ratio, and Pearson correlation coefficient. The results show that the signal-to-noise ratio of the hybrid DAE-LSTM model is 10.42 dB, PSNR of 22.54 dB, and PCC of 0.9408. As compared to all DL models, DAE shows the least value of MSE of 0.1099. These results indicate that ECG signals are completely recovering from the noise, and a better prediction of cardiovascular disease is possible. Also, the hybrid DL model has a wide scope in the biomedical sector for the reliable and accurate prediction of cardiovascular diseases by referring to the ECG signal pattern. The proposed approach is reliable and an Artificial Intelligence (AI) enabled health care approach. Apart from this, the proposed hybrid DL model can be used in smart wearable cardiac monitoring devices for improving the accuracy.

1. INTRODUCTION

The cardiovascular diseases, especially myocardial infarction, arrhythmia, and abnormalities in conduction, can be identified using the pattern of the Electrocardiogram (ECG) signals. The important features of ECG-based cardiovascular diagnosis are that it is a non-invasive technique. The ECG pattern comprises the P wave, QRS complex, and T wave, which are most essential for the prediction of cardiovascular disorders. The decision-making, such as whether the patient has a disorder or not, is done in accordance with the waveform pattern. By analysing the waveform, it is possible to predict whether the patient is suffering from cardiovascular disease or not. Nevertheless, the noise signal spoils the quality of ECG signals, which leads to wrong decision-making by the medical practitioner. In this regard, removal of noise signal from the original signal, technically known as ECG signal denoising [1], is essential for predicting cardiovascular disorders.

There are several reasons for noise signal generation in ECG signal devices, such as patient movement, respiration activity, electrode movement, electromagnetic interference, and electromyographic interference due to muscle activities. The electromagnetic interference is also known as powerline interference or cross-talking, which generates the noise signal in the range of 50 to 60 Hz. The noise signals generated from the different sources overlap the original ECG signal, which distorts the original pattern of the ECG signal. Therefore, a suitable ECG signal denoising technique is desirable to analyse the pattern of the ECG signal and predict the cardiovascular disorders.

There are conventional signal denoising techniques, such as wavelet-based techniques, adaptive filtering, and bandpass filtering, which are quite popular in the biomedical sector. Those traditional signal denoising methods are computationally efficient, but operate on predefined assumptions about noise and signal character. The main disadvantage of traditional methods is that there is no generalization with real-time scenarios and realistic conditions. Furthermore, the adaptive and band-pass filtering techniques damage the essential morphological features of the ECG signal, typically the QRS pattern, which is not an effective and reliable approach.

In the past few years, machine learning (ML) methods have been adopted for the ECG signal denoising technique, which works on data-driven decision making. The most popular ML models are regression models and support vector machine (SVM) models. Those traditional ML models rely on handcrafted features and failed to find any non-linear relationship in the ECG signal. Moreover, traditional ML models are not shown to be effective in modelling temporal dependencies inherent in physiological signals.

Deep learning (DL) is a powerful alternative that has the capability of automatically learning hierarchical representations from the raw data, unlike how ML models work. The Denoising Autoencoders (DAE) [2] is a popular DL model that showcases solid features in reconstructing a clear signal from the noisy input by analyzing and learning the latent feature representation. The recurrent neural network (RNNs) is another important DL model that is suggested to be used for ECG signal denoising methods. Also, Long-Short Term Memory (LSTM) network is a type of RNN that is a suitable option for modelling temporal dependencies in sequential data such as ECG signals. The recent literature focuses only on one of the performance parameters, such as mean squared error (MSE), which is not suitable to capture the morphological quality of the reconstructed signal and perceptual features.

The simplified single denoising model alone is unable to meet the ECG real-time signal denoising. In a real-time situation, there is a combination of noise signals superimposed on the original ECG signal. In the recent articles, the impact of Gaussian noise is only considered, whereas other types of noise are not taken into consideration. In real circumstances, other kinds of noise signals must be considered. The single DL model is not fit for the condition where multiple noises are generated simultaneously. This problem restricts the use of a single DL model in smart wearable cardiovascular monitoring devices in real-time situations.

In order to overcome the issue of a single DL model in a real-time application, a hybrid DL model is introduced. The salient features of hybrid DL models are the integration of the strengths of spatial and temporal features. The suitable combination of hybrid DL models is DAE-LSTM and CNN-BiLSTM, which are capable of extracting morphological features and long-range temporal dependencies. To showcase the robustness of the hybrid DL model for the ECG signal denoising, combining different noise signals such as Gaussian noise, baseline wander, muscle artifacts, electrode movement, and electromagnetic interference acted simultaneously in real-time conditions. The proposed model's performance is not only evaluated by MSE, but also by using signal-to-noise ratio (SNR), peak signal to noise ratio (PSNR), and Pearson correlation coefficient (PCC) [3]. The suggested evaluation matrix provides clarity on waveform preservation, quality of signal reconstruction, and clinical significance. Considering SME as a single performance evaluation matrix is not a scientific approach. The general block diagram of the proposed hybrid DL architecture for ECG signal denoising is shown in Figure 1.

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eISSN: 2583-1194

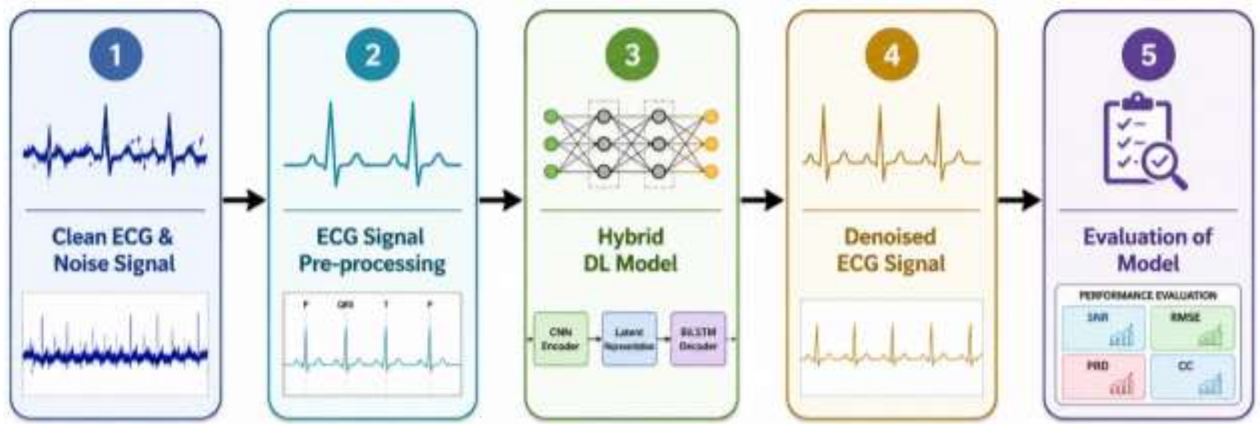

Figure 1. Proposed hybrid DL architecture for ECG signal denoising

2. LITERATURE REVIEW

Since more research and development (R&D) is in progress in the cardiac diagnosis system, ECG signal denoising plays an important role in the present research. In this research area, denoising techniques began from a traditional approach, and denoising is conducted using advanced deep learning (DL) models. An extensive study is carried out in conventional, machine learning, and deep learning-based ECG signal denoising approaches. Those studies help to identify the research gap.

In the early stages, ECG signal denoising is carried out using band-pass filtering, adaptive filtering, and wavelet transform approaches. According to V. A. Raj et al. the bandpass filtering [5] is a computationally efficient and simple method that is used to surpass low-frequency baseline wander and high-frequency noise range. Using band pass filtering, signals are restricted within the pre-defined band of frequency, but the important morphological features are unable to be maintained using the band pass filtering approach. In failure to maintain important morphological features using a band pass filtering approach is most effective in ECG signal denoising. A. Bharath et al. provided an overview of the wavelet transform method [6] used in ECG signal denoising application. The wavelet transform is a well-known ECG signal denoising technique that is capable of selective noise removal. It has the ability to figure out time-frequency localisation. The method is efficient if and only if the wavelet basis function and thresholding strategies are optimized optimally. Inappropriate selection of wavelet basis functions and thresholding strategies leads to the least efficient noise removal and loss of critical information from the denoised output.

B. Soni et al. mentioned that the adaptive filtering method [7] is a traditional ECG signal denoising approach that is suited for removing the low-frequency signal from the power line interference. M. Dias et al. suggested that the important adaptive filtering methods are least mean square (LMS) and recursive least square (RLS) [8]; these methods need a reference noise signal and are difficult to generalize and identify fast-moving and multiple noise signals. In such cases, the noise signal remains unchanged, and ECG signal denoising becomes ineffective. In general, the traditional ECG signal denoising method follows certain assumptions and thumb rules. In order to handle real-world noise signals, those traditional methods are not well-suited.

Machine learning (ML) approaches such as support vector machines (SVM), K-nearest neighbour (K-NN) and random forest (RF) models [9] are commonly used for ECG signal denoising. F. Zabihi et al. stated that those methods perform well compared to the traditional approach, which works based on the relation between the noisy ECG signal and the clean ECG signal. These approaches follow a supervised learning method to predict the noise-free output. The model training is important in these ML-based approaches. These models face difficulty generalizing the different kinds of noises and real-world scenarios. The ECG signal exhibits strong temporal correlation and is unable to find the dependencies. This adversely affects the ECG signal denoising performance.

In order to overcome the mentioned setbacks of ML-based ECG signal denoising, deep learning (DL) based models are implemented. G. Gunawan et al. claimed that the DL model [10] is capable of automatically learning the hierarchical and temporal variations from the available raw data. The DL model is well-suited to learn any complex non-linear mapping directly from the given raw data. There are many suitable DL algorithms [11] available, among which the denoising autoencoder (DAE) [12] is widely used for reconstructing a clean ECG signal from noisy input effectively. DAE's operation mainly depends on an encoder-decoder structure, which is used to maintain important features during ECG signal denoising.

Convolutional Neural Networks (CNN's) are another DL model suited for ECG signal denoising, which is capable of extracting local spatial features from the real-time series raw data. Also, CNN is effective in capturing morphological features of the ECG signal, such as P wave, T wave, and QRS complex pattern. The drawback of the CNN model is the presence of long-term temporal dependencies, which adversely affect the effectiveness of ECG signal denoising. Another DL model, the Recurrent Neural Network (RNN), is suitable for ECG signal denoising. In RNN, one of the popular subclasses is the Long Short-Term Memory network (LSTM), which shows an excellent performance while modelling the sequential data. K. K. Reddy et al. stated that LSTM [13] has an advantage of capturing long-range dependencies as it has been developed with additional memory. LSTM is well-suited when temporal dependencies are the most important feature. Recently, hybrid DL models have been developed for ECG signal denoising, which follow both spatial and temporal features. N. Pasha et al. suggested that, in spite of using a standalone independent DL model, hybrid models [14] are suggested to be used for the ECG signal denoting model.

After the extensive survey of literature, the research gaps are identified. Even though the DL models are advanced for ECG signal denoising, a few limitations are observed. Independent DL models are highly used in recent research, but have yet to explore the development of a hybrid DL model for the improvement in capturing more spatial and temporal features. In addition to that, most of the research articles focus only on independent noise models, but real-world scenarios need multiple noise models, that is, combined noise models. Also, observed that many recent studies focus on a single matrix model to evaluate the model performance, but the multi-matrix evaluation of the model is desirable.

3. MATERIALS AND METHODS

In this section, the overall methodology related to ECG signal denoising using a hybrid deep learning (DL) model [15] is presented. Mainly, the details of the datasets used in this work, the procedure for pre-processing, noise modelling with real-time features, dataset preparation, architecture of the model for denoising, procedure for training the model, and functioning of the models are explained. The model simulation is presented with the realistic conditions, and the procedure to evaluate the proposed hybrid DL model is also presented.

3.1 Specifications of dataset

The proposed research is conducted on cardiac signal processing. In connection with the work, the MIT-BIH Artificial Fibrillation Database (AFDB) [16] is used, and this dataset is widely accepted by the world. There are many ECG recordings with special cases included in this dataset. In order to provide a proper temporal solution to find the actual cardiac activity, the signals are sampled at a frequency of 250 Hz. This research is carried out in such a way that ECG recordings are divided into a fixed window length of 5 s. Also, 1250 samples per segment are considered here. The purpose of segmentation is to ensure that the input size is uniform, which helps the DL model for the effective training and evaluation of results.

3.2 ECG signal pre-processing

The dataset consists of inconsistent and conceptual segments, which must be removed before the training of the model. Therefore, ECG signal pre-processing is carried out in this work before training the DL model. The corrupted and inconsistent signals can be avoided as much as possible using this pre-processing stage. The first step of ECG signal pre-processing is R-peak detection, which ensures accurate segmentation of the ECG cycle. R-peak detection ensures preservation of the important morphological features. The second stage is signal segmentation, which follows continuous ECG signal recordings that are segmented into fixed-length parts to ensure the standard input size for training the DL model effectively. The third step of ECG signal pre-processing is quality assessment (QA) filtering [17], which excludes the missing and corrupted data for the improvement of signal denoising, thereby increasing the robustness of the model. The last step of ECG signal pre-processing is normalization, which follows minimum-maximum scaling to bring the height of the signal within the standard limit. The purpose of min-max scaling is to improve convergence during training and prevent numerical instability. The ECG pre-processing stage comprises the following steps, shown in Figure 2.

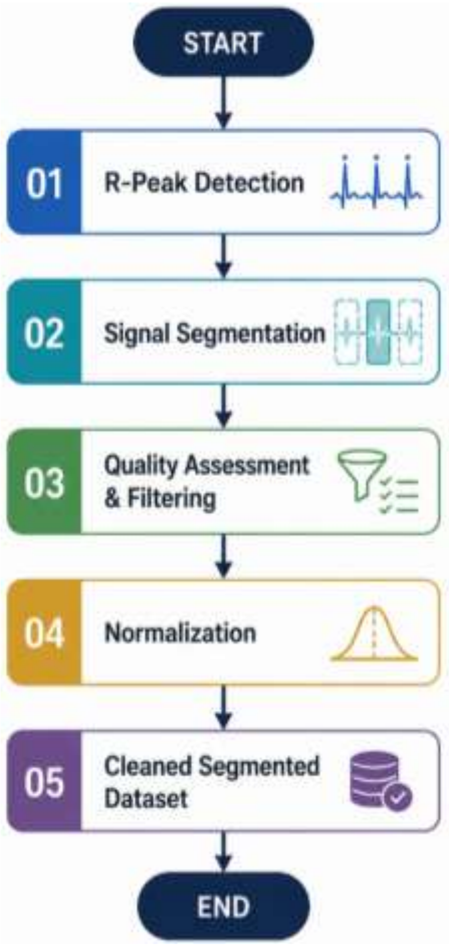

Figure 2.ECG signal pre-processing stages

3.3 Realistic Noise Modelling

In order to get the real-time simulation and test the model, artificial noise needs to be produced at the right time. The probable noise signals are generated. In this research, the isolated noise type, which includes the combination of physiological and external noise components, is modelled. The ECG noise signal is mathematically represented as shown in equation (1)

$$Xnoisy(t)=xclear(t) + ng(t) + nbw(t) + nem(t) + nemg(t) + npli(t) \quad (1)$$

In equation (1) , Xnoisy(t) is denoted as the ECG noise signal, xclear(t) is the clean ECG signal, ng(t) is the Gaussian noise, nbw(t) is represented as baseline wander, nemg(t) represents muscle artifacts noise, nem(t) indicates electrode motion artifacts, and npli(t) denotes the power line interference or cross talking. The noise components are briefly illustrated below: Among the different types of noise signals, the Gaussian noise signal simulates random noise, the baseline wander modelled at a lower frequency sinusoidal drift signal, Muscle Artifact (EMG) [18] represents high frequency interface due to muscle activity, electrode motion represents sudden transient disturbance, and power line interference represents sinusoidal noise at 50 Hz. These are the important noise components mentioned in the system. The noises are acting as a signal and a combination way. However, these noises ensure that datasets perfectly reflect the real-time clinical scenarios (clinical condition).

3.4 Preparation of dataset

In the dataset preparation stage, a supervised learning method is adopted. Here, each ECG signal noise segment is paired with a clean ECG signal. The input is an ECG noise signal, where the output is a clean ECG segment. The overall dataset is segmented as follows: 70% of the dataset is the training dataset, 15% of the dataset is the validation dataset, and 15% of the dataset is considered as the test set. The purpose of systematic splitting of the dataset is to minimize the overfitting problem and activate the unbiased performance evaluation.

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3.4 ECG signal denoising architecture

In order to perform the ECG signal denoising, there are four models implemented. The important DL models are the denoising encoder (DAE), Long Short-Term Memory (LSTM), the hybrid DAE-LSTM model, which is a proposed approach, and the CNN-BiLSTM model [19]. Each architecture is briefly discussed here.

(a) Denoisng autoencoder

A denoising autoencoder is a DL model that consists of an encoder-decoder architecture. DAE learns a compressed representation of the input signal and effectively reconstructs a denoised output of the given ECG signal. DAE has convolutional layers, and the purpose of the convolution layer is to capture the local features of the ECG waveform. The encoder is known as a learner or compressor used to filter out the signal, which is not a part of the heart rhythm known as noise, and the decoder reconstructs the heart rhythm, which is a desirable ECG signal. The latent stage is shown in Figure 3, which is considered a bottleneck because it abstracts the representation of heart rhythm. The diagram represents the functionality of the denoising encoder technique.

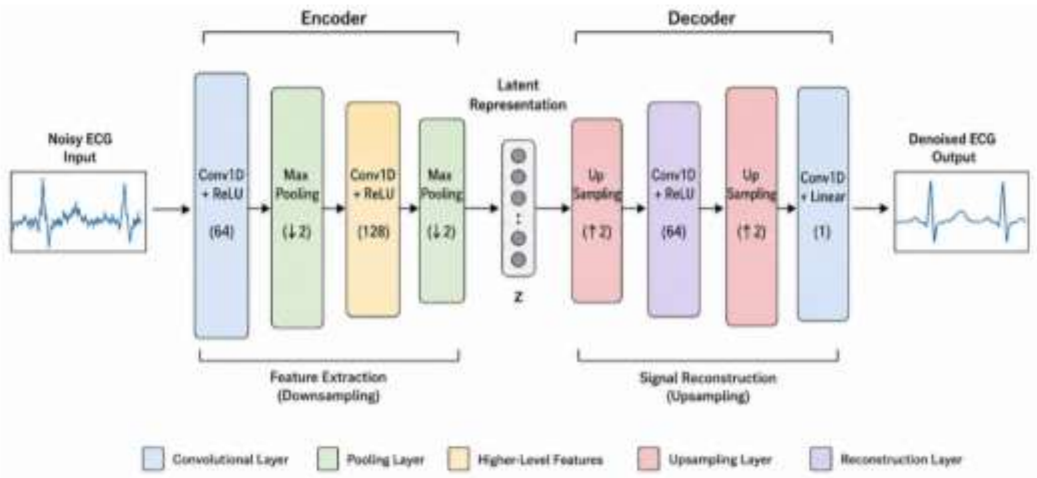

Figure 3.ECG signal denoising by DAE method

(b) Long short-term memory

The purpose of developing an LSTM model is to capture the temporal dependencies in the ECG signal. LSTM [20] works in such a way that it processes sequential data and keeps the long-term information, which is important for retaining the continuity of the signal. The LSTM architecture model is shown in Figure 4.

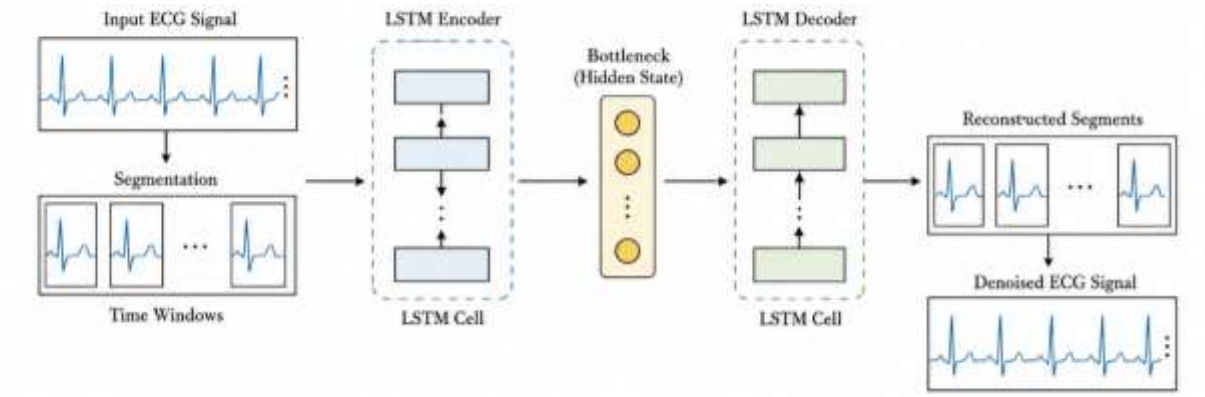

Figure 4.ECG signal denoising by LSTM model

LSTM is derived from the Recurrent Neural Network (RNNs) [21] . It is a specialised model of RNNs designed to model the segmental data by recovering the vanishing gradient issue inherent in the traditional RNNs. LSTM regulates the flow of information, enabling the network to have long-term dependencies and eliminating irrelevant noise. The proposed LSTM architecture captures the temporal morphological pattern and ensures signal continuity across the full cardiac cycle. Both capturing the morphological pattern and maintaining the signal continuity throughout the cardiac cycle are important for feature representation.

(c) Hybrid DAE-LSTM model

The proposed hybrid DAE-LSTM model follows the combined features of the Autoencoder and LSTM model. The function of DAE is to extract spatial features, while LSTM helps to extract the temporal features. The hybrid DAE-LSTM model improves the waveform preservation of the ECG signal with noise suppression. The architecture of the hybrid DAE-LSTM model is shown in Figure 5.

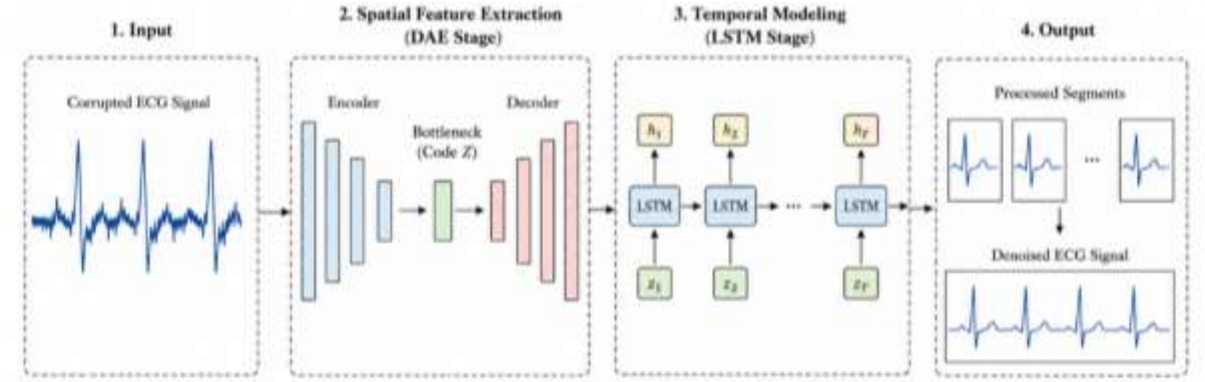

Figure 5.ECG signal denoising by DAE-LSTM model

In the case of a hybrid DAE-LSTM model, DAE removes the spatial noise signal, whereas LSTM tries to make the heart beat pattern consistently and regular over a period of time. Stage 1 is spatial cleaning by DAE, and stage 2 is LSTM for temporal refinement.

(d) CNN-BiLSTM model

In this model, convolutional layers are used for extracting the features. Both the convolutional layer and LSTM are combined to focus on feature extraction of the ECG signal. The BiLSTM function [22] in both directions (to and fro (front and back)) to extract the maximum number of features. The CNN model is computationally efficient to extract the local features such as P-wave, QRS complex and T wave from the raw data provided from the dataset. The ECG signals are in the form of time series data. The feature of ECG is such that the present state depends on previous and future states. The BiLSTM model adds the bidirectional features to the hybrid model. The CNN-BiLSTM model is presented in Figure 6.

3.5 Strategies in Model Training

All the models used in this research are trained by a supervised learning method. The main reason for using supervised learning is to minimize the reconstruction error. The model learns how a noisy ECG signal is converted into a clean ECG signal. The model works to maintain the output as accurately as possible to the clean ECG signal. In order to measure the error, Mean Squared Error (MSE) [23] is used, which comes under the loss function. The MSE can be evaluated using Equation (2)

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(x_{clean,i} - x_{denoised,i}\right)^2 \qquad (2)$$

Equation (1) compares each point of the signal, taking the square difference and taking the average. Better denoising is estimated by checking a lower value of MSE. In equation (2), N represents the number of samples. The leading algorithm used here is Adam. The feature of adam algorithm [24] is adjusting the model step by step, supporting the model to learn quicker and more accurately. For each error adam helps to improve from each mistake. In spite of training on a full dataset, the model learns from 32 samples at a time, which helps with faster computation and stable learning.

3.6 Evaluation of Performance Matrix

The multiple evaluation matrix is used for a reliable and comprehensive assessment of the model. The single matric model is not capable of capturing the quality of the reconstructed ECG signal, such as noise suppression and preservation of morphological features. The multi-metric evaluation strategy includes MSE, signal-to-noise ratio (SNR), Pearson correlation coefficient (PCC), and peak signal-to-noise ratio (PSNR) [25].

(a)Mean Squared Error

The mean squared error (MSE) is defined as the average squared difference between the cleared ECG signal and the denoised ECG signal. The MSE value shows the accuracy of the reconstruction of the signal. The MSE can be estimated using the standard equation shown in (2). If the model is accurate and acceptable, the MSE value will be small.

(b)Signal to Noise Ratio

The signal-to-noise (SNR) is the effectiveness of noise suppression by comparing the power of the clean signal to the power of residual noise. Mathematically, SNR is estimated using equation (3)

$$SNR = 10\ log_{10}\left(\frac{\sum_{i=1}^{N} x_{clean,i}^2}{\sum_{i=1}^{N}(x_{clean,i}-x_{denoised,i})^2}\right) \quad (3)$$

The higher value of SNR indicates better noise removal and the high clarity of the ECG signal.

(c)Pearson Correlation Coefficient

The person correlation coefficient (PCC) [26] indicates the linear correlation between the clean and reconstructed ECG signal , revealing the preservation of the morphology of the waveform. The PCC is estimated using equation (4)

$$\text{PCC} = \frac{\sum_{i=1}^{N}(x_{clean,i}-\mu_{clean,i})(x_{denoised,i}-\mu_{denoised,i})}{\sqrt{\sum_{i=1}^{N}(x_{clean,i}-\mu_{clean})^2\sum_{i=1}^{N}(x_{denoised,i}-\mu_{denoised})^2}} \quad (4)$$

In the equation (4) $\mu_{clean,i}$ denotes the mean value of clean ECG signal., and $\mu_{denoised,i}$ represents the mean value of reconstructed signal. In general, the PCC value ranges from -1 to 1. The desirable value of PCC is closer to 1, which shows strong similarity. The model considered 50 to 100 epochs, where one epoch is nothing but the model seeing the entire dataset at once. In this context, 50 to 100 epochs are considered. In this regard, the model learns multiple times. That is the model practice again and again for the betterment. The model prevents overfitting in such a way that it stops the training at right time to avoid overlearning.

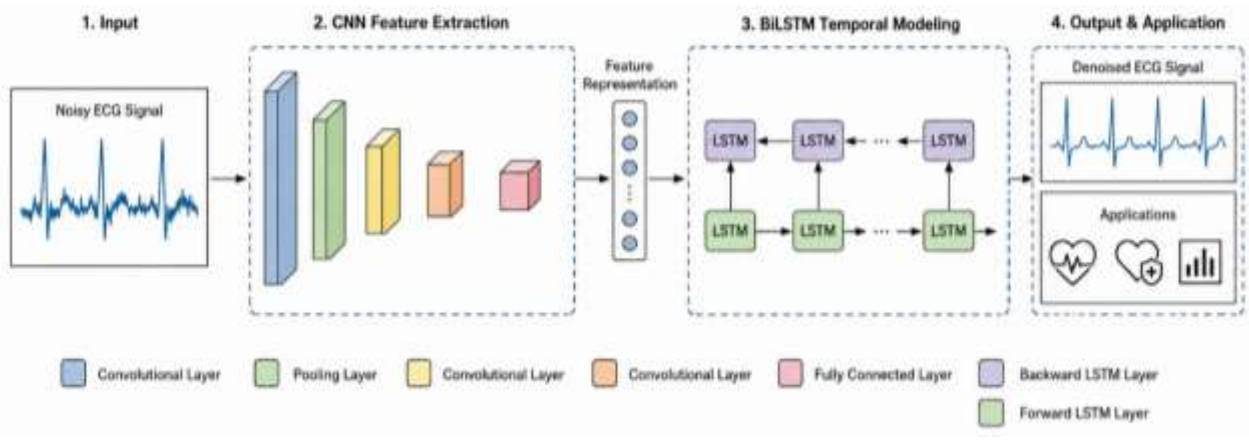

Figure 6.ECG signal denoising by CNN-BiLSTM model

The proposed model uses a two-stage hybrid architecture to restore the features of the ECG signal. In the first stage ,it can be seen that a combined CNN-DAE is developed for extracting the spatial features and eliminating the noise signal . It also ensures maintaining the morphological features of the ECG signal. The proposed hybrid Model is shown in Figure 7.

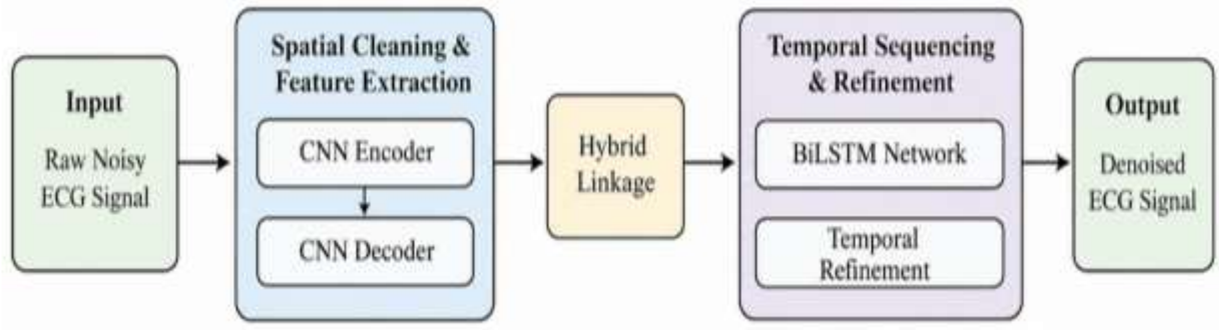

Figure 7.ECG signal denoising by proposed hybrid DL model

In the second stage, a bidirectional long short-term memory network is used and the output of the first stage is passed to the second stage. The second stage acts as a temporal modelling engine, and the signal processing takes place in both forward and reverse directions. This feature ensures maintaining the structured ECG signal output for a long period.

(d)Peak Signal to Noise Ratio

The peak signal-to-noise ratio (PSNR) [27] gives an extra measure of ECG signal quality by comparing the maximum possible signal value to the reconstructed error. PSNR is evaluated using the expression (5)

$$\mathrm{PSNR} = 10\log_{10}\left(\frac{\mathrm{MAX}^2}{\mathrm{MSE}}\right) \tag{5}$$

In equation (5), MAX indicates the maximum possible amplitude of the ECG signal. The PSNR value indicates better reconstruction quality. MSE measures reconstruction error, SNR evaluates noise suppression capability, PCC assesses similarity of the waveform, and PSNR indicates signal quality. In this context, a multi-metric approach is the most effective and reliable assessment method. In this method, integrate real-time noise modelling, a hybrid DL architecture [28] and multimeric evaluation to develop a reliable ECG denoising framework. The proposed hybrid approach overcomes the limitations of the existing method, which improves signal reconstruction under practical and real-time scenarios. In order to test each DL model with real-time noise signals, noise models are developed using equation (6).

$$x_{noisy}(t) = x_{clean}(t) + \sum_{k=1}^{k} n_k(t) \tag{6}$$

In the equation (6), nk(t) represents different noise components.

4. RESULTS AND DISCUSSION

The complete chapter discusses on the artificial noise modelling and simulation first, then the simulation results of hybrid DL denoising model, and performance comparison using multi-matric model. The perfect ECG signal free from noise is illustrated in Figure 7.

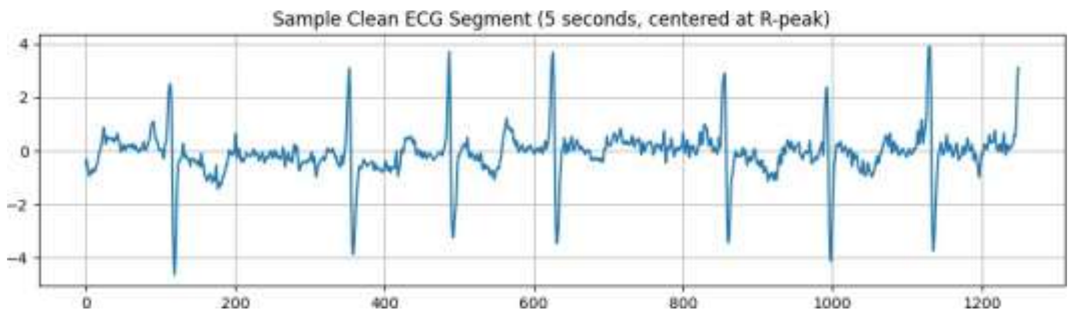

Figure 7. Standard ECG signal free from noise signal

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4.1 Simulation of noise signals

In order to verify the performance of the DL ECG denoising model, realistic noise models are generated. The generated noise signals are passed through the DL denoising models are evaluated the multi metric parameters. Initially, artificial noise signals are generated with a standard specification. Initially, the Gaussian noise model is developed and the waveform of Gaussian noise model is shown in Figure 8.

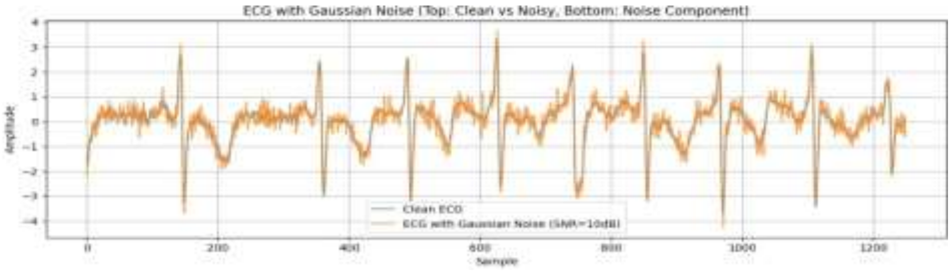

Figure 8.ECG signal with Gaussian noise

The diagram shown in Figure 7 represents the addition of Gaussian noise to the ECG signal. The Gaussian noise, which is commonly known as a random electrical noise signal, has a constant power spectral density. It follows a normal distribution of probability. Basically, a Gaussian noise signal is the typical representation of a thermal noise signal. Once the ECG signal denoising technique is applied, the separated Gaussian noise signals are shown in Figure 9.

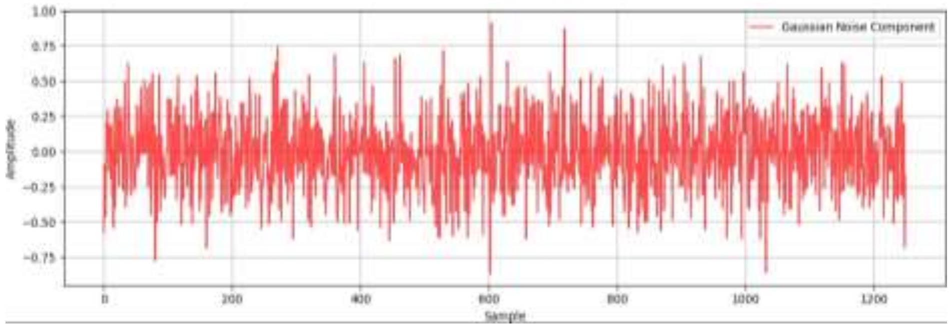

Figure 9. Gaussian noise signal

The following situations, such as movement during respiration, patient movement, poor connection of electrodes in the human body, and changes in the electrode impedance, are denoted using a low-frequency sinusoidal waveform, which is known as baseline wander. The respiratory motion of humans is a reason for baseline wander noise shown in Figure 10.

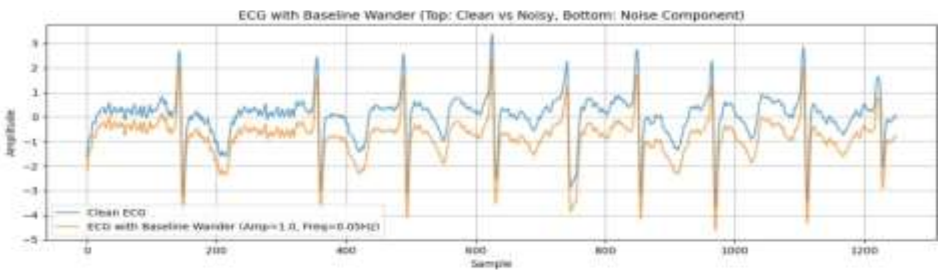

Figure 10. ECG signal with base line wander noise

The baseline wander is a sinusoidal function, which is presented in equation (7) for better clarification.

$$BW(t) = Asin(2\pi ft + \emptyset) \tag{7}$$

In equation (7), A represents the amplitude, f is the low frequency component, and is the phase angle in radians. The baseline wander component can be observed in Figure 11. The amplitude A denotes the drift magnitude.

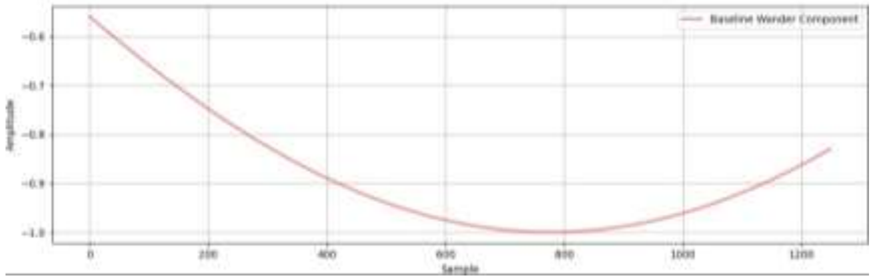

Figure 11. ECG signal with base line wander noise

The frequent muscle contraction leads to the electromyographic noise (EMG). The sources of EMG are shivering, muscle tension, and slight movement. The nature of EMG is irregular and spiky. The simulated diagram of EMG superimposed with the original ECG signal is shown in Figure 12.

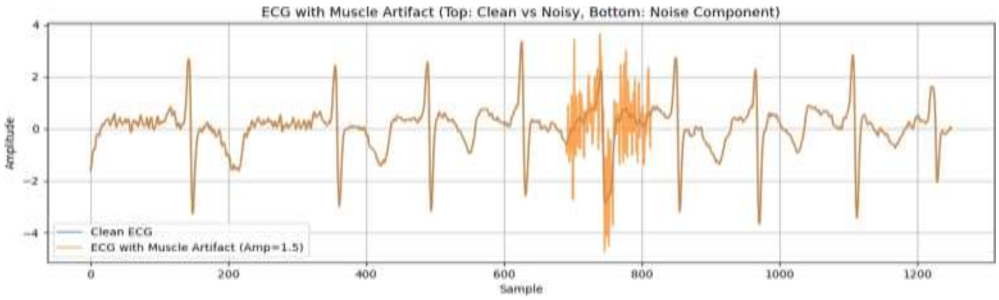

Figure 12. ECG signal with EMG noise signal

The following simulation approach is carried out for EMG noise signal [29] generation: generating white noise, bandpass filtering, and applying a short burst across the signal. The EMG noise component is shown in Figure 13.

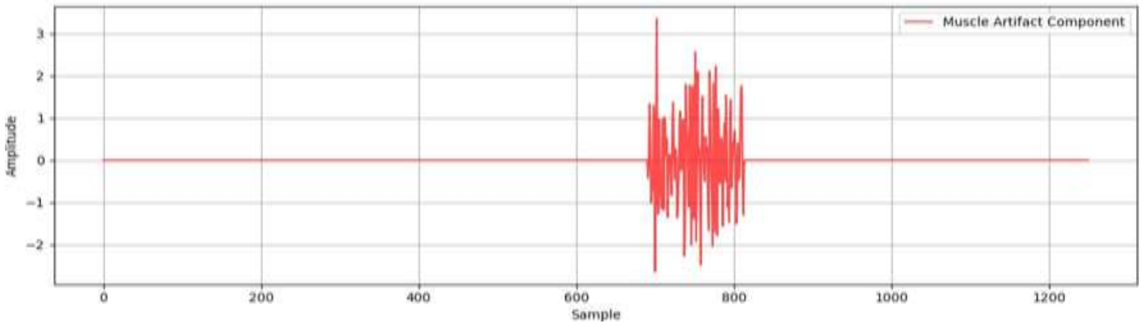

Figure 13. Simulated EMG noise signal

The electrode motion artefacts are a type of noise source that occurs whenever there is a movement of skin and electrode, resulting in variation in the skin-electrode impedance. As a result of this noise, a sudden irregular transient spike is generated. This noise signal is similar to the T-wave and QRS complex, as the reader falls into confusion. The electrode motion artefacts are presented in Figure 14.

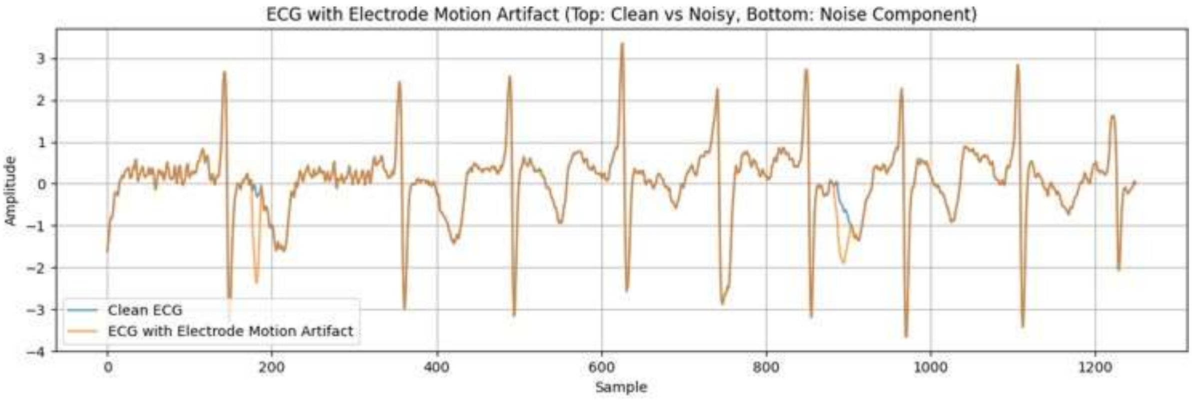

Figure 14. Simulated EMG noise signal superimposed wit ECG signal

In order to generate the EMG noise signal, the following algorithm is used: Initially, select the signal location randomly, secondly add the large amplitude disturbances and finally distort the waveform locally. The EMG noise signal is presented in Figure 15.

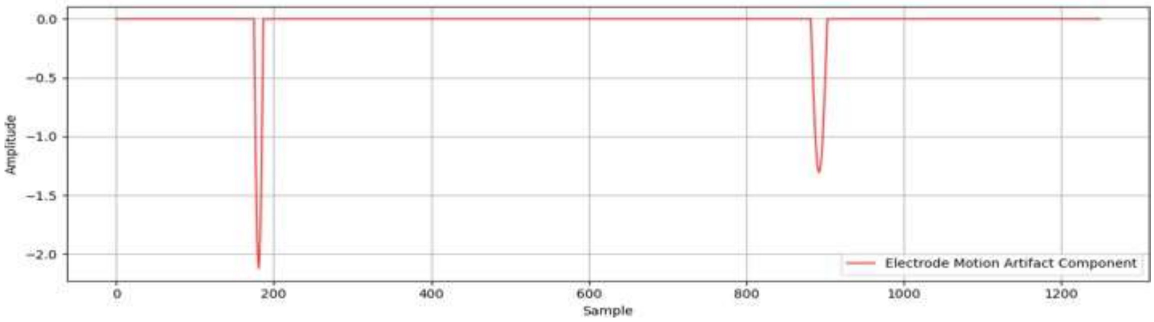

Figure 15. Simulated EMG noise signal

The power line interference is caused by the electromagnetic fields generated from the AC power supplies, which cross-talk with the ECG signals. In this case, a low-frequency sinusoidal signal is superimposed on the ECG signal, which can distort the ECG signal harmfully. Ultimately, the observer faces difficulty in identifying the P, QRS, and T wave patterns of the ECG signal. The superimposed power line signal with the ECG signal is simulated as shown in Figure 16.

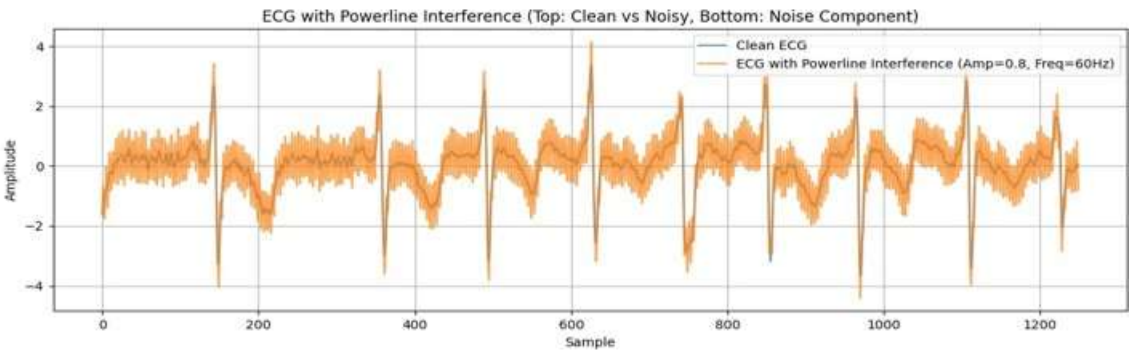

Figure 16. Simulation of ECG signal interference with power line

The typical frequencies included are 50 Hz and 60 Hz. In India, the supply frequency is 50 Hz, and in the USA, the supply frequency is considered 60 Hz. The power line interference results from electromagnetic coupling with power systems. The powerline interference component is shown in Figure 17.

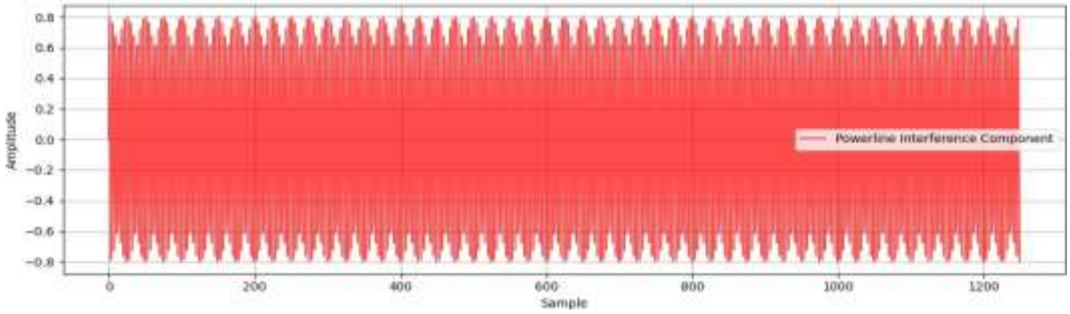

Figure 17. Simulation of Powerline interference component

In order to have a realistic noise experience, all the noise types are combined. The MIT-BIH Noise Stress Test Database (NSTDB) [30] is a valuable source to combine all the types of noise. The command used for combining all the noise signals is add_nstdb_like_noise(). The noise components included are Gaussian noise, baseline wander, muscle artifacts, electrode motion artifacts, and power line interference. The noisy dataset is generated as x_noisy, which is presented in Figure 18 and 19. The reason for using a combined noise signal is that it gives a realistic situation. In a real-time situation, the generation of a noise signal is highly unpredictable. Also, there are fewer chances of the generation of individual types of noise signals. Instead of generating individual noise signals, combined noise signals are usually generated.

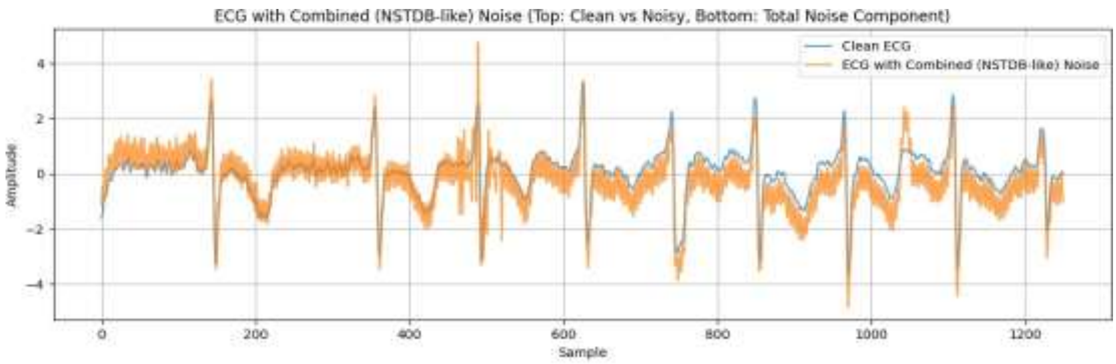

Figure 18. Simulation of ECG signal with combined noise signal

In Figure 18, the superimposition of the ECG signal with all the combination noise signals is included. The separate combination of noise signals is presented in Figure 19, which helps to understand the pattern of the combined noise signal.

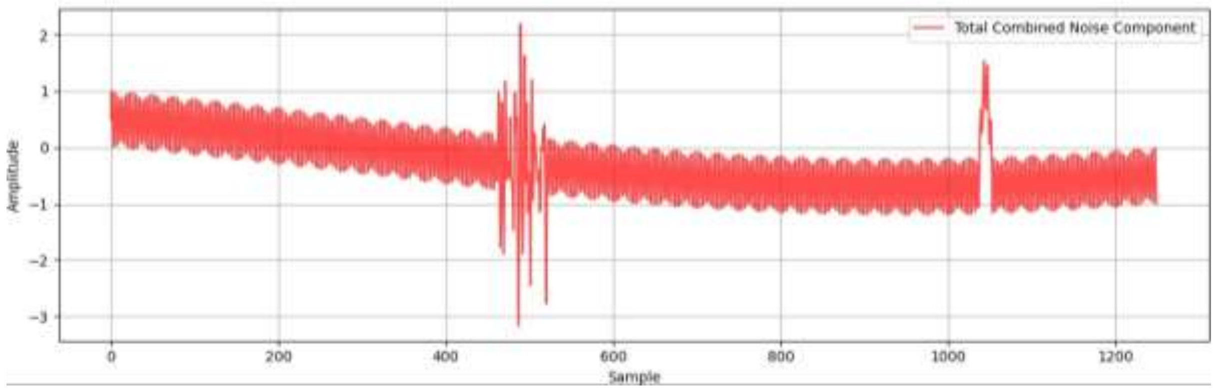

Figure 19. Simulation of noise signal

While preparing the dataset, the noisy dataset is paired with the clean dataset. The data set is prepared such that x_noisy is given as the input, x_clean is given as the target. The 80% of the data set is used for model training, 10% of the data set is used for hyperparameter tuning, and 10% of the data set is dedicated to performance evaluation. After the fine-tuning, the combined ECG and noise signals are shown in Figure 20.

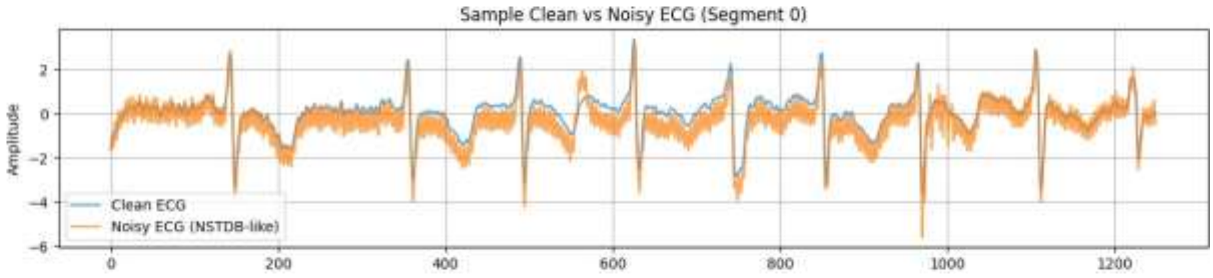

Figure 20. Simulation of combined ECG signal and noise signal after fine tuning

In Figure 19, the noise signals are separated and analysed separately. The combined noise signals are presented in the given pattern as shown in Figure 21.

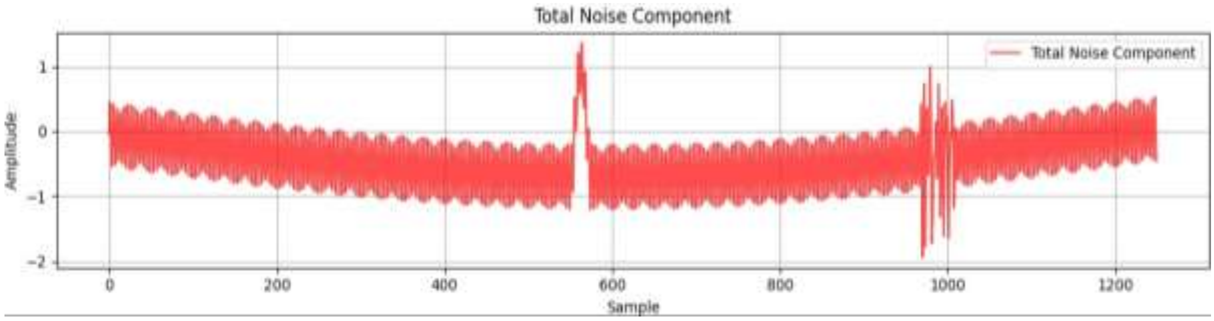

Figure 21. Simulation of noise signal after fine tuning

4.2 Simulation of DL denoising model

The denoising autoencoder (DAE) is a kind of neural network that is used to learn to reconstruct a clean input from the corrupted, noisy input from the ECG-generating devices. A proper training is given to the model for the reconstruction of the original signal from the corrupted signal. The encoder used in DAE compresses the input into a low-dimensional representation, and the decoder reconstructs the output from the representation. While observing the architecture, Conv1D is converted into MaxPool, Upsampling is converted into Conv1D, and finally, the required output is obtained in the output layer.The total parameter taken is 7905, and the same quantity is considered as trainable parameters, and the size is considered as 30.88 kB. The DAE training history details are presented in Figure 22. It is found that after 10 to 15 epochs, the losses reduce and the model attains more stability. As a result, the model achieves good convergence with minimal overfitting.

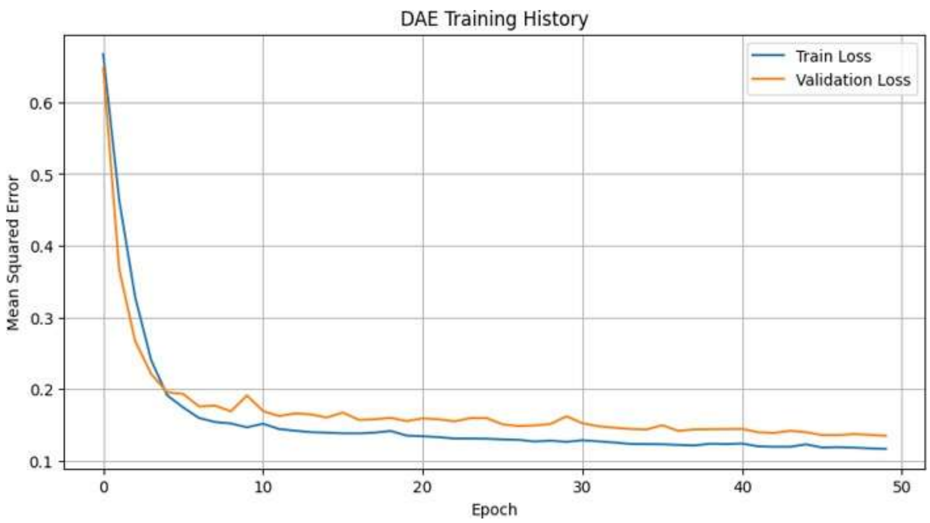

Figure 22. Simulation of DAE training history

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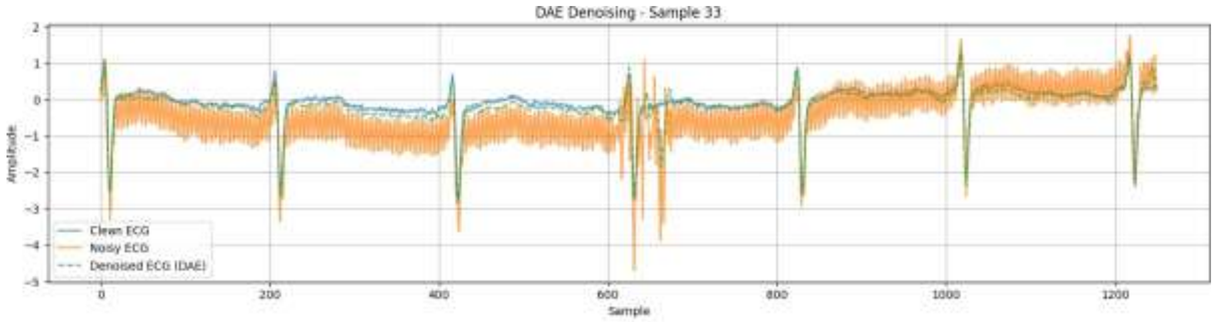
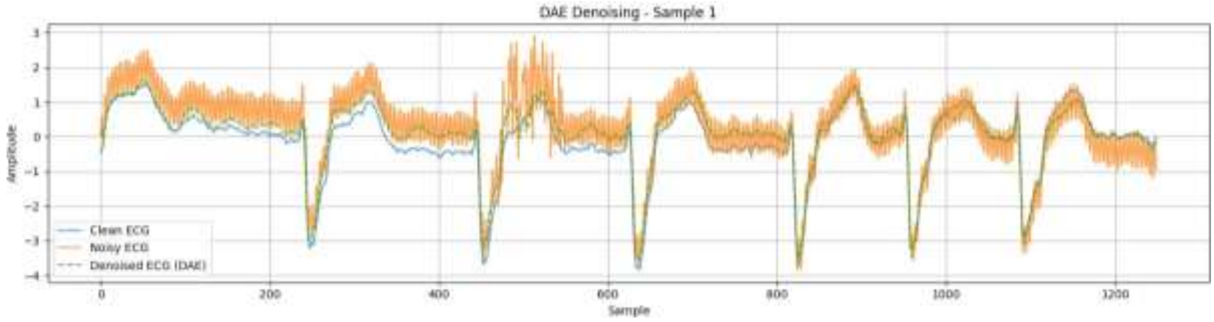
eISSN: 2583-1194

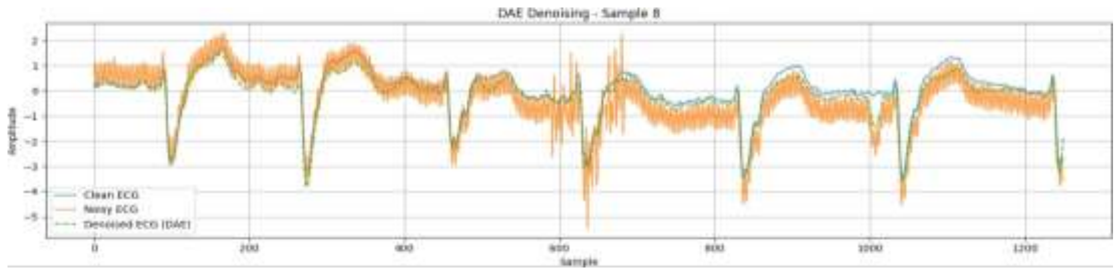
The visualization of the denoising results in different samples is shown in Figure 23 (a), 23 (b), and 23 (c), respectively.



(a)



(b)



(c)

Figure 23. DAE denoising (a) for sample 33(b)sample 1, and (c) sample 8

In all the sample waveforms, it is observed that DAE can preserve all the important morphological features, especially the QRS complex. Also, the DAE model is capable of reducing the noise signal and reconstructing the ECG signal for the analysis. LSTM is another model, which is a form of recurrent neural network (RNN) capable of learning order dependence in sequence prediction problems. LSTM is particularly well-suited for time-series data like ECG signals because it can maintain information in memory for the long term, which is crucial for capturing temporal dependencies in the waveform. The total parameter considered is 29,345 with the memory size of 114.63 KB. Even 29,345 trainable parameters are considered. The LSTM training history is shown in Figure 24. In the Figure 24, It is observed that LSTM training history indicates that gradual convergence with closely aligned training and validation losses.

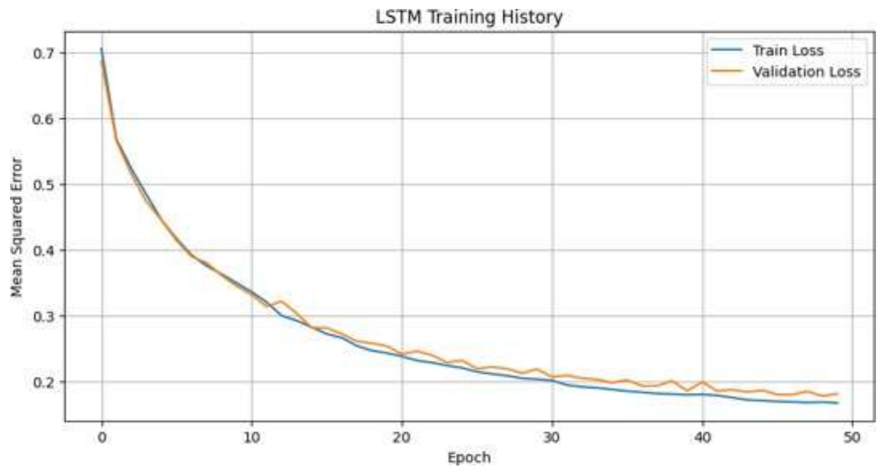
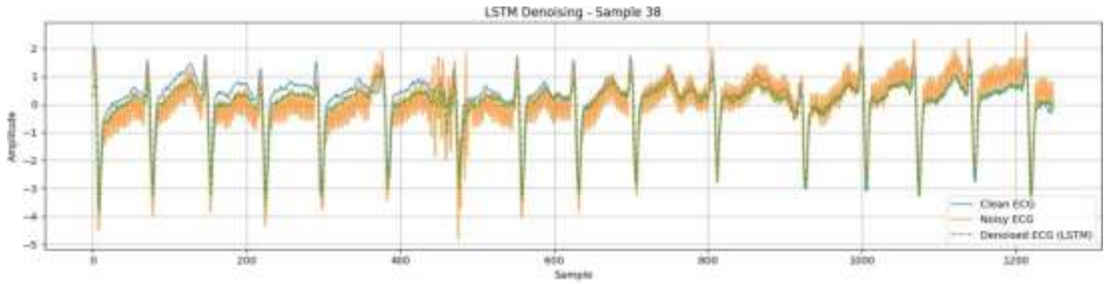
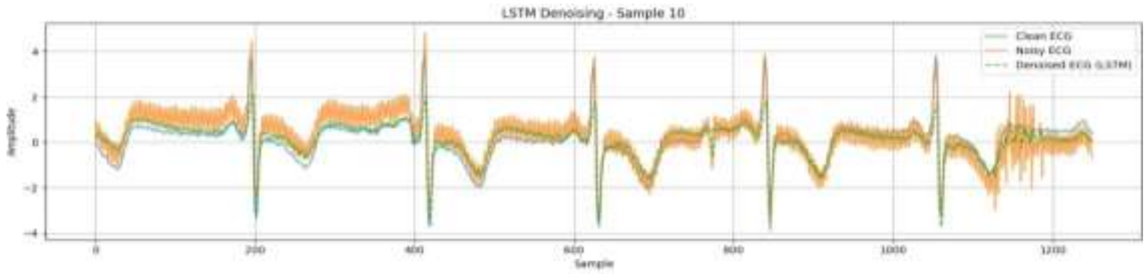


Figure 24. Simulation of LSTM training history

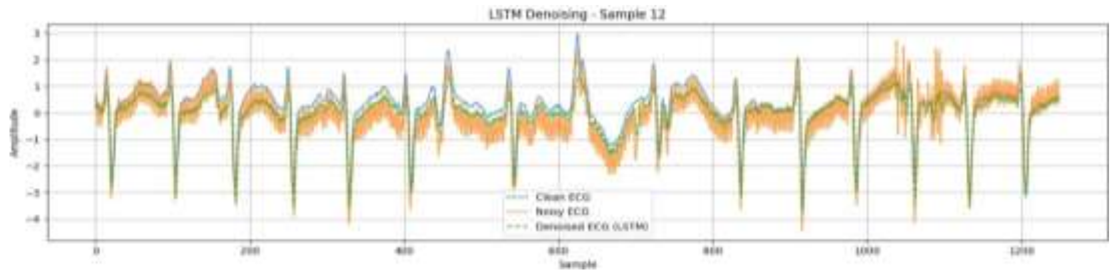
It indicates that LSTM shows reduced overfitting with stable learning pattern. The denoising performance at each sample are shown in Figure 25 (a), (b), and (c).



(a)



(b)



(c)

Figure 25. LSTM denoising performance for (a) sample 38, (b) sample 10 and, (c) sample 12

Figure 25 (a), (b), and (c) clearly depict that LSTM effectively supports ECG signal denoising and is able to reconstruct a clean ECG signal while maintaining all important features. This observation is applicable to all the simulated samples. In order to improve the performance, both the DAE and LSTM models are combined, and their performance is simulated. The total parameters are considered to be 105,617 with 412.57 KB memory size. The main feature of the DAE-LSTM model is that the gap between training and validation loss is minimal. Another feature of the model is the steady loss reduction and better convergence, which is presented in Figure 26.

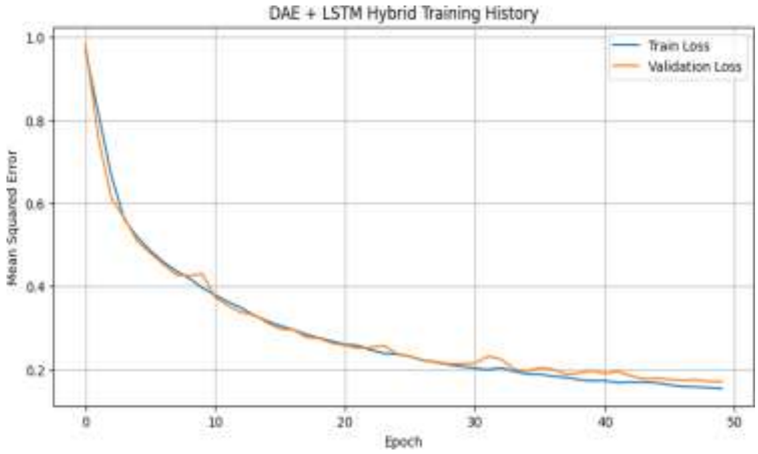
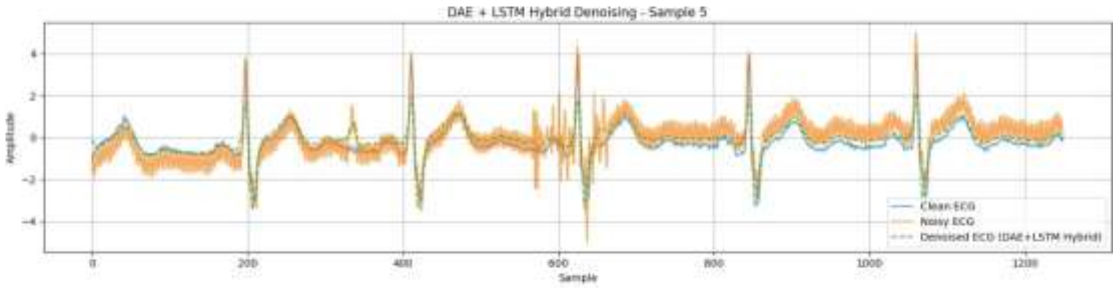
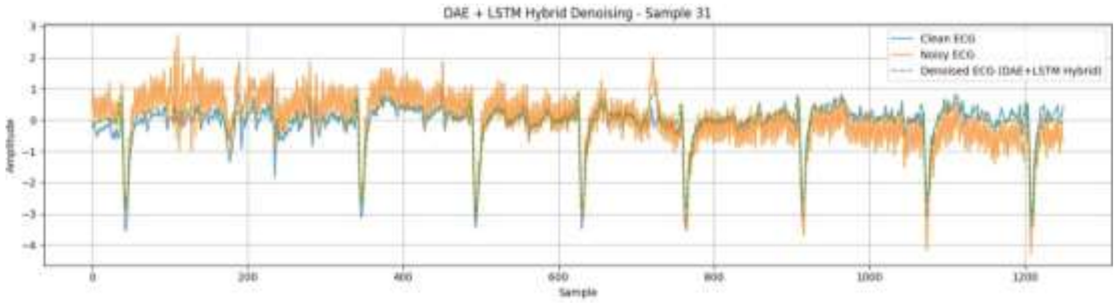


Figure 26. Simulation of hybrid DAE-LSTM model

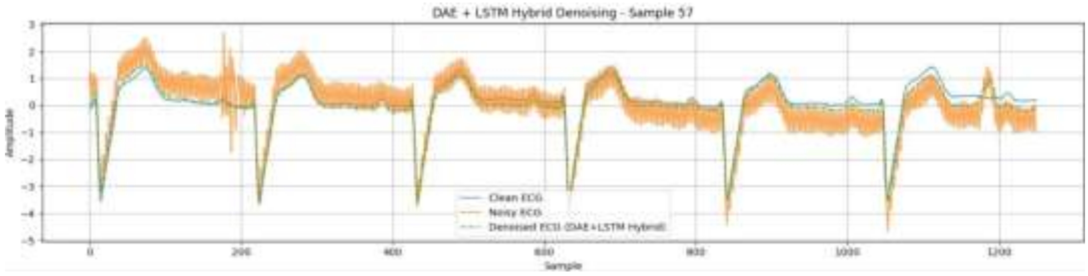
The denoising performance of the hybrid DAE-LSTM model is shown in Figure 27. The superior performance of the DAE-LSTM model can be observed from each sample shown in Figure 27 (a), (b), and (c).



(a)



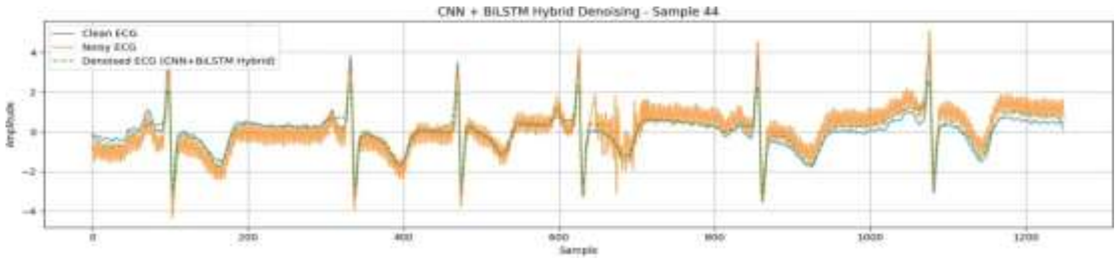
(b)



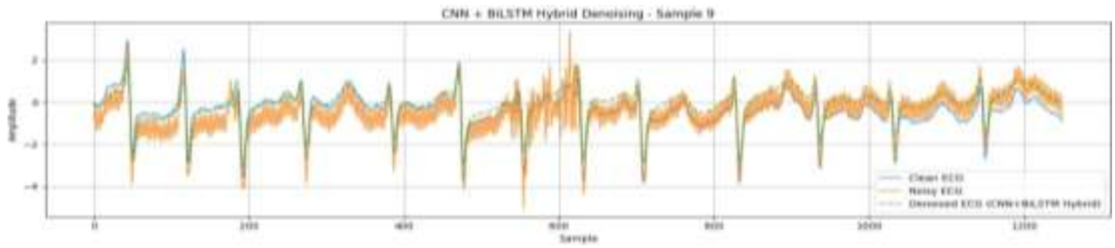
(c)

Figure 27. DAE-LSTM denoising performance for (a) sample 5, (b) sample 31 and, (c) sample 57

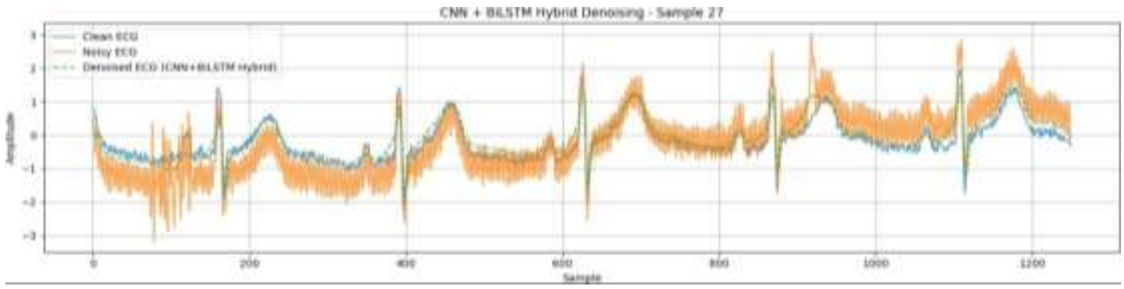
The Hybrid CNN + BiLSTM model is considered another model in this research. The total parameters used for the model development are 32,097, with the memory size of 125.38 kb. The denoising and signal reconstruction features at different samples are shown in Figure 28 (a), (b), and (c).



(a)



(b)



(c)

Figure 28. Hybrid CNN + BiLSTM denoisng performance for (a) sample 44, (b)sample 9, and (c)sample 27

The CNN + BiLSTM hybrid model [31] shows reduced error value and smooth convergence of the model. It is observed that a drastic reduction of both training and validation loss over epochs presents temporal modelling and efficient feature learning. In this model, overall overfitting is minimal and minor fluctuations indicate stable performance of the hybrid model. The performance of the CNN + BiLSTM hybrid model is shown in Figure 29.

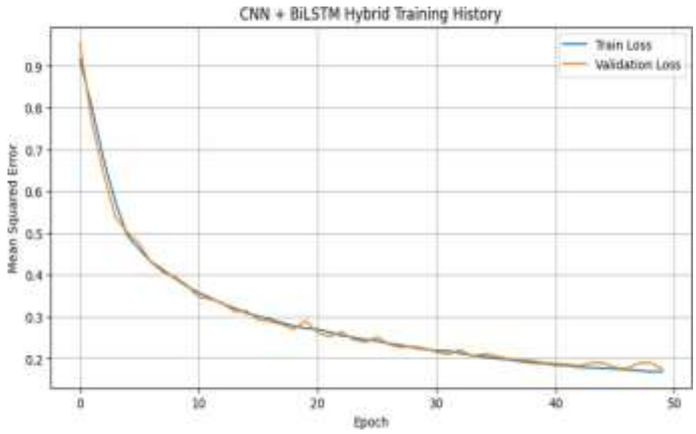


Figure 29. Simulation of CNN-BiLSTM training history

4.3. Performance evaluation of models

The performance of important DL models is evaluated using multimeric parameters. The evaluated performance parameters are tabulated in Table 1.

Table I. Performance evaluation of DL model

Sl. No	Name of the DL model	MSE	SNR (dB)	PCC	PSNR (dB)
1	DAE	0.1099	8.57	0.9220	20.69
2	LSTM	0.1482	8.19	0.9057	20.31
3	DAE + LSTM	0.1391	10.42	0.9408	22.54
4	CNN + BiLSTM	0.1444	9.91	0.9328	22.02

Table I presents the performance evaluation of the DL model using the multi-metric parameters such as MSE, SNR, PCC, and PSNR. It is observed that among the four DL models, the hybrid DAE and LSTM model outperforms the other DL models. The hybrid DAE-LSTM model shows the performance with the highest SNR (10.42 dB), PSNR (22.54 dB), and PCC (0.9408), showing superior noise minimization and signal reconstruction capability. Another observation made on the DAE model regarding its least MSE value, but the performance with respect to SNR, PCC and PSNR is lower. The hybrid CNN + BiLSTM model shows a consistent performance with respect to all parameters. The all-together hybrid model performs superior compared to the individual model in terms of spatial and temporal features. However, among all four models, the hybrid DAE + LSTM model shows superior performance in terms of ECG signal denoising and signal reconstruction features. The performance comparison of the DL model is graphically represented in Figure 30.

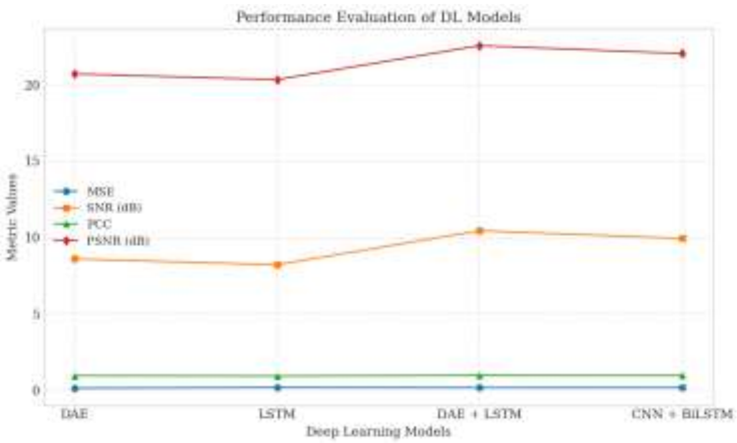


Figure 30. Performance evaluation of DL model

The hybrid CNN and BiLSTM model shows competitive performance in terms of performance parameters. However, the hybrid DAE-LSTM model shows superiority over the CNN and BiLSTM models.

5. CONCLUSION

This research presents a hybrid DL model which performs ECG signal denoising and reconstruction of the original ECG signal for real-time biomedical conditions. There are four DL models developed in this work, among which two models follow a hybrid approach. The important DL models used in this research are DAE, LSTM, hybrid DAE-LSTM, and hybrid CNN-BiLSTM. In order to test the model in realistic conditions, artificial noise models are implemented, such as Gaussian noise, baseline wander, muscle artifacts, electrode motion, and powerline interference. The simulation results show that the DAE model performs well with respect to MSE, whereas the hybrid DAE-LSTM model outperforms in the case of SNR, PCC and PSNR. The simulation result clearly shows that hybrid models are well-suited for ECG signal denoising and original reconstruction of the ECG signal without losing any features. The DAE-LSTM model shows superior performance in terms of the following numerical results: signal-to-noise ratio of 10.42 dB, peak signal-to-noise ratio of 22.54 dB, and Pearson correlation coefficient of 0.9408. The results illustrate that the hybrid models are well-suited for the clinical conditions. Also, these hybrid models can be inculcated into the smart wearable cardiac monitoring systems.

ACKNOWLEDGEMENTS

The authors sincerely acknowledge the support and encouragement received from the Principal, Management, faculty members, and colleagues of Vivekananda Institute of Technology – Research Centre, Bengaluru, for providing the necessary facilities and a supportive environment to carry out this research work. The authors express their sincere gratitude to Visvesvaraya Technological University (VTU), Bengaluru, for providing the academic platform and research opportunities that supported the successful completion of this work. The authors also acknowledge the valuable guidance, discussions, and support received throughout the course of this research, which greatly contributed to the successful completion of the work.

AUTHOR CONTRIBUTIONS

Nadeem Pasha: Conceptualization, Investigation, Methodology, Laboratory Analysis.

K M Ravikumar: Data Curation, Formal Analysis, Supervision, Writing—Review & Editing.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

ETHICS STATEMENT

Ethical approval was not required for this study.

DATA AVAILABILITY STATEMENT

Data supporting the findings of this study are available from the corresponding author upon reasonable request.

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