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Deep Learning Autoencoder Study on ECG Signals

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A B S T R A C T

Arrhythmia refers to an irregular heart rhythm resulting from disruptions in the heart's electrical activity. To identify arrhythmias, an electrocardiogram (ECG) is commonly employed, as it can record the heart's electrical signals. However, ECGs may encounter interference from sources like electromagnetic waves and electrode motion. Several researchers have investigated the denoising of electrocardiogram signals for arrhythmia detection using deep autoencoder models. Unfortunately, these studies have yielded suboptimal results, indicated by low Signal-to-Noise Ratio (SNR) values and relatively large Root Mean Square Error (RMSE). This study addresses these limitations by proposing the utilization of a Deep LSTM Autoencoder to effectively denoise ECG signals for arrhythmia detection. The model's denoising performance is evaluated based on achieved SNR and RMSE values. The results of the denoising evaluations using the Deep LSTM Autoencoder on the AFDB dataset show SNR and RMSE values of 56.16 and 0.00037, respectively. Meanwhile, for the MITDB dataset, the corresponding values are 65.22 and 0.00018. These findings demonstrate significant improvement compared to previous research. However, it's important to note a limitation in this study—the restricted availability of arrhythmia datasets from MITDB and AFDB. Future researchers are encouraged to explore and acquire a more extensive collection of arrhythmia data to further enhance denoising performance.

INTRODUCTION

Cardiovascular disease, identified by the World Health Organization (WHO) as the leading global cause of death [1], has been a significant contributor to high mortality rates in China, as reported by Liu, et al. [2] in early 2022. A critical aspect of cardiovascular issues is arrhythmia, a condition marked by irregularities in the heart's rhythm, involving disturbances in the frequency, regulation, and origin of its electrical impulses [3]. Arrhythmias, including more severe forms like Atrial Fibrillation (AF), can significantly contribute to the progression of heart disease. Atrial fibrillation (AF) is identified as the most prevalent clinical arrhythmia, carrying substantial risks to patient health and markedly increasing morbidity, mortality, and healthcare costs [4]. The main signal utilized for examining arrhythmias is the electrocardiogram (ECG) signal.

The main method in medical practice for evaluating the electrical activity of the human heart is through the recording and analysis of the Electrocardiogram (ECG) signal [4, 5]. The identification of morphological changes in ECG signals serves as a crucial tool for doctors in detecting and predicting heart diseases, including arrhythmias. Arrhythmia, the most prevalent heart rhythm disorder, is identifiable by observing deviations in the ECG signal. Even minor alterations in the ECG pattern possess the potential to instigate cardiac arrhythmias, leading to fluctuations in heart rate and disruptions in heart muscle conduction. Clinically, symptoms of arrhythmia manifest as chest pain, fatigue, and instances of patient loss of consciousness [6]. Cardiac arrhythmias encompass various types, with some posing life-threatening risks, while others are less severe but still necessitate comprehensive analysis to avert potential clinical complications [7].

ECG signals are highly susceptible to noise, and the accuracy of arrhythmia analysis is compromised when noise is present [8, 9]. Numerous studies [9-12] have explored the use of deep autoencoder-based ECG signal denoising to enhance arrhythmia detection, but they face challenges, and the obtained results often fall short of optimal. This is evident through low Signal-to-Noise Ratio (SNR) and Root Mean Square Error (RMSE) values. SNR serves as a metric comparing the quality of the desired signal to the existing noise [11]. In the context of ECG signal denoising for arrhythmia detection, a high SNR indicates that the ECG signal reconstructed by the Deep Autoencoder exhibits high clarity and accuracy with minimal noise. This clarity is crucial for ensuring that the analyzed ECG signals for arrhythmia detection are easily

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interpretable and provide precise diagnostic information. Conversely, a low RMSE signifies that the Deep Autoencoder model effectively removes noise and variability, resulting in a reconstructed signal that closely aligns with the original signal with minimal error [8]. The pursuit of optimal SNR and RMSE values involves experiments with various Deep Autoencoder configurations, including the exploration of the number of layers, the number of units in each layer, and different training methods in those studies.

Numerous researchers, including Chiang, et al. [11], Singh and Sharma [9], have delved into autoencoder denoising applied to arrhythmia signals. Chiang, et al. [11] specifically explored the efficacy of a Fully Connected Network (FCN) in detecting arrhythmia signals, noting a remarkable improvement of 31.83% in SNR_{imp} and a significant relative reduction in RMSE by 32.98% when compared to alternative models like DNN and CNN. Similarly, Singh and Sharma [9] developed a model surpassing prior efforts, achieving an average SNR improvement of 19.07 ± 1.67 and PRD of 11.0% at 0-dB SNR. Their models exhibited robust classification performance, validated through a five-fold cross-validation strategy. Deevi, et al. [12] achieved noteworthy results in their denoising research, obtaining SNR values of 22.4501%, 13.8266%, and 17.0403%, with the highest accuracy reaching 99.53%. Hou, et al. [8] applied a denoising autoencoder to an arrhythmia dataset, resulting in a substantial increase in SNR by 88.57%. Meanwhile, Shi, et al. [13] contributed to the field by conducting research on arrhythmia classification using a denoising autoencoder, achieving an average SNR of 17.48dB. These collective findings showcase advancements in autoencoder-based denoising techniques for improving the analysis and detection of arrhythmia signals.

This study aims to overcome the limitations observed in previous research, specifically targeting suboptimal denoising performance characterized by low Signal-to-Noise Ratio (SNR) levels and large Root Mean Square Error (RMSE) values. To tackle this challenge more effectively, the research proposes a study that combines deep learning techniques with signal processing methods. The overarching goal is to enhance denoising performance, evident through increased SNR and decreased RMSE values. The research focuses on developing a layer-denoising autoencoder model for the denoising of ECG signals, utilizing the Deep LSTM Autoencoder. The performance of this model in detecting ECG signals will be rigorously compared with the work conducted by Marwan, et al. [14], with a specific emphasis on evaluating SNR and RMSE metrics. Through this comparative analysis, the study aims to demonstrate the effectiveness of the proposed approach in achieving superior denoising results, thereby contributing to advancements in signal processing for ECG analysis.

METHODOLOGY

Marwan, et al. [14] employed single and double hidden layer autoencoder methods to denoise ECG signals. However, these methods exhibited limitations as the achieved SNR and RMSE results were not notably high. To tackle this issue, our research aims to enhance SNR and RMSE outcomes by integrating a deep-learning autoencoder algorithm.

Materials

Data Sources

The ECG data utilized in this study originate from the MIT-BIH Atrial Fibrillation Database (AFDB), detailed in [6, 15, 16] and the MIT-BIH Arrhythmia Database (MITDB) discussed in research [17-19] . The MITDB database serves as a reference for arrhythmias, while the AFDB database is specifically a reference for Atrial Fibrillation (AF). Notably, two datasets in AFDB, i.e, data 00735 and 03665, will be excluded from our research due to being empty datasets, as noted by [4, 20].

Hyperparameter For Experiments

Hyperparameters are critical parameters influencing the outcomes of model training. These parameters encompass the number of epochs, batch size, and window size. Table 1, Hyperparameters, outlines the specific hyperparameters employed in training the model for this research, aligning with the explanations provided by Marwan, et al. [14]. Table 1 shows the hyperparameters used for training the models.

Table 1. Hyperparameters Used for Training the Models

Parameter	MITDB	AFDB
Epoch	100	100
Batch Size	128	128
Window Size	1	1
Optimizer	Adam	Adam
K-Fold	5	5
EarlyStopping	10	10

Metrics

The evaluation metrics applied to assess the proposed algorithm's performance in this research are consistent with those employed by Hou, et al. [8]. The evaluation metrics considers two main aspects: reconstruction quality and compression efficiency, gauged through various metrics. Key performance criteria are defined by SNR and RMSE [13]. Furthermore, equations (1) and (2) present the formulas for both SNR and RMSE:

$$SNR = 10 \times lg \frac{\sum_{i=1}^{n}(D_0(i) - D_\mathrm{m})^2}{\sum_{i=1}^{n}(D_0(i) - D_\mathrm{r}(i))^2} \quad (1)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(D_0(i) - D_\mathrm{r}(i))^2}{L}} \quad (2)$$

In this context, let the original signal be denoted as Do, the reconstructed signal as Dr, and the average value of the original signal as Dm, with the signal length represented by L. Root mean square (RMS) serves as a metric quantifying the disparity between the original signal and its reconstructed counterpart. Additionally, the SNR is employed to assess the relative magnitude of the true signal against the background noise [13].

Deep Learning Autoencoder Process Flow

The method used in this research is shown in Figure 1.

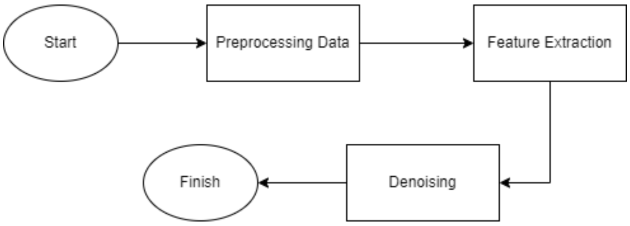

Figure 1. Deep Learning Methods

As shown in Figure 1., the method begins with preprocessing. Preprocessing is a stage to denoise character images from noise, allowing them to be effectively used in the feature extraction phase as explained in [21]. Feature extraction is the stage of data analysis used to determine the characteristics of arrhythmia diseases. The data extraction method utilized in this study is morphology-based feature extraction as in Bahri, et al. [22]. Last but not least, the final stage of the method is denoising. Denoising is a technique used to reduce noise in ECG signals [23]. The parameter used in this research utilizes a Deep LSTM Autoencoder algorithm.

RESULTS AND DISCUSSION

Here are the results of denoising analysis using deep LSTM autoencoder to achieve the best results considering SNR and RMSE values.

Atrial Fibrillation Database (AFDB)

The denoising performance results, assessed through both SNR and RMSE using the Deep LSTM Autoencoder for ECG signals from the AFDB database, are detailed in Table 2. These results encompass all records, excluding record numbers 00735 and 03665.

Table 2. AFDB SNR and RMSE values

K-Fold	SNR	RMSE
1	50.06	0.00073
2	**56.16**	**0.00037**
3	54.50	0.00044
4	54.66	0.00044
5	54.24	0.00045

As shown from Table 2, this study validated the denoised ECG signal through k-fold validation spanning folds 1 to 5. The SNR and RMSE values for each fold are presented in the table. In the first fold, the SNR value is 50.06, and the RMSE value is 0.00073, with the initial termination occurring at epoch 16. The second fold yields an SNR value of 56.15 and an RMSE value of 0.00037, with the initial termination occurring at epoch 15. The third fold results in an SNR value of 54.50 and an RMSE value of 0.00044, with an early stop at epoch 27. The fourth fold produces an SNR value of 54.66 and an RMSE value of 0.00044, with an early stop at epoch 16. Lastly, the fifth fold generates an SNR value of 54.24 and an RMSE value of 0.00045, with an early stop at epoch 34. From these outcomes, it is evident that the most favorable SNR and RMSE values were achieved in the second fold, with an SNR of 56.16 and an RMSE of 0.00037.

Figures 2 to 7 provide a visual representation, featuring snapshots of the original ECG signals juxtaposed with the corresponding denoising outcomes for AFDB record signals numbered 00735 across fold 1 until fold 5.

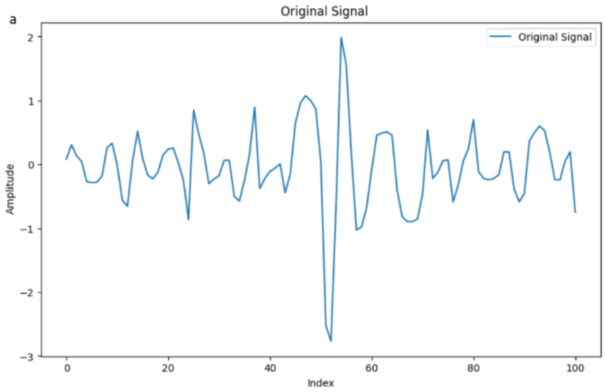

Figure 2. A Snapshot of Original ECG Signal from record number 00735

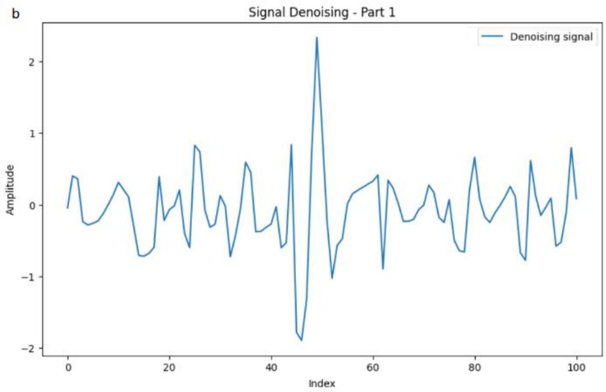

Figure 3. Result of Denoising Signal from record number 00735 at Fold 1

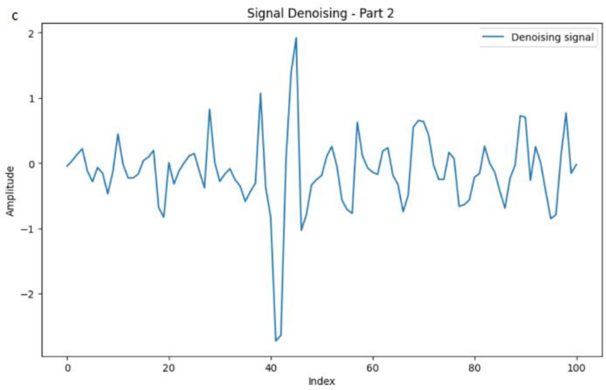

Figure 4. Result of Denoising Signal from record number 00735 at Fold 2

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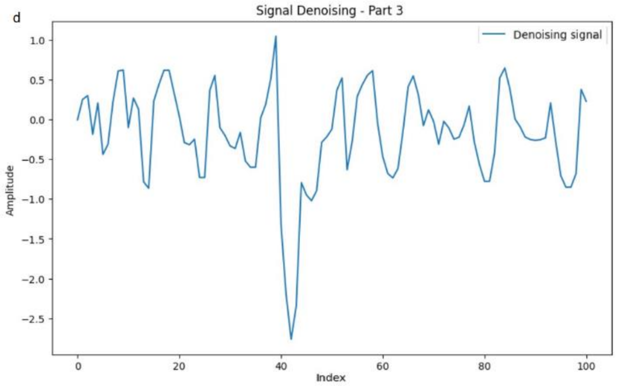

Figure 5. Result of Denoising Signal from record number 00735 at Fold 3

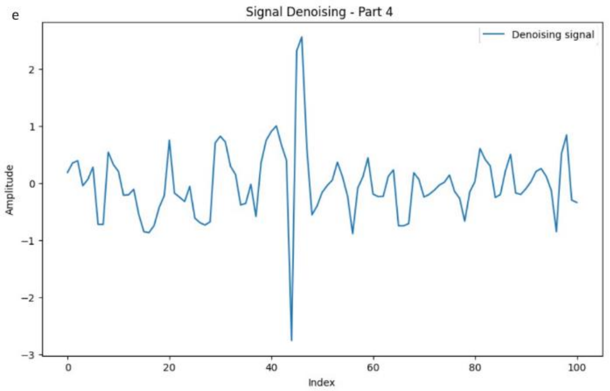

Figure 6. Result of Denoising Signal from record number 00735 at Fold 4

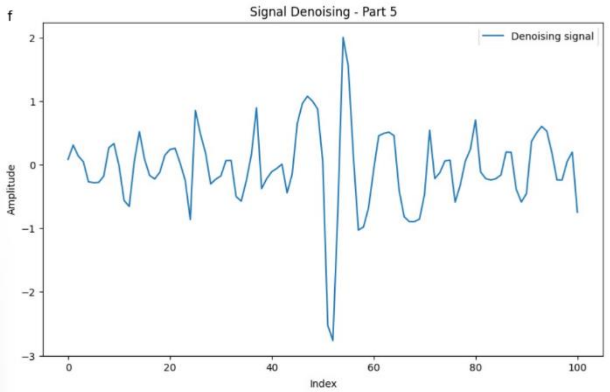

Figure 7. Result of Denoising Signal from record number 00735 at Fold 5

MIT-BIH Arrhythmia Database (MITDB)

Table 3 outlines the outcomes of ECG signal denoising on the MITDB database, covering all records through k-fold validation from folds 1 to 5. The table employs SNR and RMSE metrics to measure the performance of each fold in the k-fold validation process. In the first fold, the results reveal an SNR value of 62.23 and an RMSE value of 0.00027, with an early stop occurring at epoch 47. The third fold demonstrates an SNR value of 64.98 and an RMSE value of 0.00019, with an early stop at epoch 28. The fourth fold displays an SNR value of 62.03 and an RMSE value of 0.00027, with an initial stop at epoch 40. Finally, the fifth fold yields an SNR value of 65.22 and an RMSE value of 0.00018, with an initial stop at epoch 36.

From these findings, it is evident that the most favorable SNR and RMSE values were achieved in the fifth fold, with an SNR of 65.22 and an RMSE of 0.00018.

Table 3. MITDB SNR and RMSE values

K-Fold	SNR	RMSE
1	62.23	0.00027
2	61.30	0.00030
3	64.98	0.00019
4	62.03	0.00027
5	**65.22**	**0.00018**

Figures 8 to 13 depict the visualization of the MITDB signal from the 100th record, alongside the outcomes of the denoising process facilitated by the Deep LSTM Autoencoder across fold 1 until fold 5.

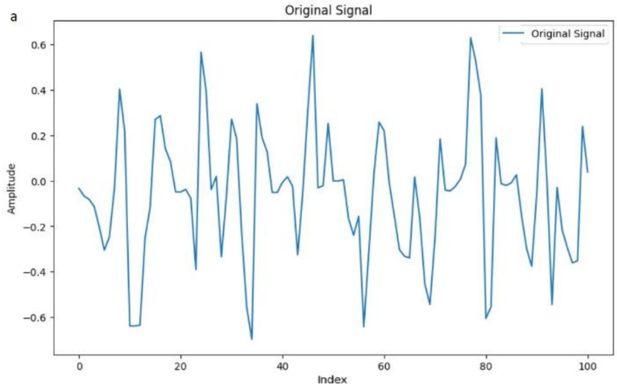

Figure 8. A Snapshot of Original ECG Signal from record number 100

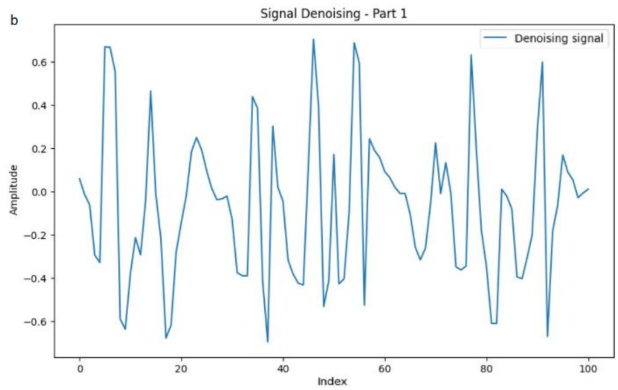

Figure 9. Result of Denoising Signal from record number 100 at Fold 1

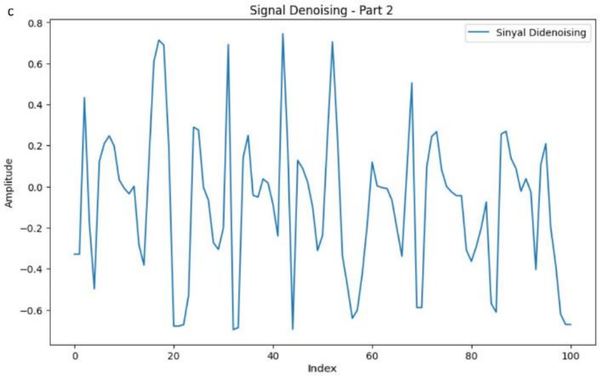

Figure 10. Result of Denoising Signal from record number 100 at Fold 2

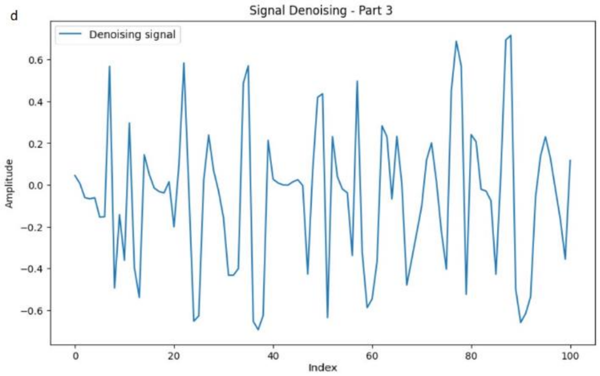

Figure 11. Result of Denoising Signal from record number 100 at Fold 3

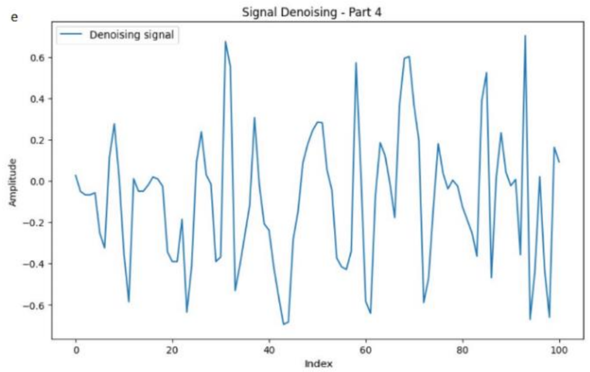

Figure 12. Result of Denoising Signal from record number 100 at Fold 4

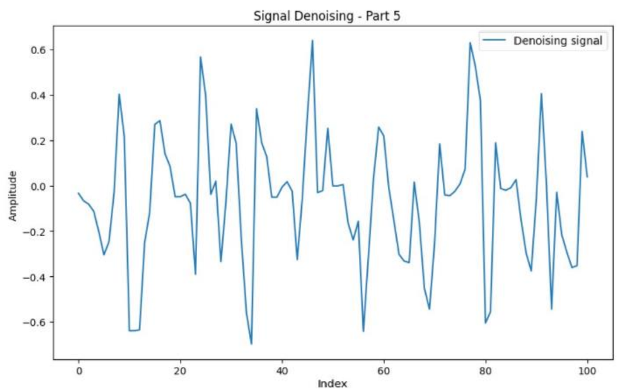

Figure 13. Result of Denoising Signal from record number 100 at Fold 5

Discussion

The discussion focuses on the denoising results obtained from two different datasets, namely AFDB and MITDB, using k-fold validation. In Figure 2 and Figure 8, the test signals to be denoised are presented, while Figures 3 to 7 and Figures 9 to 13 display the denoising outcomes for each fold, respectively. The corresponding SNR and RMSE values for each fold in the k-fold validation are summarized in Table 2 and Table 3.

For the AFDB dataset, the denoising results revealed that the second fold achieved the best performance, with an SNR value of 56.15 and an RMSE value of 0.00037. This fold demonstrated higher signal clarity in relation to noise and a smaller difference between the denoised signal and the original signal. The early stopping occurred at epoch 15, indicating that the model achieved satisfactory convergence within a relatively short training period. These findings suggest that the second fold exhibited the most effective denoising capability for the AFDB dataset.

Similarly, for the MITDB dataset, the fifth fold displayed the best denoising performance, with an SNR value of 65.22 and an RMSE value of 0.00018. This fold achieved the highest signal clarity and the closest resemblance to the original signal after denoising. The early stopping occurred at epoch 36, suggesting that the model reached a desirable level of convergence within a reasonable training time. Hence, the fifth fold demonstrated the most effective denoising performance for the MITDB dataset.

The comparison of the results between the two datasets highlights the dataset-dependent nature of the denoising process. Different datasets may have unique characteristics, noise levels, and signal variations, which can impact the denoising outcomes. Therefore, it is crucial to evaluate and optimize the denoising approach based on the specific dataset under consideration.

Overall, the denoising results obtained using the deep LSTM autoencoder model showcased its effectiveness in reducing noise and improving the quality of the arrhythmia signals. The achieved SNR and RMSE values indicate the model's ability to successfully denoise the signals while preserving important features. These findings have significant implications for enhancing the accuracy of arrhythmia diagnosis and facilitating further signal analysis in clinical settings. However, additional research and validation on larger datasets and diverse arrhythmia types are recommended to confirm the generalizability and robustness of the proposed denoising approach. Table 4 presents a comparative analysis of denoising outcomes achieved through the Deep LSTM Autoencoder on both AFDB and MITDB datasets.

Best of Comparison

Table 4. Best of SNR Comparison

	SNR	RMSE
AFDB	56.16	0.00037
MITDB	65.22	0.00018

Based on the findings presented in Table 4, the LSTM autoencoder algorithm demonstrates superior denoising performance in the AFDB dataset, yielding an SNR of 56.16 and an RMSE of 0.00037. Conversely, for the MITDB dataset, the

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LSTM autoencoder algorithm achieves an SNR of 65.22 and an RMSE of 0.00018. In comparison, Marwan, et al. [14] reported relatively lower SNR and RMSE values in their experiments, with the best SNR of 16.01 and the best RMSE of 0.88. These variations in denoising results arise because Marwan, et al. [14] utilized the Single Hidden Layer Autoencoder and Multiple Hidden Layer Autoencoder algorithms, whereas this research employs the LSTM autoencoder algorithm. Furthermore, the approach in this research integrates Deep Learning and Artificial Intelligence (AI) for ECG signal denoising, whereas Marwan et al. rely on layer-based methods without incorporating AI to mitigate ECG signal interference. The distinct methodologies contribute to the observed differences in denoising measurement results between the two studies.

CONCLUSIONS

Based on the denoising test results using the Deep LSTM Autoencoder algorithm, the evaluation on AFDB dataset results the best SNR and RMSE values at 56.16 and 0.00037, respectively. Meanwhile, for the MITDB dataset, the corresponding values are 65.22 and 0.00018. Notably, this research exhibits a significant advantage as the achieved SNR and RMSE values surpass those of comparable studies. Nevertheless, the limitations of this research stem from the constrained availability of arrhythmia datasets from MITDB and AFDB. We recommend future researchers to explore and acquire a more extensive collection of arrhythmia data to further enhance denoising performance.

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CONFLICT OF INTEREST STATEMENT

One of the authors of this article, Satria Mandala, is a member of the editorial team of this journal. This relationship could potentially create a conflict of interest. However, several steps have been taken to ensure the review and publication process's integrity, transparency, and fairness.

1. The author was not involved in any stage of the article's editorial decision-making process.
2. The article was subjected to the same rigorous peer-review process as any other submissions, handled independently by another editorial board member.
3. Satria Mandala has no access to the review reports or any other privileged information regarding his manuscript's submission.

REFERENCES

[1] N. Wenninger, C. Bernhart, W. Kappaun, A. Kollau, K. Kalcher, and A. Ortner, "High-performance amperometric determination of nitric oxide released by endothelial cells using flow injection analysis," Talanta, vol. 253, p. 123810, 2023/02/01/ 2023.

[2] R. Liu et al., "An artificial intelligence-based risk prediction model of myocardial infarction," BMC Bioinformatics, vol. 23, no. 1, p. 217, 2022/06/07 2022.

[3] R. A. Cahya, C. Dewi, and B. Rahayudi, "Klasifikasi Aritmia Dari Hasil Elektrokardiogram Menggunakan Support Vector Machine Dengan Seleksi Fitur Menggunakan Algoritma Genetika," Jurnal Pengembangan Teknologi Informasi dan Ilmu Komputer, vol. 2, no. 3, pp. 1170-1178, 08/28 2017.

[4] S. Hori, T. Shouo, K. Gyohten, H. Ohki, T. Takami, and N. Sato, "Arrhythmia Detection Based on Patient-Specific Normal ECGs Using Deep Learning," in 2020 Computing in Cardiology, 2020, pp. 1-4.

[5] S. Nurmaini, A. Darmawahyuni, A. N. Sakti Mukti, M. N. Rachmatullah, F. Firdaus, and B. Tutuko, "Deep Learning-Based Stacked Denoising and Autoencoder for ECG Heartbeat Classification," Electronics, vol. 9, no. 1, p. 135, 2020.

[6] M. Thill, W. Konen, H. Wang, and T. Bäck, "Temporal convolutional autoencoder for unsupervised anomaly detection in time series," Applied Soft Computing, vol. 112, p. 107751, 2021/11/01/ 2021.

[7] S. G. Chickaramanna et al., "Classification of Arrhythmia Using Machine Learning Algorithm," Revue d'Intelligence Artificielle, vol. 36, no. 4, pp. 529-534, 2022.

[8] Y. Hou, R. Liu, M. Shu, and C. Chen, "An ECG denoising method based on adversarial denoising convolutional neural network," Biomedical Signal Processing and Control, vol. 84, p. 104964, 2023/07/01/ 2023.

[9] P. Singh and A. Sharma, "Attention-Based Convolutional Denoising Autoencoder for Two-Lead ECG Denoising and Arrhythmia Classification," IEEE Transactions on Instrumentation and Measurement, vol. 71, pp. 1-10, 2022.

[10] J. Park, Y. Seo, and J. Cho, "Unsupervised outlier detection for time-series data of indoor air quality using LSTM autoencoder with ensemble method," Journal of Big Data, vol. 10, no. 1, p. 66, 2023/05/17 2023.

[11] H. T. Chiang, Y. Y. Hsieh, S. W. Fu, K. H. Hung, Y. Tsao, and S. Y. Chien, "Noise Reduction in ECG Signals Using Fully Convolutional Denoising Autoencoders," IEEE Access, vol. 7, pp. 60806-60813, 2019.

[12] S. A. Deevi, C. P. Kaniraja, V. D. Mani, D. Mishra, S. Ummar, and C. Satheesh, "HeartNetEC: a deep representation learning approach for ECG beat classification," Biomedical Engineering Letters, vol. 11, no. 1, pp. 69-84, 2021/02/01 2021.

[13] J. Shi et al., "New ECG Compression Method for Portable ECG Monitoring System Merged with Binary Convolutional Auto-Encoder and Residual Error Compensation," Biosensors, vol. 12, no. 7, p. 524, 2022.

[14] B. Marwan, F. Samann, and T. Schanze, "Denoising of ECG with single and multiple hidden layer autoencoders," Current Directions in Biomedical Engineering, vol. 8, no. 2, pp. 652-655, 2022.

[15] S. Śmigiel, "ECG Classification Using Orthogonal Matching Pursuit and Machine Learning," Sensors, vol. 22, no. 13, p. 4960, 2022.

[16] K. Fujiwara, S. Miyatani, A. Goda, M. Miyajima, T. Sasano, and M. Kano, "Autoencoder-Based Extrasystole Detection and Modification of RRI Data for Precise Heart Rate Variability Analysis," Sensors, vol. 21, no. 9, p. 3235, 2021.

[17] S. Modak, L. Y. Taha, and E. Abdel-Raheem, "A Novel Method of QRS Detection Using Time and Amplitude Thresholds With Statistical False Peak Elimination," IEEE Access, vol. 9, pp. 46079-46092, 2021.

[18] J. Hua, J. Rao, Y. Peng, J. Liu, and J. Tang, "Deep Compressive Sensing on ECG Signals with Modified

Inception Block and LSTM," Entropy, vol. 24, no. 8, p. 1024, 2022.
[19] B.-H. Kim and J.-Y. Pyun, "ECG Identification For Personal Authentication Using LSTM-Based Deep Recurrent Neural Networks," Sensors, vol. 20, no. 11, p. 3069, 2020.
[20] J. Torres-Soto and E. A. Ashley, "Multi-task deep learning for cardiac rhythm detection in wearable devices," npj Digital Medicine, vol. 3, no. 1, p. 116, 2020/09/09 2020.
[21] Safrizal, F. Arnia, and R. Muharar, "Pengenalan Aksara Jawi Tulisan Tangan Menggunakan Freemen Chain Code (FCC), Support Vector Machine (SVM) dan Aturan Pengambilan Keputusan," Jurnal Nasional Teknik Elektro, vol. 5, no. 1, pp. 45-55, 03/04 2016.
[22] S. Bahri, K. Saddami, F. Arnia, and K. Muchtar, "Perbandingan Kinerja Support Vector Machine (SVM) Dalam Mengenali Wajah Menggunakan SURF DAN GLCM," Jurnal Nasional Teknik Elektro, vol. 8, no. 2, pp. 65 – 74, 06/26 2019.
[23] Y. Zhou, L. Li, Y. Liu, Z. Zhang, and T. Matsui, "Clustering analysis of acoustic emission signals in the monitoring of stone monuments: case of the freeze–thaw deterioration of tuffs," Heritage Science, vol. 11, no. 1, p. 119, 2023/06/07 2023..

NOMENCLATURE

Do meaning of original signal
Dr, meaning of reconstructed signal
L_c meaning of signal is denoted.

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