iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: VII Month of publication: July 2025

DOI: https://doi.org/10.22214/ijraset.2025.73216

www.ijraset.com

Call: 08813907089 | E-mail ID: ijraset@gmail.com

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue VII July 2025- Available at www.ijraset.com

Revolutionizing Cardiac Care with Regenerative AI and GANs

ASHIA MONACHAN
ANNA UNIVERSITY UDAYA SCHOOL OF ENGINEERING INDIA

Abstract: The human heart's limited regenerative capacity poses significant challenges in treating myocardial infarctions and other cardiac diseases. Traditional therapeutic approaches, such as medications, stents, and transplants, primarily focus on symptom management rather than reversing underlying myocardial damage. Recent breakthroughs in regenerative artificial intelligence, particularly through the use of generative adversarial networks, offer promising avenues for cardiac repair. GANs have been successfully applied in cardiovascular research to enhance imaging analysis and simulate realistic data, improving diagnostic accuracy and treatment outcomes. Building on this foundation, we propose a novel approach to cardiac signal regeneration using GAN-based AI. This methodology enables the reconstruction and enhancement of degraded or missing electrocardiogram signals, significantly improving diagnostic accuracy. Moreover, it opens new possibilities for AI-assisted myocardial tissue regeneration by predicting and simulating healthy cardiac patterns. These regenerated signals can be integrated into pacemakers and other cardiac devices to optimize pacing and improve heart function. By leveraging AI-driven insights, this approach not only enhances diagnostic capabilities but also paves the way for personalized, data-driven interventions that transcend traditional symptomatic management, potentially revolutionizing cardiac care and offering new hope for patients with cardiac diseases.
Keywords: ECG signal regeneration, Generative Adversarial Networks, cardiac care, heartbeat classification, AI-powered pacemakers.

I. INTRODUCTION

Cardiac diseases is the major cause of morbidity and mortality throughout the world, affecting millions annually and continued as a tremendous demand for healthcare systems [1]. The irreversible death of heart muscle tissue caused by restricted blood flow leads to myocardial infarctions, referred to as heart attacks. The human heart has naturally limited regenerative capacity, making one of the most extreme treatments of such conditions [2]. All treatments in this treatment category, like pharmacological agents, angioplasty with stent placements or even heart transplants, seek mostly to manage symptoms, or prevent further deterioration or restore blood flow mechanically. Nevertheless, such repair or regeneration of damaged myocardial tissue is largely missing [3]. Consequently, patients may have long term impairment to heart function with chronic heart failure or impaired quality of life. With these limitations, there is an increasing demand for new strategies that abandon symptomatic treatment and initiate actual regeneration of cardiac tissue [4]. It is far from an understatement to say that regenerative AI, especially through the use of GANs, is close to becoming a frontier. It has been shown that GANs have proved to be capable of synthesizing realistic biomedical data, facilitating medical imaging, as well as reconstructing degraded physiological signals [5]. The aim of this research is to investigate how regen AI, fuelled by GANs, can improve the outcome in cardiac care by improving diagnosis precision and using the myocardial tissue regen. In particular, ECG signal reconstruction and enhancement as well as simulation of healthy cardiac patterns is focused on. This approach aims at creating a revolution in the current cardiac therapy modalities and propelling patients suffering from cardiac diseases to obtain new hope [6].

1) Created a custom designed GAN architecture for the task of reconstructing and augmenting ECG signals.
2) The artificial intelligence used regenerated signals to model healthy cardiac patterns in order to create AI assisted myocardial tissue regeneration.
3) It proposed a method for inserting regenerated ECG patterns within pacemakers to optimally pace a heart and enhance cardiac function.
4) It also showed that AI regenerated signals give great increased precision in cardiac disease diagnosis over traditional degraded signals.

Despite many advances in cardiac care, current approaches largely rely on symptomatic treatment without tissue regeneration or personalized treatment.

These traditional methods, including meds, stents, transplants are restricted by the human heart's inability to completely regenerate. However, existing works on ECG signal classification leverage such machine learning techniques as CNN and RNN and are often limited to the classification based on completeness or the absence of noise [7]. While using ECG signals to regenerate the signal has been under explored in the literature, including in the context of real time queries. In order to address this gap, this work will use GAN in order to enhance the signal as well as regenerate myocardial tissue thereby taking the field of personalized cardiac care to a new level [8].

The technique and literature review are presented in sections II and section III is explained the research Methodology in detailed manner, Section IV consist the results, and Section and Section V consist the Conclusion and the future Work of the study.

II. LITERATURE REVIEW

The advances that newer research brings to focus are those related to electrical as well as mechanical stimulation for improving cardiac repair and regeneration. As stated in [9], there cannot be straightforward dependence upon ECG signal analysis; indeed, very comprehensive needs must deal with the complexity of interactions between impulses with electromagnetism and mechanical forces incorporated within the heart. Understanding the fundamental bases of mechanisms behind cardiac regeneration in will give very significant insights for directing regenerative therapies. It probes the pathways involved in signalling-their influence on behaviour of stem cells, how such action can lead to cellular reprogramming, and sets the stage for developing those AI-enabled therapies that will be geared specifically towards energizing heart repair [10]. As published in [11], the researchers suggested a wireless ECG monitoring system for small animal models and that data can be collected continuously without disturbing natural animal behaviours caused by installed external measurements. The innovation removed the cables traditionally used in such systems to allow observation of how interventions affect the electrical activity of the heart during regeneration. In this paper, a new methodology for ECG feature extraction and regeneration of signals using a hybrid recurrent neural network-connected second-order dynamic system is suggested [12]. It goes beyond the most essential amplitude and frequency properties, capturing core dynamic properties and permitting the building of synthetic ECG data such that it will likely find applications, such as data augmentation and training AI models.

Unsupervised deep learning approaches for ECG signal quality assessment were presented in [13]. Since the data quality directly affects the reliability of AI-based diagnostic systems, the method qualifies bad or low-quality recordings, boosting the performance of subsequent analytical models in a good way. To bypass data scarcity, the work presented in [14] proposed the use of Gene-rative Adversarial Networks in generating realistic multi-channel ECGs. The improvement of the fidelity and diversity of generated signals by employing different loss functions is the reason behind the study's importance that can benefit the cardiac AI trainings and testing significantly. In a separate work, [15] presented a data-driven approach to extract the gating signals from PET imaging. The method uses information from many cardiac signals, ECG, and blood pressure, to synchronize PET images to the cardiac cycle more accurately indeed and improve the diagnostic imaging of cardiac function and metabolism. The technique described in [16] combined total variation denoising with Morlet continuous wavelet transforms to extract features of interest from ECG signals for the classification of cardiac diseases. The processed features were then provided as input to machine learning classifiers, thus assisting in the early identification of heart abnormalities.

III. RESEARCH METHODOLOGY

The GAN based methodology for ECG signal regeneration and classification is demonstrated using MIT-BIH arrhythmia dataset. A noise reduction, normalization and segmentation into fixed length windows is done to the dataset. A custom GAN architecture uses a generator that reconstructs degraded ECG signals and a discriminator that determines if a given signal is real or generated. Finally, to evaluate the performance of the model, metrics are given to compare with other models like CNN, RNN and LSTM. It shows possibilities of GANs to improve ECG signal quality and to identify heart disease by ECG signal quality improvement.

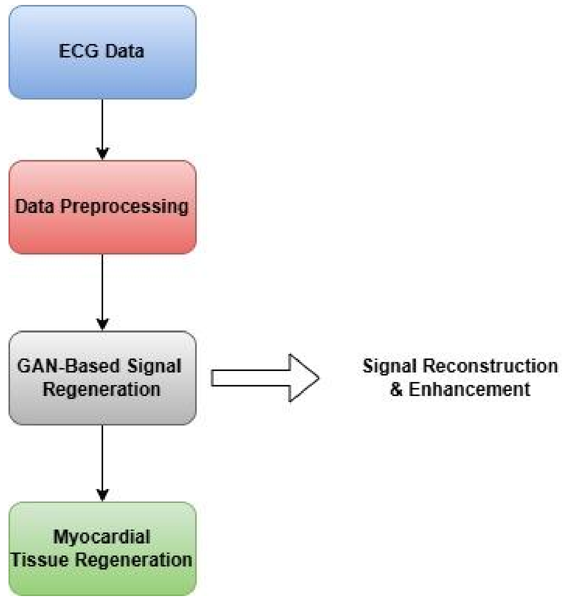

Fig. 1. Flow of Cardiac Care with Regenerative AI and GANs

Fig. 2.

A. Data Collection

The dataset from the Kaggle data [17]. The Social Media Advertising dataset has impression, click, ad spend, demographic targeting, and conversion rate details over different platforms like Facebook, Instagram, Pinterest, and Twitter. Also, it helps what channels and strategies that make a campaign be successful. This demographic data allows for audience segmentation for the targeting and personalization of the buy advertisement campaign. Calculation of return on investment on ads spend, conversion rates and generated revenue can be done by analysis of relationship between ad spend and conversion rates. Furthermore, click through rates and engagement metrics identify areas to optimize for future campaign success. Future of campaign performance can be predicted using predictive modeling techniques which can give an insight of how this should be refined and can be the best channel for efficient marketing.

B. Data Pre-processing

Digital bandpass filters are applied first to remove baseline drift, muscle noise, and high frequency interference on the raw ECG signals before denoising. Signals pass through noise reduction, are normalized to standard range (e.g. $[-1,1]$) to make amplitude and time scaling uniform. Small fixed sized windows are then extracted out of long ECG recordings for the purpose of model training. Corrupted or physiologically implausible signals are removed using outlier removal. If there are any missing values, then they are interpolated. With this preprocessing pipeline, GAN training is receiving clean data, with the data being consistent and high quality.

$$S_n(t) = \frac{S(t) - min\,(S)}{(S)\, - min\,(S)} \tag{1}$$

C. ReGen-ECGNet

1) GAN Architecture for Signal Regeneration

A one-dimensional custom Generative Adversarial Network had been developed for processing one dimensional data like ECG signals, which deviates from the traditional two-dimensional GAN model commonly used in image processing. For this reason, the generator network was created for degraded or incomplete ECG signals as input and to output generated reconstructed high-fidelity versions of normal heart beat activity. The generator architecture was made up of stacked 1D convolutional layers, up sampling blocks, and the activation function used was ReLU, and tanh. Into the discriminator network was structured so that the discriminator network can distinguish between realistic healthy ECG signals and those provided by the GAN. First, there were 1D convolutional layers along with dense layers, then a final sigmoid function to output a probability score for authenticity. Two loss functions were used during the training which was adversarial loss to force the generator to generate realistic outputs and reconstruction loss which ensured fidelity of the generated outputs to the ground truth signals. Then, they were trained alternately with mini-batch stochastic gradient descent with schemes like Wasserstein GAN with Gradient Penalty to improve training stability. The RMSE, PSNR, and SSI were calculated as signal similarity metrics to evaluate the model performance during training.

$$L_{recon} = E_{x,y}[||y - G(x)||1] \quad (2)$$

2) Signal Reconstruction and Enhancement

A signal degradation simulation, which induces noise, simulates missing leads, or ignores signal segments, was performed to build the model's resilience against various real-world imperfections of ECGs. ECG signals with a degraded quality were then fed into the trained generator network to reconstruct the complete and high-quality ECG signals. Reconstructed signals, if desired obtained through post processing techniques such as smoothing and denoising were then applied to improve their quality, and to remove any minor artifacts caused by the process of regeneration. The purpose of this step was to make sure that the output signals were not only correct but also clinical in nature.

$$\hat{y} = G(x_d) \quad (3)$$

3) AI-Driven Engagement Score Prediction

The reconstructed signals were built on, and the system was used to simulate healthy myocardial electrical activity. Digital models of normal cardiac patterns were modeled and extended by using the GAN outputs, on which to base the simulation of the regeneration of myocardium in digital settings. Next, these regenerated ECG patterns were incorporated into AI based pacemaker simulations and pacing strategies were designed so as to best resemble the reconstructed healthy rhythms. The aim with this approach was to improve the heart's ability to beat by aligning device assisted pacing more to the natural electrical signalling patterns of the body.

$$Yhealthy = G(x_{damaged}) \quad (4)$$

4) Ethical Considerations

The privacy, unlink ability and anonymization of all of the data that were used in this research was strict, to avoid any possible harm on the patients. It was created where synthetic data was generated, but in a manner of creating synthetic data to ensure privacy but not clinical relevance. This study further complied with practicing establishing ethical guidelines for biomedical AI research in terms of transparency, reproducibility and patient safety. To address ethical considerations for real world technology integration into clinical medical systems, future step towards clinical deployment of the proposed technology will be rigorous compliance with healthcare regulatory standards.

IV. RESULT AND DISCUSSION

Analysis of different approaches reveals that the GAN based model results have the best overall accuracy metrices. Consequently, this shows that the GAN model has strongly and effectively reconstructed the ECG signals and heartbeats. The CNN based model is strong in its performance in all metrics and closely resembles the abovementioned. In recall, the LSTM model also performs well, and unfortunately, slightly behind in accuracy too. Generally, the results demonstrate that GANs are superior for ECG signal regeneration and classification tasks.

A. Heartbeat Class Distribution According to AAMI Standards

The type of heartbeat, that is labelled ECG signal, classifies in five main classes in the MIT BIH arrhythmia dataset. Among the Normal Beat (NB) class, there are 90,589 beats, which are most common and the healthiest heartbeats. The total number of the arrhythmias is 8,039 and part of them is the Supraventricular Beat class (SB) consists of arrhythmias originated from atria. 7,236 beats are belonging to the Ventricular Beat (VB) class, related to the arrhythmias occurring from the ventricles. There are 2,776 Fusion Beat (FB) beats, which are those coming from the fusion of a normal and an abnormal beat. The third contains 803 beats, belonging to the Unknown Beat (QB) class anymore, which are either artifacts or noise in the ECG signal. This also establishes the analysis and diagnosis of different cardiac conditions.

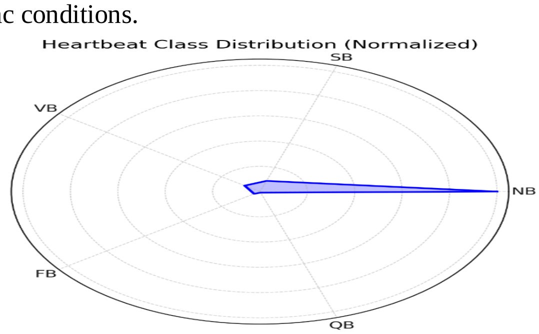

Fig. 3. Heratbeat Class Distribution

B. Data Split for Training and Testing

The training and testing sets for each heartbeat class. So, 63,412 beats are used for training of NB class and we have 27,177 beats for testing (70%) and 30% (for testing). The training set for the Supraventricular Beat (SB) class has 5,627 beats and the testing set includes 1,412 beats, both split at 70% training and 30% testing. Likewise, there are 5,065 training beats and 1,171 test beats in the Ventricular Beat (VB) class. According to the same ratio, the number of training beats for the Fusion Beat (FB) class is 1,943 and number of testing beats is 833. Lastly, the Unknown Beat (QB) class contains 562 training beats and 241 testing beats according to a 70-30 training testing percentage distribution. A balanced split ensures also a good model training and evaluation for each class.

TABLE I. DATA SPLIT FOR TRAINING AND TESTING

Model	Training Set	Testing Set	Training Percentage	Testing Percentage
NB	63,412	27,177	70%	30%
SB	5,627	1,412	70%	30%
VB	5,065	1,171	70%	30%
FB	1,943	833	70%	30%
QB	562	241	70%	30%

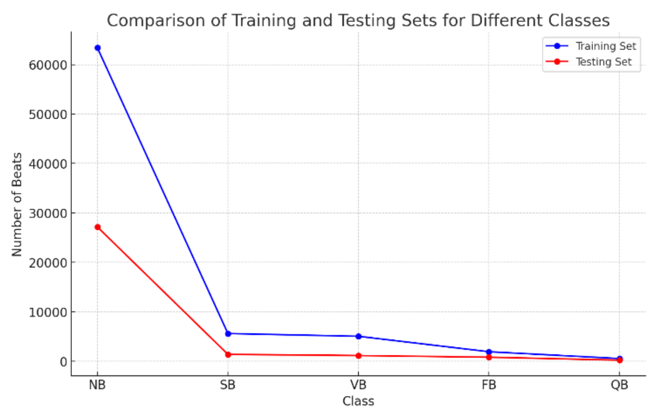

Fig. 4. Comparison of training and testing setsa

C. Comparison metrices

The presence of these figures will serve in estimating pricing Policies and Product popularity in various store locations. Results from the metrices of several models are summarized in the table below. In terms of accuracy, the CNN model gets 92.5%, the precision is 91.8%, recall is 93.0% and F1 score comes out to be 92.4%. Accuracy of the RNN model is 89.3%, precision of the RNN model is 87.5%, recall of the RNN model is 90.2%, and F1 score of the RNN model is 88.8%. The precision and recall are 87.5% and 86.0 respectively, F1-score is 86.7% and the accuracy is 88.0%. However, the accuracy of the CNN model is lower than that of the LSTM model, which is 91.2%, 90.3%, 91.8%, and 91.0% respectively for the metrices. Finally, the GAN model outperforms all other models, with the highest values: 98.1% accuracy, 98.5% precision, 98.8% recall, and 98.1% F1-score.

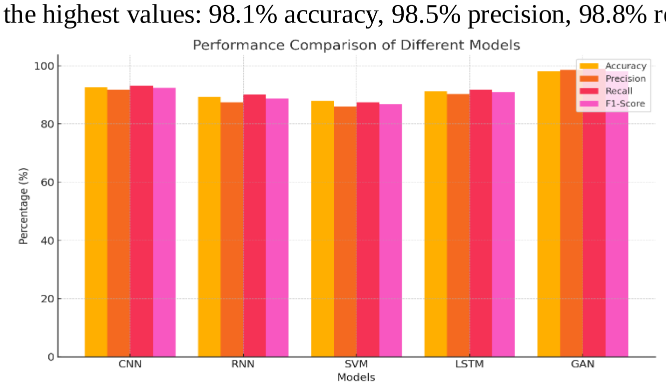

Fig. 5. Performance Comparison

V. CONCLUSION AND FUTURE WORK

The capabilities of Generative Adversarial Networks for ECG signal regression and classification in the area of cardiac care are shown in this study. In comparison to traditional model such as CNN, RNN and LSTM GAN based approach demonstrated significance in metrics which validates that GAN have potential enhancement to the diagnostic capability by reconstructing degraded ECG signals. An attempt at advancing real time cardiac monitoring and personalized treatment can be made by combining the AI driven insights.

The future research will further improve the GAN architecture for even better signal regeneration by experimenting with such advanced variations of the GANs as WGANs and cGANs to be more stable and efficient. Moreover, the application of this approach to wearable devices and integration of such in AI-based cardiac devices could enhance the heart function. Another direction of future work is to further validate the large-scale clinical applicability using real world healthcare settings for ensuring the practical applicability and safety of AI assisted cardiac care.

REFERENCES

[1] "The Lancet Commission to reduce the global burden of sudden cardiac death: a call for multidisciplinary action - The Lancet." Accessed: Apr. 28, 2025. [Online]. Available: https://www.thelancet.com/journals/lancet/article/PIIS0140-6736(23)00875-9/abstract

[2] "The Real Need for Regenerative Medicine in the Future of Congenital Heart Disease Treatment." Accessed: Apr. 28, 2025. [Online]. Available: https://www.mdpi.com/2227-9059/9/5/478

[3] G. A. Fishbein, M. C. Fishbein, J. Wang, and L. M. Buja, "Chapter 10 - Myocardial ischemia and its complications," in Cardiovascular Pathology (Fifth Edition), L. M. Buja and J. Butany, Eds., Academic Press, 2022, pp. 407–445. doi: 10.1016/B978-0-12-822224-9.00022-0.

[4] H. Peng, K. Shindo, R. R. Donahue, and A. Abdel-Latif, "Cardiac Cell Therapy: Insights into the Mechanisms of Tissue Repair," Int. J. Mol. Sci., vol. 22, no. 3, Art. no. 3, Jan. 2021, doi: 10.3390/ijms22031201.

[5] R. K. Pandey and Y. K. Rathore, "Deep learning in 3D cardiac reconstruction: a systematic review of methodologies and dataset," Med. Biol. Eng. Comput., Jan. 2025, doi: 10.1007/s11517-024-03273-y.

[6] V. M. Saceleanu et al., "Integrative Approaches in Acute Ischemic Stroke: From Symptom Recognition to Future Innovations," Biomedicines, vol. 11, no. 10, Art. no. 10, Oct. 2023, doi: 10.3390/biomedicines11102617.

[7] "Deep Learning Methods for Heart Sounds Classification: A Systematic Review." Accessed: Apr. 28, 2025. [Online]. Available: https://www.mdpi.com/1099-4300/23/6/667

[8] "Cardiac regeneration – Past advancements, current challenges, and future directions - ScienceDirect." Accessed: Apr. 28, 2025. [Online]. Available: https://www.sciencedirect.com/science/article/abs/pii/S0022282823001153

[9] M. A. Serhani, H. T. El Kassabi, H. Ismail, and A. Nujum Navaz, "ECG Monitoring Systems: Review, Architecture, Processes, and Key Challenges," Sensors, vol. 20, no. 6, p. 1796, Mar. 2020, doi: 10.3390/s20061796.

[10] L. Wei et al., "Advancements and challenges in stem cell transplantation for regenerative medicine," Heliyon, vol. 10, no. 16, p. e35836, Aug. 2024, doi: 10.1016/j.heliyon.2024.e35836.

[11] V. T. N. Linh, S. Han, E. Koh, S. Kim, H. S. Jung, and J. Koo, "Advances in wearable electronics for monitoring human organs: Bridging external and internal health assessments," Biomaterials, vol. 314, p. 122865, Mar. 2025, doi: 10.1016/j.biomaterials.2024.122865.

[12] S. Matin Malakouti, "Heart disease classification based on ECG using machine learning models," Biomed. Signal Process. Control, vol. 84, p. 104796, Jul. 2023, doi: 10.1016/j.bspc.2023.104796.

[13] M. F. Safdar, R. M. Nowak, and P. Pałka, "Pre-Processing techniques and artificial intelligence algorithms for electrocardiogram (ECG) signals analysis: A comprehensive review," Comput. Biol. Med., vol. 170, p. 107908, Mar. 2024, doi: 10.1016/j.compbiomed.2023.107908.

[14] E. Brophy, M. De Vos, G. Boylan, and T. Ward, "Multivariate Generative Adversarial Networks and Their Loss Functions for Synthesis of Multichannel ECGs," IEEE Access, vol. 9, pp. 158936–158945, 2021, doi: 10.1109/ACCESS.2021.3130421.

[15] M. D. Walker, A. J. Morgan, K. M. Bradley, and D. R. McGowan, "Data-Driven Respiratory Gating Outperforms Device-Based Gating for Clinical ^{18}F-FDG PET/CT," J. Nucl. Med., vol. 61, no. 11, pp. 1678–1683, Nov. 2020, doi: 10.2967/jnumed.120.242248.

[16] "(PDF) Cardiac Disease Classification Using Denoising and Wavelet Transformation of ECG Signals," ResearchGate, Apr. 2025, Accessed: Apr. 28, 2025. [Online]. Available: https://www.researchgate.net/publication/362544772_Cardiac_Disease_Classification_Using_Denoising_and_Wavelet_Transformation_of_ECG_Signals

[17] S. Bhattacharyya, S. Majumder, P. Debnath, and M. Chanda, "Arrhythmic Heartbeat Classification Using Ensemble of Random Forest and Support Vector Machine Algorithm," IEEE Trans. Artif. Intell., vol. 2, no. 3, pp. 260–268, Jun. 2021, doi: 10.1109/TAI.2021.3083689.