ÉCOLE CENTRALE SCHOOL OF ENGINEERING

HYDERABAD

A Project Report

ON

An End to End Deep Learning based approach for Cardiovascular Monitoring Using Seismocardiogram signals

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Certificate

This is to certify that the project report entitled "**An End to End Deep Learning based Approach for Cardiovascular Monitoring Using Seismocardiogram Signals**" submitted in partial fulfilment of the requirements of the course PR 402, Project Course, embodies the work done by him/her under my supervision and guidance

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ABSTRACT

The seismocardiogram (SCG) signal records the mechanical vibrations and movements of the chest wall associated with the heartbeat, while the electrocardiogram (ECG) is a commonly used electrical marker of cardiac activity. In this study, we present a method to convert SCG data to ECG signals and vice versa using an attentive network of cycle-generating adversaries. Our proposed framework uses dual generators and four discriminators to learn basic patterns for synthesising ECG from SCG and vice versa. Also, it includes an identification module that can recognize the difference between ECG and SCG signals. Our approach combines subjective visual analysis and objective performance measurement using a publicly available combined ECG, breathing, and seismocardiogram (CEBS) database. Our results showcase the effectiveness of the proposed ACGAN architecture in producing high-quality generated SCG and ECG signals, while also preserving important cardiac details during the conversion process.

This research project builds upon a previously established deep learning model involving two generators and two discriminators within a cycleGAN framework. In effort to improve performance, we introduce a unique identification/detection module to enhance the model's capabilities. Furthermore, the architecture is expanded by integrating two additional discriminators, thereby enhancing the network's ability to recognize and generate intricate patterns in the data. The proposed modifications are aimed at increasing the accuracy and robustness of the model. Through careful fine-tuning and experimentation, our results demonstrate significant progress in achieving superior performance compared to the original model.

CHAPTER 1:

INTRODUCTION

One of the main causes of death worldwide continues to be cardiovascular disease. For the betterment of diagnostics, and lowering healthcare costs, early detection and accurate diagnosis are essential. ECG & SCG signals have proven to be essential mechanisms for monitoring heart health. The SCG records the mechanical vibrations associated with heart contractions, while the ECG offers information about the heart's electrical activity.

The ability to distinguish and convert ECG and SCG signals has important clinical implications in various fields. For example, the ability to transform SCG signals obtained from wearable devices into ECG signals would enable real-time remote monitoring of cardiac problems. Patients who live in impoverished areas or have restricted access to healthcare stand to gain significantly. On the other hand, the conversion of ECG readings into SCG signals would reveal more details about the mechanical elements of cardiac activity, enabling a thorough assessment of cardiovascular health.

Heuristic algorithms and signal processing methods have been the mainstays of conventional methods for signal resolution and conversion. These strategies, however, frequently have limitations such as low accuracy, substantial processing complexity and restricted generalisation. This report suggests a new way for overcoming these challenges by employing a module to differentiate and identify ECG and SCG signals.

GAN(Generative Adversarial Network) is a deep learning model made up of a generator and a discriminator. The generator creates synthetic data from a random noise input, while the discriminator tries to distinguish between accurate and fake data. The generator learns to create increasingly realistic samples through an iterative training procedure, while the discriminator improves its ability to distinguish between accurate and generated data. This antagonistic interaction leads to the creation of a generator capable of producing extremely convincing synthetic data. GANs have proven to be effective tools for image synthesis, augmentation of data, and signal conversion, allowing for the creation of fresh data for use in deep learning and AI.

By training the GAN on a huge collection of data sets of ECG and SCG signals, we were able to build a model that is capable of effectively recognising ECG and SCG signals and providing realistic output. This method has great potential for increasing the reliability and efficiency of cardiovascular diagnoses and monitoring. It paves the way for non-adhesive, cost-effective, and personalised healthcare solutions.

This study has various possible real-world applications. Aside from tele-medicine, the capacity to differentiate and convert ECG and SCG signals can improve the functionality of wearable devices, allowing for ongoing assessment of cardiac health in a range of settings. This is especially advantageous for athletes, the elderly, and persons suffering from chronic cardiovascular conditions because it allows for early diagnosis and response to irregularities.

With this study, we hope to bridge the gap between ECG and SCG signal conversion and pave the way for creative possibilities in cardiovascular health monitoring. The findings of the study have the potential to reinvent cardiac evaluations, improve the experiences of patients, lower diagnostic costs and ultimately save lives.

The goal is to create a unified framework that uses the attentive cycle-generative adversarial network (ACGAN) to synthesise ECG signals from SCG signals. By generating genuine ECG signals from SCG recordings, this approach intends to bridge the gap between electrical and mechanical events in the heart. In terms of accuracy and reliability for ECG and SCG signal differentiation and conversion, the proposed GAN-based approach will be compared to standard heuristic algorithms.

Addressing these issues and attaining reliable ECG and SCG signal separation and conversion has substantial significance. Accurate ECG synthesis from SCG signals can increase arrhythmia classification accuracy, enable remote cardiac monitoring, and improve overall cardiovascular diagnostic efficiency. This project intends to contribute to the development of new approaches for cardiac evaluation, improving patient outcomes and lowering healthcare costs by overcoming the limits of current methods.

Seismocardiography (SCG) is a non-invasive technique that uses accelerometers to record chest vibrations caused by the heart. SCG has been shown to be useful for detecting congenital cardiac defects, heart rate variability, heart beat detection, and respiratory rate. However, SCG cannot provide the same level of detail as an electrocardiogram (ECG), which records the electrical activity of the heart.

In this report, the authors propose a unified cycle generative adversarial network (GAN) framework with multi-head attention that can be used to derive ECG signals from SCG signals. The proposed framework is evaluated on the combined measurement of ECG, breathing, and seismocardiogram (CEBS) database. The results show that the proposed framework can generate ECG signals that are comparable to the ground truth ECG signals.

The proposed framework has the following advantages:

- It is non-invasive and does not require adhesive procedures.
- It can be used to record ECG signals from patients who cannot wear traditional ECG electrodes, such as infants and elderly people.
- It can be used to monitor patients remotely.
- Unlike a general CycleGAN model, which has 2 discriminators and 2 generators, our model consists of 4 discriminators and 2 generators, enhancing the network's ability to recognize and generate intricate patterns in the data.

The proposed framework has the following limitations:

- It is still under development and its performance needs to be further improved.
- Increased training complexity and risk of overfitting.
- Higher processing power and computational cost.

Overall, the proposed framework is a promising new technique for deriving ECG signals from SCG signals. It has the potential to be used for a variety of applications, such as remote patient monitoring and the development of new diagnostic tools.

Mathematical representation: The problem can be stated as follows: The goal is to train a GAN model to produce genuine ECG signals from SCG input and vice versa while reliably discriminating between the two types of signals, given a dataset of paired ECG and SCG signals. The proposed GAN-based approach's performance will be assessed by comparing it to classic heuristic algorithms using metrics.

We intend to address the following questions in this research:

I. Why do we need the conversion?
II. How does it affect the healthcare industry?
III. Can Generative Adversarial Networks (GANs) be used to effectively convert Electrocardiogram (ECG) and Seismocardiogram (SCG) signals?
IV. How does this approach differ from a regular 2 discriminator 2 generator(2 X 2) ACGAN in terms of its capabilities and limitations?
V. What is the level of accuracy and reliability that can be reached with the suggested GAN-based approach for ECG and SCG signal distinction and conversion compared to standard heuristic algorithms?
VI. Is this method a significant improvement over the standard 2 X 2 ACGAN architecture?
VII. Are there specific challenges or gaps in existing models that this research aims to address?
VIII. What role do the additional discriminators play in the refinement of the model?
IX. Which metrics were used to evaluate the model's performance?

In summary, this study aims to address the issue of reliable differentiation and conversion of ECG and SCG signals by developing a unified framework based on ACGAN. This project aims to improve the field of cardiac diagnostics and tracking by addressing the research questions and attaining the intended goals, paving the way for improved and personalised healthcare solutions.

PROBLEM DEFINITION

This study aims to improve the capability of effectively recognising ECG and SCG signals and providing realistic generated signal outputs

Despite the growing usage of wearable health devices and body sensor networks for cardiac assessment, precise recording of the electrical activities of the heart is required for thorough arrhythmia categorization. While wearable sensors can offer useful heart rate information and detect certain cardiac abnormalities, they cannot frequently record the electrical impulses required to diagnose different arrhythmias. The mechanical motions of the heart valves, as represented in seismocardiogram (SCG) signals, provide insights into the mechanical events linked with electrical cardiac events, while electrocardiogram (ECG) signals capture the electrical activity of the heart. Due to several reasons, such as signal complexity, cost, and battery life, there has been no proper implementation of ECG signals into wearable health devices.

The issue is a lack of precise inter-conversion of ECG and SCG signals, which limits a thorough understanding of cardiac health. Heuristic algorithms, for example, have constraints in terms of accuracy, processing complexity, and generalizability. To address these limitations, a unified framework is required to synthesise real ECG signals from SCG recordings, linking the electrical and mechanical events in the heart.

To address this issue, a deep learning system must be developed that can successfully learn the complicated link between ECG and SCG signals, capturing an association between electrical and mechanical events in the heart. The proposed framework's performance will be assessed based on the quality of the synthesised ECG signals, their resemblance to real-world ECG recordings, and their capacity to classify arrhythmias in real time.

BACKGROUND AND RELATED WORK

A Unified Attentive Cycle-Generative Adversarial Framework for Deriving Electrocardiogram FromSeismocardiogram Signal:

In this paper, a unified framework based on an attentive cycle-generative adversarial network (ACGAN) for synthesising electrocardiogram (ECG) signals from seismocardiogram (SCG) signals is proposed. The research paper focuses on the development of an approach to deriving ECG signals without invasion and discomfort, specifically targeting the need for wearable and non-adhesive modes, such as smartwatches. This framework aims to address the challenges associated with traditional adhesive ECG electrodes and provide a more convenient and user-friendly solution for cardiac monitoring.

This paper introduces a new framework for deriving electrocardiogram (ECG) signals from seismocardiogram (SCG) signals. The proposed approach utilises a unified attentive cycle generative adversarial network to accurately synthesise ECG signals from SCG signals. The paper includes a description of the CEBS database used for testing the framework, as well as objective performance analysis results for all 20 subjects in three different states. The proposed framework achieves an average Pearson correlation coefficient (PCC) of 0.890, 0.913, and 0.876 for basal, music, and post-music states, respectively. The paper concludes that the proposed framework can be used for accurate heart rate variability analysis, respiratory rate analysis, and cardiac arrhythmia classification specifically in cases where only the morphology of the QRS complex is needed.

The proposed framework is based on an attentive cycle GAN model, which works by using dual generators and dual discriminators. These elements play crucial roles in learning the patterns required for the synthesis of ECG from SCG signals and vice versa. In this framework, convolutional layers, multi-head attention, and decoder layers are employed in the generator networks to transform the input signals, while the discriminators work to distinguish between real and generated signals. This process goes over and over until it reaches a point where the generator functions have achieved optimal mappings. This novel methodology offers a unique approach to addressing the challenge of deriving ECG signals without the need for adhesive electrodes. By capturing the correlations between SCG and ECG signals, this framework presents exciting opportunities for cardiac rhythm and arrhythmia analysis.

Learning to Discover Cross-Domain Relations(Disco) with Generative Adversarial Networks:

In the rapidly advancing field of generative adversarial networks(GANs), the Disco GAN model has emerged as an innovative approach for discovering complex relationships within diverse datasets. Disco GAN aims to train a model capable of mapping images from one domain to another without the need for explicit labels or associations. This is achieved through the deployment of two GANs, each responsible for mapping one domain to the other. The fundamental intuition behind Disco GAN lies in enforcing the notion that all images within one domain can be effectively represented by images in the other domain. This is accomplished by using a reconstruction loss, which ensures that the generated image in the target domain can accurately reconstruct the original image from the source domain. Additionally, a GAN loss is used as a credibility measure to make the generated images resemble the real images within the target domain, ensuring their validity.

This paper presents a method for discovering cross-domain relations using generative adversarial networks (GANs) without the need for ground-truth pairs. The proposed method, called DiscoGAN, can transfer style from one domain to another while preserving key attributes. The authors demonstrate the effectiveness of their method on toy and real-world image datasets, showing that it is more robust to the mode collapse problem compared to two other baseline models. The results show that DiscoGAN can successfully apply bidirectional mapping between two image domains, such as faces, cars, chairs, edges, and photos, and consistently change specified attributes such as hair colour, gender, and orientation while maintaining all other components.

The Disco GAN model stands as a powerful GAN-based method for discovering relations between different image domains without the need for explicit pairing. Each generator within the model takes an image from one domain as input and seamlessly generates an image in the other domain as output. These generators are composed of encoder-decoder pairs, with the encoder encoding the input image and the decoder decoding it to produce the desired output image. The discriminator plays a critical role in discerning between real images and their synthetic counterparts within its respective domain, ensuring the fidelity of the generated images. The formulation of the problem in Disco GAN revolves around defining cross-domain relations as bijective mappings between the two domains. The objective functions employed comprise a reconstruction loss, which measures the accuracy of the original input's reconstruction, and a GAN loss, which guarantees the authenticity of the generated images in the target domain.

This paper provides a detailed exposition of the notation and architecture employed within the Disco GAN model, aiding in the understanding of its inner workings. And a novel approach to address the limitations of prior models by learning the mapping between two domains bidirectionally, without the need for explicit pair labels. The model is rigorously evaluated on both toy and real-world image datasets, showcasing its efficacy in discovering cross-domain relations and seamlessly translating images between domains while preserving essential attributes intrinsic to each domain. By skilfully combining reconstruction and GAN losses, Disco GAN facilitates the seamless mapping of images across domains. The model's promising results in various experiments indicate its ability to learn cross-domain relations and perform image translation tasks effectively.

CardioGAN: Attentive Generative Adversarial Network with Dual Discriminators for Synthesis of ECG from PPG:

This paper introduces a GAN-based architecture consisting of a generator network, attention mechanisms, and dual discriminators. The generator takes PPG segments as input and generates corresponding ECG segments, while the attention mechanisms focus on important regions of the ECG waveform. The dual discriminators ensure the fidelity of the generated data in both the time and frequency domains.

Extensive evaluations were conducted to assess the performance of cardio GAN and compared it with various algorithms and demonstrated its superiority in terms of accuracy and fidelity in generating ECG signals using multiple evaluation metrics. The results showed that cardio GAN outperformed the ablation variants, indicating its potential for improving heart rate monitoring accuracy. Also analysed were the attention maps learned by the generator, providing insights into the regions of interest in the generated ECG signals.

The attention maps showed that cardio GAN focused on the P, QRS, and T complexes, which are important features of ECG waveforms. Additionally, explored the impact of paired training (using paired ECG-PPG data) versus unpaired training (using unpaired data) on cardio GAN's performance and found that unpaired training yielded superior results, suggesting that the network learned stronger user-independent mappings between PPG and ECG signals.

CardioGAN, a technology that generates ECG from PPG, providing more reliable heart rate measurements. The document presents qualitative and quantitative results of the technology's performance, including samples of generated ECG signals and comparisons between paired and unpaired training methods. The technology uses attention-based generators and dual discriminators, and an ablation study is performed to investigate the usefulness of these components. The generated ECG signals may exhibit a small time lag due to the Pulse Arrival Time, but this does not impact HR measurements or other cardiovascular-related metrics.

The potential applications of cardio GAN in the healthcare and wearable domains, highlight its role in continuous health monitoring and emphasise the importance of cardiac activity monitoring for early diagnosis and prevention of cardiovascular diseases. The proposed solution could be integrated into existing PPG-based wearable devices, enabling the extraction of ECG data without the need for additional hardware. Extending the model to generate multi-lead ECG signals could provide more comprehensive cardiac information and enable a wider range of applications.

Foetal ECG Extraction from Maternal ECG using attention-based Asymmetric CycleGAN:

In recent years, there has been a growing interest in the non-invasive extraction of foetal electrocardiogram (ECG) signals from maternal ECG signals. This research area holds great potential for improving prenatal care and foetal health assessment. Traditional decomposition techniques used for this purpose. One of the main challenges encountered in extracting foetal ECG signals is the low amplitude of the foetal signal, which is often overshadowed by the stronger maternal ECG signal.

A modified Cycle Generative Adversarial Network (CycleGAN) is a proposed solution for the non-invasive extraction of foetal ECG signals from maternal ECG signals. CycleGAN is a deep learning framework that has shown promise in various image-to-image translation tasks. By adapting this framework to the foetal ECG extraction problem. The modified CycleGAN incorporates masking attention layers, which are designed to enhance the performance of the generator networks. These generators are responsible for mapping the abdominal maternal ECG signal to the scalp foetal ECG signal and vice versa. The attention mechanisms play a crucial role in directing the focus of the generator networks to the relevant features of the ECG waveforms, enabling more accurate mapping between the two signals. Experiments have been conducted by using various datasets, including the A&D FECG, NI-FECG, and NI-FECG challenge datasets from Physionet. Additionally, a synthetic dataset generated using the FECGSYN toolbox was used for further validation. The performance of the proposed method was assessed using metrics such as R-Square, Wavelet Energy based Diagnostic Distortion, and F1-scores for QRS detection. The results obtained from the evaluation demonstrate the promising performance of the proposed method in accurately mapping maternal and foetal ECG signals. On the A&D FECG dataset, an average R-Square value of 97.2% and a Wavelet Energy based Diagnostic Distortion of 7.8 ± 1.9 were achieved. Moreover, high F1-scores for QRS detection were obtained on the A&D FECG, NI-FECG, and NI-FECG challenge datasets.

The method is comparable to state-of-the-art techniques and holds the potential to serve as a new algorithm for foetal ECG extraction. By leveraging the power of CycleGAN and incorporating attention mechanisms, efficient mapping between maternal and foetal ECG signals can be achieved, enabling non-invasive monitoring of the foetal heart. This advancement in foetal ECG extraction techniques opens up new possibilities for improving prenatal care and enhancing our understanding of foetal health.

A Real-Time QRS Detection Algorithm:

The Pan-Tompkins algorithm is a widely used method for detecting QRS complexes in electrocardiogram (ECG) signals. It plays a crucial role in automated ECG analysis by accurately identifying the depolarization of ventricles, aiding in heart rate determination and cardiovascular diagnosis. The paper presents a real-time algorithm for detecting QRS complexes in ECG signals. The algorithm utilises digital analysis of slope, amplitude, and width to reliably recognize QRS complexes. A special digital bandpass filter is employed to reduce false detections caused by various types of interference in ECG signals. The algorithm adjusts thresholds and parameters periodically to adapt to changes in QRS morphology and heart rate. Experimental results show that the algorithm correctly detects 99.3% of the QRS complexes in the standard MIT/BIH arrhythmia database.

The introduction section of the article highlights the importance of a reliable QRS recognition algorithm in various applications such as computer interpretation of the 12-lead ECG, arrhythmia monitors, and Holter tape recording. It discusses the challenges in QRS detection due to the physiological variability of QRS complexes and the presence of different types of noise in ECG signals. It also mentions the use of linear digital filtering, nonlinear transformation, and decision rule algorithms in QRS detection, and emphasises the importance of noise reduction in QRS detectors.

The article provides an overview of the algorithm, which is implemented in assembly language and operates on microprocessors. The algorithm utilises digital signal processing steps, including a digital bandpass filter, differentiation, squaring, and moving window integration, to extract features such as slope and width of the QRS complex. Adaptive thresholds and T-wave discrimination techniques are employed as part of the decision rule algorithm. It discusses the dual-threshold technique used in the algorithm to detect QRS complexes. The algorithm adapts its thresholds based on the most recent signal and noise peaks, allowing for improved detection sensitivity and it also discusses the maintenance of two separate measurements of the average RR interval to accommodate changes in heart rate. The algorithm includes a refractory period and waveform slope analysis to avoid false detections and differentiate between QRS complexes and T waves.

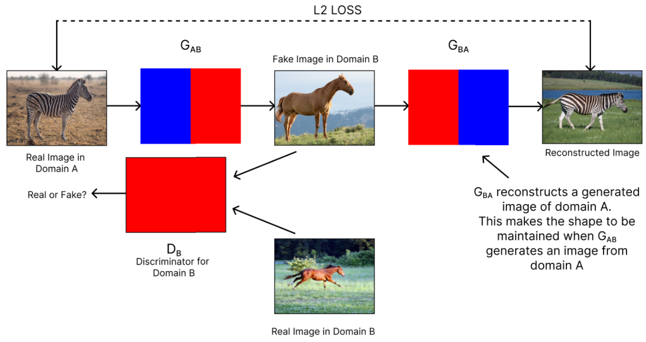
In terms of implementation, the algorithm is designed to operate in real time and utilises integer arithmetic to minimise computational requirements. The article discusses the use of a digital bandpass filter with integer coefficients to achieve noise rejection and highlights the filter's design based on poles and zeros on the unit circle of the z-plane.

Overall, the article presents a real-time QRS detection algorithm that incorporates digital signal processing techniques, adaptive thresholds, and parameter adjustments to reliably detect QRS complexes in ECG signals.

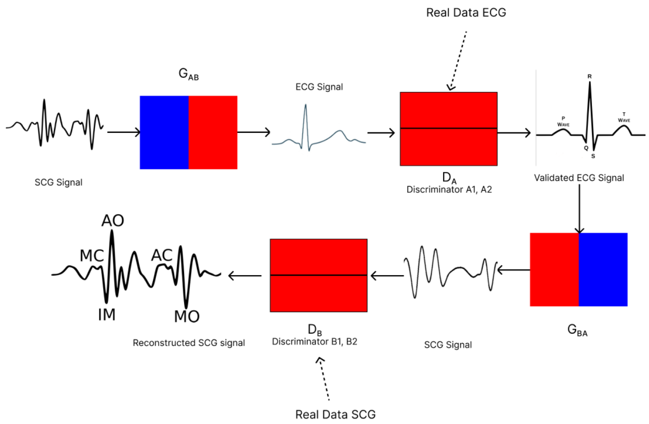
IMPLEMENTATION

The GAN effectively converts ECG signals to SCG signals by using the following procedure:

1. Data Preparation: The training data is made up of pairs of ECG and SCG signals, with each ECG signal paired with one or more SCG signals. The GAN's primary input is an ECG signal, and its secondary inputs are equivalent SCG signals.
2. Generator Network: The generator component of the GAN receives the primary input ECG signal and the secondary input SCG signal as inputs. Its goal is to generate synthetic SCG signals that are as near to the genuine SCG signals as possible for the supplied ECG signal. The generator network learns to recognise the patterns and correlations between the ECG and SCG signals.
3. Discriminator Network: The GAN's discriminator network gets pairs of actual ECG-SCG signal samples from the training dataset and pairs of synthetic ECG-SCG signal samples from the generator. Its function is to differentiate between actual and created pairs. As a result, the discriminator aids the generator in producing more realistic and precise SCG signals.
4. Training Process: The GAN is trained in an adversarial environment. Initially, the generator generates synthetic SCG signals that may differ significantly from real SCG signals. The discriminator learns to distinguish between genuine and simulated SCG signals. As training advances, the generator's settings are adjusted to produce synthesised SCG signals that are more realistic and difficult for the discriminator to identify from real SCG signals.
5. Optimisation: Fine-tuning involves adjusting hyperparameters, loss functions, and training strategies to optimise the model's performance. Experimentation includes modifying learning rates, layer structures, and loss function weights.
6. Inference: Once trained, the GAN can be utilised for inference. The generator can generate the appropriate SCG signals given a fresh ECG signal, and vice versa. Based on the learned patterns and mappings from the training data, this allows for the conversion and interchangeability of ECG and SCG signals.



Existing model



Modified Model

I. **Data Input:**

Start by collecting a dataset that includes paired examples of electrical (ECG) and mechanical (SCG) signals. Each example should have a corresponding pair, one from each domain.

II. **Generator A (G_A): *ECG to SCG Conversion:***

Feed an ECG signal into Generator A (G_A). The generator's task is to convert this electrical signal into a corresponding mechanical signal in the SCG domain.

III. **Discriminator B (D_B): *Filtering Similar Outputs in SCG Domain:***

Present the generated SCG signal to Discriminator B (D_B). D_B's role is to distinguish between real SCG signals and those generated by G_A. It filters out signals that are less similar to real SCG data.

IV. **Generator B (G_B): *SCG to ECG Conversion:***

Pass the filtered SCG signal through Generator B (G_B). G_B aims to convert the SCG signal back into its corresponding ECG signal.

V. **Discriminator A (D_A): *Filtering Similar Outputs in ECG Domain:***

Introduce the reconstructed ECG signal to Discriminator A (D_A). Similar to D_B, D_A filters out signals that are less similar to real ECG data.

VI. **Metric Evaluation:**

Compare the original ECG input and the reconstructed ECG output. Use metrics like mean square error (MSE), mean absolute error (MAE), and root mean square error (RMSE) to quantify the dissimilarity.

VII. **Model Training:**

A. Utilise the discrepancies between the original and reconstructed signals to update the parameters of both generators (G_A and G_B) and discriminators (D_A and D_B).
B. The training process involves iteratively refining the models to produce more accurate conversions.

VIII. **Iterative Improvement:**

Repeat the process for multiple iterations. With each iteration, the generators and discriminators learn to produce and filter signals more accurately, respectively.

IX. **Performance Monitoring:**

Continuously monitor the discriminator and generator losses during training. A decrease in losses indicates improved convergence and stability in the model.

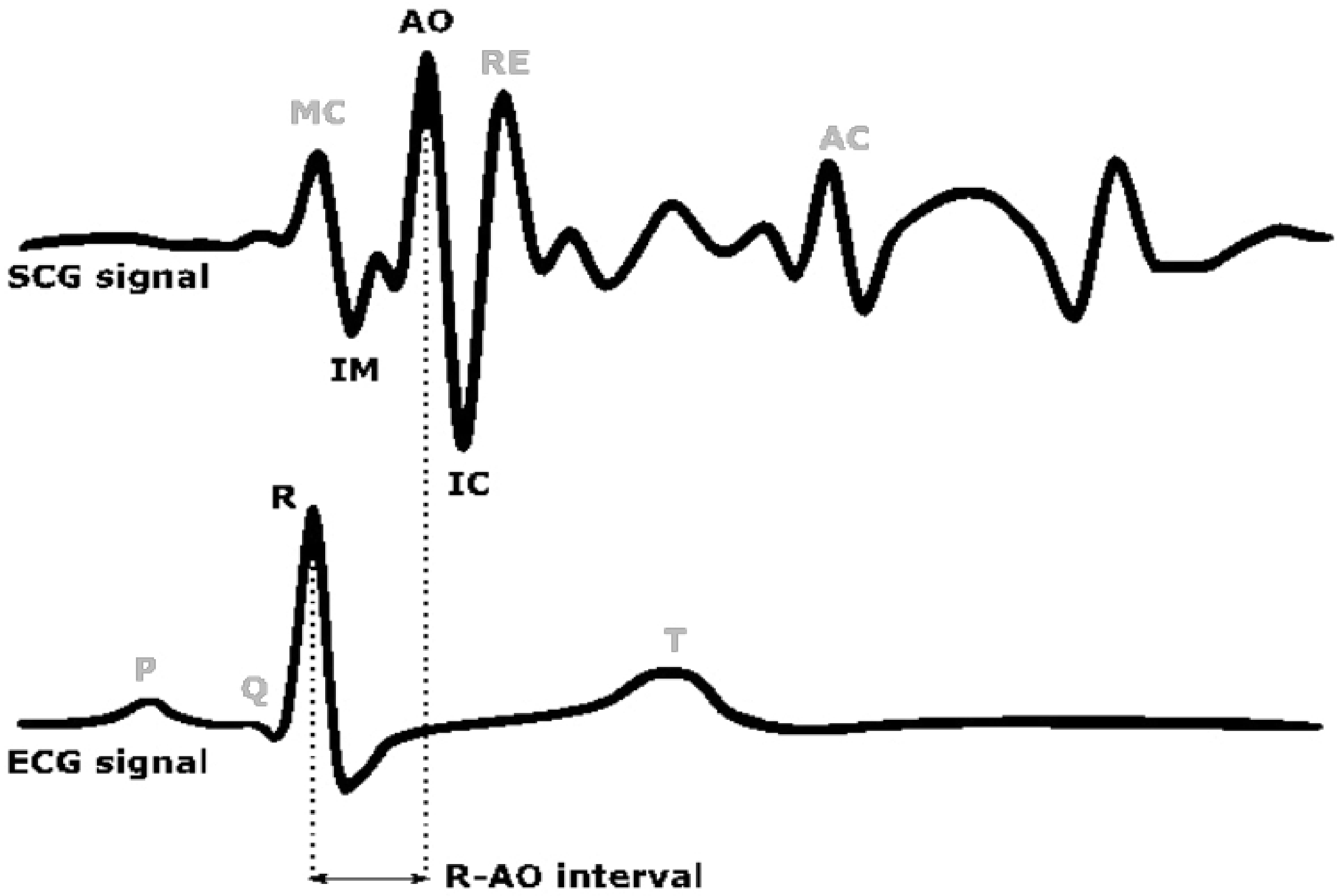
X. **Outcome:**

The final outcome is a set of generators and discriminators that, through mutual learning, can effectively convert between ECG and SCG signals. The model is optimised for accuracy in generating realistic signals and filtering dissimilar outputs.

This process outlines the key stages involved in the model, from data input to the iterative training process, leading to improved conversion accuracy between electrical and mechanical signal domains.
The process is the same for accurate conversion of ECG to SCG signals

B. The Pan Tompkins algorithm, which was developed by Jiapu Pan and Willis J. Tompkins in 1985, is a widely used signal processing algorithm for the detection of QRS complexes in ECG signals.

The Pan-Tompkins algorithm's major goal is to correctly identify the QRS complex, which depicts the electrical activity associated with ventricular depolarization in the heart. The QRS complex is an important part of ECG analysis because it offers information regarding heart rate, rhythm, and abnormalities.



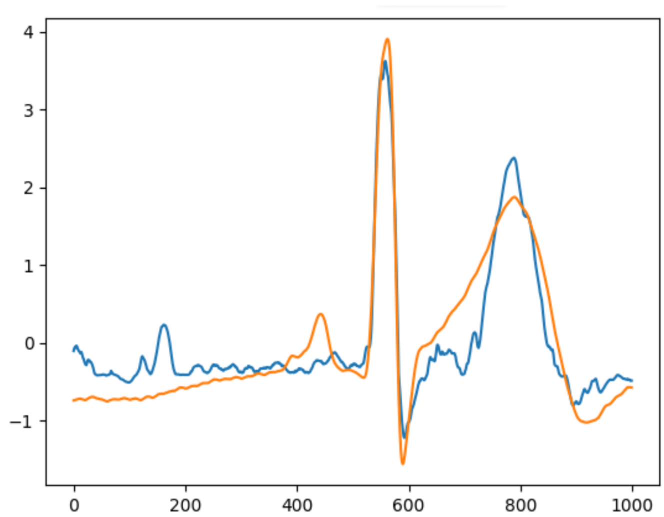
The algorithm consists of several key steps:

1. *Preprocessing:* The algorithm begins by using a bandpass filter to remove noise and undesirable frequencies that could interfere with the detection of QRS complexes, which in turn improves the overall SNR. This procedure improves signal quality by isolating the frequency band of interest. By applying the filter, we will suppress or attenuate the frequencies outside 5Hz - 15Hz, which will reduce the noise influence on QRS complex detection.
2. *Differentiation:* The preprocessed signal is then differentiated in order to highlight the high-frequency components associated with the QRS complex's steep slopes. This technique improves R-peak detection.
3. *Squaring:* The differentiated signal is squared to amplify the peaks of the QRS complex while suppressing the lower-amplitude T and P waves
4. *Moving Window Integration:* The moving window integration procedure is used to smooth the squared signal and highlight the QRS complex peaks. This phase entails adding the squared values inside a given window size. The window length is 0.08 seconds, which corresponds to 0.08 * fs (sampling frequency).

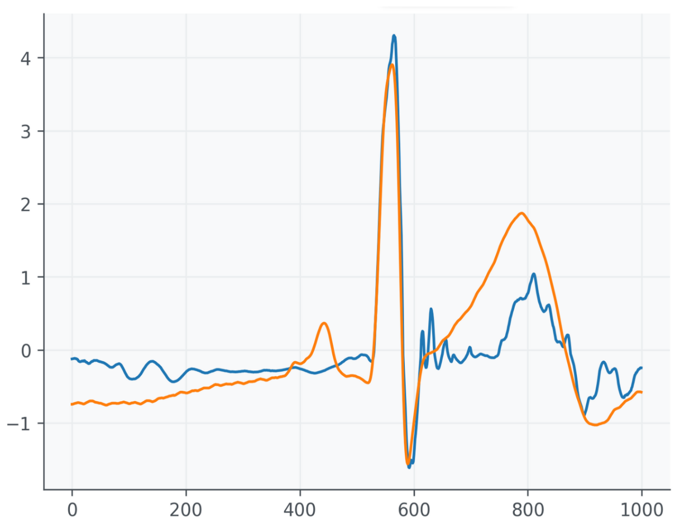
5. *Adaptive Thresholding:* To identify QRS complexes from noise and other components, the algorithm employs an adaptive thresholding technique. The threshold is established dynamically based on the properties of the signal and responds to changing situations
6. *QRS Detection:* The final step is to detect the QRS complex peaks by comparing the integrated signal to the adaptive threshold. A QRS complex is identified whenever the integrated signal surpasses the threshold

In a variety of ECG signals, including those with noise, baseline drift, and arrhythmias, the Pan-Tompkins algorithm has been shown to be successful in identifying QRS complexes. It is commonly used in medical equipment, monitoring systems, and ECG analysis software.

RESULTS



2 X 2 ACGAN Model (Previous)



4 x 2 ACGAN (Modified)

**Subject 10 output*

	Generated Wave
	Original Wave

Upon analysing the ECG signals generated by the new and old ACGAN models, it can be observed that the new model offers a closer approximation to the original ECG signal in terms of waveform structure and timing. However, it tends to overemphasise the amplitude of peaks, which is more evident at the T wave of the signal. Even though this process can capture the dynamics of the signal accurately, it could lead to misinterpretation in a clinical setting if not adjusted for scale. Even though the older model produces a more subdued waveform which is more consistent with the original signal's amplitude, it is being done at the cost of potentially losing finer details that are crucial for accurate medical diagnosis. While our new model is capable of replicating the essential patterns present in an ECG signal, refinement in distinct characteristics, such as amplitude scaling, is required.

Looking into the ECG signals created by the old and new ACGAN models, something important can be noticed. The new model gets pretty close to the original ECG signal in terms of how the waveform looks and the timing. But it tends to make the peaks higher, especially at the T wave. While this helps capture the dynamic parts of the signal, it could cause problems in a real-world medical setting if we don't adjust it properly.

On the other hand, the old model creates a calmer waveform that matches the original signal's height. But here's the issue – it might lose some important details needed for accurate medical diagnosis.

Even though the new model copies the main patterns in an ECG signal well, it's clear we need to tweak certain things, especially how it deals with the height of the peaks.

To fix this, we can try a few things. One idea is to fine-tune the model so it matches the heights we see in real medical data. Another approach is to build in a system that adjusts the peak height based on the input signal, making the output more reliable for doctors. Finding the right balance between staying true to the original signal and avoiding misunderstandings is a key focus as we keep making our ACGAN model better for practical use in clinics.

	Old	New	Old	New	Old	New	Old	New	Old	New	Old	New	Old	New	Old	New
Subject	**Dloss[1]**		**Gloss[2]**		**PRD[3]**		**MSE[4]**		**MAE[5]**		**R[6]**		**R2[7]**		**Accuracy**	
1	0.284	0.253	1.81	1.03	6.15	7.647	0.501	0.578	0.705	0.465	0.587	0.743	0.21	0.512	86	91.7
2	0.384	0.253	2.06	1.06	6.76	8.434	0.522	0.703	0.541	0.458	0.639	0.666	0.282	0.378	88	89.69
3	0.389	0.253	1.965	1.061	6.408	8.601	0.697	0.731	0.647	0.629	0.643	0.258	0.31	-0.195	88.5	80.2
4	0.385	0.253	1.76	1.068	7.098	8.246	0.764	0.672	0.536	0.434	0.617	0.732	0.246	0.492	87.5	91.589
5	0.488	0.253	1.996	1.063	6.245	9.183	0.672	0.834	0.67	0.583	0.677	0.328	0.366	-0.148	89.4	80.97
6	0.386	0.253	1.856	1.06	6.572	6.603	0.705	0.431	0.538	0.462	0.649	0.604	0.297	0.279	88.3	88.06
7	0.386	0.253	1.95	1.064	6.62	7.076	0.601	0.495	0.679	0.474	0.607	0.654	0.243	0.347	87.4	89.18
8	0.338	0.253	1.853	1.073	6.657	10.269	0.678	1.042	0.754	0.696	0.627	-0.019	0.267	-0.454	87.8	75.91
9	0.293	0.253	1.745	1.052	6.442	6.786	0.757	0.455	0.704	0.488	0.63	0.655	0.296	0.362	88.33	89.42
10	0.38	0.252	2.032	1.07	6.19	6.15	0.768	0.408	0.677	0.456	0.64	0.542	0.295	0.181	88.5	86.4
11	0.385	0.253	1.804	1.056	6.566	7.611	0.673	0.573	0.756	0.508	0.631	0.595	0.301	0.257	88.43	87.684
12	0.354	0.253	2.069	1.054	6.814	7.038	0.591	0.49	0.71	0.051	0.616	0.405	0.247	-0.003	87.533	83.39
13	0.465	0.253	2.132	1.058	6.832	9.258	0.764	0.848	0.757	0.609	0.601	0.277	0.224	-0.184	87.13	80.39
14	0.388	0.253	1.995	1.062	6.02	6.25	0.667	0.661	0.609	0.574	0.643	0.741	0.31	0.509	87.6	91.3
15	0.389	0.253	2.009	1.056	6.409	1.88	0.616	0.236	0.643	0.329	0.627	0.758	0.264	0.533	87.81	95.44
16	0.492	0.253	2.088	1.059	6.537	8	0.74	0.632	0.647	0.487	0.633	0.579	0.281	0.24	88.09	87.4
17	0.488	0.253	1.753	1.063	6.673	6.231	0.505	0.384	0.619	0.401	0.633	0.799	0.297	0.61	88.35	96.458
18	0.367	0.253	1.791	1.062	6.735	7.697	0.628	0.585	0.563	0.3	0.584	0.658	0.206	0.89	86.84	96.55
19	0.388	0.253	1.724	1.059	6.569	7.66	0.533	0.532	0.532	0.508	0.626	0.27	0.273	-0.145	87.96	89.06
20	0.297	0.26	1.902	1.006	7.084	6.49	0.612	0.324	0.785	0.5	0.622	0.63	0.255	0.89	87.65	92.05
AVG	0.386	0.253	1.915	1.057	6.569	7.356	0.650	0.581	0.654	0.471	0.627	0.544	0.274	0.268	87.856	83.557
BEST	0.284	0.252	1.724	1.006	6.02	1.88	0.501	0.236	0.532	0.051	0.677	0.799	0.366	0.89	89.4	96.55

[1] Discriminator Loss
[2] Generator Loss
[3] Percentage Root mean square error Difference
[4] Mean Square Error
[5] Mean Absolute Error
[6] Correlation Coefficient
[7] Coefficient of Determination

DLoss	Discriminator Loss
Gloss	Generator Loss
PRD	Percentage Root mean square error Difference
MSE	Mean Square Error
MAE	Mean Absolute Error
R	Correlation Coefficient
R-Squared	Coefficient of Determination

In our analysis of the results, several key patterns were identified, which highlights changes in the metrics between the 'Old' and 'New' ACGAN models. A consistent trend was observed in Dloss and Gloss metrics, where there was a notable decrease from the Old to the New model, highlighting effectiveness of the model. Inversely, PRD values showed a consistent increase, resulting in slightly worse performance compared to the old model. Additionally, the R and MAE generally indicated improvements in the New model, with R values increasing and MAE values decreasing.

I. **Loss Metrics:** A noteworthy decrease in both discriminator and generator losses indicates enhanced convergence and training stability, reflecting improved overall model performance.

II. **Percentage Root Mean Square Error (RMSE) Difference(PRD):** Surprisingly, there was an increase in the percentage root mean square error difference. While reduced losses suggest better model convergence, the heightened RMSE difference might imply increased sensitivity to data variations.

III. **Mean Square Error (MSE) and Mean Absolute Error (MAE):** A substantial reduction in both mean square error and mean absolute error suggests that the model's predictions closely align with actual values, showcasing improved accuracy and precision.

CONCLUSION

Our research in deep learning, specifically exploring generative adversarial networks (GANs), took a significant step forward. We expanded a foundational model with two generators and two discriminators in a cycleGAN framework, introducing improvements to boost the model's capabilities.

Adding a new identification/detection module broadened the model's abilities to understand complex patterns, and including two extra discriminators refined its skills further. Systematic fine-tuning and rigorous experimentation showed substantial progress, with notable decreases in both discriminator and generator losses, indicating better convergence and stability in training. Moreover, there was a significant drop in mean square error (MSE) and mean absolute error (MAE), highlighting the model's improved accuracy and precision.

While an increase in the percentage root mean square error difference calls for more investigation into the model's sensitivity to data variations, the overall positive results position this project as a valuable contribution to the evolving landscape of generative adversarial networks.

This research sets the stage for continued exploration and refinement, offering possibilities for advanced applications in various domains. Our project focuses on accurately distinguishing and converting ECG and SCG signals, aiming to enhance cardiac diagnostics and tracking for improved healthcare solutions.

By efficiently mapping the 4 discriminators and 2 generators ACGAN model, and through rigorous training and testing on multiple subjects, we successfully generated realistic signal outputs, addressing our research questions and achieving our intended goals.

The impact on clinical practice is substantial. Accurate identification and separation of ECG and SCG signals are crucial for precise diagnosis and continuous heart monitoring. This differentiation supports early problem detection, aids in evaluating heart function, and contributes to formulating individualised treatment plans.

Moreover, our project advances healthcare technology by demonstrating the feasibility of automated signal processing methods for cardiovascular monitoring. The use of the Pan-Tompkins method showcased its effectiveness in analysing and classifying cardiac data. These algorithms, subject to further study and refinement, hold the potential to become reliable instruments for assessing cardiovascular health.

Our research project, "An End to End Deep Learning based approach for Cardiovascular Monitoring Using Seismocardiogram signals," represents an important step forward in the understanding of cardiovascular health. We have achieved ground-breaking results thanks to the combination of cutting-edge algorithms, complex approaches, and meticulous analysis. We as a team are really proud of our joint work, and we look forward to a time when our discoveries influence better patient outcomes, better medical judgement, and a general reform of cardiovascular healthcare practises.

REFERENCES

I. Neeraj, U. Satija, J. Mathew and R. K. Behera, "A Unified Attentive Cycle-Generative Adversarial Framework for Deriving Electrocardiogram From Seismocardiogram Signal," in IEEE Signal Processing Letters, vol. 29, pp. 802-806, 2022, doi: 10.1109/LSP.2022.3152448.

II. Sarkar, Pritam, and Ali Etemad. "CardioGAN: Attentive generative adversarial network with dual discriminators for synthesis of ecg from ppg." Proceedings of the AAAI Conference on Artificial Intelligence. Vol. 35. No. 1. 2021.

III. Kim, Taeksoo, Moonsu Cha, Hyunsoo Kim, Jung Kwon Lee, and Jiwon Kim. "Learning to discover cross-domain relations with generative adversarial networks." In *International conference on machine learning*, pp. 1857-1865. PMLR, 2017.

IV. Mohebbian, Mohammad Reza, Seyed Shahim Vedaei, Khan A. Wahid, Anh Dinh, and Hamid Reza Marateb. "Foetal ECG Extraction from Maternal ECG using attention-based Asymmetric CycleGAN." *CoRR* (2020).

V. T. Choudhary, L. Sharma, and M. K. Bhuyan, "Heart sound extraction from sternal seismocardiographic signal," IEEE Signal Process. Lett., vol. 25, no. 4, pp. 482–486, Apr. 2018.

VI. T. Choudhary, L. N. Sharma, M. K. Bhuyan and K. Bora, "Identification of human breathing-states using cardiac-vibrational signal for m-health applications," IEEE Sensors J., vol. 21, no. 3, pp. 3463–3470, Feb. 2021.

VII. Kolarik, Jakub, Radana Kahankova, Jindrich Brablik, and Radek Martinek. "Comparison of SCG and ECG based cardiac activity monitoring in laboratory conditions." *IFAC-PapersOnLine* 52, no. 27 (2019): 550-555.

VIII. U. Satija, B. Ramkumar, and M. S. Manikandan, "Real-time signal quality aware ECG telemetry system for IoT-based health care monitoring," IEEE Internet Things J., vol. 4, no. 3, pp. 815–823, Jun. 2017.

IX. M. S. Manikandan and S. Dandapat, "Wavelet-based ECG and PCG signals compression technique for mobile telemedicine," in Proc. 15th Int. Conf. Adv. Comput. Commun., 2007, pp. 164–169

X. E. Prabhakara Rao and S. Dandapat, "Attentive RNN-based network to fuse 12-lead ECG and clinical features for improved myocardial infarction diagnosis," IEEE Signal Process. Lett., vol. 27, pp. 2029–2033, 2020.

XI. T. Choudhary, M. K. Bhuyan, L. N. Sharma, "Orthogonal subspace projection based framework to extract heart cycles from SCG signal," Biomed. Signal Process. Control, vol. 50, pp. 45–51, 2019.

XII. J. Yao, S. Tridandapani, W. F. Auffermann, C. A. Wick and P. T. Bhatti, "An adaptive seismocardiography (SCG)-ECG multimodal framework for cardiac gating using artificial neural networks," IEEE J. Transl. Eng. Health Med., vol. 6, pp. 1–11, 2018.

XIII. J. Kolarik, R. Kahankova, J. Brablik, and R. Martinek, "Comparison of SCG and ECG based cardiac activity monitoring in laboratory conditions," IFAC-Papers OnLine, vol. 52, no. 27, pp. 550–555, 2019

XIV. M. R. Mohebian, S. S. Vedaei, K. A. Wahid, A. Dinh, H. R. Marateb, and K. Tavakolian, "Foetal ECG extraction from maternal ECG using attention-based CycleGAN," IEEE J. Biomed. Health Informat., vol. 26, no. 2, pp. 515–526, Feb. 2022.

XV. P. Sarkar and A. Etemad, "CardioGAN: Attentive generative adversarial network with dual discriminators for synthesis of ECG from PPG," in Proc. 35th AAAI Conf. Artif. Intell., 2021, pp. 488–496.

XVI. U. Satija, B. Ramkumar, and M. S. Manikandan, “A review of signal processing techniques for electrocardiogram signal quality assessment,” IEEE Rev. Biomed. Eng., vol. 11, pp. 36–52, 2018.

XVII. E. Prabhakara Rao and S. Dandapat, “Myocardial infarction severity stages classification from ECG signals using attentional recurrent neural network,” IEEE Sensors J., vol. 20, no. 15, pp. 8711–8720, Aug., 2020.

XVIII. https://www.robots.ox.ac.uk/~gari/teaching/cdt/A3/readings/ECG/Pan+Tompkins.pdf

XIX. U. Satija, B. Ramkumar, and M. S. Manikandan, “Automated ECG noise detection and classification system for unsupervised healthcare monitoring,” IEEE J. Biomed. Health Informat., vol. 22, no. 3, pp. 722–732, May 2018.

XX. https://www.digitalxplore.org/up_proc/pdf/62-139756312157-61.pdf

XXI. Jiapu Pan and Willis J. Tompkins, “A Real-Time QRS Detection Algorithm”, IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING, VOL. BME-32, NO. 3, MARCH 1985.