Enhanced ECG Classification Using Dual-Lead Gramian Angular Field Transformation and Deep Learning

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Abstract

Background and Objective: Accurate detection of Chagas cardiomyopathy from electrocardiograms (ECGs) is critical for timely intervention, particularly in resource-limited settings. While conventional methods rely on handcrafted features or limited lead information, we explore the effectiveness of transformer-based deep learning models to detect Chagas disease from 12-lead ECGs across multiple populations and datasets.

Methods: We developed a hybrid CNN-transformer model to classify Chagas cardiomyopathy from 12-lead ECG signals. The model architecture begins with a series of convolutional layers to extract local temporal patterns, followed by max-pooling to downsample the feature maps. This is followed by stacked transformer encoder blocks that capture global dependencies across the signal through multi-head self-attention and feed-forward convolutional layers. The output is aggregated using global average pooling and passed through fully connected layers before producing a sigmoid-activated binary classification output. The model was trained using ECGs from the SaMi-Trop and CODE-15% datasets and PTB-XL dataset..

Results: The transformer classifier demonstrated strong generalization. Our team Mainchagas achieved challenge score of 0.691. These results suggest that the model can identify Chagas-related patterns in ECGs, even when evaluated on geographically and demographically distinct datasets.

Conclusion: This study highlights the potential of transformer-based architectures for robust ECG interpretation in the context of Chagas disease. The pipeline's performance across diverse datasets underscores its viability for deployment in scalable screening programs.

1. Introduction

Cardiovascular diseases (CVDs) represent the most significant cause of global mortality, accounting for nearly 18 million deaths each year. [1, 2]. Conditions such as coronary artery disease, heart failure, arrhythmias, and hypertensive heart disease contribute to this burden. Early detection and precise diagnosis are essential to improve patient outcomes and reduce the risk of severe complications [3, 4]. Electrocardiograms (ECGs) remain a central tool for identifying cardiac abnormalities [5]. However, conventional approaches often treat ECGs as 1D signals, limiting the ability to apply advanced image-based learning techniques that have transformed computer vision [6, 7]. To overcome this limitation, Gramian Angular Field (GAF) transformation has been proposed to convert 1D ECG signals into 2D representations. This technique preserves temporal dynamics while enabling the use of powerful convolutional and modern image-based neural networks. In this study, we examine the utility of GAF transformations for ECG classification, with particular emphasis on dual-lead configurations. Our goal is to achieve a balance between diagnostic accuracy and computational efficiency, offering a framework suitable for scalable clinical and wearable applications.

2. Methods

The experimental workflow for this study consists of several key stages, starting from data acquisition to the final evaluation of classification performance (Figure 1). The process begins with the use of the PTB-XL dataset, a comprehensive open-source ECG database that provides multi-lead ECG recordings. The data undergoes preprocessing, including filtering and normalization steps to prepare the signals for further analysis.

In the experimental setup, three configurations of ECG leads are considered: single Lead II, dual leads (Lead II and V1), and the full 12-lead ECG, to assess the impact of lead selection on classification performance. The ECG signals are transformed into Gramian Angular Fields, converting the 1D time-series data into 2D image representations. Three different GAF sizes—5000x5000, 512x512, and 256x256—are evaluated to determine the optimal image resolution for model performance,

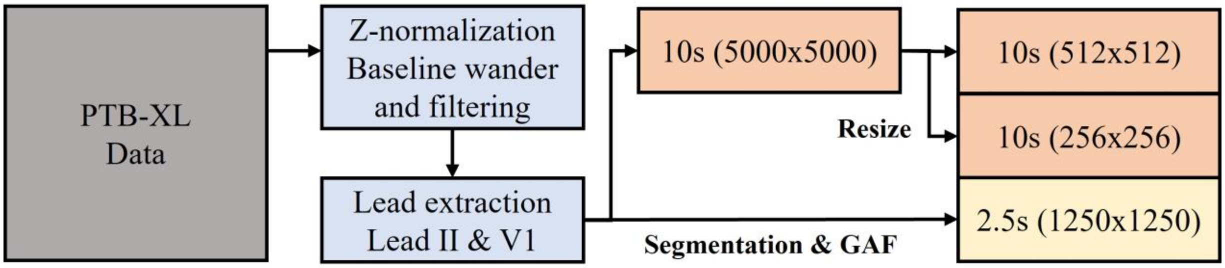

Figure 1. Overview of the proposed method. Generated ECG and real ECG signals are equally preprocessed, trained, and classified using the same ResNet model. The output of the classification model is normal, A-fib, CLBBB, CRBBB, LVH, and RVH.

balancing between computational efficiency and accuracy. Finally, the classification performance is evaluated using metrics such as accuracy, precision, recall, and F1-score to assess the effectiveness of the different lead configurations and GAF sizes. The results guide the selection of the most suitable approach for ECG classification, highlighting the potential of using multi-lead GAF transformations combined with advanced deep learning models for diagnosing cardiovascular conditions.

2.1. Datasets and Preprocessing

This study used the PTB-XL dataset, which contains more than 21,000 ECG records from nearly 19,000 patients, each sampled at 500 Hz over 10 seconds. Four diagnostic categories were considered: Normal, atrial fibrillation (AFib), left ventricular hypertrophy (LVH), and right ventricular hypertrophy (RVH). Records were filtered to reduce noise, normalized using z-score scaling, and divided into training, validation, and test sets in an 80:20 split. The 12-lead ECG data used in this study are the PTB-XL dataset, which were publicly available and provided by the PhysioNet [8]. PTB-XL dataset has 7528 normal ECG records, 1514 records of AFib, 2137 records of LVH and 126 records of RVH.

2.2. *Gramian Angular Field Transformation*

The raw 1D ECG signals were transformed into 2D images using the Gramian Angular Field (GAF) technique. GAF encodes time-series data into structured matrices that capture temporal dependencies between points. This is achieved by representing the normalized signal in polar coordinates and applying trigonometric operations. Two common variants are used: the Gramian Angular Summation Field (GASF) and the Gramian Angular Difference Field (GADF).
The GASF employs the cosine function to compute pairwise angular summations:

$$GASF = cos(\phi_i + \phi_j) \quad (1)$$

where ϕ_i and ϕ_j are the angles corresponding to normalized values of the time-series points. This emphasizes similarity and accumulation patterns. In contrast, the GADF uses the sine function to highlight angular differences:

$$GADF = sin(\phi_i - \phi_j) \quad (2)$$

Both variants preserve important temporal relationships while enabling the application of image-based deep learning models. In this study, we evaluated three GAF resolutions—5000×5000, 512×512, and 256×256—to investigate trade-offs between computational cost and classification accuracy.

2.3. Evaluation Method

Performance was quantified with accuracy, precision, recall, and F1-score. These metrics provided a comprehensive assessment of the classification results across experimental setups.

$$Accuracy = \frac{True\ Positive + True\ Negative}{True\ positive + True\ Negative + False\ Positive + False\ Negative} \quad (3)$$

$$Precision = \frac{True\ Positive}{True\ positive + False\ Positive} \quad (4)$$

$$Recall = \frac{True\ Positive}{True\ positive + False\ Negative} \quad (5)$$

$$F1\ Score = \frac{2}{\frac{1}{Precision} + \frac{1}{Recall}} \quad (6)$$

Table 1 Performance Comparison of ECG Classification Methods Using Different GAF Sizes and Segmentation

Method	F1-score			
	A-fib	LVH	RVH	Normal
5000x5000	0.776	0.715	0.412	0.775
512x512	0.781	0.71	0.521	0.792
256x256	0.651	0.691	0.424	0.721
2.5 Segmentation	0.762	0.722	0.551	0.778

3. Results

Table 1 summarizes classification outcomes across GAF image sizes and segmentation settings. ConvNeXt consistently outperformed ResNet, delivering higher accuracy and F1-scores across all experiments. The 5000×5000 GAF resolution yielded the best raw performance but required extensive computational resources. The 256×256 resolution reduced resource demand but lost fine-grained detail, resulting in lower accuracy. The 512×512 resolution provided the most favorable balance, particularly when combined with segmentation, which enhanced detection of arrhythmias and hypertrophic patterns.

4. Discussion

Our findings confirm that dual-lead GAF transformation combined with ConvNeXt provides a strong alternative to conventional 12-lead ECG analysis. The dual-lead configuration achieved accuracy levels close to full 12-lead models while requiring fewer inputs, which is highly relevant for wearable and low-resource applications. This balance of efficiency and diagnostic capability underscores the clinical value of the approach.

Segmentation further improved performance by isolating diagnostically significant segments of the ECG trace. By focusing learning on critical intervals, the models were less affected by irrelevant signal variation and noise, yielding better recognition of arrhythmias and hypertrophic conditions. These results are consistent with previous findings that emphasize the importance of both spatial and temporal localization in ECG interpretation.

Another important observation is the impact of GAF resolution. Although the 5000×5000 GAF provided slightly higher performance, the 512×512 resolution offered a much better trade-off between computation and accuracy, making it a practical choice for real-world deployment. The 256×256 resolution demonstrated that aggressive downsampling sacrifices critical signal detail, which can hinder diagnostic reliability.

Despite these encouraging results, the study has limitations. Only selected conditions were examined, and generalization to other cardiovascular diseases remains to be tested. The PTB-XL dataset, while comprehensive, may not fully capture the diversity of global populations or continuous monitoring scenarios. Additionally, transformation parameters for GAF may not be universally optimal, leaving room for future tuning or alternative encoding strategies.

Future work should explore multimodal integration, combining ECG data with echocardiography, imaging, demographics, or genetic information to enrich model predictions. Investigating advanced sequence models, such as transformers adapted to GAF images, may further improve long-range temporal feature capture. Finally, applying the method to streaming or wearable ECG data could validate its utility in continuous monitoring and early warning systems.

5. Conclusion

This study shows that dual-lead GAF transformation with ConvNeXt offers an efficient yet accurate framework for automated ECG classification. The method significantly improves over single-lead models and approaches the performance of 12-lead systems, while reducing complexity and computational demands. These characteristics make it highly suitable for deployment in wearable health technologies and large-scale screening programs.

Key contributions of this work include demonstrating the utility of GAF transformation for dual-lead ECGs, highlighting the advantages of ConvNeXt over conventional CNNs, and showing the benefits of segmentation in focusing on clinically relevant features. While the approach has limitations related to dataset scope, selected conditions, and reliance on static ECGs, it provides a solid foundation for future advancements.

In conclusion, this framework bridges the gap between traditional single-lead wearable recordings and comprehensive 12-lead diagnostics. With further validation on diverse populations and continuous ECG data, dual-lead GAF models may play a significant role in enabling scalable, accessible, and reliable cardiovascular disease screening. This study demonstrates that dual-lead GAF transformation with ConvNeXt enables efficient and accurate ECG classification. The approach narrows the gap between single- and 12-lead performance, supporting practical applications in wearable devices and screening systems. Limitations include reliance on PTB-XL data and a focus on selected conditions, which may not fully capture real-world variability. Moreover, the analysis was based on static ECGs; future evaluation on continuous monitoring data is needed to ensure broader generalizability.

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References

[1] G. A. Roth *et al.*, "Global, Regional, and National Burden of Cardiovascular Diseases for 10 Causes, 1990 to 2015," (in eng), *J Am Coll Cardiol,* vol. 70, no. 1, pp. 1-25, Jul 4 2017, doi: 10.1016/j.jacc.2017.04.052.

[2] W. H. Organization. "World Health Organization. Cardiovascular diseases (CVDs)." https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds) (accessed.

[3] A. Rillig *et al.*, "Early rhythm control therapy in patients with atrial fibrillation and heart failure," *Circulation,* vol. 144, no. 11, pp. 845-858, 2021.

[4] M. P. Turakhia *et al.*, "Economic burden of undiagnosed nonvalvular atrial fibrillation in the United States," *The American journal of cardiology,* vol. 116, no. 5, pp. 733-739, 2015.

[5] S. S. Al-Zaiti, Z. Faramand, K. Rjoob, D. Finlay, and R. Bond, "Chapter 3 - The role of automated 12-lead ECG interpretation in the diagnosis and risk stratification of cardiovascular disease," in *Cardiovascular and Coronary Artery Imaging*, A. S. El-Baz and J. S. Suri Eds.: Academic Press, 2022, pp. 45-87.

[6] S. Kiranyaz, O. Avci, O. Abdeljaber, T. Ince, M. Gabbouj, and D. J. Inman, "1D convolutional neural networks and applications: A survey," *Mechanical systems and signal processing,* vol. 151, p. 107398, 2021.

[7] H. Narotamo, M. Dias, R. Santos, A. V. Carreiro, H. Gamboa, and M. Silveira, "Deep learning for ECG classification: A comparative study of 1D and 2D representations and multimodal fusion approaches," *Biomedical Signal Processing and Control,* vol. 93, p. 106141, 2024.

[8] P. Wagner *et al.*, "PTB-XL, a large publicly available electrocardiography dataset," *Scientific Data,* vol. 7, no. 1, p. 154, 2020/05/25 2020, doi: 10.1038/s41597-020-0495-6.

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