Enhanced 12-Lead ECG Reconstruction from Single-Lead Data Using WaveNet

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Abstract. The Electrocardiogram (ECG) is a fundamental tool in clinical practice for diagnosing a variety of heart conditions. Traditional ECG systems require a complete set of 12 leads collected in a clinical environment, which can be time-consuming and costly. Recent advancements in wearable technology, such as smartwatches, allow for the collection of ECG signals in a more convenient manner, but typically only provide a single lead. This paper presents a novel approach to reconstructing the full 12-lead ECG from a single lead using WaveNet. The WaveNet model offers flexibility in handling signal segments of varying durations, while exceling in capturing complex data dependencies. Our models achieve superior performance in terms of signal reconstruction quality, demonstrated by a significant improvement in Pearson correlation coefficients, RMSE and SSIM. This work paves the way for more accessible and cost-effective ECG diagnostics, potentially revolutionizing cardiac care with wearable devices.

Keywords: Electrocardiogram (ECG), 12-Lead ECG, WaveNet, Signal Reconstruction, Wearable Devices

1 Introduction

The Electrocardiogram (ECG) test has been a cornerstone in the field of cardiology for over a century, providing critical insights into heart health through the analysis of electrical signals generated by the heart **[1]**. Traditionally, a 12-lead ECG system is employed, requiring multiple electrodes placed on the patient's body to capture comprehensive cardiac activity**[2]**. This setup, while effective, necessitates a clinical environment and the expertise of healthcare professionals, leading to increased time and financial costs**[3]**.

With the advent of wearable technology, such as smartwatches, the landscape of ECG testing is changing. These devices offer the capability to perform ECG tests more comfortably and frequently, albeit typically capturing only a single lead (Lead I). While valuable for preliminary arrhythmia detection, a single lead is insufficient for a complete clinical assessment**[4]**.

Recent research efforts **[5]** have focused on overcoming this limitation by reconstructing the full set of 12 ECG leads from fewer leads, including attempts to use a single lead. However, existing methods often face challenges such as the need for fixed-length segments or alignment of single heartbeats, limiting their practical application.

In this paper, we propose a new method for the direct conversion of a single ECG lead to the full 12-lead set using WaveNet **[6]**. The WaveNet model is known for its ability to handle varying signal segment lengths without requiring architectural changes, making it robust against diverse ECG signal characteristics.

Our study demonstrates that this new approach significantly enhance the quality of ECG lead reconstruction, achieving better values of Pearson correlation coefficients, RMSE and SSIM compared to existing methods. The flexibility and accuracy of this model have the potential to transform ECG diagnostics, making comprehensive cardiac monitoring accessible outside of clinical settings through wearable devices.

The structure of this paper is as follows: **Section 2** reviews related work, examining existing methods, limitations, and the advantages of neural network models. **Section 3** details the methodology, including data sources, data processing and the WaveNet model. **Section 4** presents the results, covering performance metrics and comparative analysis. **Section 5** discusses the findings, practical implications, and potential integration with wearable devices. Finally, **Section 6** provides the conclusion, summarizing key findings and implications for future research.

2 Related Work

2.1 ECG Background

The electrocardiogram (ECG) is a diagnostic test that captures the heart's electrical activity through electrodes placed on the skin. These electrodes detect and record signals, providing valuable information about heart rate and rhythm, and aiding in the diagnosis of heart conditions. As a non-invasive procedure, the ECG is

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widely used for diagnosing and monitoring heart diseases. In the following sections, we will discuss the collection of ECG signals and the configuration of the lead system used in the process **[7]**.

The collection of the ECG signal occurs through electrodes strategically placed on the patient's body. Each pair of electrodes measures, over time, the electrical potential difference (voltage) between the regions where they are placed. This pair of electrodes is called a lead, and given a set of electrodes, different leads arise from the combination of different pairs. The signals from the different leads together make up an ECG test. How many electrodes will be used, where they will be positioned, and the leads formed from them form a Lead System. Some Lead Systems have been proposed and used over the years; however, the most applied currently is the 12-Lead System **[8].**

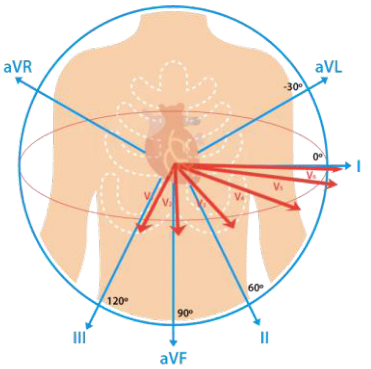

Fig. 1. Leads placement on the human body. **[9]**

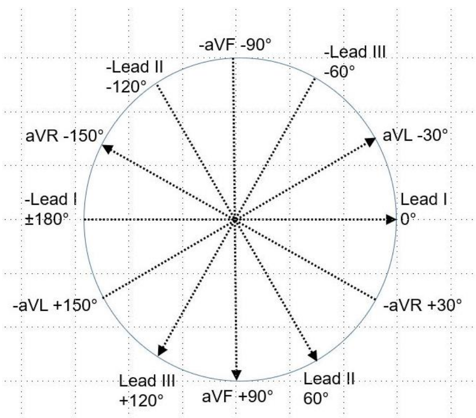

Fig.2. Planes in 12-Lead System **[10]**

As the name suggests, the 12-Lead System comprises signals from 12 leads derived from nine electrodes. Three electrodes are placed on the patient's limbs, generating the six limb leads, and the other six electrodes are on the chest, each generating a single lead called chest leads or precordial leads. The first set, referring to the limbs, is composed of leads LI, LII, LIII, aVl, aVr, and aVf, while the second set contains leads V1, V2, ..., and V6 **[11]**. The leads in this system lie on two perpendicular planes: the limb leads on the frontal plane and the precordial leads on the horizontal plane. The positioning of the limb leads follows a specific angulation necessary for accurate medical evaluation **[12]**, whereas the placement of the precordial leads is influenced by the patient's anatomy **[13].**

2.2 ECG Reconstruction Methods

The primary related work is the paper by Beco et al. **[14]**, which proposes a strategy based on the U-Net model **[15]** for converting ECG signal segments of fixed length. This study focuses on the 12-Lead System, assuming a single lead as input and the remaining 11 leads as output. The U-Net architecture, which utilizes an encoding-decoding framework, presents two model variations: the first employs a shared encoder for all leads, while the second uses an individual encoder for each lead. Their evaluations were conducted using the three datasets detailed in Section 6.2. Beco et al. **[14]** achieved the best results in the literature for converting Lead I into the remaining 11 leads from arbitrary segments, making it a benchmark for comparison in our study.

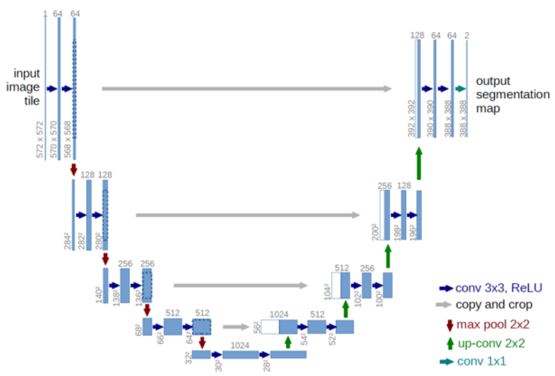

Fig. 3. U-Net architecture schema for lead conversion.**[14]**

Additional related works include the study by Grande-Fidalgo et al. **[15],** which used linear regression and dense neural networks to reconstruct the standard 12-lead ECG from a subset of three input leads. Similarly, Sohn et al. **[16]** employed Long Short-Term Memory (LSTM) networks for 12-lead reconstruction from a three-lead patch-type device. However, both approaches require more than a single lead as input, limiting their direct comparability to single-lead solutions.

Lee et al. **[17]** contributed one of the few works that used only a single lead as input, utilizing a Generative Adversarial Network (GAN) for ECG signal reconstruction. Their method required the input segments to be single heartbeats aligned in time, necessitating preprocessing of the signals. This limitation contrasts with our approach, which aims to handle variable-length segments without the need for such alignment.

In summary, while significant advancements have been made in multi-lead ECG reconstruction, the challenge of achieving accurate and practical single-lead to 12-lead conversion remains a critical area of research, addressed in our study through the use of the WaveNet model.

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3 Methodology

The task that we want to perform is to convert lead I to the other leads.

3.1 Data sources

We utilized three sets of ECG data, each containing, among other information, the 12 leads. The datasets are available on PhysioNet **[18]**

The PTB database **[19]** comprises 549 records from 290 subjects, aged between 17 and 87. Each record includes 15 signals: the 12 conventional leads and the 3 Frank lead ECGs (vx, vy, vz). The signals are digitized at a sampling rate of 1000 samples per second with a 16-bit resolution range of ±16.384 mV. Most ECG records provide a comprehensive clinical summary in the header file, which includes details on age, gender, diagnosis, medical history, medication, interventions, coronary artery pathology, ventriculography, echocardiography, and hemodynamics.

The PTB-XL ECG dataset **[20, 21]** contains 21,799 12-lead ECG records, each lasting 10 seconds, from 18,869 patients. This dataset is annotated by up to two cardiologists and covers 71 distinct ECG statements. These annotations are grouped into five superclasses: NORM (normal ECG), MI (myocardial infarction), STTC (ST/T change), CD (conduction disturbance), and HYP (hypertrophy). Additionally, the dataset provides extensive metadata on demographics, infarction characteristics, likelihoods for diagnostic ECG statements, and annotated signal properties.

The INCART database includes 75 annotated recordings captured using a Holter monitor. Each record spans 30 minutes and contains 12 standard leads recorded at a frequency of 257 Hz. The records in this database were predominantly selected from subjects with consistent ECG patterns and diagnoses such as ischemia, coronary artery disease, conduction abnormalities, and arrhythmias.

3.2 Data preprocessing

We adopted an approach similar to that of Beco et al. **[14]**. The training was conducted on the PTB dataset, while evaluations were performed using the PTB-XL and INCART datasets.

For the PTB dataset, recordings were segmented into 5-second intervals (5000 samples). Each segment underwent noise reduction through a second-order Butterworth bandpass filter with cutoff frequencies of fc = [1, 40] Hz, preserving essential ECG information. The amplitudes of each signal were min-max normalized to the range [−1, 1]. This preprocessing resulted in 11,871 segments, which were divided into 90% for the train set and 10% for the validation set.

Regarding the INCART dataset, ECG signals were first resampled to 1 kHz, followed by the same preprocessing steps as those applied to the PTB dataset. This process yielded 27,000 segments.

For the PTB-XL dataset, we selected 16,272 recordings that did not have conflicting superclass annotations. From each recording, the first 5 seconds were extracted, resampled to 1 kHz, and processed in the same manner as described for the PTB dataset.

3.3 WaveNet

WaveNet is a deep neural network that was proposed in **[6]** for raw audio generation. The model is fully probabilistic and autoregressive, with the predictive distribution for each audio sample conditioned on all previous ones. The model operate audio waveforms, which are similar to ECG signals.

The conditional probability distribution in WaveNet is modeled by a stack of dilated causal convolutional layers which are specifically crafted to deal with long-range temporal dependencies.

The causal aspect ensure that the model respects the temporal order of the data, meaning that predictions at a given time step do not depend on future time steps. This principle is similar to masked convolutions used in image modeling. For 1-D data like audio or ECG signals, causal convolutions are achieved by shifting the output of a regular convolution by a few time steps.

The dilation aspect is responsible for increasing the receptive field of the model without requiring large filters or a lot of layers. A dilated convolution expands the filter's region by skipping input values with a specified step, effectively acting like a larger filter derived from the original through zero-padding, but more efficiently.

WaveNet does not use pooling layers which insure that the output has the same time dimensionality as the input.

In the paper [6], the conditional distributions are modeled as a softmax distributions. The data is first transformed using a μ-law companding transformation (ITU-T, 1988) and then quantized to 256 values. This leaves the softmax layer with only 256 probabilities per timestep instead of 65536 for the typical 16-bit integer representation of raw audio. WaveNet is then trained using a cross entropy loss.

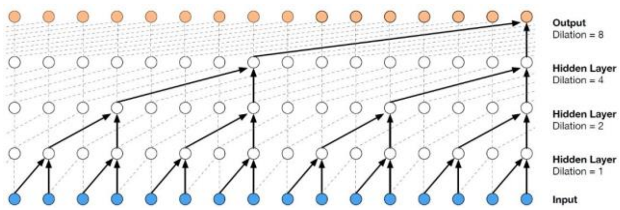

Fig. 4. Visualization of a stack of dilated causal convolutional layers **[6]**

In this work we fed the processed lead I signals directly to WaveNet and reconstructed the corresponding eleven ECG leads. The training was done using the L1 loss.

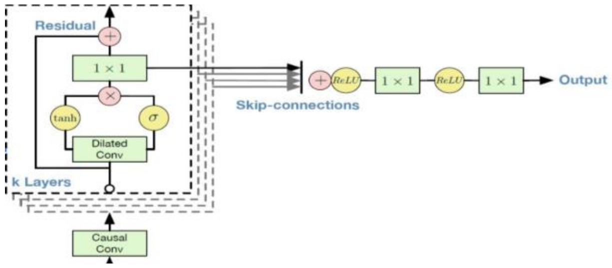

Fig. 5. Overview of the residual block and the entire architecture **[6]**

3.4 Model training

We used a WaveNet model with 3 blocks and 5 layers each. The training was done using the l1-loss between the model outputs and the corresponding ground-truth signals as the objective function. The reduction method used is "sum".

The Adam optimiser was used with an initial learning rate of 1 × 10−4, over 13 epochs with batch size 32.

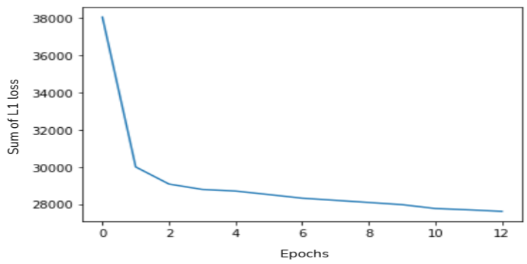

Fig. 6. Evolution of training loss over 13 epochs

4 Results and discussion

In this section, we present the results of our study, evaluating the performance of the WaveNet model in reconstructing the full 12-lead ECG from a single lead. We discuss the evaluation metrics used, provide a detailed analysis of the results, and examine the practical implications and limitations of our findings.

To evaluate the model's performance, we employed three metrics: the average Pearson Correlation Coefficient (avg r), the average Root Mean Squared Error (RMSE), and the average Structural Similarity Index Measure (SSIM). The Pearson Correlation Coefficient (PCC) quantifies the linear correlation between the predicted and actual ECG signals, with higher values indicating stronger correlations and better reconstruction quality. The RMSE assesses the average squared difference between the predicted and actual ECG signals, where lower values denote higher accuracy. The SSIM evaluates the perceived quality of the reconstructed signals, considering aspects such as luminance, contrast, and structure.

The WaveNet model achieved an average PCC of 0.73 across the 12 leads for PTB-XL Dataset and 0.48 for the INCART Dataset, demonstrating a solid correlation between the predicted and actual signals. The model obtained an average RMSE of 0.10 for PTB-XL Dataset and 0.22 for INCART Dataset, indicating high accuracy in signal reconstruction.

Visual inspection of the reconstructed signals (see figure 1) showed that they closely resembled the actual ECG signals, especially for leads LII, LIII, aVR, aVF, aVL, V1, and V6, with low variance in waveform morphology. Despite some discrepancies in specific leads, such as V2, V3, V4, and V5, where the signal amplitude was occasionally underestimated, the reconstructed signals remained realistic with only minor variations compared to the actual signals.

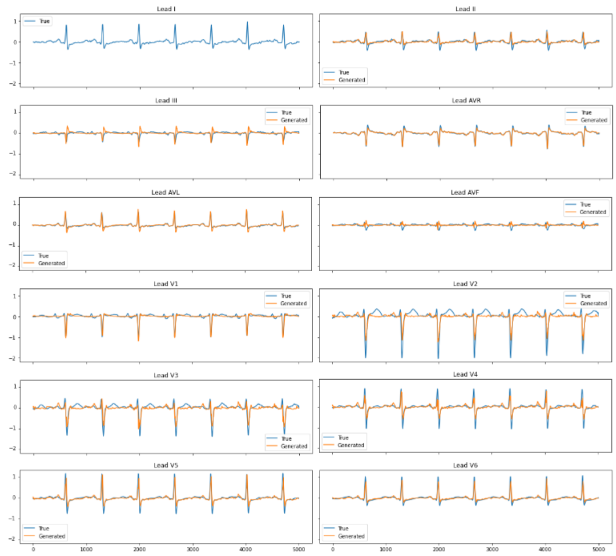

Fig. 7. Example result of lead I to all conversion on a random example from PTB-XL dataset (the horizontal axis represents time, while the vertical axis corresponds to the normalised signal amplitude)

Table 1 illustrates the comparative results across three metrics utilized in assessing the model using the PTB-XL dataset. This work outperforms in all leads for the (r avg) and RMSE metrics, and it also shows superior average values for the SSIM metric. When the same evaluation was conducted with the INCART dataset, as depicted in Table 2, the average values for the r (avg.) and RMSE metrics were notably higher in this study. However, for the SSIM metric, the values from Beco et al. **[14]** were slightly superior by 0.04.

Table 1. Comparison between the results of the work by Beco et al. **[14]** and the present work for an evaluation between different datasets (training performed with PTB and evaluation performed with PTB-XL).

Lead	r (avg.)		SSIM		RMSE	
	Beco et al.	This work	Beco et al.	This work	Beco et al.	This work
II	0.60	**0.76**	0.23	**0.58**	0.33	**0.08**
III	0.31	**0.38**	**0.43**	0.24	0.38	**0.08**
aVR	-0.61	**0.93**	0.09	**0.78**	0.74	**0.04**
aVL	-0.63	**0.81**	0.11	**0.62**	0.75	**0.04**
aVF	0.29	**0.42**	0.23	**0.32**	0.41	**0.08**
V1	0.79	**0.84**	**0.91**	0.47	0.16	**0.09**
V2	0.71	**0.74**	**0.84**	0.35	0.22	**0.18**
V3	0.65	**0.65**	**0.64**	0.43	0.29	**0.18**
V4	0.62	**0.74**	0.30	**0.54**	0.32	**0.16**
V5	0.76	**0.86**	0.35	**0.67**	0.24	**0.11**
V6	0.80	**0.89**	0.53	**0.68**	0.20	**0.08**
Average	0.39	**0.73**	0.42	**0.52**	0.37	**0.10**

Table 2. Comparison between the results of the work by Beco et al. [14] and the present work for an evaluation between

different datasets (training performed with PTB and evaluation performed with INCART).

Lead	r (avg.)		SSIM		RMSE	
	Beco et al.	This work	Beco et al.	This work	Beco et al.	This work
II	0.36	**0.52**	0.19	**0.41**	0.37	**0.27**
III	**0.17**	0.11	**0.28**	0.22	0.43	**0.27**
aVR	0.67	**0.69**	**0.83**	0.57	0.22	**0.14**
aVL	**0.36**	0.30	**0.47**	0.30	0.35	**0.14**
aVF	0.17	**0.34**	0.22	**0.30**	0.41	**0.27**
V1	0.57	**0.65**	**0.79**	0.38	0.32	**0.16**
V2	**0.50**	0.49	**0.73**	0.28	0.49	**0.26**
V3	0.36	**0.43**	**0.44**	0.39	0.37	**0.26**
V4	0.34	**0.42**	0.19	**0.39**	0.38	**0.23**
V5	0.45	**0.62**	0.11	**0.47**	0.35	**0.22**
V6	0.45	**0.63**	0.21	**0.46**	0.34	**0.23**
Average	0.40	**0.47**	**0.41**	0.37	0.34	**0.22**

The redevelopment of a 12-lead ECG from a single lead via the WaveNet model presents pivotal implications for both clinical settings and the enhancement of wearable technologies. Enabling in-depth ECG diagnostics through single-lead wearable devices could revolutionize cardiac health monitoring, making it both more affordable and widely accessible. Such devices, when integrated with this model, offer the possibility of continuous heart monitoring, which can play a crucial role in the early detection of arrhythmic events and other cardiac anomalies, potentially easing the clinical load on healthcare systems.

However, the findings do present certain constraints that warrant attention. The integrity of input ECG signals plays a crucial role in the accuracy of signal reconstruction, where noise and other data anomalies might compromise model performance. Moreover, the model's training on a confined dataset poses questions about its applicability to other datasets or practical environments. The computational demands for training and running the WaveNet model also pose challenges for its integration into low-powered wearable technologies.

In addition to employing the WaveNet model, our study also explored the use of TimeGAN, a Generative Adversarial Network specifically designed for time-series data. TimeGAN is renowned for its ability to learn complex data distributions and replicate intricate temporal dynamics, which is crucial for realistic synthetic data generation. This model leverages a unique architecture that combines an embedding network, a recovery network, a generator, and a discriminator. The embedding network encodes the input data into a latent space that captures the temporal dynamics, while the recovery network aims to reconstruct the original data from this encoded form, ensuring the model's ability to preserve essential characteristics of the ECG signals.

The adversarial setup of TimeGAN, comprising the generator and discriminator, enhances the model's capability to generate synthetic but realistic sequences. The generator tries to produce data sequences that mimic the real data's statistical properties, and the discriminator assesses whether the sequences are real or generated, promoting an ongoing optimization of data fidelity. This adversarial process is crucial for the model to learn detailed and complex patterns in ECG data, such as those associated with various cardiac conditions.

Our comparative analysis involved evaluating the performance of both WaveNet and TimeGAN in reconstructing 12-lead ECG from a single lead. While TimeGAN showed potential in learning and replicating complex data distributions, it did not surpass the performance metrics achieved by WaveNet. Specifically, TimeGAN achieved an average RMSE of 0.12 across the 11 leads, compared to WaveNet's more favorable RMSE of 0.09. These findings directed our focus towards WaveNet due to its superior accuracy and efficiency, particularly significant for real-time applications in wearable devices.

5 Conclusion

Our research underscores the capacity of the WaveNet neural network model to reconstruct 12-lead ECG signals from a solitary lead, achieving commendable fidelity in signal replication. This breakthrough could significantly alter the landscape of cardiac diagnostics, enhancing the feasibility and cost-efficiency of thorough ECG monitoring through wearable technologies.

Future research should aim at refining the model's resilience to poor-quality input data, including enhancing its ability to adaptively manage noise variations, and at boosting its generalization capability across diverse datasets. Optimizing the model for computational efficiency to suit low-powered devices remains critical. Investigative efforts towards amalgamating WaveNet's capabilities with other methodologies might also enhance performance metrics. Crucially, integrating and validating this model in real-world clinical settings, in collaboration with medical professionals, will be essential to evaluate its practical effectiveness. In essence, the WaveNet model is poised to make substantial contributions to ECG diagnostics, improving both the accessibility and precision of cardiac monitoring, thus potentially enriching patient care. Continued innovation and exploration in this field are essential to realize the full potential of advancements in medical technology.

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