

# Single-Lead to Multi-Lead Electrocardiogram Reconstruction Using a Modified Attention U-Net Framework

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**Abstract**—With Cardiovascular Diseases on the rise around the world, Electrocardiograms (ECGs) play a crucial role in their diagnosis owing to their non-invasive nature and simplicity. Medical professionals typically use 12-lead ECGs for medical analysis but gathering 12-lead ECG data is an arduous task outside clinical setting. Modern wearables can collect an ECG with fewer leads than the standard 12 leads. However, medical professionals and conventional ECG analysis software find this reduced lead set data challenging to interpret. By using the reduced lead set data to create standard 12-lead ECG data, ECG reconstruction can solve this issue. This paper proposes a novel single-lead to multi-lead ECG reconstruction solution using a modified Attention U-net framework. Using only the lead II of ECG, our model is able to reproduce the other 11 leads of conventional 12-lead ECG with a Pearson correlation, Mean square error and R-squared value of 0.805, 0.0122 and 0.639, respectively. Further, a single combined model is used to reconstruct all 11 leads simultaneously, improving performance and simultaneously reducing the computational resources needed for training compared to current literature in the field. In comparison to previous works, which only reconstruct small ECG segments, our model is trained to reconstruct longer 10-second ECG signals. We demonstrate our model’s ability for real-life utilisation using a cardiovascular disease classification task. A deep learning model was trained for multi-disease classification on actual 12-lead ECG data and was tested on both original and reconstructed 12-lead ECG signals. The classification accuracies for the original and reconstructed signals were comparable, portraying that our reconstruction model can preserve diagnostically relevant artefacts in its reconstructed signals. This work provides a new promising solution in the field of single-lead ECG reconstruction, taking us a step closer to bridging the divide between reduced lead set data and existing 12-lead ECG end users like clinicians and automatic ECG classifiers.

## I. INTRODUCTION

An Electrocardiogram (ECG) is a non-invasive medical procedure used for heart activity monitoring. This procedure is widely used owing to its speed and effectiveness in detecting heart-related problems [1], [2]. An ECG can record the electrical activity generated by the heart by using electrodes placed on the patient’s skin in various locations, giving us information about the heart rhythm and health. These

electrodes are conductive and are able to record the voltage present on the skin, which is then processed before being presented to the clinician for further diagnosis.

ECGs have multiple variations depending on the number of leads used, but the 12-lead ECG is by far the most commonly used in health centres worldwide [3]. Even though it is called a 12-lead ECG, it only involves ten electrodes comprising four limb electrodes (placed on all four limbs of the patient) and six pre-cordial electrodes. An apparent problem with this type of ECG is the precision needed in placing the electrodes at suitable locations [4]. As clinicians are dependent on the collected signals to make a diagnosis, a small error in their placement can result in the production of unwanted artefacts in the signals, leading to a possibility of an erroneous diagnosis. Knight et al. [5] showed that 38% of 500 electrophysiologists who participated in their study misdiagnosed an artefact as ventricular tachycardia. Even though other variations of ECGs that need lesser leads do exist, they are relatively inaccurate compared to the 12-lead variant. This becomes a major hassle for patients who need continuous monitoring, where they are forced to sacrifice the accuracy of a 12-lead ECG for the portability and ease of use of lesser lead variants.

Although the 12-lead ECG only requires 10 electrodes, the 12 leads in the name stands for the processed signals obtained from these electrodes. The 12 generated leads can be divided into frontal plane limb leads (I, II, III, aVF, aVL and aVR) and chest leads (V1, V2, V3, V4, V5 and V6). The lead I is calculated by computing the electrical differences between the left and right arm electrodes. The lead II is calculated by computing the electrical difference between the left leg and right arm electrodes. The lead III is calculated by computing the electrical differences between the left leg and left arm electrodes. The remaining three frontal plane limbs are called the augmented vector (aV) leads, where the F, L and R in their names represent the Foot, Left arm and Right Arm, respectively. These leads are mathematically derived from the first three limb leads. Using Kirchoff’s law on electrical current, which states the sum of all currents in a closed circuit is zero [6], we can mathematically generate all frontal plane

limb leads using any two of the frontal plane limb lead values. The chest leads are not interrelated like the frontal plane limb leads and hence have to be recorded individually using separate electrodes (V1 to V6). The electrode on the right leg is not used to generate any lead; instead, it is used as ground to prevent artefacts in the other leads. [7]

Due to various intricacies involved, the usage of the 12-lead ECG is restricted in pre-hospital, ambulatory and home-care settings. With cardiac-related issues becoming more prominent around the world [8], accurate but easy-to-use ECG devices are needed more than ever. Even though devices like the Holter monitor [9] exist, which measure the standard 12-lead ECG, their utility is limited by the movement constraints they put on their user. With recent technological advances, we have witnessed much growth in the wearable technology field, from smartwatches used by the masses to more sophisticated straps used by athletes. The major drawback with such devices is that they almost always only collect a subset of the twelve leads. Even though this information is helpful, a clinician is usually trained to interpret a 12-lead ECG, thus handicapping the utility of such devices. ECG reconstruction can help bridge this gap by converting reduced lead set ECG to standard, more interpretable 12-lead ECG. It is important to note that ECG reconstruction does not add new information to reduced lead set data. Instead, it just converts all the information captured in the reduced lead data into a 12-lead version. As the human heart-torso electrical system is theoretically linear and quasi-stationary, the initial reconstruction efforts using Machine Learning (ML) techniques were limited to the use of Linear Regressors [10], [11]. However, as computational capabilities have improved in recent times, researchers found eminent success in synthesising more accurate signals using neural networks.

Several studies [12]–[15] have achieved good reconstruction results from a reduced lead set. Kapfo et al. [14] presented a patient-specific approach for reconstructing the standard 12-lead ECG. They also use a discrete wavelet transform (DWT) combined with Long Short-Term Memory (LSTM) to predict the standard 12 leads using just three input leads. They achieved an average correlation constant of 0.98, and a root mean squared error of 78. Jangjay et al. [15] were able to achieve an average correlation coefficient of 0.95 for their reconstructed signals using LSTMs. However, all the mentioned studies were dependent on three different leads (two frontal limb leads and one pre-cordial lead). This hinders their practical use, as they would still require multiple electrodes to be placed on the chest and multiple limbs to collect the required information. To fast-track the adoption of such reconstruction techniques by the wearable device industry, we need to reduce the amount of data they need to collect.

Gundlapalle et al. [16] proposed a novel single-lead to 12-lead ECG reconstruction method using convolutional neural networks (CNNs), long short-term memory units (LSTMs) and multi-layer perceptrons (MLPs). Using only lead II as input, they generate all other 11 leads. They were able to achieve an average correlation coefficient of 0.973 and a regression

coefficient of 0.959. Yoon et al. [17] presented a generative adversarial network (GAN) for generating all 12 leads of an ECG using a single lead (lead I). As part of their GAN, a U-net is used as their generator and a patch discriminator as their discriminator. They were able to reconstruct signals with a mean frechet distance (FD) score of 11.321 and a mean square error (MSE) of 0.038.

To the best of our knowledge, these were the only studies performing ECG lead reconstruction using a single lead. Both these works suffer from some critical drawbacks. Both works segment their signals to shorter lengths (1 second and 2.5 seconds) while generating the other leads for relatively easier reconstruction. However, as traditionally, ECG is recorded for 10 seconds [18], to use the proposed approaches in real life, one would need to develop algorithms to connect the reconstructed segments together, which might reduce the effectiveness of the overall reconstruction. Both works use a complex set of deep-learning algorithms. Yoon et al. [17] used a GAN, which is hampered by unstable learning and takes a very long time to train [19]. Gunlapelle et al. used a combination of CNNs, LSTMs and MLPs, making the overall pipeline very complex. Gunlapelle et al. also segmented the ECG signals into 1-second segments, which were then randomly divided into train and test sets. This could have caused 1-second ECG segments belonging to the same ECG signal to be present in the train and the test set. This leakage of data might have inflated the reported results. Although both studies produced good signal reconstruction, they did not establish whether the reconstructed signals can be used in real-life applications.

In this study, we present a novel Modified Attention U-Net based framework for Single-Lead to Multi-Lead Electrocardiogram Reconstruction. We used the lead II to reconstruct the remaining 11 leads with a mean Pearson Correlation coefficient of 0.805. Since only lead II is used as an input, the desired data can easily be calculated using just two electrodes placed on the left leg and right arm. We improve on the drawbacks of previous works and also demonstrate that the reconstructed ECG signal can be used by a classification model trained on a standard 12-lead ECG data to detect cardiovascular diseases efficiently. Our contributions are:

- Instead of using shorter ECG segments for reconstruction, we reconstruct the complete 10-second ECG signal at once.
- We propose a model architecture which only employs convolutions, making them easily malleable to work with any size input segments while training is faster.
- We propose a modified variant of Attention U-Net performing better than the standard U-Net and Attention U-Net.
- Unlike the past studies, which use a separate model for each lead reconstruction leading to a total of 11 models, we use a single model for all 11 lead reconstructions. By using a single model, not only were we able to reduce the number of trainable parameters but also were able to improve upon the performance.
- We test our reconstructed signals on an existing 12-

lead disease classification model to accurately measure how well our method can preserve anomalies in the input signal that the classification model uses for disease detection.

## II. METHODS

### A. Dataset and preprocessing

For the study, we used the large publicly available PTBXL dataset [20]. The dataset has 21837, 10-second length, 12-lead ECG data from 18885 patients collected over a period of seven years. The ECG signals are provided with sampling rates of 100Hz and 500Hz. For this study, we employed ECG signals sampled at 500Hz. The dataset includes a large portion of healthy records as well as a wide range of diagnostic classes like myocardial infarction, hypertrophy, etc. As part of the data preprocessing, we first used a Butterworth [21], [22] highpass filter set at 0.5Hz to remove the low-frequency noise and artefacts. This was followed by a Butterworth lowpass filter set at 200Hz to remove the high-frequency noise. Finally, all the ECG signals were smoothed using Savitzky-Golay Filter [23]. The dataset was then divided into train and test sets using an 80%-20% train-test split. The train set comprised 17469 ECG recordings, and the test set included 4368 ECG recordings.

### B. Model Architecture

Fig. 1 represents the proposed Deep Learning architecture we use for lead reconstruction. We propose a single model which takes the lead II of the original ECG as input to reconstruct the remaining 11 leads. Since both input and output data are time series signals, we use 1D convolutions to design the network. The input is a single channel 5000-length signal representing a 10-second recording of the lead II sampled at 500Hz. The output comprises 11 channels of 5000 in length, where each channel represents the different leads of the reconstructed ECG signal.

The model architecture used in the study is a modified version of the Attention U-Net proposed by Oktay et al. [24]. A U-Net architecture first downscales the input and then upscales the downscaled input back to generate the output. The skip connections are employed to tackle any data loss. In the proposed model architecture, we downscale the input lead II signal thrice, which is then upscaled thrice to get the reconstructed leads. Standard attention U-Net employs max-pooling for downscaling the signals while upsampling layer is used for upscaling. The convolution layer provides a kernel with learnable parameters, which the max-pooling layer lacks; hence we replace the max-pooling in the original attention U-Net with a 1D convolution of kernel size 3 and stride 2. Similarly, the upsampling layer is replaced by a 1D Transpose Convolution [25] of kernel size 3 and stride 2. The standard attention U-Net applies attention to the skip connection to get the attention-gated skip connection. This attention-gated skip connection is then used for concatenation with the upscaled signal from the 1D Transpose Convolution. For the proposed model, we concatenate the raw skip connection in addition to the attention-gated skip connection with the upscaled signal.

### C. Model Training and Testing

The proposed model is trained on the training set for 50 Epochs. The ADAM optimiser is used for optimisation [26] and Mean Squared Error is used as the target loss function. The Batch Size was set at 32 for training. The learning rate was initially set at 0.0001, which was reduced on plateauing of the loss using a scheduler. The trained model was then tested on the hold-out test set, and different evaluation metrics were used to evaluate the quality of signal reconstruction. The model was trained and evaluated using NVIDIA GeForce GTX 3090Ti with 24 GB memory. Pytorch version '1.12.1' [27] was used for the realisation of the model. Similar training and testing regimes were followed for all the other models mentioned in the Results and Experiments Section.

### D. Evaluation Metrics

To evaluate the quality of ECG reconstruction, we used the three metrics.

- The Pearson Correlation coefficient( $\rho$ ) represents the similarity between the reconstructed and the original signal.  $\rho$  ranges from -1 to 1, where 1 represents that the two signals are exactly the same, while -1 represents that the two signals are exactly opposite.

$$\rho = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 \sum_{i=1}^n (y_i - \bar{y})^2}} \quad (1)$$

- The Mean squared error (MSE) measures the average error between the generated and the original signal. Thus the lower the MSE, the better the signal reconstruction, and an MSE of 0 will represent that the reconstructed signal is exactly identical to the original signal.

$$MSE = \frac{1}{n} \sum_{i=1}^n (x_i - y_i)^2 \quad (2)$$

- The level of association between the original and generated signals has been assessed using  $R^2$  statistics. The  $R^2$  value of a perfectly reconstructed signal will be 1.

$$R^2 = 1 - \frac{\sum_{i=1}^n (x_i - y_i)^2}{\sum_{i=1}^n (x_i - \bar{x})^2} \quad (3)$$

Here  $x_i$  is the  $i^{\text{th}}$  data point of the original signal and  $y_i$  is the  $i^{\text{th}}$  datapoint of the reconstructed signal.  $\bar{x}$  and  $\bar{y}$  are the sample means of the original and reconstructed signal respectively, and  $n$  is the number of data points in the signal.

## III. EXPERIMENTS AND RESULTS

### A. Performance Analysis and Comparison

The proposed model was able to reconstruct the 11 leads from lead II with a mean Pearson Correlation coefficient ( $\rho$ ) of 0.805, MSE of 0.0122,  $R^2$  of 0.639. We compare the results of the proposed model with other models using

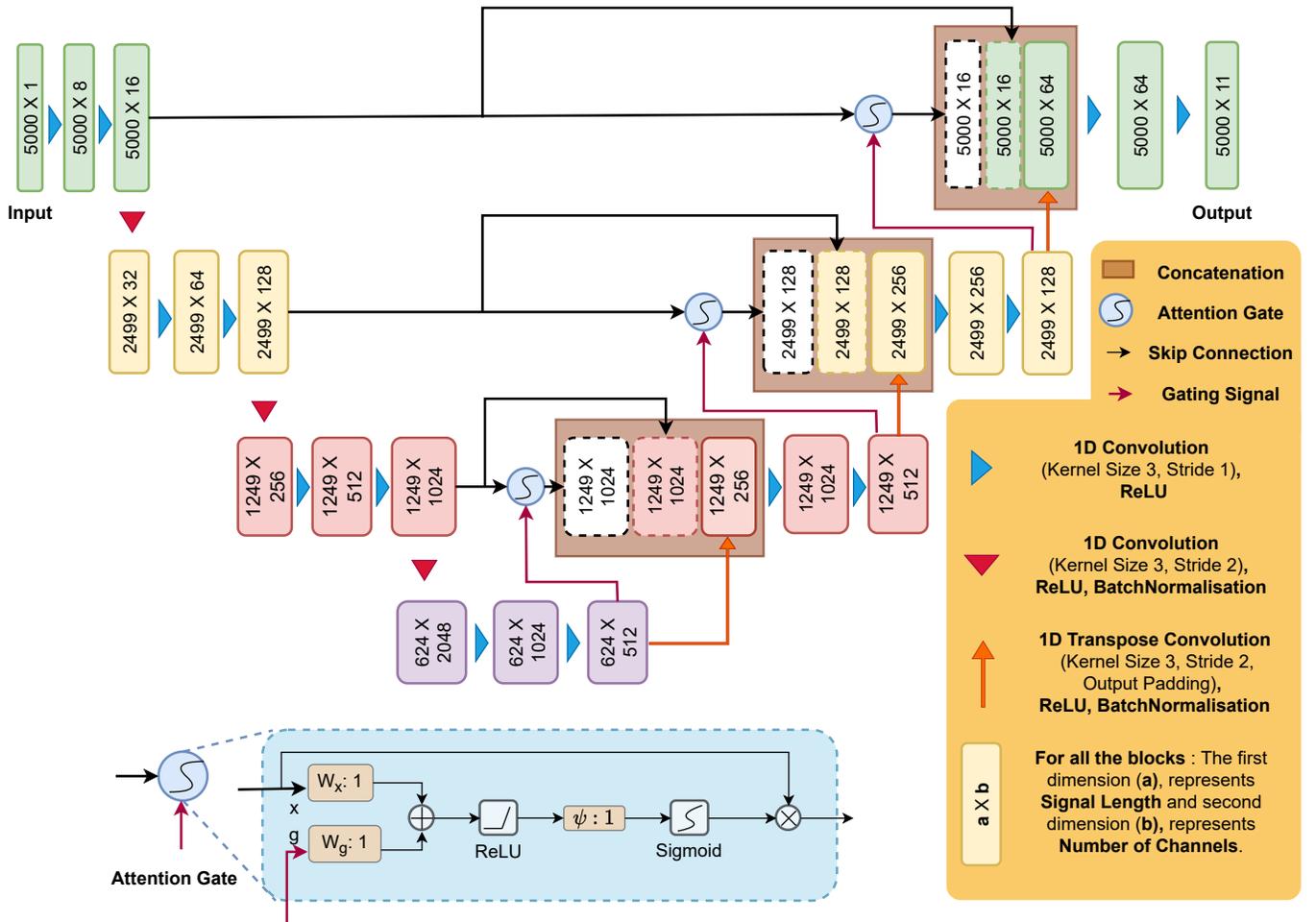


Fig. 1. Model Architecture of the proposed model

Table I. A standard U-Net with 3 downscaling and upscaling layers similar to the proposed model gave a mean Pearson Correlation Coefficient of 0.750. Given that 1D Convolutions have learnable parameters, we replaced the Max-Pool layer in the standard U-Net with a 1D Convolution with Kernel size 3 and stride 2. Similarly, the Upsampling layer was replaced with a 1D Transpose Convolution of kernel size 3 and stride 2. We can refer to this model as a modified U-Net. This modified U-Net improved upon the conventional U-Net with a mean Pearson correlation coefficient score of 0.784. The improvement of results validates the use of 1D Convolutions and 1D Transpose Convolutions over max-pooling and up-sampling. Attention can further help in better localization and can help the model understand which part of the input needs to be focused upon [28]. Thus adding attention to the skip connection could help the network to localise to the area of importance in the skip connection. An attention block inspired by Oktay et al. [24] was added to the skip connection of the modified U-Net where the max-pooling layer was already changed with the 1D Convolution layer, and the upsampling layer was changed with the 1D Transpose Convolution. We

can refer to this model as Modified U-Net with Attention. This model further improved the results to a mean Pearson Correlation coefficient of 0.790. Thus attention helped the model better understand the lead reconstruction task. This modified U-Net with attention just like the standard attention U-Net used the attention to the skip connection. Then the attention-gated skip connections are concatenated with the upsampled signal coming from the 1D Transpose Convolution. For the proposed model, we experimented by concatenating the raw skip connection in addition to the attention-gated skip connection with the upsampled signal. The proposed model gave the best metrics with a mean Pearson Correlation coefficient of 0.805. We also tested the GAN architecture similar to the one proposed by Yoon et al. [17] but modified to work with the 10-second length ECG signal. Although the GAN took significantly longer to train, the results produced were not able to beat the proposed model. We can inspect the quality of ECG reconstruction for the frontal plane limb leads using Fig. 2, and Fig. 3 can be used to examine the reconstruction of the chest leads.

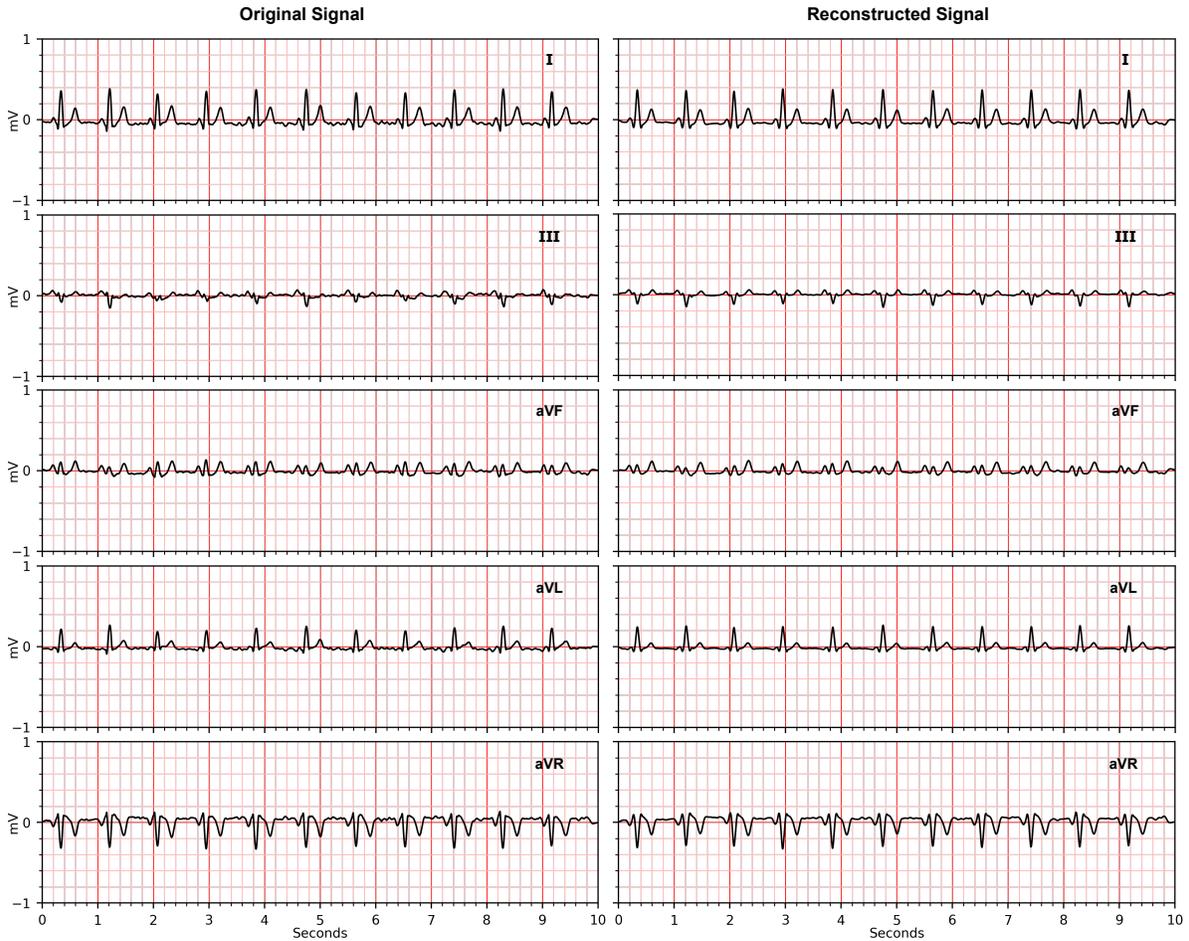


Fig. 2. The original and the reconstructed signals for the frontal plane limb leads I, III, aVF, aVL and aVR using the proposed model.

TABLE I  
PERFORMANCE ANALYSIS OF THE PROPOSED MODEL FOR LEAD II TO 12-LEAD RECONSTRUCTION TASK. ALL MODEL IMPROVEMENTS WERE STATISTICALLY SIGNIFICANT WITH P-VALUES  $\ll 0.05$ .

Model	$\rho$	MSE	$R^2$
U-Net	0.750	0.0159	0.528
Modified U-Net	0.784	0.0138	0.591
Modified U-Net with Attention	0.790	0.0132	0.610
Proposed Model	<b>0.805</b>	<b>0.0122</b>	<b>0.639</b>

### B. Comparison between Single-to-Multi lead model & Single-to-Single lead Model

Yoon et al. [17], and Gundlapalle et al. [16] both used 11 deep learning models, each responsible for converting the original lead to a single lead. We compared the results between the single-to-multi lead model, where a single model is responsible for converting the lead II to the 11 other leads to that of single-to-single lead models, where each model is responsible for converting the lead II to one of the 11 other leads. We used the same model architecture proposed in the Methods section for the single-to-multi lead model. For the single-to-single lead

model, we changed the last layer of the proposed model so that instead of outputting 11 channels; the model has a single-channel output. Both the models were trained and tested using the regime explained in the Methods section. Table II provides the results for each lead conversion for the single-to-single lead and single-to-multi lead models. We can observe that the single-to-multi lead model performed better for the signal reconstruction for all 11 leads compared to the single-to-single lead models with respect to all three evaluation metrics. The single-to-multi lead model might be performing better owing to its ability to employ the backpropagating gradients from all 11 leads and combine them to get a better latent space representation of the lead II. The single-to-single lead model only has information concerning a single lead it is trying to reconstruct; thus, the latent space representation for the model might be inferior to that of the single-to-multi lead model.

### C. Cardiovascular Disease Classification

In our previous experiments, our concern has always been how well the model performs for the chosen evaluation metrics. However, we realized that the main aim of performing lead reconstruction should be making sure that the final gen-

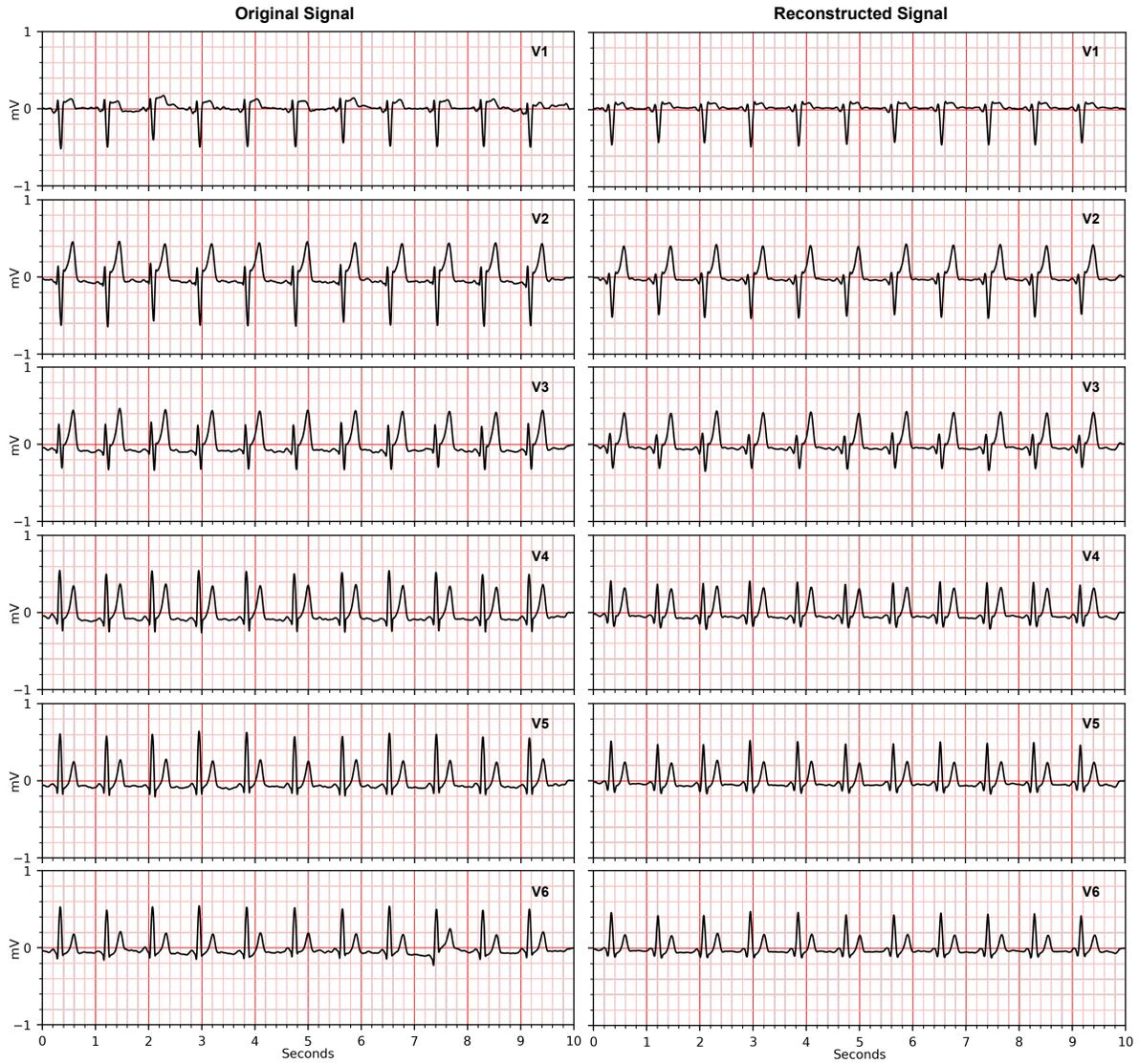


Fig. 3. The original and the reconstructed signals for the chest leads V1, V2, V3, V4, V5, V6 using the proposed model.

TABLE II

PERFORMANCE COMPARISON OF THE SINGLE-TO-SINGLE LEAD MODELS WITH THE SINGLE-TO-MULTI LEAD MODEL FOR LEAD II TO 12-LEAD ECG RECONSTRUCTION TASK. FOR ALL THE LEADS EXCEPT AVR THE P-VALUE WAS  $\ll 0.05$ , SUGGESTING STATISTICAL SIGNIFICANCE OF THE RESULTS. THE P-VALUE FOR AVR LEAD WAS 0.191.

2*Lead	Single-to-Single lead			Single-to-Multi lead		
	$\rho$	MSE	$R^2$	$\rho$	MSE	$R^2$
I	0.841	0.0053	0.610	<b>0.847</b>	<b>0.0049</b>	<b>0.633</b>
III	0.657	0.0055	0.611	<b>0.663</b>	<b>0.0047</b>	<b>0.658</b>
aVL	0.616	0.0052	0.491	<b>0.659</b>	<b>0.0047</b>	<b>0.536</b>
aVR	0.934	0.0015	0.850	<b>0.935</b>	<b>0.0015</b>	<b>0.853</b>
aVF	0.883	0.0015	0.855	<b>0.892</b>	<b>0.0013</b>	<b>0.873</b>
V1	0.811	0.0135	0.539	<b>0.818</b>	<b>0.0113</b>	<b>0.611</b>
V2	0.767	0.0349	0.507	<b>0.778</b>	<b>0.0317</b>	<b>0.552</b>
V3	0.722	0.0360	0.428	<b>0.728</b>	<b>0.0333</b>	<b>0.470</b>
V4	0.772	0.0234	0.473	<b>0.785</b>	<b>0.0222</b>	<b>0.499</b>
V5	0.857	0.0120	0.640	<b>0.859</b>	<b>0.0120</b>	<b>0.641</b>
V6	0.884	0.0076	0.678	<b>0.888</b>	<b>0.0071</b>	<b>0.698</b>

erated signals are usable in real-world scenarios by clinicians, classification models, etc. That is, these generated signals should be able to act as a replacement for standard 12-lead ECG without any other intervention. From this perspective, even though evaluation metrics can tell us how well the signals as a whole have been reconstructed, they cannot tell us if essential artefacts in the signals used by clinicians for diagnosis and machine learning pipelines for classification have been conserved. There are chances where the signal has been reconstructed well, as all the rhythmic heartbeats have been preserved. However, the signal might still lack the artefacts needed by a clinician to diagnose the patient, rendering such a reconstruction useless. All previous works in the field have only focused on evaluating the signal quality quantitatively, making it unclear if the generated signals from these works can be used as 12-lead ECG replacements. We employed this experiment to verify if our model can generate

signals conserving critical artefacts needed for diagnosis.

Ribeiro et al. [29] used an ensemble of neural networks with a Residual Network based architecture for 12-lead ECG multi-classification. They use a superset of the PTB-XL dataset, containing six databases from four different countries (United States, Russia, Germany and China) to build an end-to-end pipeline capable of classifying 12-lead ECGs according to 27 different classes. Using this work as our baseline, we utilized a single model from their ensemble as the classification model for our experiment. This classification model is a combination of a one-dimensional Residual Network containing five residual blocks and a final fully connected layer. The model was trained on all default parameters set by the authors in the original papers for 70 epochs. To ensure that our results are robust, we trained this classification model on the same training data used for training the ECG reconstruction model. We also test the model on the same test data on which the reconstruction models were evaluated. This ensures that no signals used to train the reconstruction model are used to assess the performance of the classification model. Thus, the test set is completely blind for both the reconstruction and classification models, mimicking a real-world use case. This classification model is now trained on the training set of the preprocessed PTB-XL data discussed in the Methods section, and the trained model is used for further evaluation. We test this trained model with two different approaches. First, the model was evaluated on the test set, where all 12 leads were the original leads provided in the dataset. The results can thus be used as a baseline for the following approach. We will refer to this approach as the Original Signals approach in the coming parts of the paper. In the second approach, instead of testing the classification model on the original signals, we tested it on reconstructed signals. We trained the lead reconstruction model on the training set to convert lead II to the 11 other leads. This reconstruction model was then used to reconstruct the 12-lead ECG from the lead II signals of the test set. This set of original lead II and reconstructed 11 leads were then given as input to the classification model. We must note that for both approaches, the classification model was trained on the training set where all 12 leads were the original signals, just that the testing regimes were different. Thus, the classification model was never trained on a reconstructed ECG signal. We will refer to the second approach as the Reconstructed Signals approach. We can observe the results of the two approaches using Table III.

TABLE III  
PERFORMANCE COMPARISON OF CARDIOVASCULAR DISEASE DETECTION FOR THE ORIGINAL AND RECONSTRUCTED SIGNALS.

Model	AUROC	Accuracy
Original signals	0.810	0.456
Reconstructed Signals	0.752	0.426

We obtained an accuracy of 45.6% and an Area Under the Receiver Operating Characteristic curve (AUC) of 0.810 for the original signals approach, and we obtained an accuracy

of 42.6% and an AUC of 0.752 on the reconstructed data. We need to notice that this being a multi-class classification task with 27 classes, the chance accuracy would be close to zero. The drop in performance for the reconstructed signals approach was expected as the data of 11 leads has been eliminated entirely. However, the performance of the classification model using the reconstructed signal approach is comparable to the original signals approach. We can thus infer that our reconstruction model is able to preserve the necessary artefacts needed for classification from the original lead and reproduce it in all the reconstructed leads. This experiment shows that our reconstruction model is able to use data from a single lead and present it in such a way that a classification model trained to classify only based on 12-lead ECG is still able to work comparably.

#### IV. DISCUSSIONS AND CONCLUSIONS

ECGs play a major role in cardiovascular diagnostic decisions. With the rise in technology and increased awareness of health metric tracking, we are witnessing significant innovations in the wearable device sector using ECG signals. A considerable hurdle such device-makers face is that the wearables collect a reduced lead set of the ECG. Existing solutions in the automatic ECG classification space are built using the standard 12-Lead ECG as inputs, thus rendering the ECG unusable when only a subset of leads are collected. Likewise, in medical settings too, clinicians trained to diagnose based on a 12-lead ECG may find it challenging to interpret a reduced lead set data. ECG reconstruction primarily tries to bridge this gap between the influx of reduced lead set data from modern wearable devices and the consumption of standardised 12-Lead ECG data by clinicians and ECG analysis models. It is important to note that ECG reconstruction cannot add new information to reduced lead set data to create new 12-lead data. Instead, it rather converts all the information captured in the reduced lead data into a more interpretable 12-lead version.

In this work, we present a novel end-to-end Single-Lead to Multi-Lead Electrocardiogram Reconstruction pipeline. We use a modified attention-based U-Net model on the publicly available PTB-XL dataset to develop a method capable of using a single lead II to generate all other 11 leads of a standard 12-Lead ECG. We achieved a Pearson Correlation, Mean Square Error and R-squared value of 0.805, 0.0122 and 0.639, respectively. A significant drawback with the current ECG reconstruction studies is that they use three leads to reconstruct the 12-lead ECG signal. However, the current work overcomes significant limitations of earlier studies. Both previous studies divide the standard 10-second ECG signal into smaller segments for reconstruction. Generally, ECGs are recorded for 10 seconds; thus, one will be forced to use various algorithms to join the reconstructed segments, leaving their final performance questionable. Keeping this in mind, we developed our method to take a complete 10 seconds signal from lead II as input and reconstruct them into a 12-lead ECG of 10 seconds. Compared to past studies, we also use a relatively simple model comprising only convolutional

layers making the whole network much easier to train; also, the same network can be employed to process other lengths of ECGs as input. Instead of using multiple models for generating all leads separately like in previous works, we use a single combined model to generate all 11 leads together, reducing the total parameters needed for models to work and resulting in faster training times. Using a combined model also helped us improve performance, as observed in the above section. Looking through current works in ECG reconstruction, a very noticeable flaw in how the models are evaluated seems to exist. The metrics only seem to be representative of how well the reconstruction is but do not try to identify if the reconstructed signal can actually be used in real-life applications. Thus, we must ensure that a reconstructive model can capture the necessary artefacts from the input signal, which are essential for diagnostic uses. Therefore, we devised an experiment to see if the reconstructed signals can actually be used by existing models that use standard 12-lead ECG data to detect cardiovascular diseases. In the experiment, we train a multi-disease classifier based on existing literature on actual 12-lead ECG data and see the drop in performance when tested on reconstructed 12-lead data. We observe that the classification model's performance while using the reconstructed signals was comparable to its performance using the original signals. This shows that our reconstruction model is capable of preserving artefacts from the original data, which might prove vital for uses like diagnosis by clinicians and predictive models. The unavailability of ECG and healthcare data, in general, plays a vital role in inhibiting the growth in the adoption of Artificial Intelligence in Healthcare. Data-intensive models like transformers tend to perform poorly with the current volume of available ECG data. We believe the rapid digitisation of the healthcare industry will lead to a high influx of data in the coming future, making the utilisation of models like transformers feasible. Healthcare data tend to contain cohort-specific features, which might render a model trained on one cohort useless if tested on another. A study for ECG reconstruction employing a dataset collected across multiple cohorts for training and evaluating the models might help better establish a model's generalizability which is currently lacking in the proposed study.

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