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# Advancing Signal Processing through Transfer Learning Innovations in Health industry

Usage domain adaptation in transfer learning with pruning weight optimizations technique

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***Abstract -*** Our investigation addresses the critical deficit of high-fidelity electrocardiogram (ECG) datasets essential for detecting cardiac anomalies in advanced medical applications. In cardiology, capturing seismocardiograms (SCG) through sensors like wearable devices and smartphones during daily activities is more practical than obtaining ECGs. To facilitate the transformation of SCG to ECG, we explored advanced signal conversion architectures. Converting SCG to ECG signals is imperative, as ECGs provide a direct and reliable measure of cardiac electrical activity, crucial for accurate detection and diagnosis of cardiac anomalies. Among various models for transforming medical timeseries signals, we selected the Convolutional Neural Networks (CNN) Autoencoder SCG-to-ECG architecture as a target pipeline. We aimed to enhance the efficiency and accuracy of this architecture by incorporating domain adaptation within the framework of transfer learning. Specifically, we utilized supervised learning and unsupervised learning techniques for domain adaptation and employed homogeneous transfer learning to ensure the effective transfer of knowledge between domains. Additionally, we optimized the pretrained model weights through weight pruning, rather than traditional fine-tuning methods. This dual strategy of domain adaptation and weight pruning improves the model's ability to generalize across different datasets while reducing computational complexity and maintaining high diagnostic accuracy.

***Keywords*:** Electrocardiogram (ECG), Seismocardiograms (SCG), Cardiac anomalies detection, Wearable devices , Signal transformation architectures, Transfer learning, Domain adaptation, Weight pruning

## 1. Introduction

Recent reports from the World Health Organization and other leading health bodies have highlighted the escalating complexity of global health challenges, ranging from the persistence of chronic diseases to the emergence of new health threats. Cardiovascular diseases (CVDs) are the leading cause of death globally, and accurate monitoring of cardiac signals is crucial for early diagnosis and treatment. Traditionally, ECG have been the dominant method for detecting and monitoring heart signals. However, capturing ECG data requires professional expertise and precise placement of electrodes, making it expensive and time-consuming. In contrast, SCG measures mechanical vibrations caused by heartbeats using accelerometers or seismocardiography sensors. These sensors are widely available in daily devices such as smartphones and smartwatches, making SCG easier and more accessible to capture. For effective home monitoring and control, especially using cutting-edge devices, capturing SCG data is more feasible. However, since ECG provides more detailed and reliable information for medical professionals, converting SCG signals to ECG format is essential. This conversion allows for easier interpretation and diagnosis by doctors.

Our focus is on improving the pipeline of the Autoencoder SCG to ECG, which I inspired from Haescher et al. [1] for its potential transformer using domain adaptation methods. By utilizing advanced transfer learning techniques within 1D Convolutional Neural Networks Autoencoder, inspired by the methodology in "Transforming SCG into Electrocardiograms by Applying Convolutional Autoencoders" by Haescher et al., this project seeks to enhance signal transforming. The research will transfer weights from various source domain, including CNN, Autoencoders, Temporal Convolutional Networks (TCNN), and ECGNet, to improve the performance of the given pipeline. We strategically apply weight-pruning methods to reduce parameters, enhancing computational efficiency while maintaining diagnostic accuracy. This integration of diverse neural network architectures with weight pruning develops a robust framework for medical signal processing, potentially improving diagnostic tools in cardiology

This study uses CNN Autoencoder to transform SCG into ECG, addressing the challenge of a limited dataset by leveraging transfer learning, domain adaptation, and weight pruning. This approach enhances the model's efficacy in SCG to ECG conversion and addresses data scarcity issues. The primary research questions here are:

- How can we find the most suited approaches in domain adaptation and pruning for the given task?
- How can transfer learning and domain adaptation help solve the problem of the availability of usable datasets?

## 2. Related work

### 2.1. Domain Adaptation in Transfer Learning

In the study “Research on ECG classification based on transfer learning” by Jiang Fan et al. (2022) [2], the authors developed a CNN-based deep domain adaptation network (DAN) to enhance ECG signal categorization. Using the MIT-BIH ECG arrhythmia database for pre-training, their method achieved a 7.8% improvement in classification accuracy. Similarly, “Research on arrhythmia classification based on domain adaptation” by Luyao Chao et al. (2023) [3] utilized the inter-patient paradigm to avoid using the same patient's heartbeats in both training and test sets, addressing cross-domain generalization issues. Their model, tested on MIT-BIH, MITDB-INCARTDB, and MITDB-SVDB datasets, achieved a 95.12% accuracy. Another study, “A new transfer learning approach to detect cardiac arrhythmia from ECG signals” by Mohebbanaaz et al. (2022) [4], proposed an end-to-end transfer learning method using pre-trained CNNs (GoogleNet, ResNet18, and AlexNet). Their fine-tuned Deep-CNN model reached an impressive 99.56% accuracy, demonstrating the effectiveness of transfer learning in ECG classification.

### 2.2. Pruning Method in Transfer Learning

“Compression of Convolution Neural Network Using Structured Pruning” by Pragnes et al. (2022) [5] addresses overfitting and computational limitations in DNNs by employing structural pruning on pre-trained models such as VGGNet, ResNet, AlexNet, and GoogleNet. Their approach achieved necessary accuracy with a computational cost reduction, although accuracy decreased by 1.5 to 5.81%. In “Adaptive Pruning of Transfer Learned Deep Convolutional Neural Network for Classification of Cervical Pap Smear Images” by Wang et al. (2020) [6], adaptive pruning was applied to improve cervical cancer detection. Evaluated on various CNNs and pruning criteria, their PsiNet-TAP model achieved classification accuracies of 98.41%, 98.18%, and 98.49% for different classes, demonstrating the benefits of adaptive pruning in transfer learning. Lastly, “EvoPruneDeepTL: An Evolutionary Pruning Model for Transfer Learning based Deep Neural Networks” by Javier Poyatos et al. (2020) [7] introduced EvoPruneDeepTL, which combines sparse layers with Evolutionary Algorithms to optimize neuron activity in pre-trained models. This approach outperformed other models in accuracy and complexity, showcasing the potential of integrating evolutionary algorithms with deep learning for efficient transfer learning.

## 3. Methodology

### 3.1. Overview

Our approach leverages transfer learning to enhance the performance and robustness of predictive models, particularly autoencoders, in medical signal processing. We employ domain adaptation techniques to mitigate issues related to the scarcity of labeled data, enabling the transfer of knowledge from well-labeled source domains to less-labeled target domains. Additionally, we integrate weight pruning strategies to optimize model performance and reduce computational overhead.

### 3.2. Hypothesis

Derived from the above literature review and in dependence on the initially proposed research question, we state the following hypotheses:

• *We can mitigate the problems of scarce availability through domain adaptation methods.*

Domain adaptation methods are effective means to close the distribution gap between the source and destination domains. Adversarial domain adaptation or domain-invariant feature learning are especially promising. Related works showed promising results in bridging the gap between SCG and ECG datasets and were successfully applied in similar contexts. During our later evaluation, we will give a detailed analysis of the different approaches we applied during our implementation phase. We will compare those methods with each other as well as the recreated baseline model.

• *We can increase the performance and robustness of the given autoencoder pipeline due to elected transfer learning methods.*

Research shows the effectiveness of different homogenous transfer learning techniques for domain adaptation to avoid negative transfer and improve the performance of predictive models. Furthermore, weight pruning optimization methods appear to inherit further potential to increase the effectiveness and performance of predictive models in the context of transfer learning. These methods should affect the autoencoder's generalization abilities and efficiency when knowledge is transferred between related medical signal domains. Various studies point out the capabilities of pruning to shrink the model size, reduce computing costs, and boost prediction accuracy.

### 3.3. Domain adaptation methodology

We define a domain D as a combination of an input space **X={x1,x2,x3,…,xn}**, an output space **Y={y1,y2,y3,…,yn}**, and a probability distribution P(X). Inputs are subsets of the real space RD and are referred to as feature vectors. Outputs are classes, which can be binary (Y corresponds to [−1, +1]) or multi-class.

$$\mathbf{D= \{X, P(X)\}} \quad \textbf{(1)}$$

Given two domains, they are considered different if they differ in at least one of their components. For domains $D_1$ and $D_2$:

$$\mathbf{Y(D_1) = 1 \ \ if \ \ D_1 = D_2} \quad \textbf{(2)}$$

$$\mathbf{Y(D_1) = 0 \ \ if \ \ D_1 \neq D_2} \quad \textbf{(3)}$$

task T is defined as part of the work that needs to be completed: $\mathbf{T=\{\gamma,P(Y \mid X)\}}$

Training a model from scratch often requires a large amount of labelled data, which can be time-consuming and resource intensive. Transfer learning addresses these limitations by using knowledge from one domain (source domain) to improve learning and generalization in another (target domain). In the context of transfer learning, we define the source domain $D^s$ and target domain $D^t$ as follows:

**Source domain:** $D^s=\{X^s, P(X^s)\}$ , $T^s=\{\gamma^s, P(Y^s|X^s)\}$

**Target domain:** $D^t = \{X^t, P(X^t)\}, T^t = \{\gamma^t, P(Y^t/X^t)\}$

"Domain adaptation (DA) occurs when there exists a function $f$ such that $f: X^s \rightarrow Y^s$ and $f$ also works for $f: X^t \rightarrow Y^t$ with minimal error. This implies that the model trained on the source domain can be adapted to the target domain, even if the target domain has minimal labelled data. If $T^s$ is related to $T^t$, and the model $f$ performs well on both $D^s$ and $D^t$, then $f$ has successfully adapted to the target domain $D^t$ from the source domain $D^s$". [8]

### 3.4. Importance of Pruning weight

Pruning weights is crucial for optimizing model performance and reducing computational costs in transfer learning. The approach involves systematically removing unnecessary weights from neural networks, which helps minimize model size and enhance computational efficiency. Here, we focus on weight pruning, a specific method used in our research. Weight pruning involves reducing the number of small-magnitude weights in a model. These weights contribute minimally to the overall performance of the model, and their removal can lead to significant reductions in model size and computational requirements. The process of our weight pruning includes the following steps:

1. Identify Small Weights: During training, weights that have minimal impact on the model's predictions are identified based on their magnitude.
2. Remove Identified Weights: These small-magnitude weights are removed from the model, resulting in a sparser network.
3. Iterative Fine-tuning: After pruning, the model undergoes fine-tuning to adjust the remaining weights and ensure that the model maintains or regains its performance.

## 4. Implementation

### 4.1. Data Collection and Pre-Processing

To train the given pipeline, we searched for datasets with signals closest to ECG and SCG available on Physionet. The following datasets were gathered: SCG-RHC (73 subjects, frequencies: RHC: 250 Hz, ECG: 1 kHz, SCG: 500 Hz) for hemodynamic monitoring and heart failure management; MIT-BIH Arrhythmia (47 subjects, frequency: ECG: 360 samples per second) for arrhythmia detection and cardiac dynamics; St. Petersburg INCART (32 subjects, frequency: ECG: 257 Hz) for coronary artery disease and arrhythmias; ECG-ID (90 subjects, frequency: ECG Lead I: 500 Hz) for ECG identification and diverse population studies; and EPHNOGRAM (24 subjects, frequencies: ECG: 8 kHz, PCG: 8 kHz) for simultaneous ECG and PCG, exploring mechanical-electrical heart interrelationships.We also used the CEBS dataset, as mentioned by Haescher et al., who trained their model on this dataset. To ensure compatibility and avoid frequency sampling problems, we checked the frequency samples from the CEBS dataset with other datasets using the Nyquist rule. This allows us to compare and evaluate the performance improvements of the given pipeline in the future. Effective pre-processing is crucial for the accuracy and reliability of SCG to ECG conversion. The steps include filtering, normalization, and segmentation:

- The DC filter is applied to remove the DC component from the signal, eliminating baseline drift for all SCG and ECG signals. A Butterworth filter is used to reduce noise and improve signal quality, with a filter range of 0.5 - 30 Hz for SCG signals and 1 - 40 Hz for ECG signals.
- Signal segmentation involves dividing continuous signals into smaller segments or windows, typically 5-10 seconds in length. The sky window technique is applied for windowing the signals during analysis. For example, in the MIT-BIH Arrhythmia dataset, each 30-minute recording is segmented into non-overlapping 10-second windows.
- Normalization is performed to ensure consistency across different recordings and subjects by normalizing the amplitude of signals to a common scale, typically -1 to 1.

- Annotations are utilized to label each segment for supervised learning tasks. Signals are annotated using the .ATR feature for precise alignment and labeling. For instance, in the ECG-ID dataset, each recording includes annotated beats with R- and T-wave peaks.

### 4.2. Selecting the Domain Models

For our experiments, we selected four pre-trained models from different domains to leverage their learned features and improve our target model's performance. The selected models were the CNN1D Model, ECGNet Model, Temporal Convolutional Network (TCN) Model, and the Autoencoder Model. Each of these models was pre-trained on a combination of SCG, PCG, and ECG datasets to ensure a robust extraction of features and patterns from the diverse input data. This comprehensive pre-training approach was intended to enhance the generalization capabilities of our models across different types of cardiac signals.

### 4.3. Pre-Training Phase

During the pre-training phase, the CNN, ECGNet, TCNN, and Autoencoder models were trained on the combined SCG, PCG, and ECG datasets. This phase aimed to allow each model to learn essential features from the homogenous data inputs. The CNN and ECGNet models focused on capturing significant features and complex patterns within the cardiac data. The TCNN model was designed to capture long-range relationships and temporal dynamics, while the Autoencoder model aimed to develop robust low-dimensional representations. The pre-trained model's weights were saved in the .h5 format to facilitate easy loading and integration into the target domain model.

### 4.4. Weight Pruning for Optimization

After the pre-training phase, we applied weight pruning to the pre-trained models to enhance computational efficiency and reduce model complexity. This method involved magnitude-based pruning to remove small-magnitude weights, thereby simplifying the models while retaining essential features. The weight pruning process included the following steps:

- Training the Pre-Trained Models: The models were initially trained on the combined SCG, PCG, and ECG datasets.
- Applying Pruning: A polynomial decay function was used to progressively prune weights, ensuring a controlled reduction in model complexity.
- Fine-Tuning the Pruned Models: The pruned models were fine-tuned to ensure performance maintenance.
- The pruned models were then saved again in the .h5 format for subsequent integration into the main domain model.

The pruning process was defined by initial sparsity of 0.10, final sparsity of 0.25, beginning at step 0 and ending at step 1000. After pruning, the total parameters were reduced as follows: CNN from 13,927,041 to 10,445,280, Autoencoder from 19,403,520 to 14,552,640, TCNN from 16,002,049 to 12,001,536, and ECG-Net from 16,805,761 to 12,604,320.

### 4.5. Weight Transfer and Fine-Tuning

Weights from the pruned, pre-trained models were transferred to the target pipeline systematically. We then initialized the given pipeline and transferred the weights from the pruned models to corresponding layers in the target domain. The target domain was subsequently fine-tuned using a smaller set of labeled CEBs dataset from the target domain, allowing the pruned weights to adapt effectively to the new data.

## 5. Evaluation and Results

The evaluation process involved several key steps to assess the performance and improvements of the CNN Autoencoder model before and after applying transfer learning and weight pruning techniques. Initially, we trained the base model on the CEBS dataset to establish a baseline performance, using metrics such as Pearson Coefficient, Loss PRD, MAE, $R^2$, MSE, Xcor, NMSE, and RMS showed in Table 1. These metrics provided insights into the model's accuracy and reliability in transforming SCG signals to ECG signals.

Table 1: CNN Autoencoder (Target domain) Evaluation Results

| Metric | Training Set | Test Set |
|---|---|---|
| Pearson Coefficient | 0.8290 | 0.6942 |
| Loss PRD | 58.5011 | 87.3965 |
| MAE | 0.0454 | 0.0730 |
| R2 | 0.682 | 0.682 |
| MSE | 0.0083 | 0.014 |
| Xcor | 0.985 | 0.972 |

We evaluated the model's performance on multiple datasets which we mentioned before (Fig 1), comparing the results against the baseline metrics to quantify improvements. This comprehensive evaluation ensured that the enhancements in model performance and computational efficiency were both significant and consistent across different datasets, validating the effectiveness of our transfer learning and pruning approach.

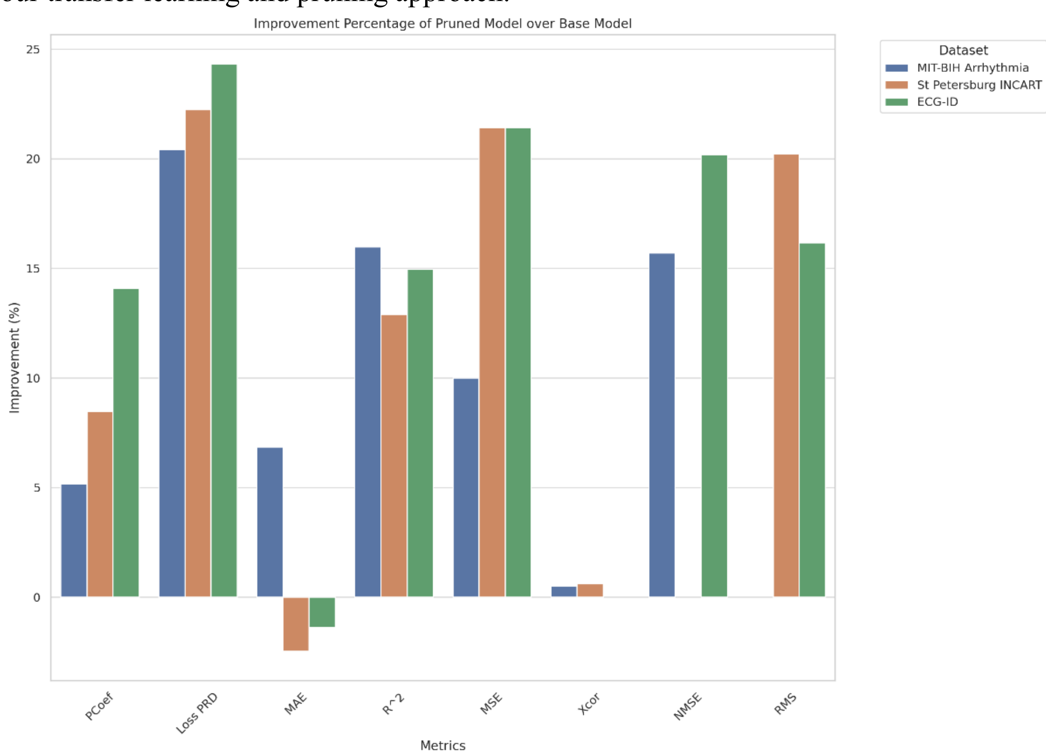

Fig. 1: Comparison of Test Performance Metrics for the CNN Model after transfer learning and prune weight

## 6. Conclusion

This study aimed to enhance the transformation of SCG signals to ECG signals through the application of advanced transfer learning and weight pruning techniques. Our results demonstrate significant improvements in model performance across multiple metrics and datasets. The evaluation process highlighted that using high-quality, large-scale datasets for pre-training substantially boosts the effectiveness of the models. The domain adaptation method with pruned weights showed marked improvements in performance: a 14.3% increase in the autoencoder, a 13.3% improvement in TCNN, a 10% enhancement in ECGNet, and a 9% gain in CNN. These improvements were particularly evident in datasets such as ECG-ID (90 subjects) and MIT-BIH Arrhythmia (47 subjects), underscoring the impact of robust pre-training data. Additionally, our findings indicate that employing the same architecture for both source and target domains is highly effective. This was particularly true for the autoencoder and TCNN models, which benefitted the most from this approach.

In conclusion, leveraging transfer learning and weight pruning not only enhances computational efficiency but also improves the accuracy and reliability of SCG to ECG signal transformation. These advancements have the potential to significantly impact medical signal processing and improve diagnostic tools in cardiology. Future work should focus on further refining these techniques and exploring their applications in other medical domains.

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