A Survey of Augmentation Techniques for Enhancing ECG Representation through Self-Supervised Contrastive Learning

D. Dade, J. Bergquist, R. MacLeod, X. Ye, R. Ranjan, B. Steinberg, T. Tasdizen

Introduction: Despite electrocardiograph's (ECG) utility, traditional analysis methods of this test are limited by human interpretation. Machine learning tools can be employed to automate task-specific detection of diseases and detect patterns that are not detectable by traditional ECG analyses. However, contemporary machine learning tools require large labeled datasets, which can be scarce for rare but serious diseases. Self-supervised learning (SSL) can address this data scarcity.

Methods: Using an extensive clinical data set of 36,519 ECGs, we implemented the Momentum Contrast framework a form of SSL with a custom SpatioTemporal Encoder. We assessed the learning using low Left ventricular ejection fraction (LVEF) detection as the downstream task using 1%, 5% and 10% of pre-train ECGs. We compared the SSL improvement of LVEF classification across different input augmentations which are crucial in challenging the encoder. We chose to test: 1) Gaussian Noise 2) Gaussian Blur 3) Scaling 4) Magnitude Warping 5) Baseline Warping 6) Time Warping 7) Window Warping

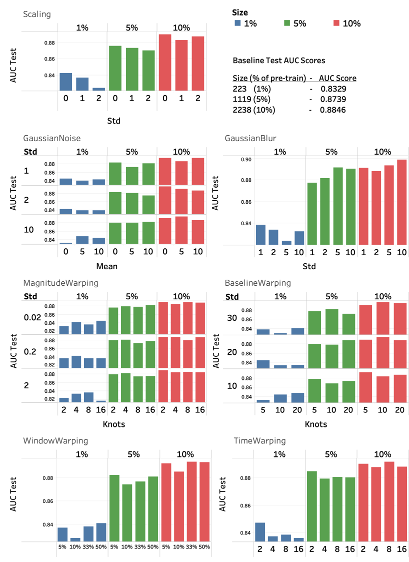

Figure 1. LVEF classification accuracy by area under the receiver operator curve (AUC) downstream of each augmentation under different hyperparameter and training set size scenarios.

Results: Figure 1 summarizes baseline classification and downstream learning after SSL augmentations. Downstream performance varied across hyperparameters, and optimal hyperparameters varied across training set sizes.

Discussion: Contrastive learning based on data augmentation techniques show a marginal improvement in AUC compared to the baseline, contrary to literature expectations. Our findings suggest that the augmentations applied to the ECG data did not markedly enhance the model's ability to discern patterns related to low LVEF detection. Future studies will address limitations, such as larger datasets for pre-training, evaluation on multiple encoders, and exploring SSL contrastive frameworks.