

Towards Invariant Soft Biometrics from Electrocardiograms

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Introduction: Medical data such as the electrocardiogram (ECG) has received an increased interest within biometric settings. One of the benefits is the difficulty in counterfeiting the information due to its hidden nature. However, the information may suffer from intra-subject variability, particularly evident in extraction of soft biometric traits. Previous studies have indicated that age prediction from ECG is heavily dependent on cardiac condition. Such correlations may be useful in diagnostics, but present a challenge for biometric purposes. This work investigates methods of lowering the variability by employing multi-task learning (MTL).

Method: MTL is deployed on a common feature extractor, with the task of predicting soft biometrics in conjunction with the underlying variance inducing variables. Three architectures are suggested: hard parameter sharing, feature sharing among the predicted property and variance causation, and the latter repeated with a Bayesian classifier. The backbone is built from a convolutional neural network based on inception blocks.

Results: Experiments are carried out predicting age and gender, with the aim of lowering estimation variance due to cardiac condition, on the datasets PTB-XL and CODE15 (see Table 1). The MTL methods show significantly better performance on PTB-XL, lowering mean average error (MAE) by up to 40% compared to previous SOTA single-task learning (STL) models on age prediction, particularly for patients with cardiovascular disease. On CODE15 the decrease in MAE is lower, perhaps due to the vast size of the dataset allowing the STL models to partly learn the correlation.

Conclusion: This paper demonstrates the benefits of using MTL to reduce variance in soft biometric extraction from ECG. Cardiac condition is included during training to improve performance in age and gender prediction, especially when data is limited.

Similarly, MTL could likely be used in other forms of ECG analysis, e.g. diagnostics, to account for related variance inducing properties.

Table 1. Benchmarking results of MTL vs SOTA STL models

PTB-XL	Age MAE			Gender AUC		
	All	Healthy	Condition	All	Healthy	Condition
MTL Model 1	7.75	7.54	7.95	0.915	0.947	0.879
MTL Model 2	7.53	7.54	7.51	0.907	0.944	0.872
MTL Model 3	9.16	9.79	8.77	0.895	0.937	0.861
STL Inception	11.3	8.00	13.8	-	-	-
STL CNN	13.7	10.4	16.1	-	-	-
CODE15						
MTL Model 1	8.05	8.00	8.45	0.942	0.947	0.901
MTL Model 2	7.93	7.89	8.14	0.950	0.953	0.921
MTL Model 3	9.80	9.78	10.1	0.925	0.930	0.896
STL Inception	8.23	8.17	8.72	-	-	-
STL CNN	8.52	8.38	9.01	-	-	-