CAPE AIME2015 Supplementary Material

1 Research Cohorts

Table 1: Baseline characteristics of the population used in the current research.

	BIDMC	*CODE*	*SHZS*	*VUMC*	*UKB*	*PTB-XL*
Location	United States	Brazil	China	United States	United Kingdom	Germany
Patients*	127,041	424,577	420,956	252,306	66,402	18,869
ECGs	1,106,886	1,123,903	1,560,551	1,412,012	70,655	21,799
Age mean	57.99	56.00	52.08	52.08	65.35	62.36
Age IQR	23.02	23.00	27.00	27.00	12.00	23.00
Male	63,006	165,285	233,808	233,808	32,191	9,640
Female	640,35	259,292	187,148	187,148	34,211	9,229
Hispanic	7,077	-	-	-	-	-
White	84,265	-	-	-	-	-
Black	17,778	-	-	-	-	-
Asian	5,315	-	-	-	-	-
Other	12,606	-	-	-	-	-
Mortality!	21%	-	-	-	-	-

* Patients with more than one ECG.
! Five-year mortality.

The cohorts explored in current research involves Beth Israel Deaconess Medical Center (*BIDMC*) [1], Clinical Outcomes in Digital Electrocardiography

($CODE$) [2], Shanghai Zhongshan Hospital cohort dataset ($SHZS$), Vanderbilt University Medical Center cohort ($VUMC$) [3], and Physikalisch-Technische Bundesanstalt (PTB-XL) dataset [4]. Table 1 presents the demographics of the population included in the study. Further details can be obtained from the corresponding references. Although the ethnicity information for most cohorts is not available, depending on the geographical location the predominant ethnicity can be inferred.

Ethics Statement Our research complies with all relevant ethical regulations and details of the ethics approval are as follows. The $BIDMC$ ethics approval is provided by the Beth Israel Deaconess Medical Center Committee on Clinical Investigations (IRB protocol #2023P000042). The $CODE$ study is approved by the Research Ethics Committee of the Universidade Federal de Minas Gerais (protocol 49368496317.7.0000.5149) and $SHZS$ by the Institutional Research Board of Zhongshan Hospital (No. B2023-253R), with a waiver of patient consent. The $VUMC$ data was reviewed and approved by the Vanderbilt Institutional Review Board (#212147). The PTB-XL is approved by the Physikalisch-Technische Bundesanstalt Institutional Ethics Committee, to publish as an anonymized open-access database (PTB-2020-1).

2 Pretraining Configuration

The pretraining uses the backbone architecture from [5, 6] with four residual blocks, and a non-linear projection head [7]. The InfoNCE [8] contrastive loss is applied to the non-linear projections of the $ECGs$. The pretraining is implemented for a batch size of 1024 (512 patients) and run for 200 epochs using Adam optimizer [9], with an initial learning rate of 0.1 and decayed according to a half-period cosine schedule [10]. This configuration is kept similar to previous research [6].

3 Supervised Training Configuration

Most supervised tasks for the current research have been implemented for pregenerated ECG features obtained using the $CAPE$ pretrained networks. The supervised training only involves the prediction head that is a two layer MLP for each $BIDMC$ labels (reported in Table 1 and Figure 2). The MLP head for age prediction has layers with sizes 256 and 128 while sex and mortality has both layers of sizes 256. The network sizes were optimised with a grid search involving 256, 128, and 64 neurons for hidden layers. The PTB-XL labels are predicted as a multi-label task with a single linear layer with one neuron for each label. Class weights are incorporated for all classification tasks. Similarly, learning rates are optimised in the interval [0.1, 0.00001]. Table 2 lists the final learning rates used for all the reported results. For fair comparison to [11], we include results where the pretrained backbone is fine-tuned following initial training

Table 2: Training hyperparameters

No.	task	learning rate
1	ResNet (Figure 2)	0.0005
2	BIDMC labels*	0.0001
3	*PTB-XL* Age and Sex	0.005
4	*PTB-XL* Super and Subclasses	0.0001

*For ≤ 5000 samples a faster rate of 0.001 is optimum.

of a linear classifier. All other experiments rely solely on frozen, precomputed features from *CAPE*.

References

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