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ElectroCardioGuard: Preventing Patient Misidentification in Electrocardiogram (ECG) Databases through Neural Networks

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1 Introduction

Accurate interpretation of ECG recordings is crucial for achieving high diagnostic accuracy and minimizing the risk of errors during diagnosis establishment and consecutive treatment. Unfortunately, in administrative practice, instances occur where physicians mislabel ECG recordings as belonging to a different patient, resulting in a corrupted database of electrocardiograms.

Our primary achievement is the design and development of an artificial neural network model capable of deciding whether two ECG recordings originate from the same individual (i.e. are *congenetic*). This model combined with a streaming clustering technique makes up ElectroCardioGuard, a system capable of detecting misidentifications of patients as true owners of collected electrocardiograms. This small model ($\sim$ 700 kB) is suitable for deployment and inference on low-end hardware and achieves similar results as a large Transformer-based ECG representational model in an ECG matching task on PTB-XL.

This work is motivated by the Institute of Clinical and Experimental Medicine (IKEM) attempting to address the issue of errors that occur in their database of ECG recordings in order to mitigate the risk of inaccurate diagnoses and other serious implications for patients.

2 Method

Our model consists of two parts: an embedding model (Figure 1a), which projects ECG recordings to an ECG vector space, and a discriminator head (Figure 1b), which classifies two ECG vectors as congenetic based on the distance between them. The embedding model is based on CDIL-CNN by Cheng et al. (2023), which is a very efficient architecture suitable for processing long sequences such as ECG recordings, and is trained using metric learning to project ECG recordings from the same patient close to one another and far away from other patients. The discriminator head is a tiny multi-layer perceptron that processes the weighted Euclidean distance between two input ECG vectors.

We train our model on CODE-15%, which is a collection of roughly 340000 ECG recordings and their patient IDs. We tune its hyper-parameters, such as pre-processing techniques, metric learning losses, etc., to maximize the worst performance across CODE-15%, PTB-XL, and a dataset collected by IKEM, in order to improve its ability to generalize.

During testing, a simulated physician with a given error rate of 2% identifies patients as owners of ECG recordings from a stream. We calculate the likelihood of these identifications

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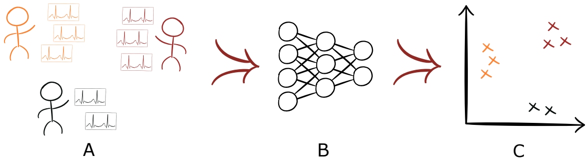
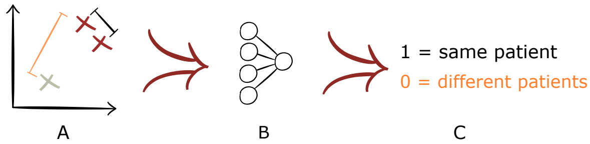


(a) Embedding model (**B**) projecting ECG recordings (**A**) to an ECG vector space (**C**).



(b) Discriminator head (**B**), which determines whether pairs of ECG vectors originate from the same individual (**C**) based on the distance between them (**A**).

Figure 1: Overview of the neural network model used in ElectroCardioGuard.

Dataset	**AUC**	**Accuracy**
CODE-15%	0.99	0.96
PTB-XL	0.986	0.95
IKEM	0.96	0.90

Table 1: Capability of our trained discriminator to decide whether two ECG recordings originate from the same individual or not.

being a mistake based on the new ECG and selected patient's ECG recordings stored in the database, which is proportional to a weighted average of discriminator outputs between the new ECG and the stored ECGs.

3 Results

The results of our model after trained on ECG recording pairs are captured by Table 1. The gallery-probe patient identification task uses a model to match a probe recording to one of the recordings in a gallery, which contains exactly one ECG recording from unique patients. The subset of PTB-XL where each patient owns at least two recordings has been used for this purpose (2000+ patients). Our model achieves similar results as Oh et al. (2022) ($\approx 58\%$) whilst using roughly 1000x less parameters.

References

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