Transfer Learning for Predicting Acute Myocardial Infarction Using Electrocardiograms

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***Abstract*— Should be 150 – 250 words, doesn't have to be "structured". Should indicate the objective of the study, methods, major results, conclusions, and one sentence significance to biomedical research.**

***Index Terms*— Machine learning, transfer learning, electrocardiography, cardiovascular diseases**

I. Introduction

WHEN it comes to machine learning, more data is almost always better. Large models are more capable of learning, but require more data to achieve good results than smaller models. In transfer learning, a model is first trained to solve a "source task" in a step called pretraining, and the pretrained model can then be finetuned to the "target" or downstream task. Transfer learning can be viewed as a way to increase the effective model size without having to obtain more data, or by exploiting other data sources that can't be otherwise used in the downstream learning task. The relationship between performance, model size, and data size depends on the details of the data and the task itself.

In this work we explore this relationship and the interplay with supervised transfer learning, for the specific target task of using electrocardiograms (ECGs) to predict acute myocardial infarction (AMI) within 30 days of arriving at the emergency department (ED) with chest pain.

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More specifically, we train and evaluate three different ResNet models that achieved state of the art on various ECG related classification tasks and compare their performance on our downstream task (predicting AMI) both with and without pretraining. We consider different sizes of both the source and target datasets, and compare different pretraining strategies. We also compare the ResNet models with a simple baseline CNN.

Our target dataset contains 38631 ECGs (one ECG per ED chest pain episode) from 32892 consecutive ED chest pain patients, where the incidence of AMI was 5.8%. The source dataset contains 877197 ECGs from 167458 consecutive non chest pain ED patients, from which we include a two year history of ECGs collected from any health-care visit in the region. The source dataset does not include any ECGs from any patients that have been included in the target dataset. All the ECGs are 12-lead 10s ECGs with a frequency of 500 Hz.

Our results confirm that when labeled data is scarce and pretraining is not available, smaller models outperform bigger ones. Whereas all models are improved by pretraining, the larger models are improved more, and with enough source data to use for pretraining, they will overtake the smaller models. From the pretraining task under consideration, age regression works best, with the best model achieving a target AUC of 83%, which is 8 percentage points better than the best model that is not using pretraining (baseline CNN, AUC 75%).

II. Related work

Strodthoff ResNet (xresnet50) [1]
Ribeiro ResNet [2]
Gustafsson ResNet [3]
S4 models [4]
PTB-XL [5]
PTB-XL benchmarks and insights [6]

III. Methods

A. Data sources

1) Target data:

2) Source data:

B. Models

C. Pretraining tasks

1) Predicting age:

2) Predicting sex:

3) *Predicting age and sex simultaneously*:

IV. Results and Discussion

We achieve a mean absolute error (MAE) of 6.62 years for the age regression pretraining task, which is in line with previous studies (Lima *et al.* achieves a MAE of 8.38 [7]. Strodthoff *et al.* achieves a MAE of 6.86 years on PTB-XL for healthy subjects and 7.38 years for non-healthy subjects [6]. Attia *et al.* achieves a MAE of 6.9 years [8].)

A. Limitations

V. Conclusions

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