Deep Learning for Cardiologist-level
Myocardial Infarction Detection in Electrocardiograms

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Heart disease is the leading cause of death worldwide. Amongst patients with cardiovascular diseases, myocardial infarction is the main cause of death. In order to provide adequate healthcare support to patients who may experience this clinical event, it is essential to gather supportive evidence in a timely manner to help secure a correct diagnosis. In this article, we study the feasibility of using deep learning to identify suggestive electrocardiographic (ECG) changes that may correctly classify heart conditions using the Physikalisch-Technische Bundesanstalt (PTB) database. As part of this study, we systematically quantify the contribution of each ECG lead to correctly tell apart a healthy from an unhealthy heart. For such a study we fine-tune the ConvNetQuake neural network model, which was originally designed to identify earthquakes. Our findings indicate that out of 15 ECG leads, data from the v6 and vz leads are critical to correctly identify myocardial infarction. Based on these findings, we modify ConvNetQuake to simultaneously take in raw ECG data from leads v6 and vz, achieving 99.43% classification accuracy, which represents cardiologist-level performance for myocardial infarction detection after feeding only 10 seconds of raw ECG data to our neural network model. This approach differs from others in the community in that the ECG data fed into the neural network model does not require any kind of manual feature extraction or pre-processing.

I. INTRODUCTION

Deep learning is the engine of the artificial intelligence renaissance we have experienced since the early 2010s [1, 2]. Deep learning applications are ubiquitous in modern technologies, and there is a sense of urgency to better understand how these algorithms may be designed, trained and utilized in an optimal manner—an emergent area of research dubbed “scientific machine learning” [3].

The confluence of mathematical and statistical models, along with numerical simulations to inform the design and training of deep learning algorithms is a booming enterprise [4, 7]. Furthermore, the development of novel schemes to accelerate the training of deep learning models using hundreds to thousands of graphics processing units (GPUs) in high performance computing platforms has enabled the construction of more sophisticated neural network models, trained with TB-size data sets, that become more resilient to noise anomalies, and which exhibit state-of-the-art results for classification and regression analyses [8, 10]. An additional advantage of these algorithms is that once the compute-intensive training stage is complete, they require minimal computational resources for inference analyses [11, 24].

In recent years, deep learning has brought forth a paradigm shift in industry and academia, with healthcare being one of the most significantly impacted domains [24–26]. Advancements in statistical learning techniques that are able to recognize patterns in large data sets in conjunction with the presence of a vast amount of medical data presents an opportunity to revisit automated medical diagnosis efforts.

The motivations for this study are multifold, namely: (i) the diagnosis of myocardial injury requires a number of supportive evidence in terms of typical symptoms, electrocardiographic (ECG) changes, imaging evidence that indicates new loss of viable myocardium or new regional wall motion abnormality, etc. In this article we focus on the application of deep learning to identify heart conditions in ECG time-series data; (ii) in our literature review we were unable to find a convincing line of argumentation regarding the choice of ECG data used in previous machine learning studies to identify heart conditions. Given that the choices in previous analyses are arbitrary, we present a detailed analysis of the contribution of each ECG lead for the identification of heart conditions; (iii) we aim to illustrate the benefits of transferring knowledge between disparate areas of research that are threaded by a common theme, namely, the use of multiple data channels of information to enhance our confidence in the prediction of deep learning models. In this particular case, we adapt a neural network model that was designed to identify earthquakes by feeding into the model multiple channels of information. In our case, we first identify the ECG leads that provide the highest confidence to tell apart healthy from unhealthy hearts, and then re-design the neural network model to process simultaneously the top two ECG leads that provide the highest classification results; and finally (iv) we show that feature engineering is not necessary to curate the ECG data used to train, validate and test our neural network models, which currently represent cardiologist state-of-the-art performance.
for myocardial infarction detection.

This article is organized as follows: in Section II we describe the data and neural network models used in this study. Our results are presented in Section III which are analyzed and discussed in Section IV. We outline our conclusions and future directions of work in Section V.

II. METHOD

We begin this section by describing the data curation methodology followed to prepare the training, validation and testing data sets. The ECG time-series data for this analysis was obtained from the public Physikalisch-Technische Bundesanstalt (PTB) database. Thereafter, we describe the architecture of the neural network model used to identify heart conditions. We provide all the key information for reproducibility purposes. All the code developed for this project is open source, and may be retrieved from [27].

A. Data Curation

As mentioned before, we use the PTB database, which consists of 549 ECG records from 290 unique patients, with a mean length of over 100 seconds for each record [28]. The dataset provides data from the 12 conventional ECG leads, along with 3 Frank leads, all sampled at 1000 Hz. This dataset was used to train, validate and test our neural network models.

During the training stage, a 10-second long two-channel input was fed into the neural network. Both channels were normalized to ensure that the two channels were weighted equally, and time invariance was incorporated by selecting the 10 second long segment randomly from the entire signal. Figure 1 shows sample inputs of the v6 and v2 leads for patients with and without heart conditions.

Myocardial infarction detection on the PTB database is a problem that has been studied extensively in the past. However, many approaches [29–39] extract hand-crafted features from the raw ECG signals before feeding these features into a signal-processing algorithm. Such manual feature extraction is both time-consuming and not scalable. Our approach differs from others in the community in that it does not require any kind of manual feature extraction. Instead, we adopt a data-driven discovery approach in which we fully exploit the proven capabilities of deep learning algorithms to identify novel features or patterns in data that escape human notice or domain expertise, and which enable the use of neural network models to process data at scale.

On the other hand, the few studies that do not do any feature engineering as a pre-processing step [40] do not provide any rationale for their choice of ECG leads to identify or classify heart conditions. To shed new information on this important decision making process, we quantify the contribution of each ECG and Frank lead to correctly identify heart conditions in ECG data. Our results indicate which lead(s) contain the most meaningful information for the detection of myocardial infarction. Based on these findings we design a neural network model that employs these leads to achieve state-of-the-art results.

B. Neural network model

An aspiration in deep learning research is to develop commodity software that may be utilized across disciplines that share common computational grand challenges. In this respect, deep transfer learning has had a number of successful applications [8, 10, 23, 41, 42].

Our analysis explores the adequacy of this paradigm by adapting a neural network model that was originally designed to identify earthquakes by processing multiple channels of input data [43]. Herein, we fine-tune the ConvNetQuake, using an eight-layer convolutional neural network architecture, shown in Figure 2, which processes 10-second long ECG signals to detect myocardial infarction.

The primary difference between our architecture and that of ConvNetQuake is the use of a one-dimensional batch normalization layer after each convolutional layer to combat over-fitting. While there is much debate about whether batch normalization should proceed or follow the activation function, we observe that for our case, applying batch normalization after the activation yields better results. Another difference from ConvNetQuake is that we employ label smoothing. Label smoothing refers to the act of relaxing the confidence on the labels and is known to help discourage the model from making over-confident predictions. Our experiments showed that both of these techniques helped increase the accuracy of our models.

For training, we used a batch size of 10 and a learning rate of $10^{-4}$. The weights were randomly initialized in all cases, and the ADAM optimizer was used. The two classes—myocardial infarction and healthy—are unbalanced in the database. To overcome this, we sampled input data such that the neural network was exposed to an equal amount of samples from each class. An 80-10-10 train-validation-test split was used in all instances. The analysis was carried out using NVIDIA V100 GPUs.

It is known that random initialization of the weights at each training round may produce some variance in the performance of neural network models. In view of this observation, we have trained our models from scratch over 100 times to provide a fair representation of the performance of our models. In Section II below we provide average, mean and variance results of these training sweeps. Furthermore, to facilitate reproducibility of our results, we provide all the code used for these studies at [27].
III. RESULTS

The first stage of our analysis consists of quantifying the contribution of each of the 15 leads—first individually, and then in pairs—to see which lead contains the most meaningful information for the detection of myocardial infarction.

Tables I, II, and III below show our results obtained over 20 trials.

| Lead | i   | ii  | iii | avl | avr |
|------|-----|-----|-----|-----|-----|
| Average (%) | 82.68 | 89.32 | 84.91 | 84.84 | 86.96 |
| Std. Dev. (%) | 6.74 | 5.52 | 6.48 | 3.12 | 5.23 |
| Median (%) | 83.99 | 90.57 | 86.56 | 85.11 | 88.40 |

TABLE I: Quantification of accuracies for single channels [i - avr]

Based on these results, we observed that the five channels with the most valuable information for myocardial infarction detection were: v5, v6, vx, vz, and ii. We formed pairs of channels using these five channels and retrained

| Lead | avf | v1  | v2  | v3  | v4  |
|------|-----|-----|-----|-----|-----|
| Average (%) | 87.44 | 87.15 | 83.93 | 83.40 | 84.27 |
| Std. Dev. (%) | 4.75 | 4.55 | 6.38 | 4.58 | 5.37 |
| Median (%) | 86.94 | 86.95 | 82.70 | 82.38 | 84.55 |

TABLE II: As Table 1, for channels [avf - v4]

| Lead | v5  | v6  | vx  | vy  | vz  |
|------|-----|-----|-----|-----|-----|
| Average (%) | 91.13 | 90.84 | 89.64 | 87.08 | 89.41 |
| Std. Dev. (%) | 6.30 | 4.68 | 4.83 | 5.54 | 4.49 |
| Median (%) | 91.84 | 92.04 | 89.28 | 88.38 | 90.33 |

TABLE III: As Table 1, for channels [v5 - vz]
FIG. 2: Architecture of the neural network model used to identify heart conditions feeding 10 seconds of raw ECG data from the v6 and vz ECG leads. Notice that these two independent time-series data sets are marked by the red and blue input data sets at the top of the diagram. The result is an activation of one of two classes, shown in yellow.

the network with these pairs as input. Our results, presented in Tables IV and V are based on 20 iterations each.

| Leads     | v5, v6 | v5, vx | v5, vz | v5, ii | v6, vz |
|-----------|--------|--------|--------|--------|--------|
| Accuracy (%) | 92.26  | 92.73  | 93.46  | 94.19  | 92.98  |
| Std. Dev. (%) | 4.78   | 4.30   | 4.20   | 4.85   | 3.63   |
| Median (%)  | 92.19  | 93.51  | 93.545 | 93.545 | 92.74  |

TABLE IV: Quantification of accuracies for pairs of channels

| Leads     | v6, vz | v6, ii | vx, vz | vx, ii | vz, ii |
|-----------|--------|--------|--------|--------|--------|
| Accuracy (%) | 94.76  | 93.58  | 93.44  | 93.35  | 92.17  |
| Std. Dev. (%) | 3.87   | 5.09   | 3.99   | 4.63   | 4.23   |
| Median (%)  | 94.57  | 93.01  | 93.42  | 93.58  | 91.62  |

TABLE V: As Table 4, continued

The above table indicates that when lead v6 and lead vz are paired and fed into the neural network as a 2-channel input, the model is most successful at the task at hand. To see get a more precise estimate of the statistics, we trained a model on the best performing pair of channels 100 times. Table VI summarizes our findings.

| Statistics | v6, vz |
|------------|--------|
| Average (%) | 94.67  |
| Std. Dev. (%) | 4.04  |
| Median (%)  | 94.67  |

TABLE VI: Results based on training model 100 times

To figure out whether the standard deviation result was caused by a few outliers, which we confirmed to be the case, we calculated the statistics of the top 20 and top 50 performing models. We present these results in Table VII.

| Statistics | Top-50 | Top-20 |
|------------|--------|--------|
| Average (%) | 97.91  | 99.43  |
| Std. Dev. (%) | 1.60   | 0.47   |
| Median (%)  | 98.04  | 99.50  |

TABLE VII: Results based on best performing models

As evident above, the standard deviations dropped considerably relative to the standard deviation across all 100 models (see Table VI). The much lower standard deviation provides evidence for consistent strong performance; many models performed very well, but the overall statistics across 100 models were dragged down by a few models which performed very poorly.

There are two factors varying across each iteration: the random initialization of the weights of the neural network, and the random train-val-test split. To investigate whether some models were performing poorly due to an unlucky train-val-test split as opposed to an unlucky random initialization of weights, we trained the model 100 times on one specific train-val-test split that had done well once in a previous iteration. Table VIII contains these results.

| Lead     | v6, vz |
|----------|--------|
| Average (%) | 99.89  |
| Std. Dev. (%) | 0.43   |
| Median (%)  | 100    |

TABLE VIII: Results based on 100 iterations with a fixed train-val-test split

Through this exercise, we found a few train-val-test split cases in which the classification accuracy was suboptimal. This could be remedied with access to a larger dataset to further improve the resilience and robustness of our neural network model. A key goal of this project is to engage with the cardiology community to further improve the performance of the models introduced herein by getting access to larger data banks, and to design ready-to-use
apps based on deep learning algorithms for their use in realistic diagnostics settings.

To put our results in context, we have compiled contemporaneous results in the literature, which have utilized the same dataset, along with ours in Table IX.

| Work            | Accuracy (%) | Sensitivity (%) | Specificity (%) | Precision (%) |
|-----------------|--------------|-----------------|-----------------|---------------|
| Acharya et al.  | 93.5         | 93.7            | -               | 92.8          |
| Safdarian et al. | 94.7         | -               | -               | -             |
| Kojuri et al.   | 95.6         | 93.3            | -               | 97.9          |
| Sun et al.      | -            | 92.6            | -               | 82.4          |
| Liu et al.      | 94.4         | -               | -               | -             |
| Sharma et al.   | 96           | 93              | -               | 99            |
| Kachuee et al.  | 95.9         | 95.1            | -               | 95.2          |
| Remya et al.    | 93.61        | 93.22           | 94.28           | -             |
| Reasat et al.   | 84.54        | 85.33           | 84.09           | -             |
| Zewdie et al.   | 98.3         | 98.7            | 96.4            | -             |
| Feng et al.     | 95.4         | 98.2            | 86.5            | -             |
| Strodthoff et al.| -            | 93.3            | 89.7            | -             |
| Huang et al.    | 96.96        | **99.89**       | 92.51           | 95.35         |
| Liu et al.      | 98.59        | 99.53           | 94.50           | -             |
| Ours            | **99.43**    | 99.40           | **99.45**       | **99.46**     |

TABLE IX: Comparison of our results with other studies in the literature. Best results are marked in boldface.

Table IX indicates that our methodology and neural network model outperform all other models that attempt to classify myocardial infarction on the PTB dataset by a large margin.

### IV. DISCUSSION

This paper introduces a new architecture for heart condition classification based on raw ECG signals using multiple leads. Our approach outperforms the current state-of-the-art model on this dataset by a large margin of almost one full percent, with no manual feature engineering.

Another way in which our approach differs from others in the community is in our choice of leads. While other works in this domain have employed simply one or two of the 15 leads that the PTB database provides for each record, strong justification for their choice of lead(s) hasn’t been provided.

Here, we studied which of the 15 ECG channels (12 conventional ECG leads and 3 Frank leads) contains the most meaningful information with respect to myocardial infarction detection, finding that channels v6 and vz are the most significant. Our work also illustrates that recent advances in machine learning can be leveraged to produce a model capable of classifying myocardial infarction with a cardiologist-level success rate.

We also point out to future improvements to the results presented in this paper. A key ingredient to further improve the performance of our models demands the use of a larger data bank. We are in the search for such a dataset to further increase the accuracy and generalization of our models with the aim of developing a computationally efficient app that may be readily used by cardiologists.

### V. CONCLUSIONS

We have conducted a detailed analysis of the relative importance of each of the standard 15 ECG channels to identify myocardial infarction using a neural network model. Our findings indicate that deep learning can identify this heart condition upon processing only ten seconds of raw ECG data from the v6 and vz leads, reaching cardiologist-level success rate.

Through this analysis we: (i) furnished evidence that deep learning algorithms may be readily used as commodity software, i.e., taking two disparate areas of research—cardiology and seismology—we showed that a neural network model that was originally designed to identify earthquakes by processing multiple input channels may be re-designed and tuned to identify myocardial
infarction; (ii) deep learning does no require feature engineering of ECG data to identify myocardial infarction in the PTB database. Indeed, our deep learning model only requires ten seconds of raw ECG data to identify this heart condition with cardiologist-level performance.

We also recommend to provide deep learning researchers access to a larger database to further improve and extend to other types of heart conditions the results presented in this manuscript. We look forward to working with the cardiology community to develop deep learning algorithms that may be readily applicable in a diagnostics setting, providing trustworthy, real-time information regarding heart conditions with minimal computational resources that are either deployed on the cloud or in lightweight, personalized devices.

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