Wettbewerb künstliche Intelligenz in der Medizin
ECG-DualNet

TECHNISCHE UNIVERSITÄT DARMSTADT

Attention Is All You Need

Christoph Reich

Supervisors

Prof. Dr.-Ing. Christoph Hoog Antink

Maurice Rohr, M. Sc.

KIS*MED

Content

TECHNISCHE
UNIVERSITÄT
DARMSTADT

Content

KIS*MED

TECHNISCHE UNIVERSITÄT DARMSTADT

Classify single-lead ECG signals with variable length.

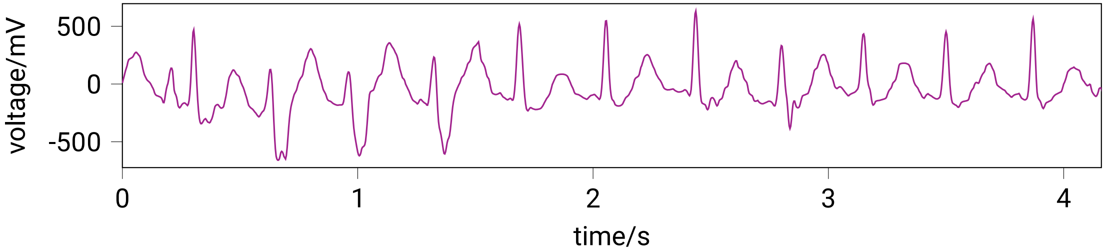


Figure: ECG signal of the 2017 PhysioNet/CinC Challenge dataset [Clifford et al., 2017] labeled as AF.

Introduction
Motivation

TECHNISCHE UNIVERSITÄT DARMSTADT

- Atrial fibrillation (AF) dangerous and often undetected
- AF one of the most common heart arrhythmia’s
- AF can lead to strokes, dementia, and heart failure
- Increasing amount of single-lead ECG edge devices available
  - No expert knowledge typically available
  - Need for automated classification of AF

[Becker, 2006]
[Herold, 2019]

Introduction

Motivation

TECHNISCHE UNIVERSITÄT DARMSTADT

- Atrial fibrillation (AF) dangerous and often undetected
- AF one of the most common heart arrhythmia's
- AF can lead to strokes, dementia, and heart failure
- Increasing amount of single-lead ECG edge devices available
  - No expert knowledge typically available
  - Need for automated classification of AF

[Becker, 2006]
[Herold, 2019]

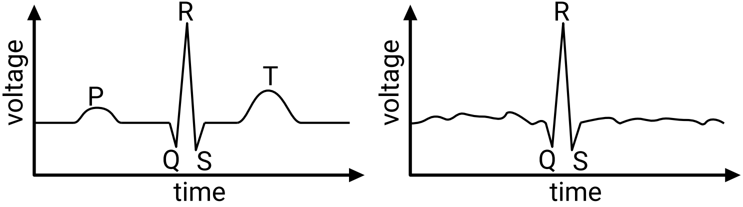


Figure: Regular heart beat left and atrial fibrillation on the right.

KIS*MED

Introduction

Related Work

Transitional ML approaches

Deep learning approaches

Introduction

Related Work

Transitional ML approaches

- Preprocessing & Feature extraction
  - Data augmentation
  - ECG timing features
  - Robust interval features
  - Waveform features
- Learnable classifier
  - Random forest
  - Support vector machines
  - XGBoost
- [Hoog Antink et al., 2017, Smíšek et al., 2017]

Deep learning approaches

Introduction
Related Work

TECHNISCHE UNIVERSITÄT DARMSTADT

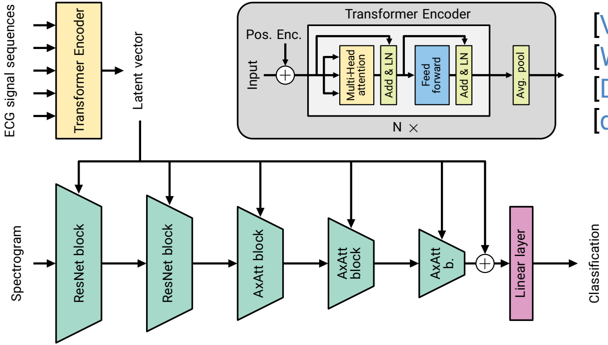
Transitional ML approaches

- Preprocessing & Feature extraction
  - Data augmentation
  - ECG timing features
  - Robust interval features
  - Waveform features
- Learnable classifier
  - Random forest
  - Support vector machines
  - XGBoost
- [Hoog Antink et al., 2017, Smíšek et al., 2017]

Deep learning approaches

- Preprocessing
  - Data augmentation
  - Data conversion (Spectrogram)
- Deep learning classifier
- [Zihlmann et al., 2017, Mousavi et al., 2019, Mashrur et al., 2019, Khriji et al., 2020, Nonaka and Seita, 2020]

Content



[Vaswani et al., 2017]
[Wang et al., 2020]
[Dosovitskiy et al., 2020]
[de Vries et al., 2017]

Figure: ECG-DualNet++ architecture with signal and spectrogram encoder

Method

Augmentation Pipeline

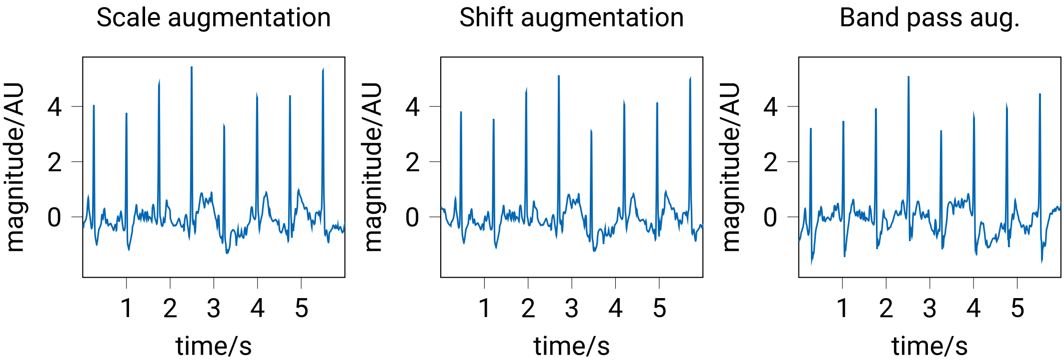


Figure: Different augmentations applied to ECG signal of the 2017 PhysioNet/CinC Challenge dataset [Clifford et al., 2017].

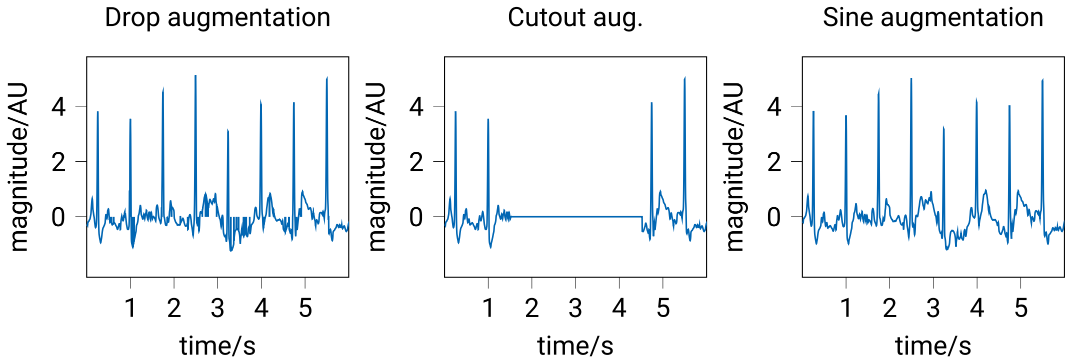


Figure: Different augmentations applied to ECG signal of the 2017 PhysioNet/CinC Challenge dataset [Clifford et al., 2017].

Method
Augmentation Pipeline

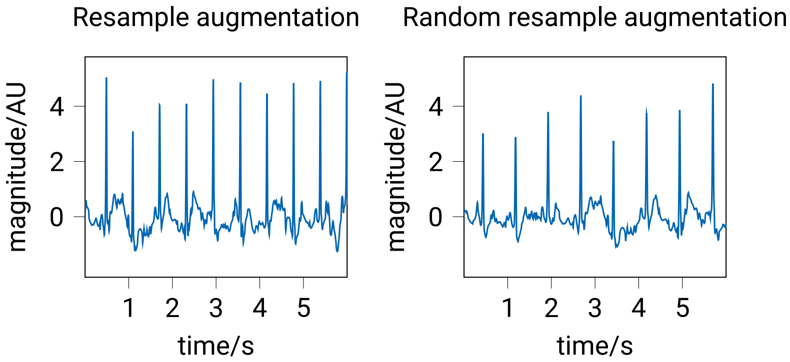


Figure: Different augmentations applied to ECG signal of the 2017 PhysioNet/CinC Challenge dataset [Clifford et al., 2017]. Random reasmple aug. inspired by 2D random elastic aug. [Simard et al., 2003].

TECHNISCHE UNIVERSITÄT DARMSTADT

Training loss (weighted cross entropy loss)

$$\mathcal{L} = -\frac{1}{N} \sum_{j=1}^{N} \sum_{i=1}^{4} \alpha_i \, y_{ji} \, \log\left(\hat{y}_{ji}\right)$$

Method

Training & Validation

TECHNISCHE UNIVERSITÄT DARMSTADT

Training loss (weighted cross entropy loss)

$$\mathcal{L} = -\frac{1}{N}\sum_{j=1}^{N}\sum_{i=1}^{4}\alpha_i\, y_{ji}\, \log\left(\hat{y}_{ji}\right)$$

Validation metrics (accuracy & F1)

$$\mathrm{ACC} = \frac{1}{n}\sum_{j=1}^{n}\delta\left(\arg\max(\mathbf{y}_j), \arg\max(\hat{\mathbf{y}}_j)\right), \quad \mathrm{F1} = \frac{1}{4}\sum_{i=1}^{4}\frac{2\mathrm{TP}_i}{2\mathrm{TP}_i + \mathrm{FP}_i + \mathrm{FN}_i}$$

KIS*MED

Content

Experiments
Datasets

TECHNISCHE UNIVERSITÄT DARMSTADT

2017 PhysioNet/CinC Challenge dataset [Clifford et al., 2017]

- Single-lead ECG signals with variable length (2714 - 18286 samples)
- 8529 publicaly available data samples (7000 train & 1528 val.)
- Labels include four classes (normal, AF, other & noisy)

Experiments

Datasets

2017 PhysioNet/CinC Challenge dataset [Clifford et al., 2017]

- Single-lead ECG signals with variable length (2714 - 18286 samples)
- 8529 publicaly available data samples (7000 train & 1528 val.)
- Labels include four classes (normal, AF, other & noisy)

Icentia11k [Tan et al., 2019]

- Single-lead ECG signals of 11k patients.
- 550k data samples with a length of 1h
- Sparse six class rhythm labels including AF
- Cropped and resampled to match target dataset

Results

ECG-DualNet Results

Table: Classification results of our proposed approaches and baselines on the 2017 PhysioNet validation set.

Model	ACC ↑	F1 ↑	# Parameters
CNN baseline* [Zihlmann et al., 2017]	0.812	0.790†	∼ 3.5M
CRNN baseline* [Zihlmann et al., 2017]	0.823	0.792†	∼ 3.5M
ECG-DualNet S	0.8527	0.8049	1.8M
ECG-DualNet M	0.8560	0.7938	4.3M
ECG-DualNet L	0.8514	0.8038	6.2M
ECG-DualNet XL	**0.8612**	**0.8164**	20.7M
ECG-DualNet++ S	0.8174	0.7291	1.8M
ECG-DualNet++ M	0.8259	0.7730	2.6M
ECG-DualNet++ L	0.8449	0.7859	3.7M
ECG-DualNet++ XL	*0.8593*	*0.8051*	8.2M
ECG-DualNet++ 130M	0.8534	0.7963	128M

* Reported literature values (private PhysioNet test set utilized).

† F1 score computed over three classes, thus not directly comparable.

Results

ECG-DualNet Results Pre-Training

Table: Classification results of our proposed approaches on the Icentia11k validation set. Only a single training for each model run was conducted.

Model	ACC ↑	F1 ↑
ECG-DualNet XL	0.8989	0.5135
ECG-DualNet++ XL	0.8899	0.5017

Results

ECG-DualNet Results Pre-Training

Table: Classification results of our proposed approaches on the Icentia11k validation set. Only a single training for each model run was conducted.

Model	ACC $\uparrow$	F1 $\uparrow$
ECG-DualNet XL	0.8989	0.5135
ECG-DualNet++ XL	0.8899	0.5017

Table: Classification results of our proposed approaches on the 2017 PhysioNet validation set and pre-trained on the Icentia11k dataset. Differences to values of no pre-training results in red.

Model	ACC $\uparrow$	F1 $\uparrow$
ECG-DualNet XL	0.8468 $(\downarrow 0.0144)$	0.8014 $(\downarrow 0.0150)$
ECG-DualNet++ XL	0.8481 $(\downarrow 0.0112)$	0.7817 $(\downarrow 0.0234)$

Table: Classification results on the 2017 PhysioNet validation for different ablations. ECG-DualNet L configuration utilized.

Data aug. & dropout	Signal encoder	Spectrogram encoder	ACC ↑	F1 ↑
✗	✓	✓	0.8272	0.7493
✓	✗	✓	0.8440	0.7855
✓	✓	✗	0.7264	0.5813
✓	✓	✓	**0.8560**	**0.7938**

Content

TECHNISCHE UNIVERSITÄT DARMSTADT

Conclusion & Discussion

TECHNISCHE
UNIVERSITÄT
DARMSTADT

Achievements

- Presented the novel ECG-DualNet for ECG classification
- Proposed an advanced augmentation pipeline
- Performed extensive experiments including pre-training

Conclusion & Discussion

TECHNISCHE UNIVERSITÄT DARMSTADT

Achievements

- Presented the novel ECG-DualNet for ECG classification
- Proposed an advanced augmentation pipeline
- Performed extensive experiments including pre-training

Observations

- Highly overparameterized models (ECG-DualNet++ 130M) does not overfit in the classical sense $\rightarrow$ Deep Double Descent [Nakkiran et al., 2020] ?
- Spectrogram encoder is the most crucial part of ECG-DualNet
- Extensive pre-training on the Icentia11k does not lead to performance benefits on the target 2017 PhysioNet dataset

References I

TECHNISCHE UNIVERSITÄT DARMSTADT

Becker, D. E. (2006).
Fundamentals of electrocardiography interpretation.
Anesthesia progress, 53(2):53–64.

Clifford, G. D., Liu, C., Moody, B., Li-wei, H. L., Silva, I., Li, Q., Johnson, A., and Mark, R. G. (2017).
AF Classification from a Short Single Lead ECG Recording: the PhysioNet/Computing in Cardiology Challenge 2017.
In *2017 Computing in Cardiology (CinC)*, pages 1–4. IEEE.

de Vries, H., Strub, F., Mary, J., Larochelle, H., Pietquin, O., and Courville, A. (2017).
Modulating early visual processing by language.
In *Advances in Neural Information Processing Systems*, pages 6597–6607.

References II

Dosovitskiy, A., Beyer, L., Kolesnikov, A., Weissenborn, D., Zhai, X., Unterthiner, T., Dehghani, M., Minderer, M., Heigold, G., Gelly, S., et al. (2020).
An image is worth 16x16 words: Transformers for image recognition at scale.
preprint arXiv:2010.11929.

Herold, G. (2019).
Innere Medizin.
Walter de Gruyter GmbH & Co KG.

Hoog Antink, C., Leonhardt, S., and Walter, M. (2017).
Fusing QRS Detection and Robust Interval Estimation with a Random Forest to Classify Atrial Fibrillation.
In *2017 Computing in Cardiology (CinC)*, pages 1–4. IEEE.

References III

Khriji, L., Fradi, M., Machhout, M., and Hossen, A. (2020).
Deep Learning-based Approach for Atrial Fibrillation Detection.
In *International Conference on Smart Homes and Health Telematics*, pages 100–113. Springer.

Mashrur, F. R., Roy, A. D., and Saha, D. K. (2019).
Automatic identification of arrhythmia from ecg using alexnet convolutional neural network.
In *2019 4th International Conference on Electrical Information and Communication Technology (EICT)*, pages 1–5. IEEE.

References IV

TECHNISCHE UNIVERSITÄT DARMSTADT

Mousavi, S., Afghah, F., Razi, A., and Acharya, U. R. (2019).
ECGNET: Learning Where to Attend for Detection of Atrial Fibrillation with Deep Visual Attention.
In *2019 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI)*, pages 1–4. IEEE.

Nakkiran, P., Kaplun, G., Bansal, Y., Yang, T., Barak, B., and Sutskever, I. (2020).
Deep double descent: Where bigger models and more data hurt.
In *International Conference on Learning Representations*.

Nonaka, N. and Seita, J. (2020).
Data Augmentation for Electrocardiogram Classification with Deep Neural Network.
preprint arXiv:2009.04398.

References V

Simard, P. Y., Steinkraus, D., Platt, J. C., et al. (2003).
Best Practices for Convolutional Neural Networks Applied to Visual Document Analysis.
In *Icdar*, volume 3.

Smíšek, R., Hejč, J., Ronzhina, M., Němcová, A., Maršánová, L., Chmelík, J., Kolářová, J., Provazník, I., Smital, L., and Vítek, M. (2017).
Svm based ecg classification using rhythm and morphology features, cluster analysis and multilevel noise estimation.
In *2017 Computing in Cardiology (CinC)*, pages 1–4.

KIS*MED

References VI

TECHNISCHE UNIVERSITÄT DARMSTADT

Tan, S., Androz, G., Chamseddine, A., Fecteau, P., Courville, A., Bengio, Y., and Cohen, J. P. (2019).
Icentia11k: An unsupervised representation learning dataset for arrhythmia subtype discovery.
preprint arXiv:1910.09570.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L. u., and Polosukhin, I. (2017).
Attention is all you need.
In *Advances in Neural Information Processing Systems*, volume 30.

Wang, H., Zhu, Y., Green, B., Adam, H., Yuille, A., and Chen, L.-C. (2020).
Axial-DeepLab: Stand-Alone Axial-Attention for Panoptic Segmentation.
In *European Conference on Computer Vision*, pages 108–126.

KIS*MED

References VII

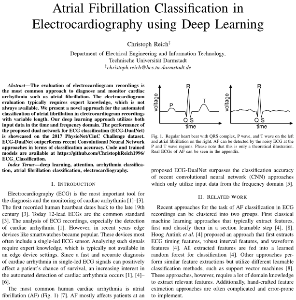
TECHNISCHE UNIVERSITÄT DARMSTADT

Zihlmann, M., Perekrestenko, D., and Tschannen, M. (2017).
Convolutional Recurrent Neural Networks for Electrocardiogram Classification.
In *2017 Computing in Cardiology (CinC)*, pages 1–4. IEEE.

KIS*MED

Code availability & Questions

Code, weights, and paper are available at:
github.com/ChristophReich1996/ECG_Classification



Atrial Fibrillation Classification in Electrocardiography using Deep Learning

Christoph Reich[‡]
Department of Electrical Engineering and Information Technology,
Technische Universität Darmstadt
[‡]christoph.reich@bcs.tu-darmstadt.de

***Abstract*—The evaluation of electrocardiogram recordings is the most common approach to diagnose and monitor cardiac arrhythmia such as atrial fibrillation. The electrocardiogram evaluation typically requires expert knowledge, which is not always available. We present a novel approach for the automated classification of atrial fibrillation in electrocardiogram recordings with variable length. Our deep learning approach utilizes both input data in the time and frequency domain. The performance of the proposed dual network for ECG classification (ECG-DualNet) is showcased on the 2017 PhysioNet/CinC Challenge dataset. ECG-DualNet outperforms recent Convolutional Neural Network approaches in terms of classification accuracy. Code and trained models are available at https://github.com/ChristophReich1996/ECG_Classification.**

***Index Terms*—deep learning, attention, arrhythmia classification, atrial fibrillation classification, electrocardiography.**

I. Introduction

Electrocardiography (ECG) is the most important tool for the diagnosis and the monitoring of cardiac arrhythmia [1]–[3]. The first recorded human heartbeat dates back to the late 19th century [3]. Today 12-lead ECGs are the common standard [3]. The analysis of ECG recordings, especially the detection of cardiac arrhythmia [1]. However, in recent years edge devices like smartwatches became popular. These devices most often include a single-led ECG sensor. Analyzing such signals require expert knowledge, which is typically not available in an edge device settings. Since a fast and accurate diagnosis of cardiac arrhythmia in single-led ECG signals can positively affect a patient's chance of survival, an increasing interest in the automated detection of cardiac arrhythmia occurs [1], [4]–[6].

The most common human cardiac arrhythmia is atrial fibrillation (AF) (Fig. 1) [7]. AF mostly affects patients at an

Fig. 1. Regular heart beat with QRS complex, P wave, and T wave on the left and atrial fibrillation on the right. AF can be detected by the noisy ECG at the P and T wave regions. Please note that this is only a theoretical illustration. Real ECGs of AF can be seen in the appendix.

proposed ECG-DualNet surpasses the classification accuracy of recent convolutional neural network (CNN) approaches which only utilize input data from the frequency domain [5].

II. Related Work

Recent approaches for the task of AF classification in ECG recordings can be clustered into two groups. First classical machine learning approaches that typically extract features, first and classify them in a section learnable step [4], [8]. Hoog Antink *et al.* [4] proposed an approach that first extracts ECG timing features, robust interval features, and waveform features [4]. All extracted features are fed into a learned random forest for classification [4]. Other approaches perform similar feature extractions but utilize different learnable classification methods, such as support vector machines [8]. These approaches, however, require a lot of domain knowledge to extract relevant features. Additionally, hand-crafted feature extraction approaches are often complicated and error-prone to implement.

Challenge Submission
Backup

- ECG-DualNet XL utilized
- Pre-training on Icentia11k
- Optimized training (8000 samples) and validation (528 samples) split used

Table: Classification results of ECG-DualNet XL pre-trained on the Icentia11k dataset and fine-tuned on the PhysioNet dataset with optimized submission split. Metric computed on the small validation set. Four class results on the top and two class results below.

Model	ACC $\uparrow$	F1 $\uparrow$
ECG-DualNet XL (4 class)	0.8840	0.8549

Model	ACC $\uparrow$	F1 $\uparrow$
ECG-DualNet XL (2 class)	0.9867	0.9684

Deep Double Decent
Backup

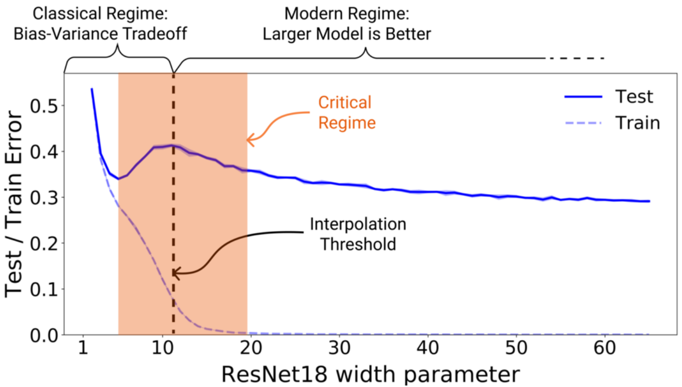


Figure: Illustration of the deep double decent phenomenon in image classification (CIFAR-10 & 15% label noise). Image taken from [Nakkiran et al., 2020].