Wettbewerb künstliche Intelligenz in der Medizin
ECG-DualNet

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Attention Is All You Need

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Supervisors

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Content

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Content

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Classify single-lead ECG signals with variable length.

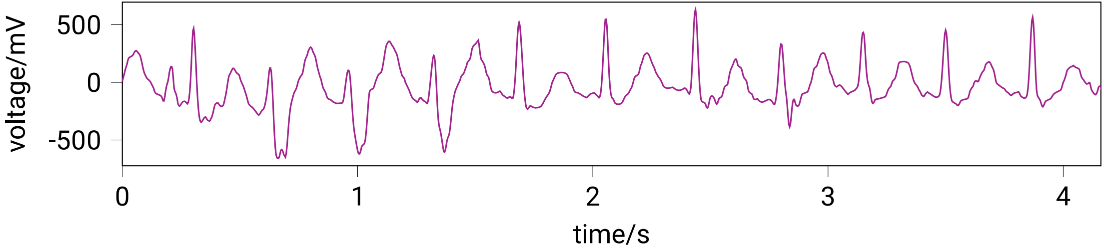

Figure: ECG signal of the 2017 PhysioNet/CinC Challenge dataset [Clifford et al., 2017] labeled as AF.

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Introduction
Motivation

- 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]

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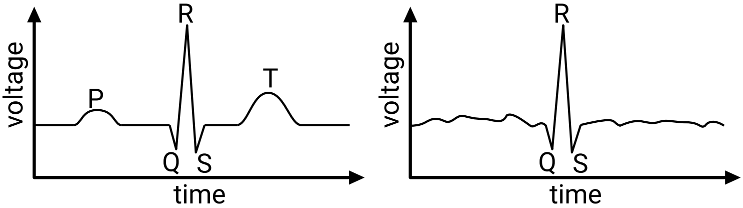

Figure: Regular heart beat left and atrial fibrillation on the right.

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Introduction
Related Work

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Transitional ML approaches

Deep learning approaches

Introduction
Related Work

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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

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- [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]

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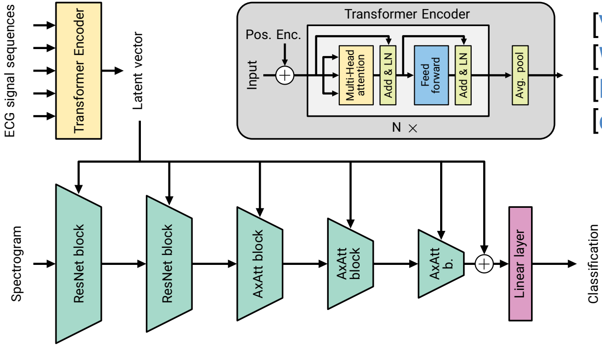
Method

ECG-DualNet(++)



[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

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Method

Augmentation Pipeline

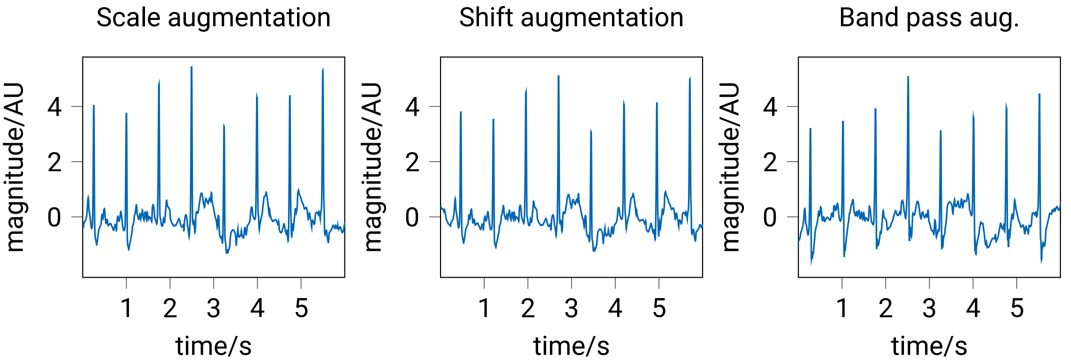

Figure: Different augmentations applied to ECG signal of the 2017 PhysioNet/CinC Challenge dataset [Clifford et al., 2017].

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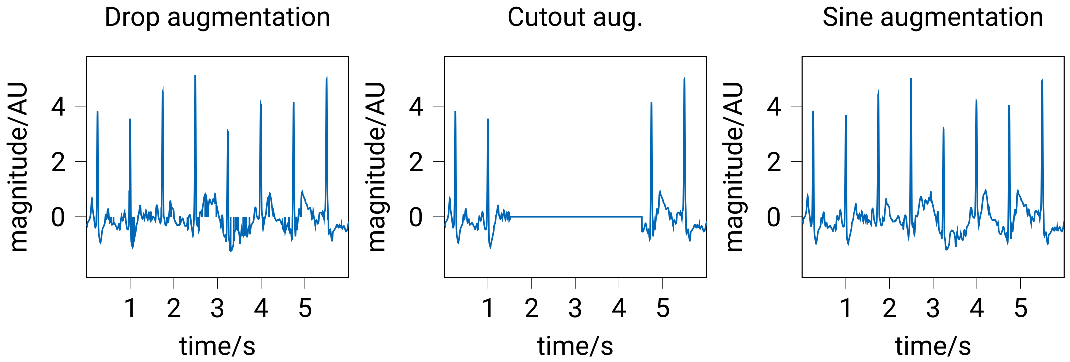
Method

Augmentation Pipeline



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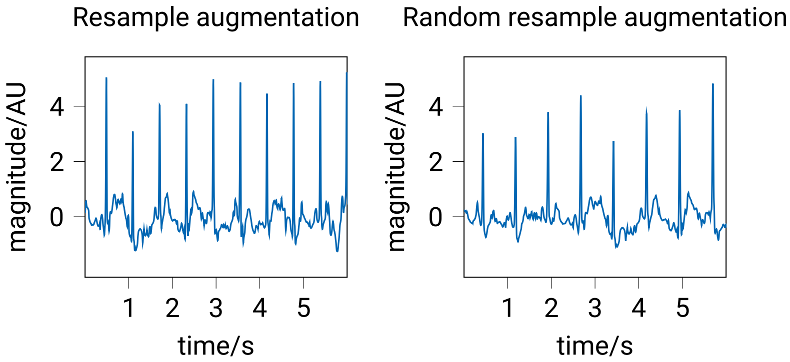

Figure: Different augmentations applied to ECG signal of the 2017 PhysioNet/CinC Challenge dataset [Clifford et al., 2017]. Random reasmple aug. inspired by 2D random elastic aug. [Simard et al., 2003].

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Training loss (weighted cross entropy loss)

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

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Validation metrics (accuracy & F1)

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

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Experiments
Datasets

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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)

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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

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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.

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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

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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 ↑	F1 ↑
ECG-DualNet XL	0.8468 (↓ 0.0144)	0.8014 (↓ 0.0150)
ECG-DualNet++ XL	0.8481 (↓ 0.0112)	0.7817 (↓ 0.0234)

Results
Ablation Study

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**

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Conclusion & Discussion

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Achievements

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

Conclusion & Discussion

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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

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Code availability & Questions

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

Atrial Fibrillation Classification in Electrocardiography using Deep Learning

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***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.**

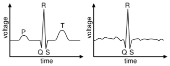

Fig. 1. Regular heart beat with QRS complex, P wave, and T wave on the left and atrial fibrillation on the right. AF can be detected by the noisy ECG at the P and T wave regions. Please note that this is only a theoretical illustration. Real ECGs of AF can be seen in the appendix.

I. Introduction

Electrocardiography (ECG) is the most important tool for the diagnosis and the monitoring of cardiac arrhythmia [1]–[3]. The first recorded human heart beat 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, requires expert knowledge [1]. This expert knowledge is sometimes not available. Since a fast and accurate diagnosis of cardiac arrhythmia can highly affect the

II. Related Work

Recent approaches for the task of AF classification in ECG recordings can be clustered in two groups. First, classical machine learning approaches [4], [9], and second, deep learning approaches [5], [10]–[13]. In general, deep learning approaches achieve better classification accuracy, however, sacrifice explainability [5], [10], [14], [15].

Classical machine learning approaches typically extract features, first and classify them in a section learnable step.

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Challenge Submission
Backup

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- 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

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Deep Double Decent

Backup

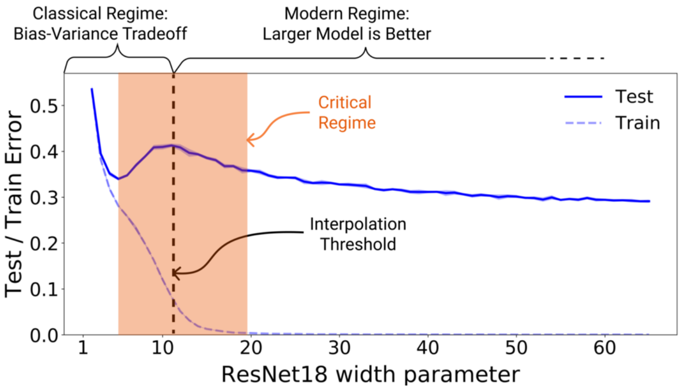

Figure: Illustration of the deep double decent phenomenon in image classification (CIFAR-10 & 15% label noise). Image taken from [Nakkiran et al., 2020].

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