Deep Spectral Features to Detect Atrial Fibrillation using Single-Lead ECG Signals

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***Abstract*—Cardiac arrhythmia is a medical condition characterized by irregular heartbeats. Globally, approximately 15-20% of all deaths each year are attributed to undiagnosed arrhythmias. While electrocardiogram (ECG) is a commonly used diagnostic tool to detect heartbeat irregularities, it requires trained experts. To address this challenge, we developed deep spectral features to detect one of the most prevalent forms of arrhythmia, atrial fibrillation, in single-lead ECG signals. Our method utilizes a 2D spectral ECG representation and compares pre-trained deep neural networks (DNNs): DenseNet121, MobileNetV2, ResNet18, and VGG16 to accurately detect atrial fibrillation. Using a single-lead ECG dataset from the PhysioNet Challenge 2017, consisting of 8,528 ECG recordings ranging from 30 to 60 seconds in duration, we achieved a mean F1-score of over 0.90 in less than 30 epochs (training). This surpasses the best-performing model in the 2017 challenge during validation. Our findings demonstrate the potential for deep spectral ECG features to enhance the accuracy and efficiency of arrhythmia detection, aiming to improve patient outcomes and reduce the burden of undiagnosed arrhythmias.**

***Index Terms*—Arrhythmia, Mel spectrogram, deep neural network, medical AI**

I. Introduction

Cardiac arrhythmia is a significant contributor to sudden death, which can be effectively treated with medication if diagnosed in a timely manner. Unfortunately, arrhythmias often go undetected due to the absence of symptoms. In cases where arrhythmias persist for more than five minutes [1], insufficient blood supply to vital organs can cause unconsciousness and eventual organ damage, including stroke, cardiac arrest, or heart failure (National Heart, Lung, and Blood Institute). In our study, we focus on Atrial fibrillation (AF) – one of the most frequent arrhythmias [2]. Diagnosis of arrhythmia typically involves the use of an electrocardiogram (ECG) that measures electrical signals emitted by the heart. Notably, prior work in this field includes analyzing and detecting arrhythmias from ECG signals, with the highest average F1-score achieved in the 2017 PhysioNet challenge at 0.8264 using morphological ECG features for classification [4]. Other studies have utilized spectral representations and multiple CNNs to analyze arrhythmias in 12-lead ECG signals [5].

While ECGs can use up to 12 sensors to monitor heart activity, inspired from Tan and Chen [3], we employ single-lead ECG. To better analyze ECGs, we propose a 2D spectral ECG representation and leverage pre-trained deep neural networks (DNNs) to accurately detect atrial fibrillation.

II. Deep spectral features

Following Fig. 1, we summarize how deep spectral features are used to classify normal, arrhythmia, noise, and other ECG signals.

Instead of analyzing raw/1D ECG signals, we adopt Mel spectrogram [6], [7] as 2D data could potentially improve CNN's performance. Mel spectrograms – visualized on a Mel scale – can better represent frequency differences. To obtain the Mel spectrogram, we transform the 1-dimensional signal into a 256X256 2-dimensional spectrum using librossa library. We then adopt the transfer learning mechanism [8], where we employ pre-trained DNNs: DenseNet121, MobileNetV2, ResNet18, and VGG16l while keeping the weights fixed during training. With Mel spectrogram representation (from 1D ECG signal), our pre-trained DNNs extract deep spectral features. Deep spectral features are used to classify (using a fully connected layer) four different cases: normal, arrhythmia, noise, and other ECG signals. Our model outperforms the 2017 PhysioNet model by more than 18.00% for AF ECG signals in less than 5 mins of training time per epoch (*ref* Tables I and II). To make it reproducible, our code is available: https://github.com/2ai-lab/ecg-classification.

III. Experiments

In addition to industry-standard evaluation metrics (precision, sensitivity, F1-score, specificity, and accuracy), we adopted the recommended metric from the PhysioNet challenge, the average F1-score [4]. The training process was conducted on a single node HPC[1]. Given the fast convergence observed during our experiments, we opted to restrict the training process to 30 epochs for each model.

Results on the validation dataset are presented in Table I, indicating that DenseNet121 and ResNet18 are the best-performing model architectures, followed by MobileNetV2 and VGG16, all with the same performance. Furthermore, a detailed analysis of the F1-scores for

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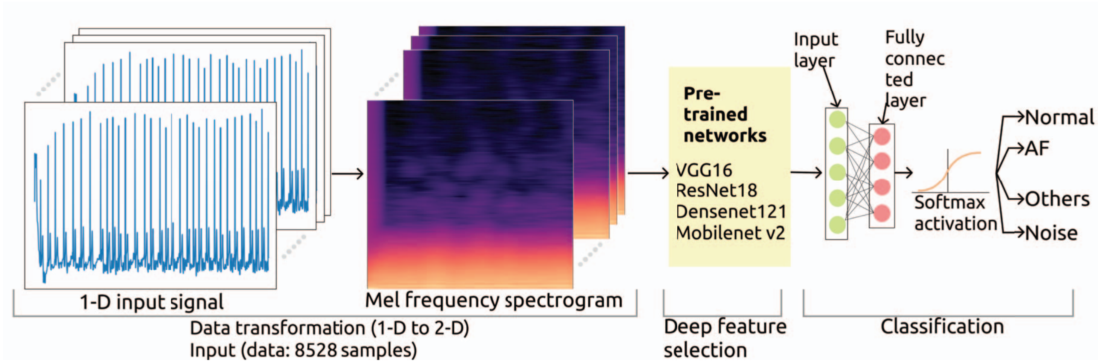

Fig. 1: Workflow: a) ECG signals are transformed into Mel spectrograms; b) 256X256 Spectrogram images are then fed into pre-trained CNNs to produce deep spectral features ; and classification is done (using fully connected layer) with four outputs: normal, arrhythmia, noise, and other signals.

TABLE I: Performance scores in %.

Model	PREC	SEN	F1-score	SPEC	ACC	Avg F1-score
MobileNetV2	1	0.97	0.98	1	0.93	0.9
ResNet18	1	1	1	1	0.94	0.92
VGG16	1	0.94	0.97	1	0.84	0.79
DenseNet121	1	1	1	1	0.94	0.92

TABLE II: Comparison using average F1-score (in %) with the state-of-the-art works

Method	Normal	AF	Others	Noise	Avg
Dutta et al [9]	0.91	0.80	0.77	0.83	0.83
Hong et al [11]	0.92	0.84	0.74	-	0.83
Mahajan et al [12]	0.89	0.76	0.72	-	0.79
Zabihi et al [13]	0.90	0.79	0.75	0.61	0.81
Ours (DenseNet121)	0.97	0.93	0.93	0.86	0.92

each class reveals that we achieved higher scores in all classes, surpassing the top-performing PhysioNet 2017 challenge model [9]. Notably, the 2017 PhysioNet model only excels in classifying normal ECG signals and suffers a heavy performance loss for other classes. Our model outperforms the 2017 PhysioNet model by a considerable margin, with an 18.75% boost in the metrics for AF ECG signals. Even though the DenseNet121 model took almost double the time to train as opposed to ResNet18, following our results, we still recommend DenseNet121 architecture.

IV. Conclusion and future works

In this study, we have leveraged deep spectral features that effectively detect AF arrhythmia from single-lead ECG signals with minimal training epochs. We have outperformed the state-of-the-art algorithms proposed in the 2017 PhysioNet Challenge. Our future works include multimodal learning and representation and time-series feature/behavior.

References

[1] Brugada et al. “Cardiac arrhythmias and sudden death.” European Society of Cardiology, 10 January 2004, https://www.escardio.org/Journals/E-Journal-of-Cardiology-Practice/Volume-2/Cardiac-Arrhythmias-and-Sudden-Death-Title-Cardiac-Arrhythmias-and-Sudden-Dea. Accessed 7 March 2023.

[2] Hassan et al. ”Overview of prediction, detection, and classification of atrial fibrillation using wavelets and AI on ECG”, Computers in Biology and Medicine, Volume 142, 2022, 105168, ISSN 0010-4825,

[3] Pathangay et al. “Arrhythmia detection in single-lead ECG by combining beat and rhythm-level information.” Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual International Conference vol. 2014 (2014): 3236-9.

[4] Clifford et al. ”AF classification from a short single lead ECG recording: The PhysioNet/computing in cardiology challenge 2017.” In 2017 Computing in Cardiology (CinC) 2017 Sep 24 (pp. 1-4). IEEE.

[5] Wong et al. ”Multilabel 12-Lead Electrocardiogram Classification Using Beat to Sequence Autoencoders,” ICASSP 2021 - 2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Toronto, ON, Canada, 2021, pp. 1270-1274,

[6] Segismundo et al. ”Spectrogram analysis of electrocardiogram with Normal Sinus Rhythm, Arrhythmia and Atrial Fibrillation,” TENCON 2012 IEEE Region 10 Conference, Cebu, Philippines, 2012, pp. 1-5,

[7] Alice et al. ”2D Respiratory Sound Analysis to Detect Lung Abnormalities. In: Santosh, K., Goyal, A., Aouada, D., Makkar, A., Chiang, YY., Singh, S.K. (eds) Recent Trends in Image Processing and Pattern Recognition”. RTIP2R 2022. Communications in Computer and Information Science, vol 1704. Springer, Cham.

[8] Tang et al. ”A Survey of Transfer Learning Applied in Medical Image Recognition,” 2021 IEEE International Conference on Advances in Electrical Engineering and Computer Applications (AEECA), Dalian, China, 2021, pp. 94-97

[9] Datta et al. “Identifying Normal, AF and other Abnormal ECG Rhythms using a Cascaded Binary Classifier.”, 2017

[10] Hannun et al. “Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network.” Nature Medicine, vol. 25, 2019, pp. 65-69.

[11] Hong et al. “ENCASE: an ENsemble ClASsifiEr for ECG Classification Using Expert Features and Deep Neural Networks.”, 2017

[12] Mahajan et al. “Cardiac Rhythm Classification from a Short Single Lead ECG Recording via Random Forest.”, 2017

[13] Zabihi et al. “Detection of Atrial Fibrillation in ECG Hand-held Devices Using a Random Forest Classifier.”, 2017