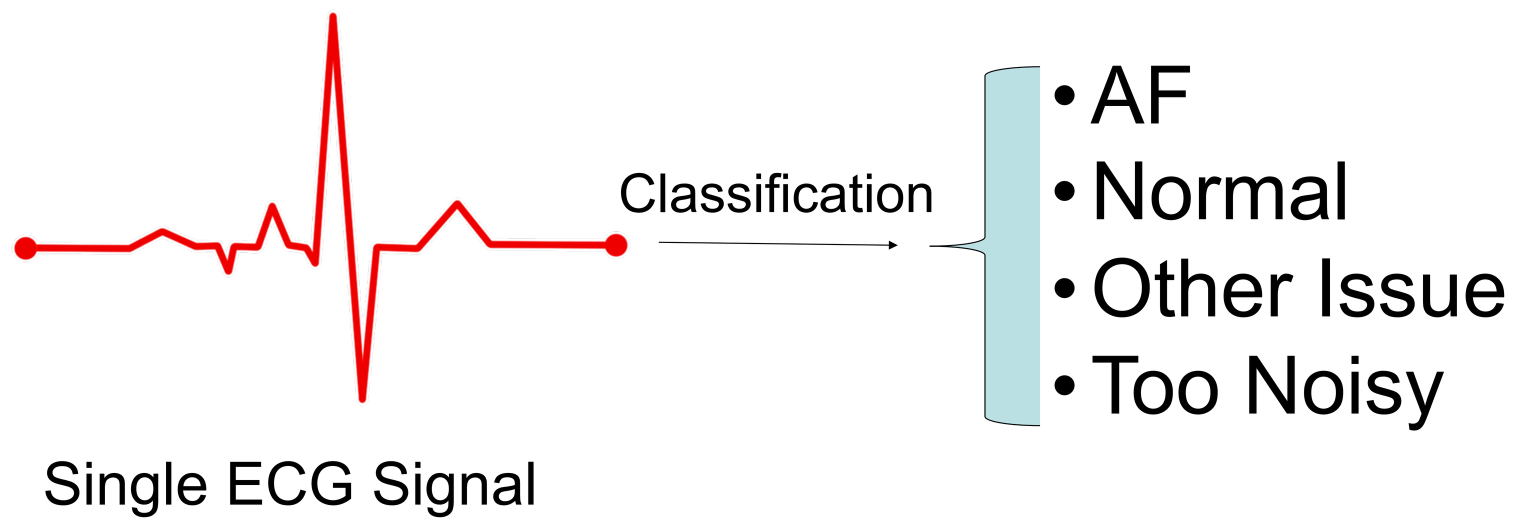
MultiFusionNet: Atrial Fibrillation Detection With Deep Neural Networks

[1]Luan Tran, [1]Yanfang Li, [1]Luciano Nocera, [1]Cyrus Shahabi, [2]Li Xiong
1. University of Southern California, Los Angeles, CA
2. Emory University, Atlanta, GA

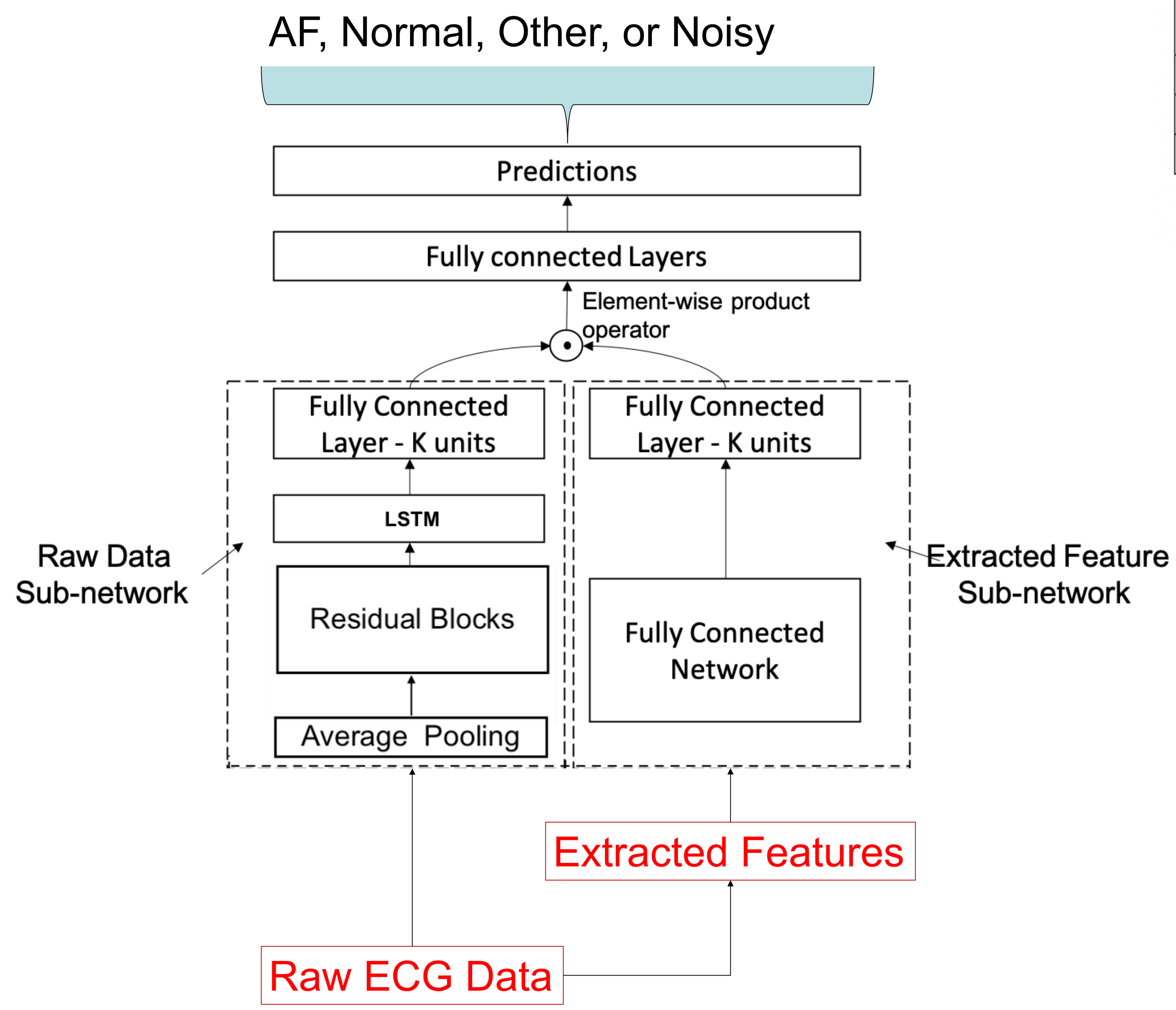
USC Viterbi School of Engineering
Integrated Media Systems Center

I. Introduction

- Electrocardiogram (ECG) is the most prevalent and useful diagnostic tool for detecting Atrial Fibrillation (AF)
- Detecting AF using single ECG is challenging because it is asymptomatic and may only appear briefly in the ECG signal
- In this paper, we are interested in detecting whether an ECG signal includes AF and distinguish it from other heart rhythm issues



II. Proposed Approach - MultiFusionNet



III. Results

- We use an ECG dataset of 8528 records of 4 labels: Normal, AF, Other, Noisy
- Baseline Algorithms:
  - ❖ Random Forest, Fully Connected Neural Networks (FCNN) use only extracted features
  - ❖ R-Resnet uses only raw ECG data

Type	No. Recordings	Time Length (s)				
		Mean	SD	Max	Median	Min
Normal	5050	31.9	10.0	61.0	30	9.0
AF	738	31.6	12.5	60	30	10.0
Other	2557	34.1	11.8	60.9	30	9.1
Noisy	46	27.1	9.0	60	30	10.2
Total	**8528**	**32.5**	**10.9**	**61.0**	**30**	**9.0**

Table 1: Statistics of the dataset.

- MultiFusionNet offers the highest F1-score and AUC_ROC

Data	Method	F1-score				AUC_ROC			
		Normal	AF	Other	Noisy	Normal	AF	Other	Noisy
Raw Data	R-Resnet	0.88	0.79	0.73	0.63	0.84	**0.88**	0.78	0.73
Extracted Features	Random Forest	0.87	0.78	0.68	0.53	0.85	0.86	0.78	0.77
	FCNN	0.87	0.74	0.67	0.55	0.82	0.81	0.73	0.69
Raw Data and Extracted Features	**MultiFusionNet**	**0.9**	**0.83**	**0.75**	**0.69**	**0.86**	**0.88**	**0.81**	**0.81**

Table 5: F1-scores and AUC_ROCs Comparison

- With noisy features and various training data sizes, MultiFusionNet always performs better than baseline algorithms

Method	Average F1-score				Average AUC_ROC			
	Without Noise	Noise $\leq 10\%$	Noise $\leq 20\%$	Noise $\leq 30\%$	Without Noise	Noise $\leq 10\%$	Noise $\leq 20\%$	Noise $\leq 30\%$
Random Forest	0.74	0.50	0.40	0.32	0.81	0.67	0.62	0.58
FCNN	0.75	0.60	0.52	0.43	0.81	0.76	0.74	0.67
MultiFusionNet	**0.80**	**0.75**	**0.69**	**0.59**	**0.85**	**0.83**	**0.78**	**0.74**

Table 7: Average F1-score and AUC_ROC when perturbing feature inputs

Data	Method	Average F1-score			Average AUC_ROC		
		W = 1000	W = 3000	W = 6000	W = 1000	W = 3000	W = 6000
Raw Data	R-Resnet	0.25	0.48	0.75	0.58	0.69	0.82
Extracted Features	Random Forest	0.60	0.63	0.74	0.72	0.74	0.81
	FCNN	0.63	0.67	0.73	0.74	0.77	0.81
Raw Data and Extracted Features	MultiFusionNet	**0.70**	**0.74**	**0.80**	**0.77**	**0.82**	**0.85**

Table 8: Varying training data size

IV. Conclusions and Future Work

- We proposed a new neural network MultiFusionNet to classify single ECG signal.
- We showed that MultiFusionNet outperforms the recent techniques which take as input the extracted features or raw data separately.
- We showed that MultiFusionNet is more robust than the state-of-the-art algorithms.
- With the detected AF signals, finding the starting and ending positions of AF can be explored in the future work.

V. Acknowledge and Support

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