INTER- AND INTRA- PATIENT ECG HEARTBEAT CLASSIFICATION FOR ARRHYTHMIA DETECTION: A SEQUENCE TO SEQUENCE DEEP LEARNING APPROACH

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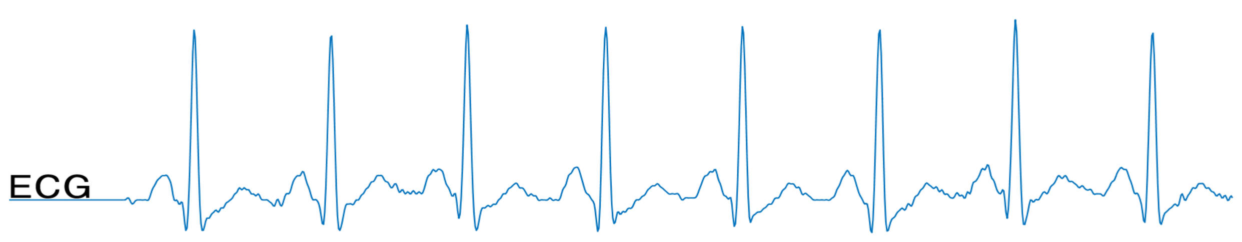
ICASSP 2019

ECG Heartbeat Classification For Arrhythmia Detection

An electrocardiogram (ECG) is a common non-invasive tool to record heart activities and detect different abnormalities in heart functionality.



Manual classification of the arrhythmic heartbeats:

- A challenging and time-consuming task for a physician
- Heartbeat hand-annotating is often prone to error

An automatic heartbeat classification:

- Diagnose arrhythmic heartbeats in real-time
- Achieve high accuracy

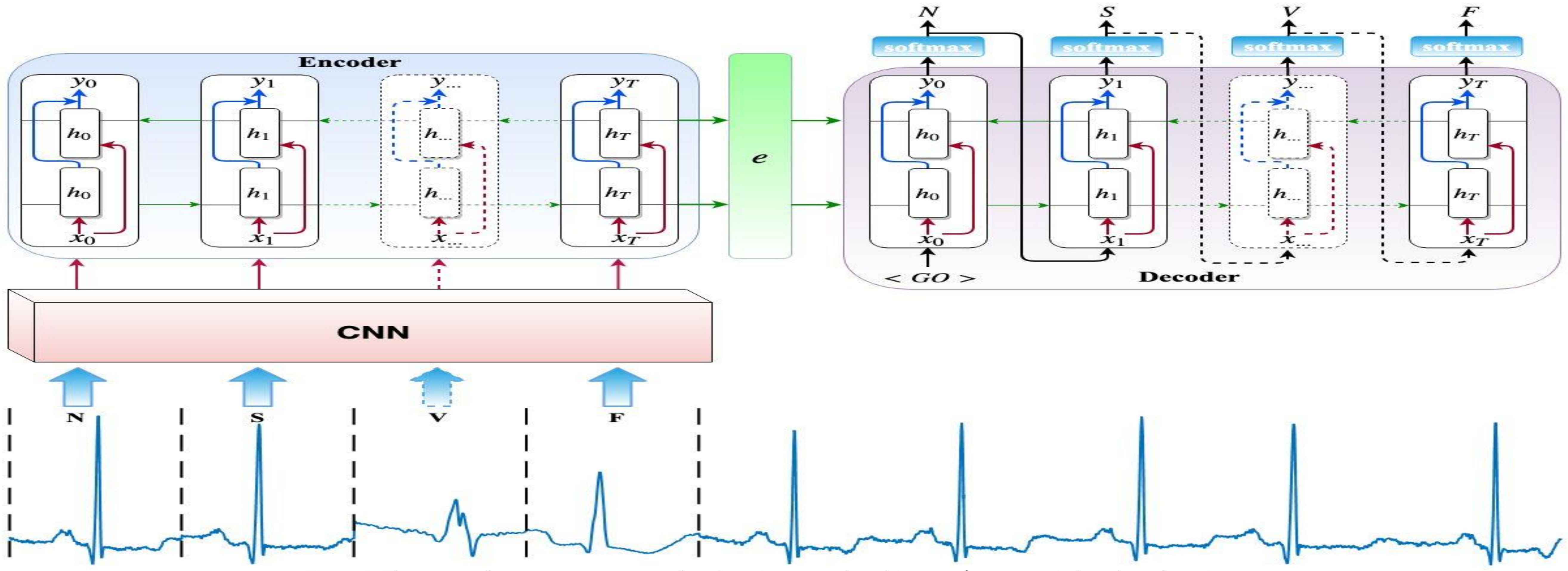


Figure I: The proposed sequence to sequence deep learning network architecture for automatic heartbeat detection.

Automatic Heartbeat Annotations Approaches

Shallow machine learning methods such as SVM, Multi-layer perceptron (MLP), Decision trees, etc.:

1. Signal pre-processing, which includes noise removal methods, heartbeat segmentation, etc.
2. Feature extraction
3. Learning/classification

Deep Learning Methods

- Automated feature extractions
- Usually end-to-end approaches

Main Limitations

- Poor performance, dealing with imbalanced datasets
- E.g. achieve a low sensitivity in the MIT-BIH arrhythmia database for ventricular escape beat (S) and fusion of ventricular, and normal beat (F) classes
- Evaluated based on intra-patient paradigm rather than the inter-patient scheme

Automatic Heartbeat Annotations Approach

- A sequence to sequence deep learning
- Using the Synthetic Minority Over-sampling Technique (SMOTE) to address the challenge with minority classes such as (S) and (F)
- Evaluating both inter-patient and intra-patient paradigms

In intra-patient paradigm, the training and evaluation datasets can include heartbeats from the same atients.

In inter-patient paradigm, a more realistic evaluation mechanism is used where the heartbeat sets for test and training come from different individuals.

Table 1: Categories of heartbeats existed in the MIT-BIH database based on AAMI.

Category	Class
N	• Normal beat (N) • Left and right bundle branch block beats (L,R) • Atrial escape beat (e) • Nodal (junctional) escape beat (j)
S	• Atrial premature beat (A) • Aberrated atrial premature beat (a) • Nodal (junctional) premature beat (J) • Supraventricular premature beat (S)
V	• Premature ventricular contraction (V) • Ventricular escape beat (E)
F	• Fusion of ventricular and normal beat (F)
Q	• Paced beat (/) • Fusion of paced and normal beat (f) • Unclassifiable beat (U)

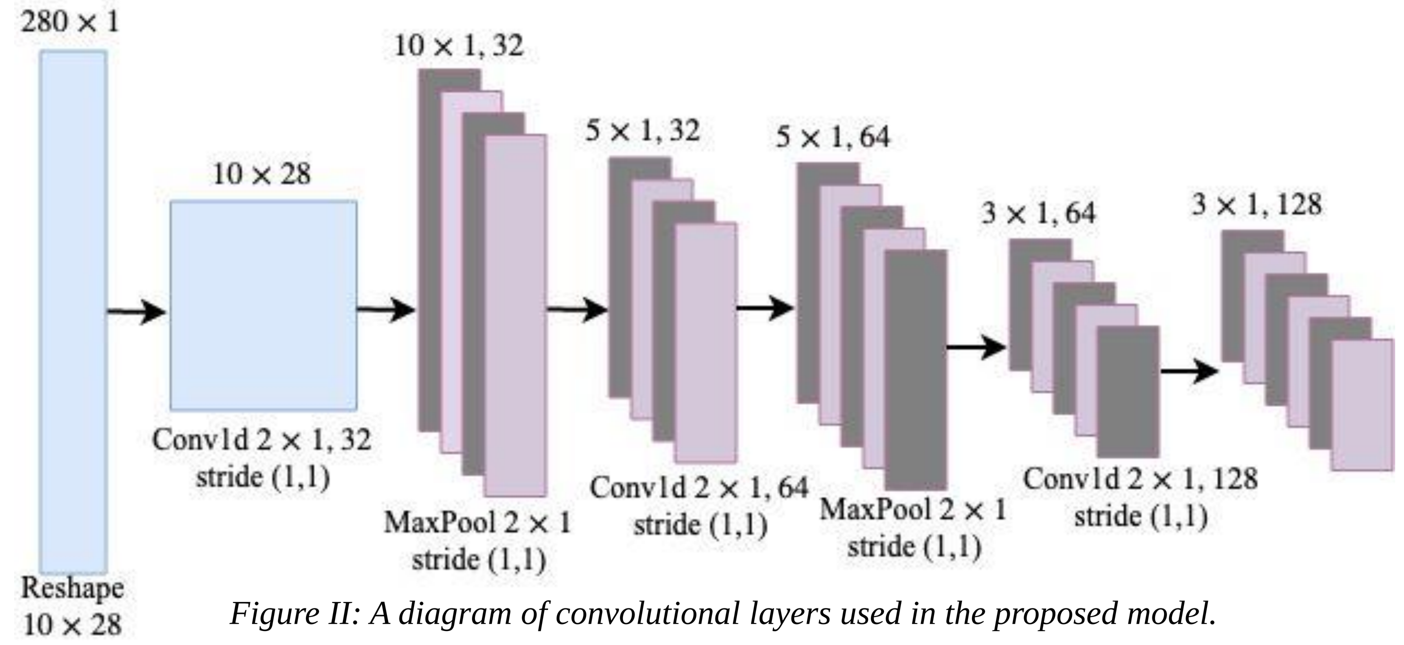


Figure II: A diagram of convolutional layers used in the proposed model.

Contributions

- Encoder-decoder deep network
- Handle imbalanced classification problem
- An end-to-end deep learning approach without providing any hand-crafted features to the network and any noise remove methods
- State-of-the-art results on the MIT-BIH PhysioNet dataset

Table 3: Inter-patient paradigm: Comparison of performance of the proposed heartbeat classifier against the state-of-the-art algorithms, considering DS1 as training dataset and DS2 as test dataset based on the MIT-BIH arrhythmia database.

Method	ACC	N			S			V			F			Q		
	%	SEN	PPV	SPEC	SEN	PPV	SPEC	SEN	PPV	SPEC	SEN	PPV	SPEC	SEN	PPV	SPEC
Proposed method	**99.53**	**99.68**	**99.55**	**96.05**	**88.94**	**92.57**	**99.72**	**99.94**	**99.50**	**99.97**	-	-	-	-	-	-
Garcia et al. (2017)	92.4	94.0	98.0	82.6	62.0	53.0	97.9	87.3	59.4	95.9	-	-	-	-	-	-
Lin and Yang (2014)	93.0	91.0	99.0	-	81.0	31.0	-	86.0	73.0	-	-	-	-	-	-	-
Ye et al. (2010)	75.2	80.2	78.2	-	3.2	10.3	-	50.2	48.5	-	-	-	-	-	-	-
Yu and Chou (2008)	75.2	78.3	79.2	-	1.8	5.9	-	83.9	66.4	-	0.3	0.1	-	-	-	-
Song et al. (2005)	76.3	78.0	83.9	-	27.0	48.3	-	80.8	38.7	-	-	-	-	-	-	-

Table 2: Intra-patient paradigm: Comparison of performance of the proposed heartbeat classifier against the state-of-the-art algorithms, considering randomly chosen sets for the training and testing based on the MIT-BIH arrhythmia database.

Method	ACC	N			S			V			F			Q		
	%	SEN	PPV	SPEC	SEN	PPV	SPEC	SEN	PPV	SPEC	SEN	PPV	SPEC	SEN	PPV	SPEC
Proposed method	**99.92**	**1.00**	**99.86**	**98.87**	**96.48**	**1.00**	**1.00**	**99.50**	**99.79**	**99.98**	**98.68**	**97.40**	**99.98**	-	-	-
Kachuee et al. (2018)	93.4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Acharya et al. (2017)	97.37	91.64	85.17	96.01	89.04	94.76	98.77	94.07	95.08	98.74	95.21	94.69	98.67	97.39	98.40	99.61
Ye et al. (2010)	96.50	98.7	96.3	-	72.4	94.5	-	82.6	97.8	-	65.6	88.6	-	95.8	99.3	-
Yu and Chou (2008)	95.4	96.9	97.3	-	73.8	88.4	-	92.3	94.3	-	51.0	73.4	-	94.1	80.8	-
Song et al. (2005)	98.7	99.5	98.9	-	86.4	94.3	-	95.8	97.4	-	73.6	90.2	-	-	-	-

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Acknowledgements

We would like to thank the National Science Foundation (NSF) and the National Institute On Minority Health And Health Disparities of the National Institutes of Health for their supports. This work was partially sponsored by NSF and NIH under grants 1657260 and U54MD012388m, respectively.