Multi-Scale and Attention based ResNet for Heartbeat Classification

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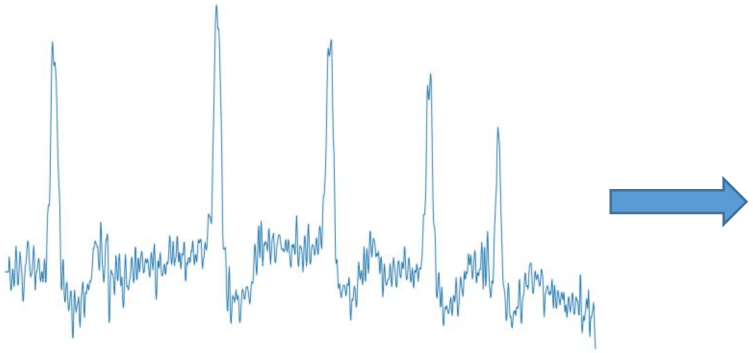
Outline

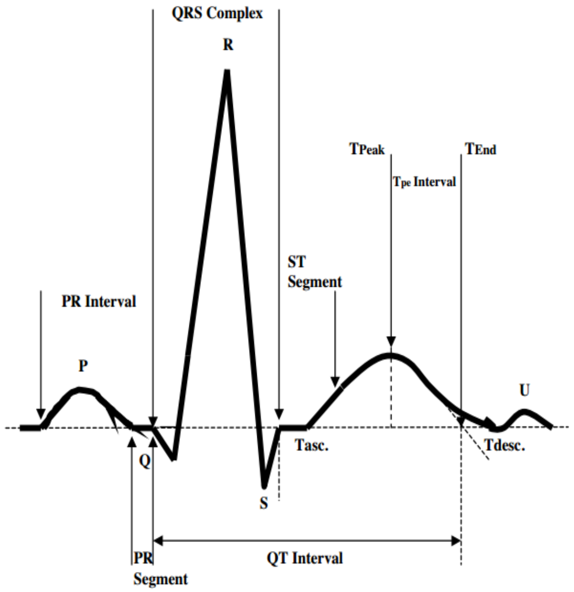
- Background
- Framework
- Experiments
- Conclusion

- Cardiovascular diseases are one of the main reasons for deaths worldwide.
- Electrocardiogram (ECG) signal exploration is one of the most effective tools for identifying arrhythmias.
- In actual medical scenarios, it is difficult and time-consuming for doctors to classify the type of arrhythmias in ECG signals. And the doctors may make a wrong diagnosis because of fatigue.

A fully automatic system for arrhythmia classification :

1. ECG signal preprocessing
2. Heartbeat segmentation
3. Feature extraction
4. Classification.





A. Preprocessing

1. Splitting the ECG record into a sequence of heartbeats based on the position of R peaks.

2. Normalizing the heartbeats to the range of zero and one.

3. Baseline correction.

4. Add RR intervals including previous RR interval, post RR interval, local RR interval and global RR interval at the end of the heartbeat.

B. Network Architecture

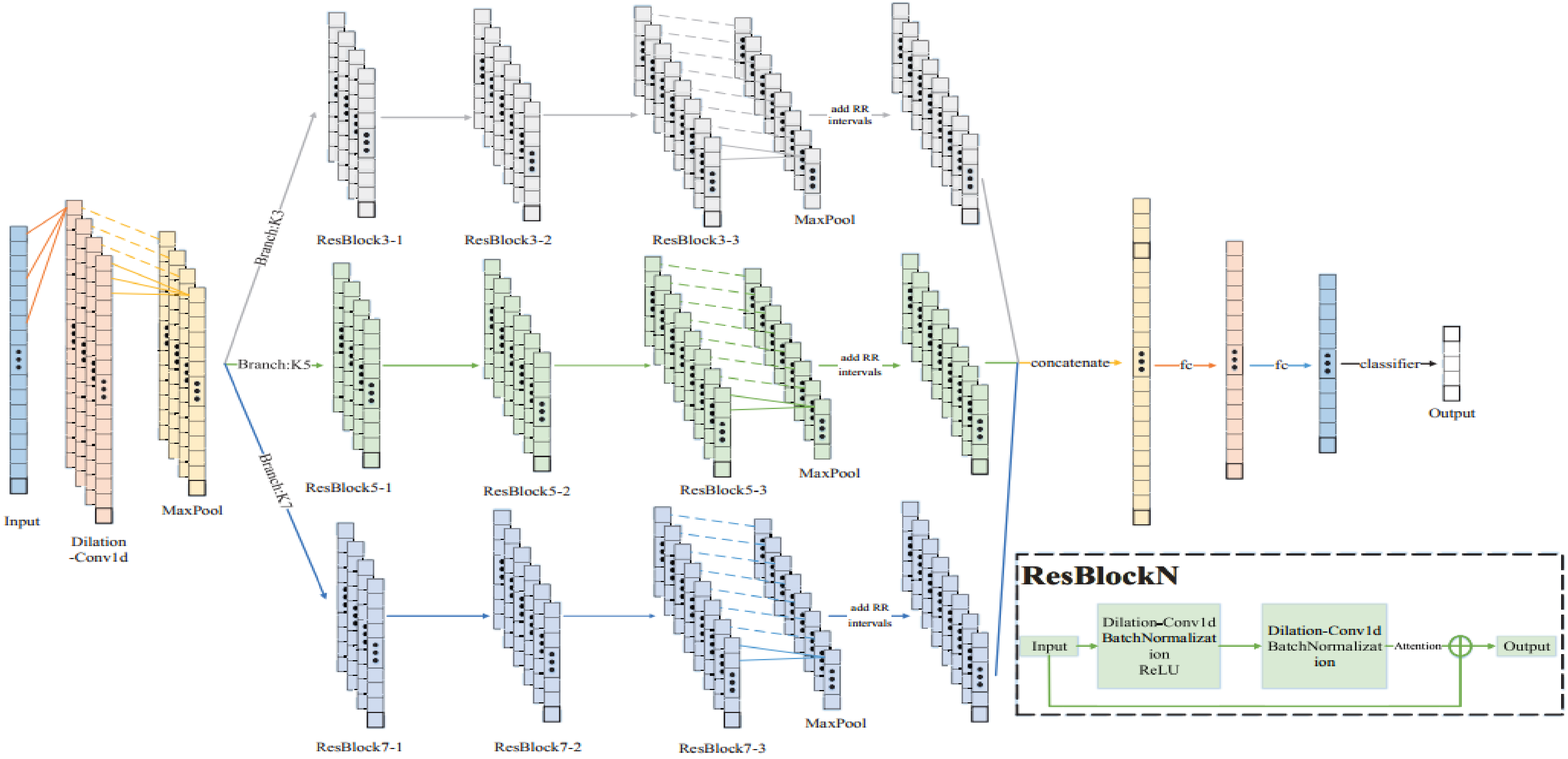


Fig. 1. Architecture of the Multi-Scale and Attention based ResNet model. ResBlockN shows the common architecture of ResBlock in each branch.

MSA-ResNet

- ✓ All convolutional layers of our model use dilated convolution.
- ✓ Residual network structure.
- ✓ The innovation of our model in attention mechanisms.

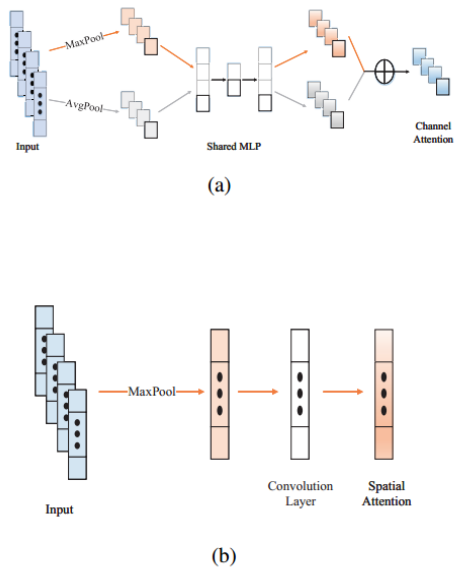


Fig. 3. (a) Architecture of channel attention module. (b) Architecture of spatial attention module.

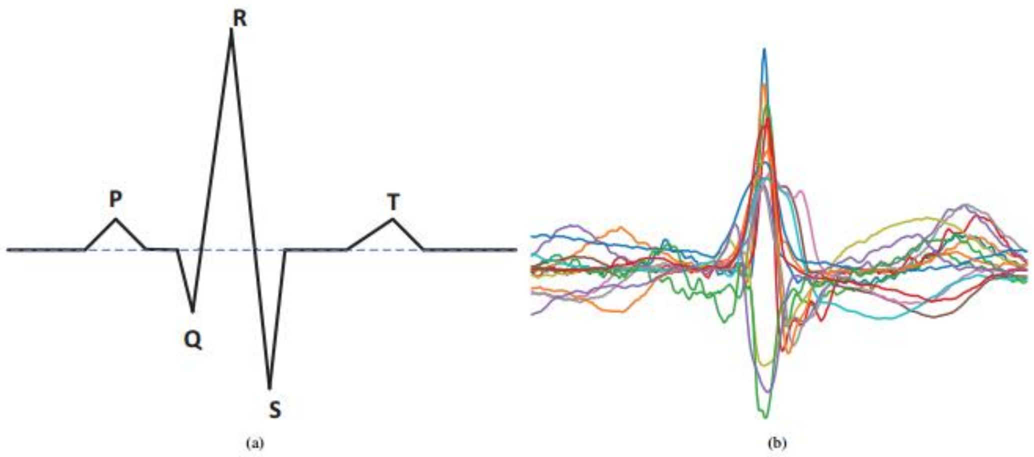


Fig. 4. (a) ecg signal structure. (b)ecg signal in the actual scene.

Performance Comparison

TABLE III
COMPARISON OF PERFORMANCE OF OUR PROPOSAL AGAINST OTHER STATE-OF-THE-ART METHODS UNDER THE INTRA-PATIENT PARADIGM

Methods	ACC %	N			S			V			F			Q		
		SEN	PPV	SPEC	SEN	PPV	SPEC	SEN	PPV	SPEC	SEN	PPV	SPEC	SEN	PPV	SPEC
Acharya et al. [21]	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	98.4	99.61
Ye et al. [22]	96.5	98.7	96.3	-	72.4	94.5	-	82.6	**97.8**	-	65.6	88.6	-	95.8	99.3	-
Yu and Chou [23]	95.4	96.9	97.3	-	73.8	88.4	-	92.3	94.3	-	51	73.4	-	94.1	80.8	-
Kachuee et al. [20]	93.4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Song et al. [24]	98.7	**99.5**	98.9	-	86.4	94.3	-	95.8	97.4	-	73.6	90.2	-	-	-	-
Our Method	**98.94**	99.34	**99.62**	**96.74**	**91.01**	90.68	**99.73**	**98.29**	96.57	**99.74**	86.88	76.37	**99.78**	-	-	-

※$SEN = TP/(TP+FN)$, $PPV = TP/(TP+FP)$, $SPEC = TN/(TN+FP)$, $ACC = TP+TN/(TN+FP+FP+FN)$

Performance Comparison

TABLE IV
COMPARISON OF PERFORMANCE OF OUR PROPOSAL AGAINST OTHER STATE-OF-THE-ART METHODS UNDER THE INTER-PATIENT PARADIGM

Methods	ACC %	N SEN	N PPV	N SPEC	S SEN	S PPV	S SPEC	V SEN	V PPV	V SPEC
Raj et al. [25]	89.9	90.9	99.4	-	80.8	48.8	-	82.2	85.4	-
Garcia et al. [26]	92.4	94	98	82.6	62	53	**97.9**	87.3	59.4	95.9
Lin & Yang [27]	90.8	91.6	99.3	-	81.4	31.6	-	86.2	73.7	-
Zhang et al. [28]	88.3	88.9	99	-	79.1	36	-	85.5	92.8	-
J. Niu et al. [14]	**96.4**	**98.9**	97.4	-	76.5	**76.6**	-	85.7	**94.1**	-
Our Method	94.82	95.07	**99.4**	**94.98**	**88.24**	45.94	**95.98**	**95.25**	88.72	**99.15**

※$SEN = TP/(TP+FN)$, $PPV = TP/(TP+FP)$, $SPEC = TN/(TN+FP)$, $ACC = TP+TN/(TN+FP+FP+FN)$

Ablation Analysis

TABLE V
ABLATION STUDIES ON OUR PROPOSED MODEL.

Methods	ACC %	N SEN	N PPV	N SPEC	S SEN	S PPV	S SPEC	V SEN	V PPV	V SPEC
K3	89.22	89.6	98.61	88.92	72.39	23.64	90.95	93.6	86.75	99
K5	94.3	95.25	98.6	88.17	68.9	47.01	97	95.71	79.69	98.3
K7	90.98	90.79	99.4	**95.19**	87.69	37.86	94.43	95.5	66.36	96.62
K3K5	86.03	85.63	99.08	93.08	77.94	20.83	88.53	96.18	73.87	97.62
K3K7	94.35	95.18	98.84	90.21	72.28	**48.61**	**97.04**	95.59	77.64	98.08
K5K7	94.72	94.96	99.38	94.78	84.75	46.49	96.22	**97.05**	85.08	98.81
No Attention Module	92.18	93.16	99.16	93.54	78.54	32.66	93.78	87.15	84.85	98.79
No RR Intervals	92.07	**95.52**	96.07	65.86	8.06	9.46	97.01	92.64	79.63	98.34
Our Method	**94.82**	95.07	**99.4**	94.98	**88.24**	45.94	95.98	95.25	**88.72**	**99.15**

- Contributions:
  - A novel deep learning framework for heartbeat classification based on CNN.
  - A novel attention mechanism based on CBAM.
  - Superior classification performance on MIT-BIH arrhythmia database, including both intra-patient paradigm and inter-patient paradigm.

- Limitation:

Our model is easy to confuse the two types of normal(N) and SVEB(S). The future work is to take possible measures such as designing new blocks or loss functions to improve the classification ability of these two categories.

Thanks！