Pytorch ECG Heartbeat Categorisation

Project Team ==4==

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Outline

The problem of cardiac health monitoring

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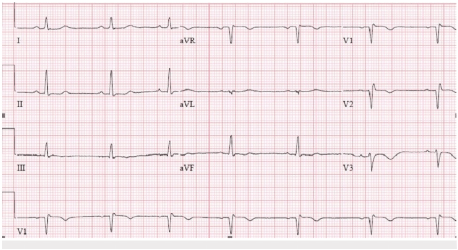

The problem of cardiac health monitoring

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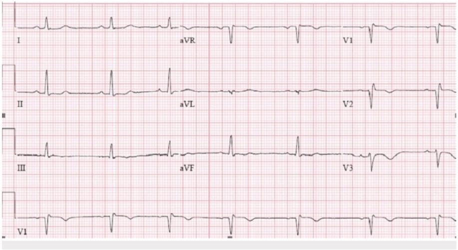

Aim: Develop an accurate model for diagnosis of arrhythmic heartbeats

Problem formulation

1. **Create a binary classifier to distinguish normal ECG signals from anomalous ECG signals**

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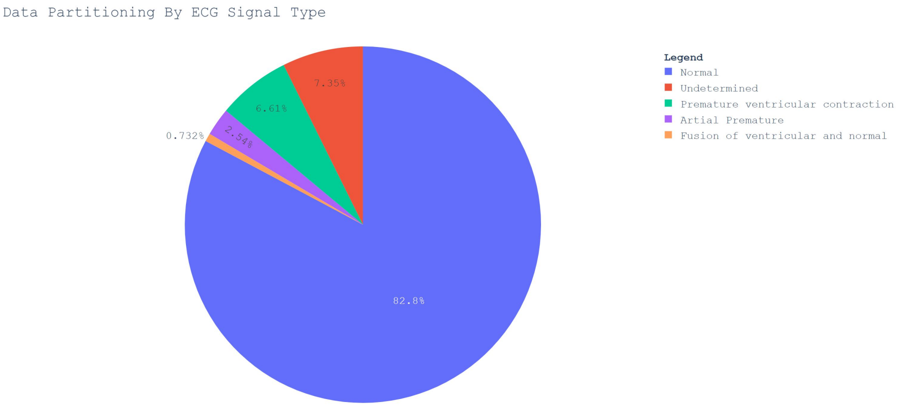
1. **Create a binary classifier to distinguish normal ECG signals from anomalous ECG signals**
2. **Improve the classifier into a multi-class classifier to determine the different types of heartbeat conditions**

Data distribution



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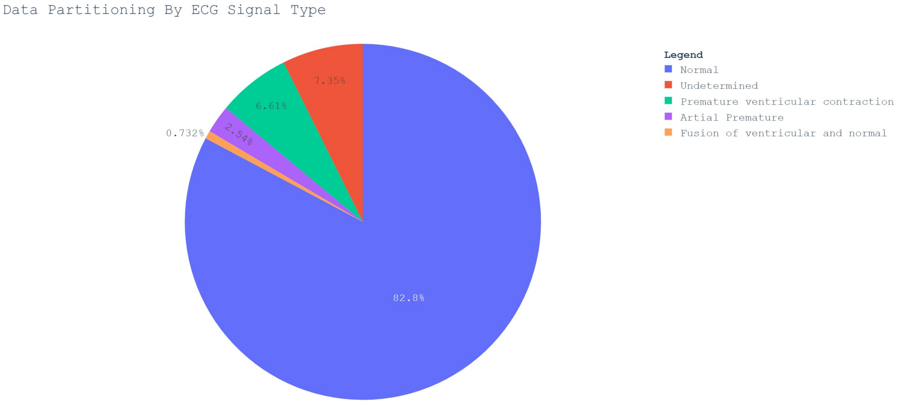
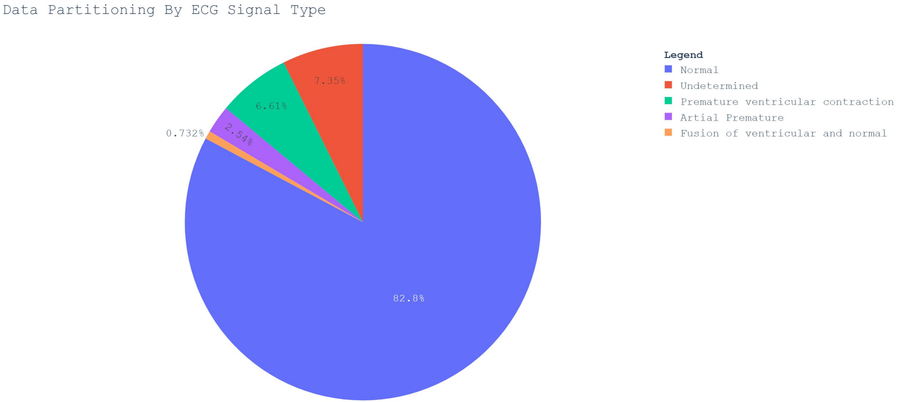


1. 5 classes

Data distribution



1. 5 classes
2. highly unbalanced - 82.8% normal signals

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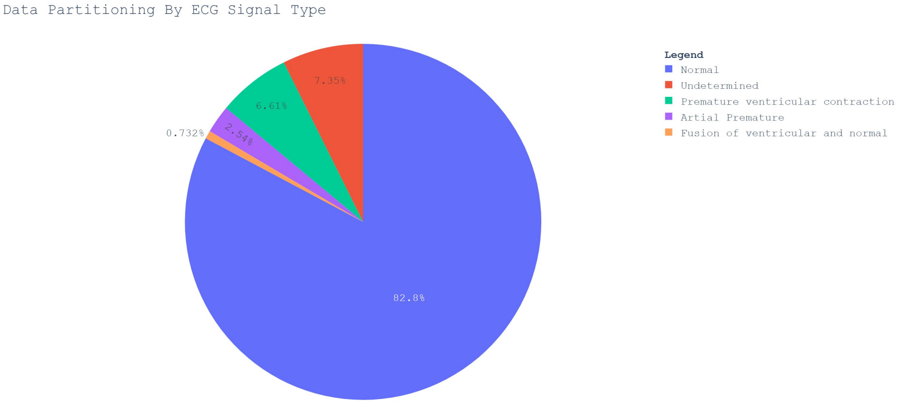

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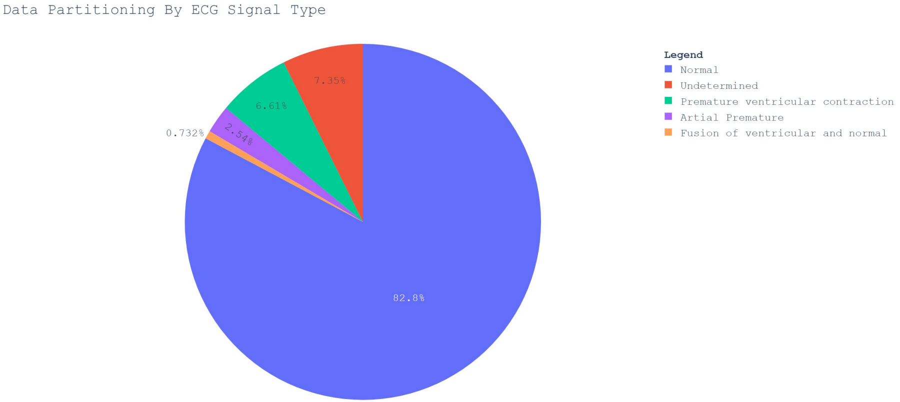

1. 5 classes
2. highly unbalanced - 82.8% normal signals
3. PV, PA, and Fusion signals are more severe
4. Undetermined is also dangerous

ECG signals

Example ECG Signal Categories
Legend
Normal
Artial Premature
Premature ventricular contraction
Fusion of ventricular and normal
Undetermined
Amplitude
Time (s)
0
0.2
0.4
0.6
0.8
1
1.2
1.4

Baseline Model

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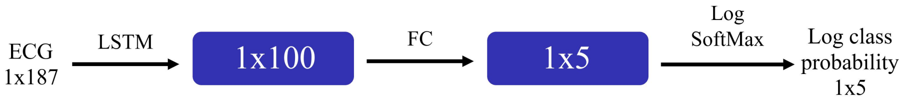

1. Input dimension = 1x187

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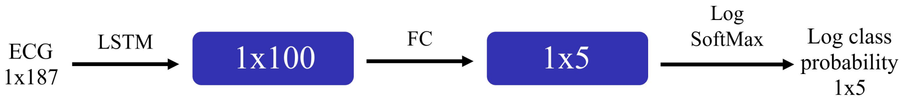

1. Input dimension = 1x187
2. Hidden layer dimension = 1x100

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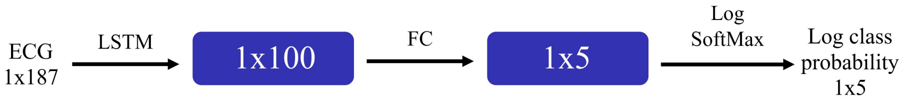

1. Input dimension = 1x187
2. Hidden layer dimension = 1x100
3. Result dimension = 1x5 (or 1x2 for binary classification)

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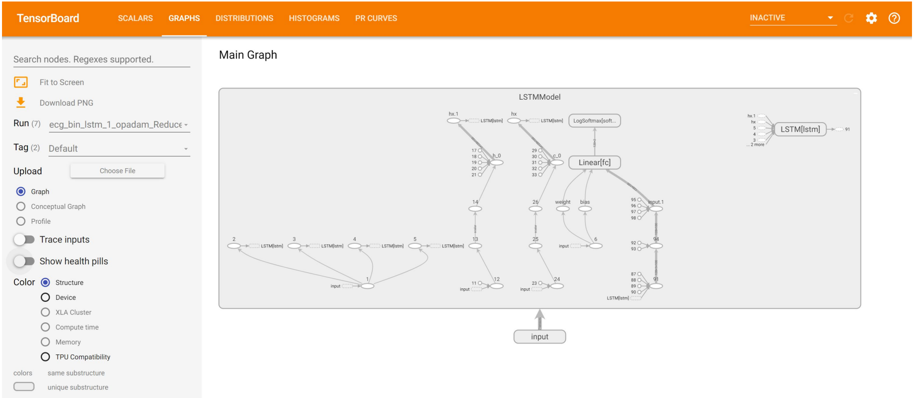

CHALLENGES

- 1 LSTM layer maybe not be sufficiently complex
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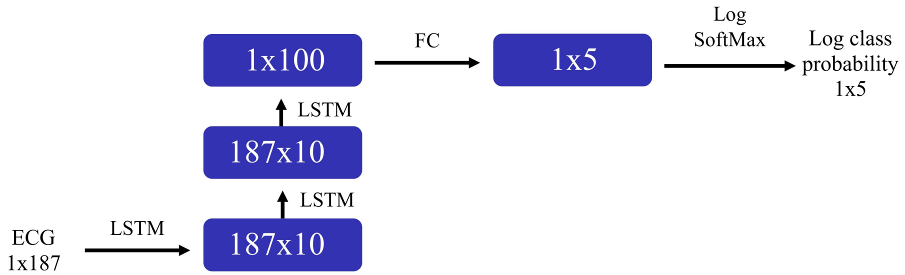
- Weighted penalization for different classes
- Masking
- Hyper-parameter tuning
- Make more models!

LSTM_3

Model 2: LSTM_3 - 3 long-short term memory layer + dense layer + log softmax



1. 3 stacked LSTM layers

LSTM_3

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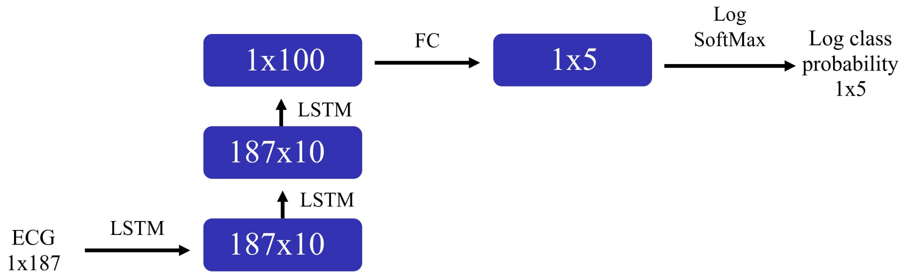
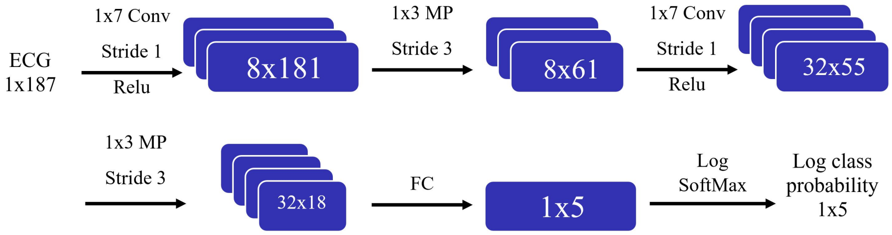


1. 3 stacked LSTM layers
2. Hidden layer dimension is tuned on Google Cloud (1x100 in image)

Model 3: 1D-CNN - 2 convolution layers + dense layer + log softmax



1D-CNN

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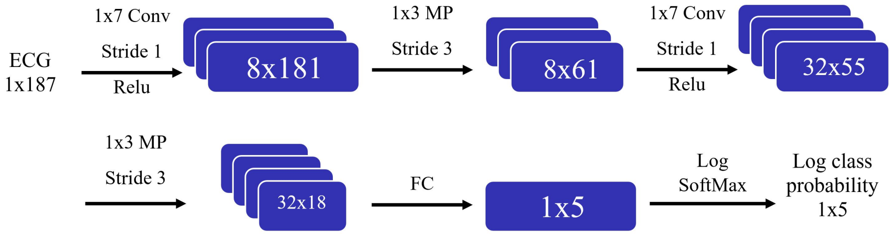

1. 2x (1D convolution layer (kernel size = 7) + Relu non-linearity + Max Pooling (3x down-sampling))

1D-CNN

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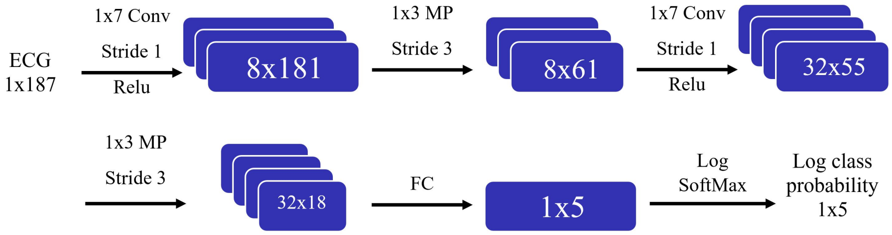

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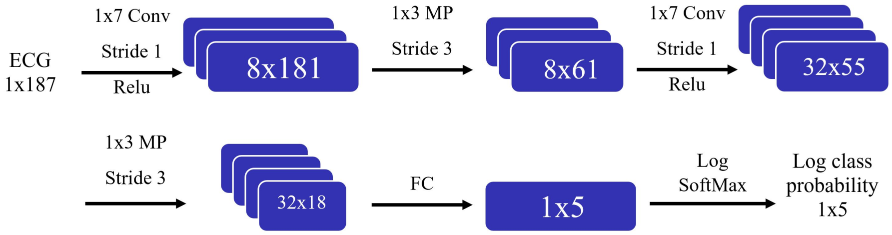
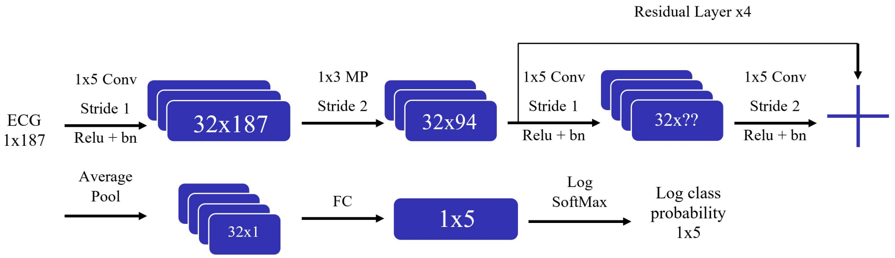


1. 2x (1D convolution layer (kernel size = 7) + Relu non-linearity + Max Pooling (3x down-sampling))
2. Masking can be activated by the flag *–masking*
3. It doesn't increase performance of the models

1D-RESNET

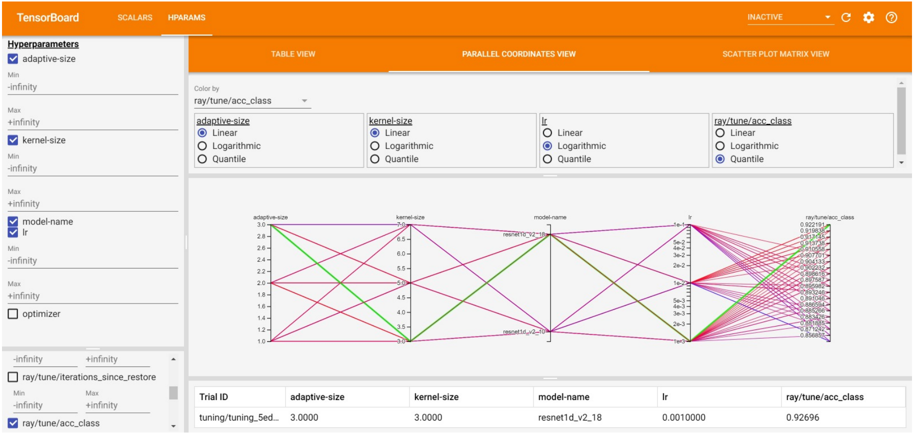
Model 4: 1D-RESNET - 1 convolution layer + 4 residual blocks + dense layer + log softmax



1. 1D convolution layer (kernel size = 5) + Relu non-linearity + Batch normalization + Max Pooling (2x down-sampling)
2. 4x (Residual block: 2x (1D convolution + Relu + Bn))
3. Average Pool + Fully connected layer

Hyperparameters tuning

Model 4: 1D-RESNET - 1 convolution layer + 4 residual blocks + dense layer + log softmax



All models

Table: Base model architectures and the principal variations that were tested[1].

Base Model	Variations
LSTM	1 LSTM layer 2 LSTM layers 3 LSTM layers
1D-CNN	2 convolutional layers
1D-RESNET	V1[2] - 2 convolutional layers per residual block V1 - 4 convolutional layers per residual block V2[3] - 2 convolutional layers per residual block V2 - 4 convolutional layers per residual block

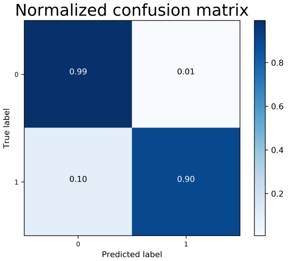
[1] Other hyper-parameters such as optimizer, learning rates, layer dimensions, weight decay and batch size are not shown but have also been experimented.

[2] Residual block has a fixed number of filters (32).

[3] Each residual block doubles the number of filters.

Binary classification results

Figure: Normalized confusion matrices for a) LSTM_1 with no sampling b) LSTM_1 with equal sampling c) 1D-RESNET_v2 with equal sampling



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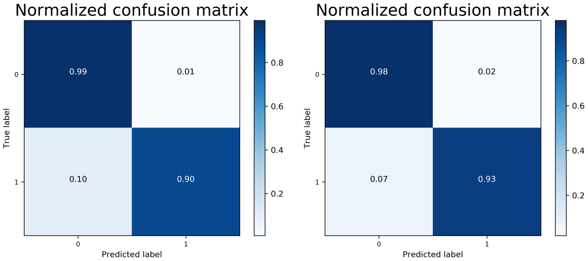

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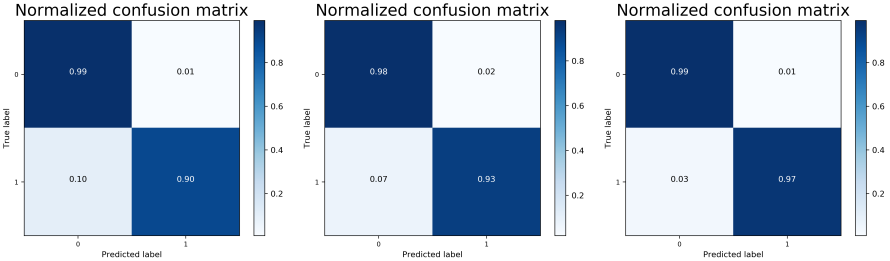

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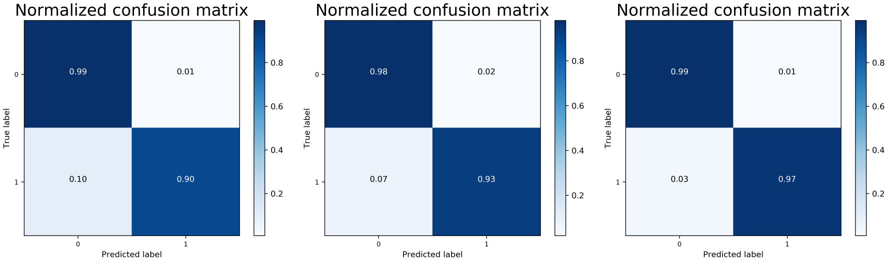

Performance is **very** good

Binary classification results

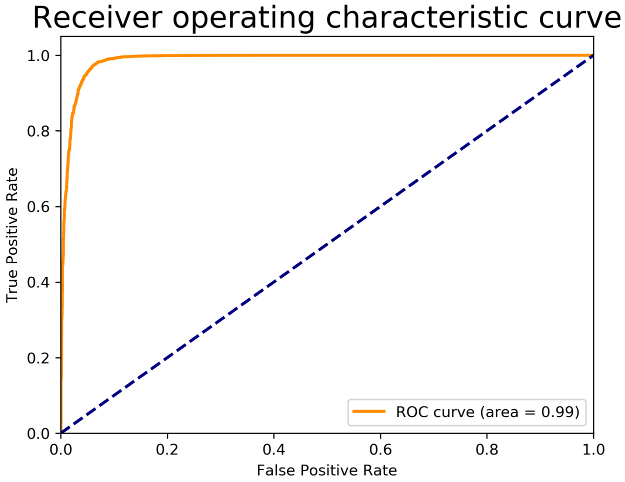

Figure: ROC curve for binary classification with 1D-RESNET_V2_10 with equal sampling

Multi-class classification results

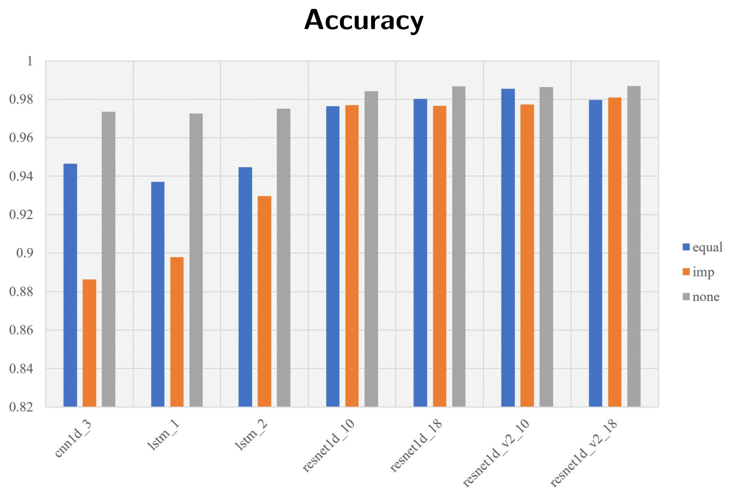

Figure: Accuracy metric on test set for multi-class classification

Multi-class classification results

Metric: Accuracy

	Sampling Type		
Model name	equal	importance	none
cnn1d_3	0.946	0.886	0.973
lstm_1	0.937	0.897	0.972
lstm_2	0.944	0.929	0.975
resnet1d_10	0.9764	0.976	0.984
resnet1d_18	0.980	0.976	0.987
resnet1d_v2_10	0.985	0.977	0.986
resnet1d_v2_18	0.980	0.981	0.987

Table: Accuracy metric on test set for multi-class classification

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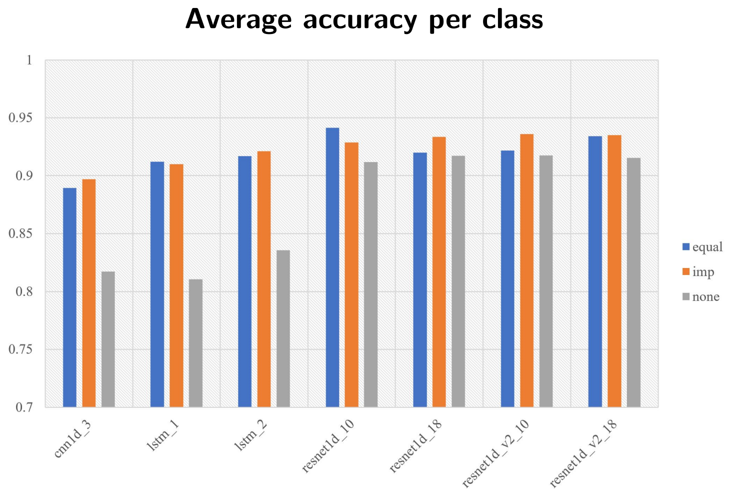

Figure: Average accuracy per class metric on test set for multi-class classification

Multi-class classification results

Metric: Average Accuracy per Class

	Sampling Type		
Model name	equal	importance	none
cnn1d_3	0.889	0.896	0.817
lstm_1	0.912	0.909	0.810
lstm_2	0.916	0.921	0.835
resnet1d_10	0.941	0.928	0.911
resnet1d_18	0.919	0.933	0.917
resnet1d_v2_10	0.921	0.936	0.917
resnet1d_v2_18	0.935	0.934	0.915

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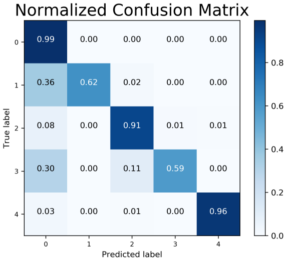

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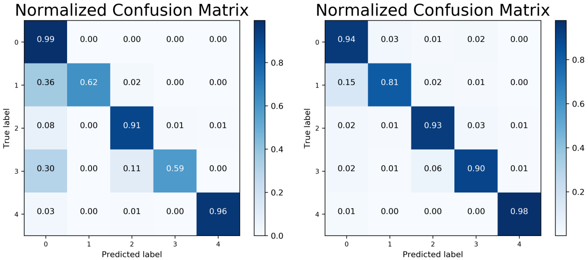

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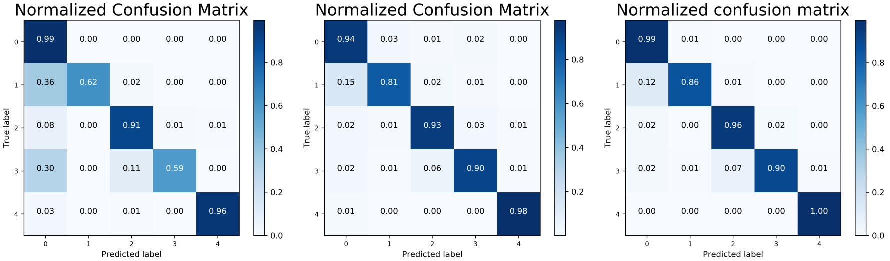

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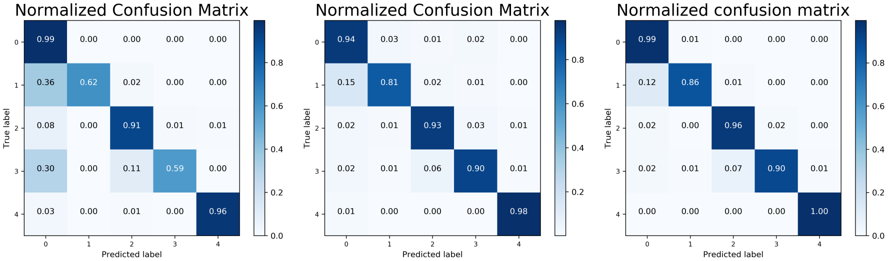

Performance is improving **significantly**

Classification Comparison

Work	Approach	Avg Acc (%)
Acharya et al[4] (2017)	Augmentation + CNN	93.5
Li et al[5] (2016)	DWT + random forest	**94.6**
Kachuee et al[6] (2018)	Deep residual CNN	93.4
Martis et al[7] (2013)	DWT + SVM	93.8
This work	Deep residual CNN	**94.1**

[4] Acharya, U
A deep convolutional neural network model to classify heartbeats.

[5] Li, Taiyong and Zhou, Min.
ECG Classification Using Wavelet Packet Entropy and Random Forests.

[6] Kachuee, Mohammad and Fazeli, Shayan and Sarrafzadeh, Majid.
ECG Heartbeat Classification: A Deep Transferable Representation.

[7] Martis.
Applications of Higher Order Cumulant Features for Cardiac Health Diagnosis using ECG Signals.

Resources

OUR WEBSITE:

`https://fv316.github.io/MAP583/`