AMAZING THINGS ARE HAPPENING HERE

Deep Learning in Cardiology

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Deep Learning Use Case: Screening for Amyloid

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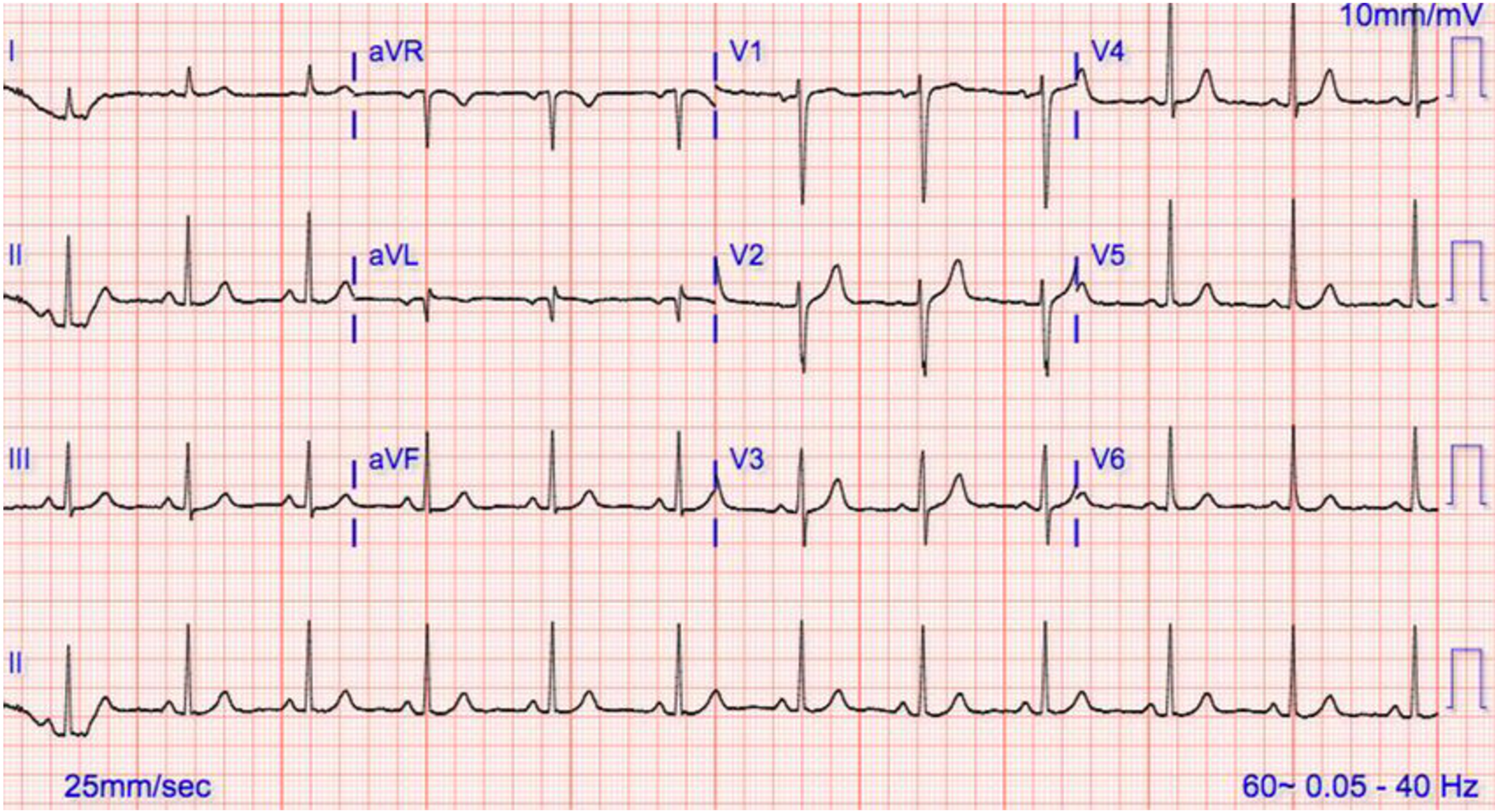
Amyloid Clinical Overview

- Protein folding disorder that leads to deposition in organs, causing heart failure over time
- ATTR cardiac amyloidosis (ATTR-CM) is caused by myocardial deposition of misfolded transthyretin (TTR or prealbumin), a circulating tetrameric transport protein for thyroid hormone and retinol
- Symptoms often present late as it's a slow-burn disease
- Diagnosis can be missed (uncommon cause of heart failure, fat pad biopsy has many false negatives, PYP scanning still not very prevalent)
- But for the first time in the history of the disease, we have therapies (and they are $$$)
- No screening test is available (remains the holy grail)



10mm/mV
I
aVR
V1
V4
II
aVL
V2
V5
III
aVF
V3
V6
II
25mm/sec
60~ 0.05 - 40 Hz

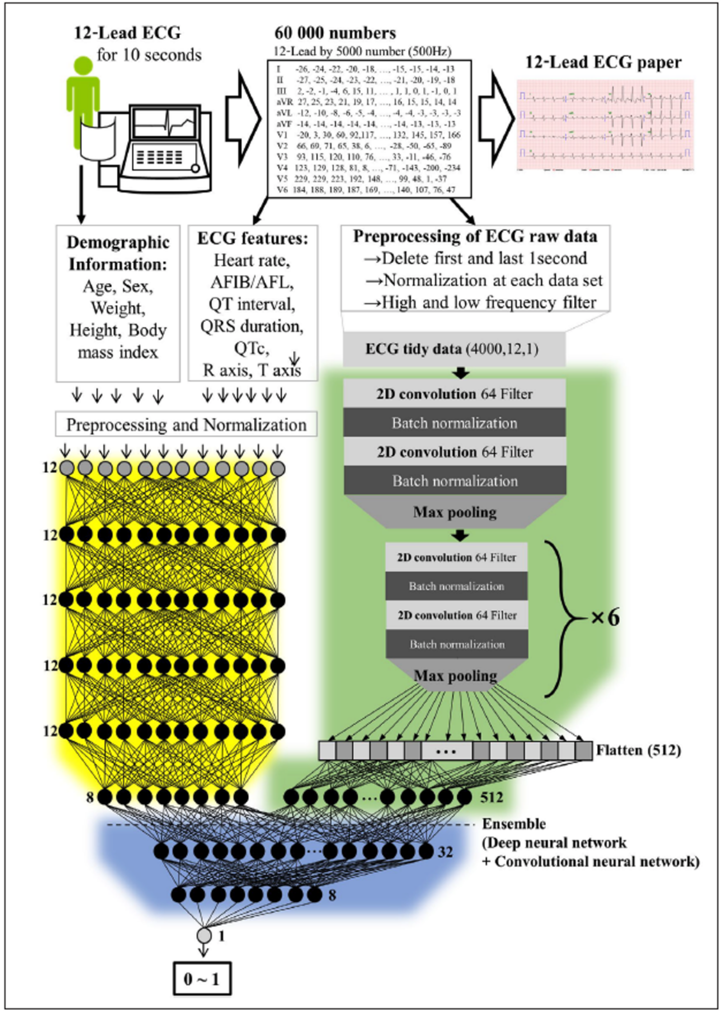


Figure 2. **ECG data and artificial intelligence algorithm.**
AFIB indicates atrial fibrillation; AFL, atrial flutter; QTc, corrected QT interval; and 2D, 2-dimensional.

Deep Learning Models for Detecting Amyloid

Alex Wan, Han Wang, Junyang Jiang, Shengqing Xia, Yuge Shen

Main Tasks

- **ECG Data Simulation**
- **Model Training**
  - For Image
    - 2-D Convolutional Neural Networks
    - Residual Neural Networks based on paper *AutoECG*
  - For Waveforms / Time Series
    - Convolutional Recurrent Neural Network
- **Hyperparameter Tuning**
- **Future Work**

Data Format

10s of ecg data
250 Hz
12 Leads
Data shape of a single sample: 2500 * 12

Synthetic Data

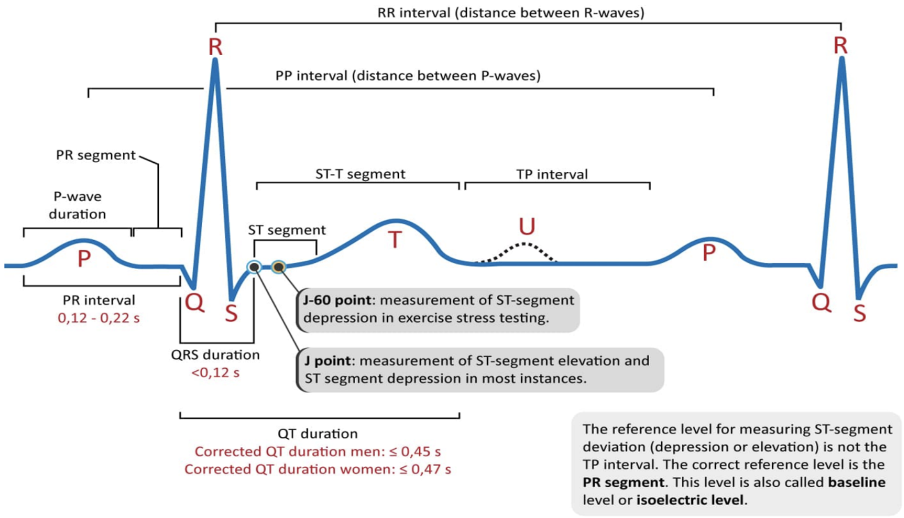
- 5000 Samples in total
- 2500 Positive
- 2500 Negative

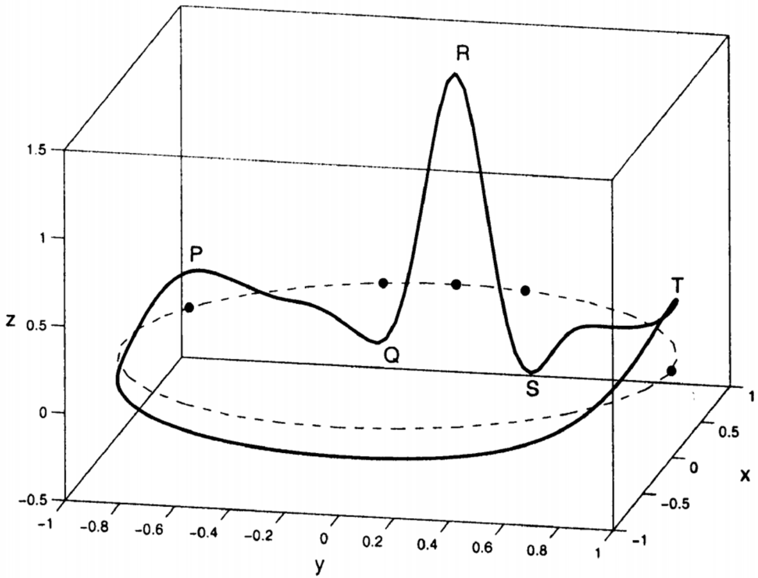
Real Data

- 5399 Samples in Total
- 1214 Positive
- 4185 Negative

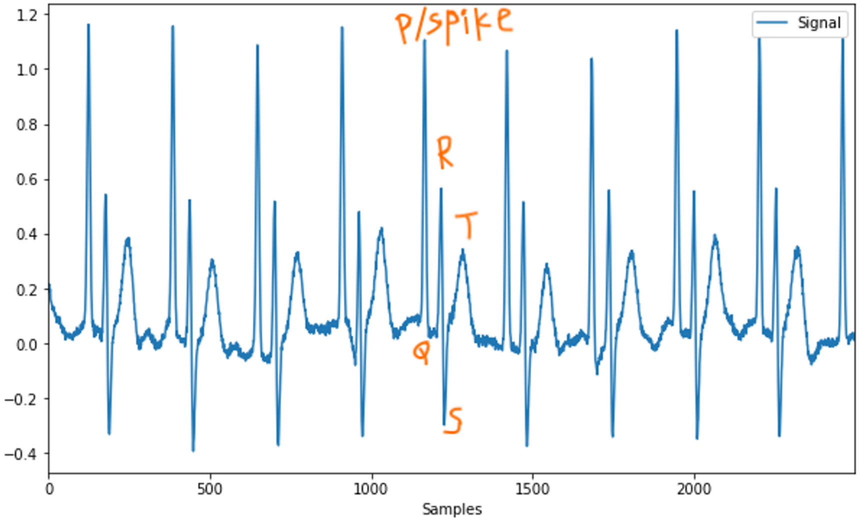
ECG Simulation

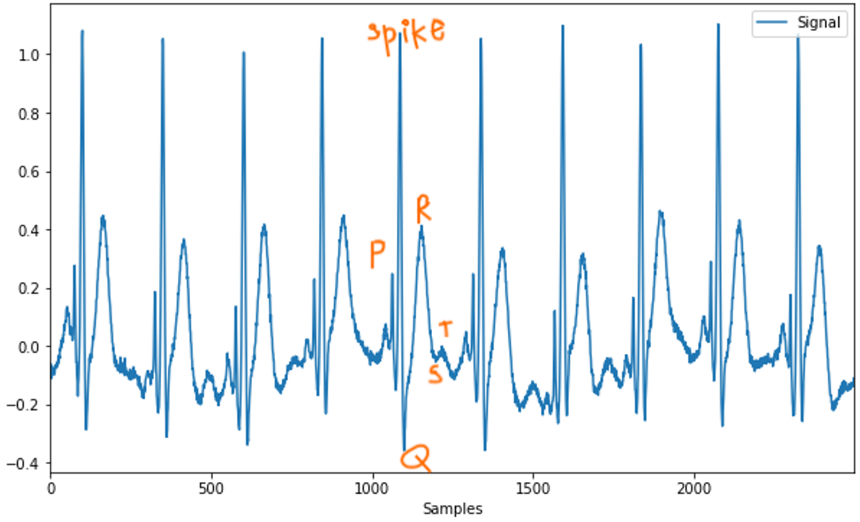
Using Neurokit 2 as Base Method





Abnormal ECG





Model Training

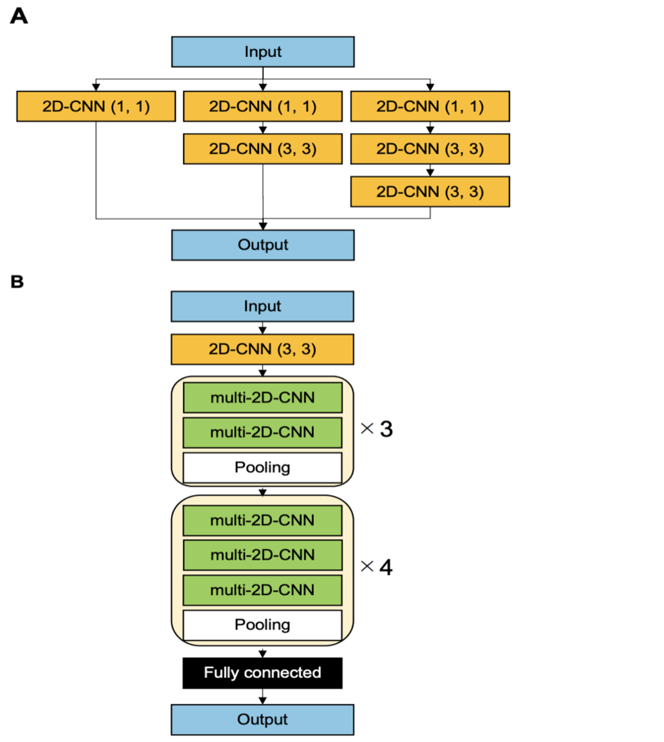
- 2D Convolutional Neural Network (CNN)
- Residual Neural Networks (RNN)
- Convolutional Recurrent Neural Network (CRNN)

Motivation

Goto et al. proposed a very powerful and complex 2D CNN based model for Cardiac Amyloidosis using ECG

However..

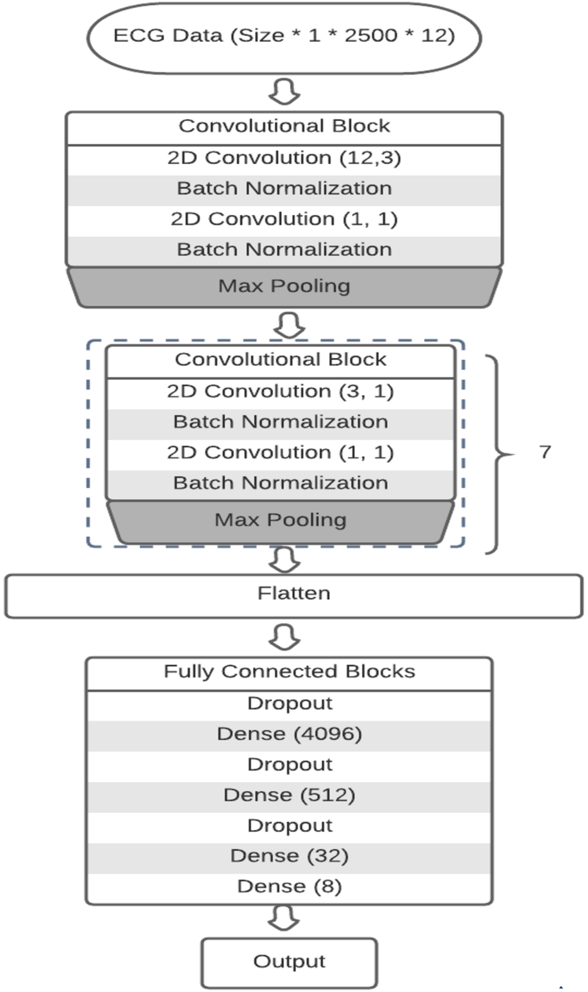
- Is such huge neural network really necessary?
- Could we simplify complexity in this computational models?
- Could we use other modern Deep Learning models for ECG?
- Should we treat ECG data input as image or waveforms when applying Deep Learning?



(A) Structure of the multi-2D-CNN module and (B) the full network structure

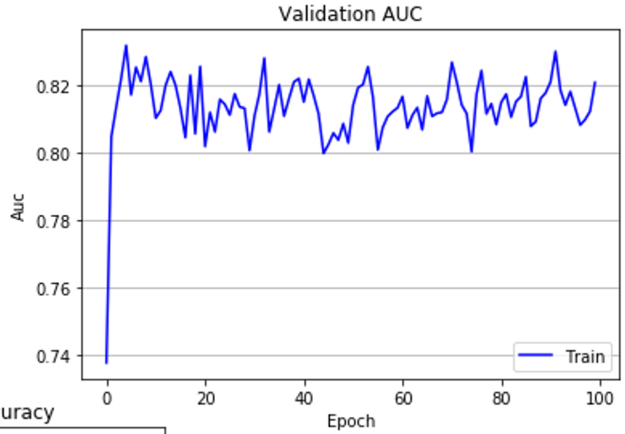
Goto, Shinichi, et al. "Artificial Intelligence-Enabled, Fully Automated Detection of Cardiac Amyloidosis Using Electrocardiograms and Echocardiograms." medRxiv (2020).

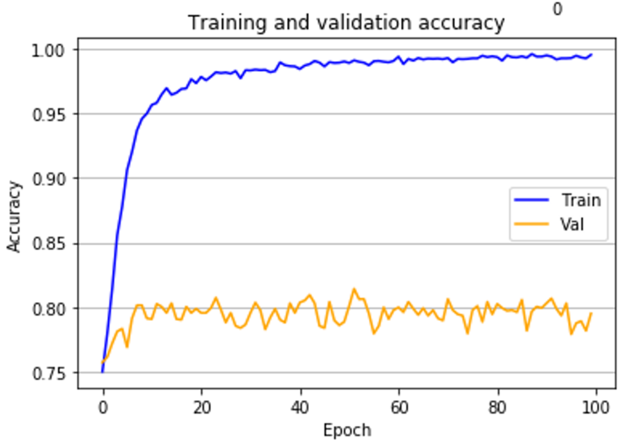
2D CNN Model


ECG Data (Size * 1 * 2500 * 12)
Convolutional Block
2D Convolution (12,3)
Batch Normalization
2D Convolution (1, 1)
Batch Normalization
Max Pooling
Convolutional Block
2D Convolution (3, 1)
Batch Normalization
2D Convolution (1, 1)
Batch Normalization
Max Pooling
7
Flatten
Fully Connected Blocks
Dropout
Dense (4096)
Dropout
Dense (512)
Dropout
Dense (32)
Dense (8)
Output

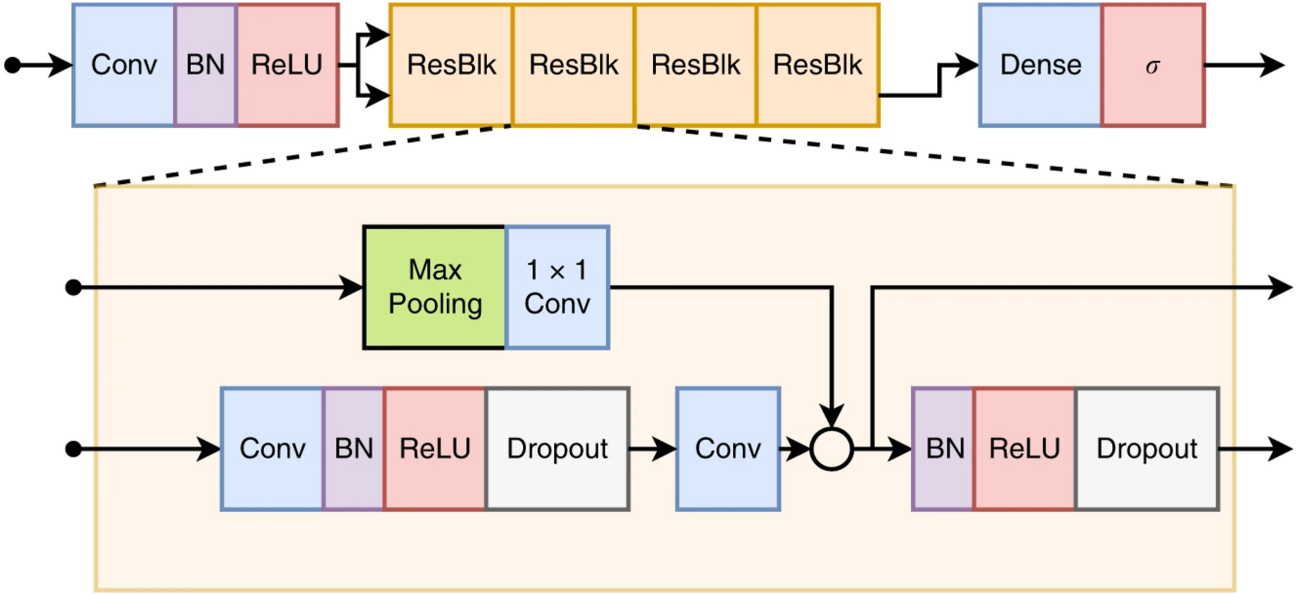
Result of 2D CNN on Real Data

	Validation Accuracy	Validation Loss	AUC
Best	0.83	0.42	0.84
Average	~0.82	0.43-0.44	0.82-0.83





Residual Neural Networks based on paper *AutoECG*



Ribeiro, A.H., Ribeiro, M.H., Paixão, G.M.M. et al. Automatic diagnosis of the 12-lead ECG using a deep neural network. Nat Commun 11, 1760 (2020).

Model Adjustment

Data in paper:

- 12 leads
- 7s to 10s
- 300 HZ to 600 HZ resampled to 400HZ
- Zero-padded to 4096 numbers
- Output six probabilities of six types of disease
- 2,322,513 ECG records from 1,676,384 different patients of 811 counties

Our Data:

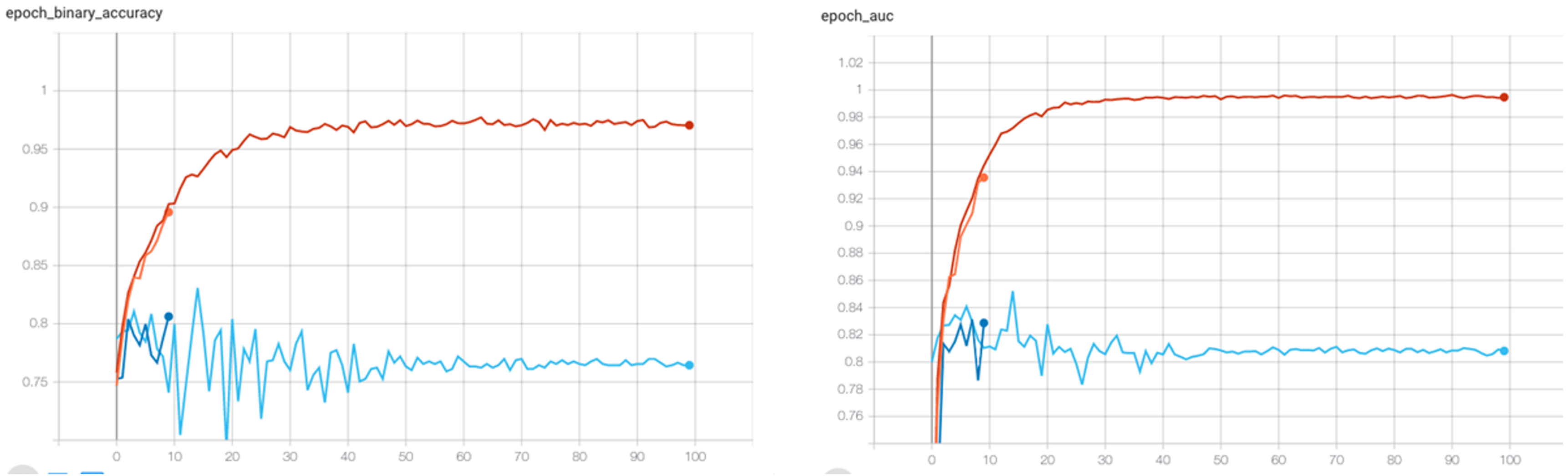
- 12 leads
- 10s
- 250HZ
- Zero-padded to 4096 numbers
- Only output probability of normal/abnormal
- 5399 ECG records from U.S. patients

Model results in paper:

	Precision	Recall	Specificity	F1 score
	DNN	DNN	DNN	DNN
1dAVb	0.958333	0.821429	0.998748	0.884615
RBBB	0.918919	1.000000	0.996217	0.957746
LBBB	1.000000	1.000000	1.000000	1.000000
SB	0.789474	0.937500	0.995068	0.857143
AF	0.846154	0.846154	0.997543	0.846154
ST	0.923077	0.972973	0.996203	0.947368

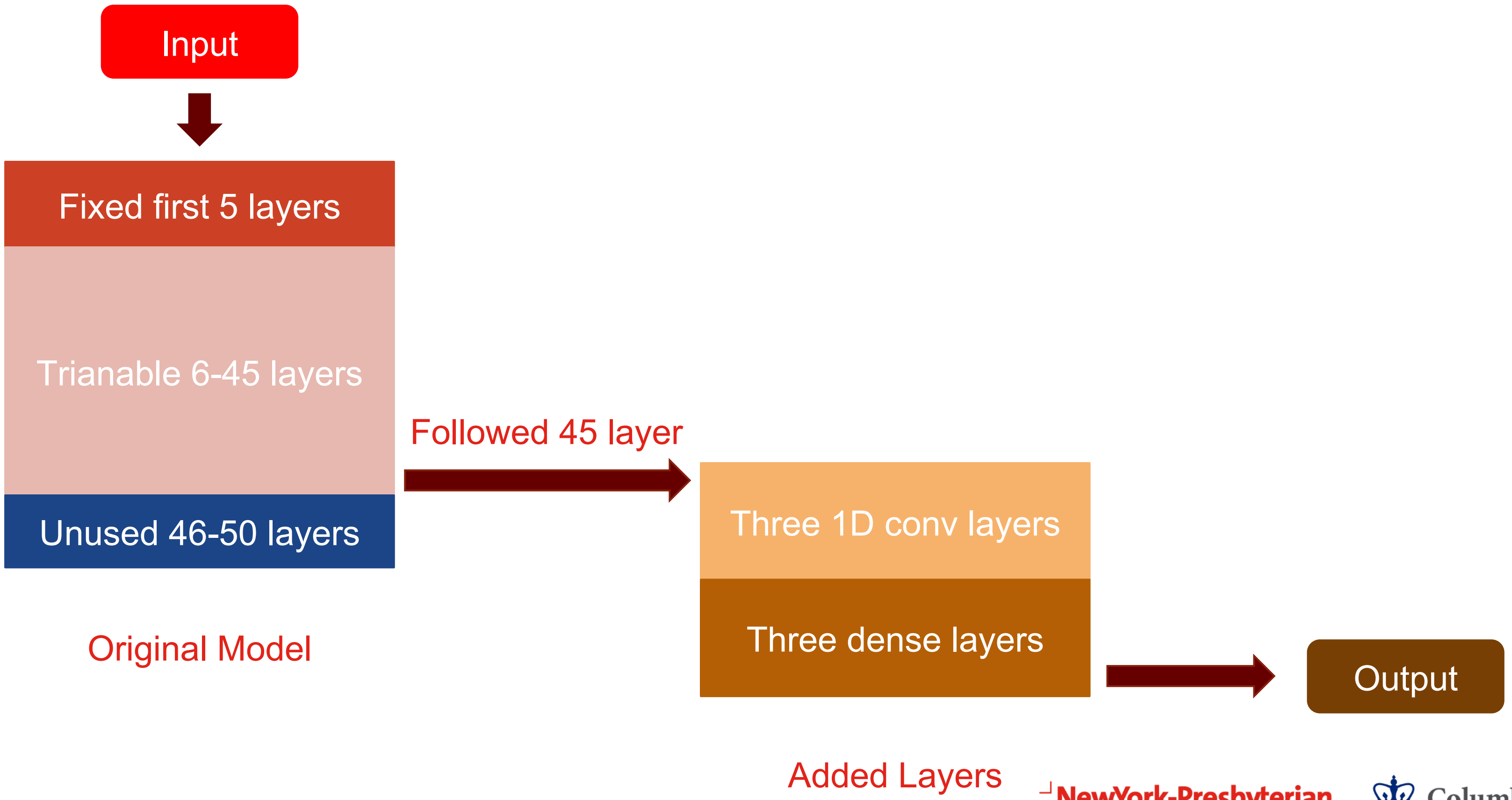
Results for Adjusted *AutoECG* Model

100 epochs with dropout rate 0.5 and learning rate scheduler



	Best Validation Accuracy	Best ROC AUC Score	# Model Parameter
Baseline	80.95%	0.84	~49,000,000
Adjusted RNN	81.91%	0.86	~6,400,000

RNN - Transfer Learning



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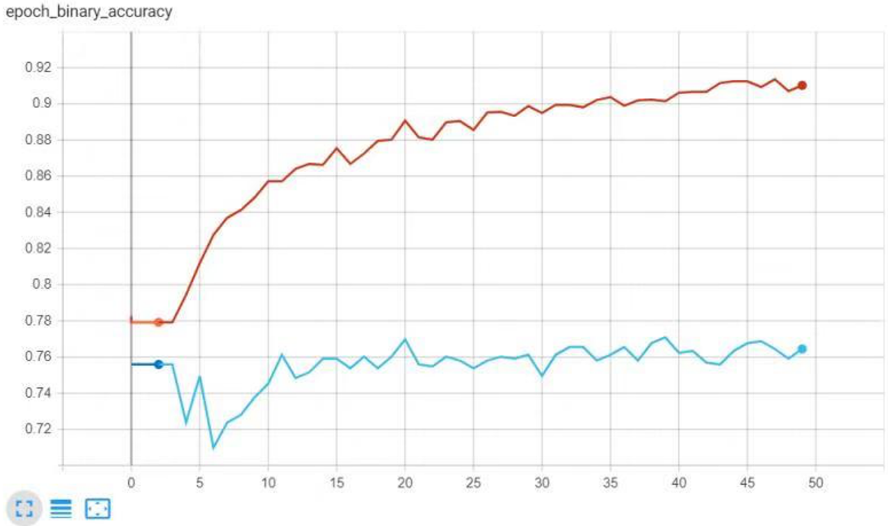
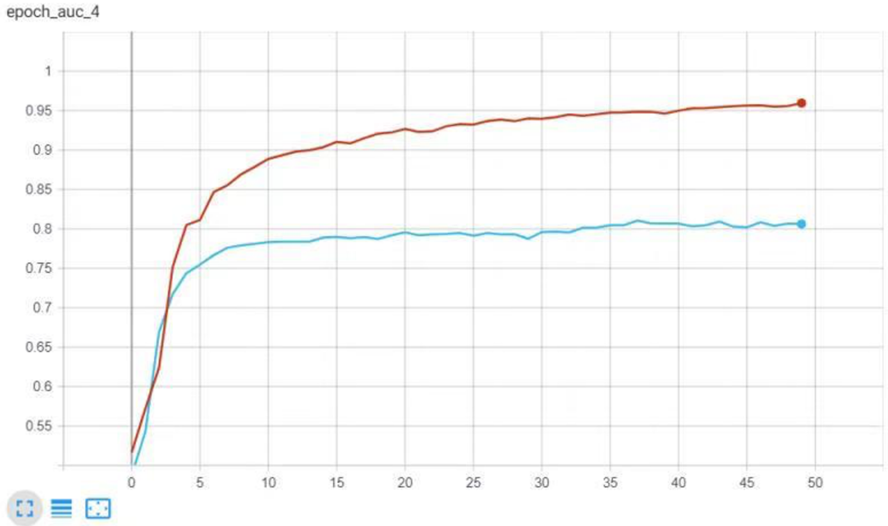
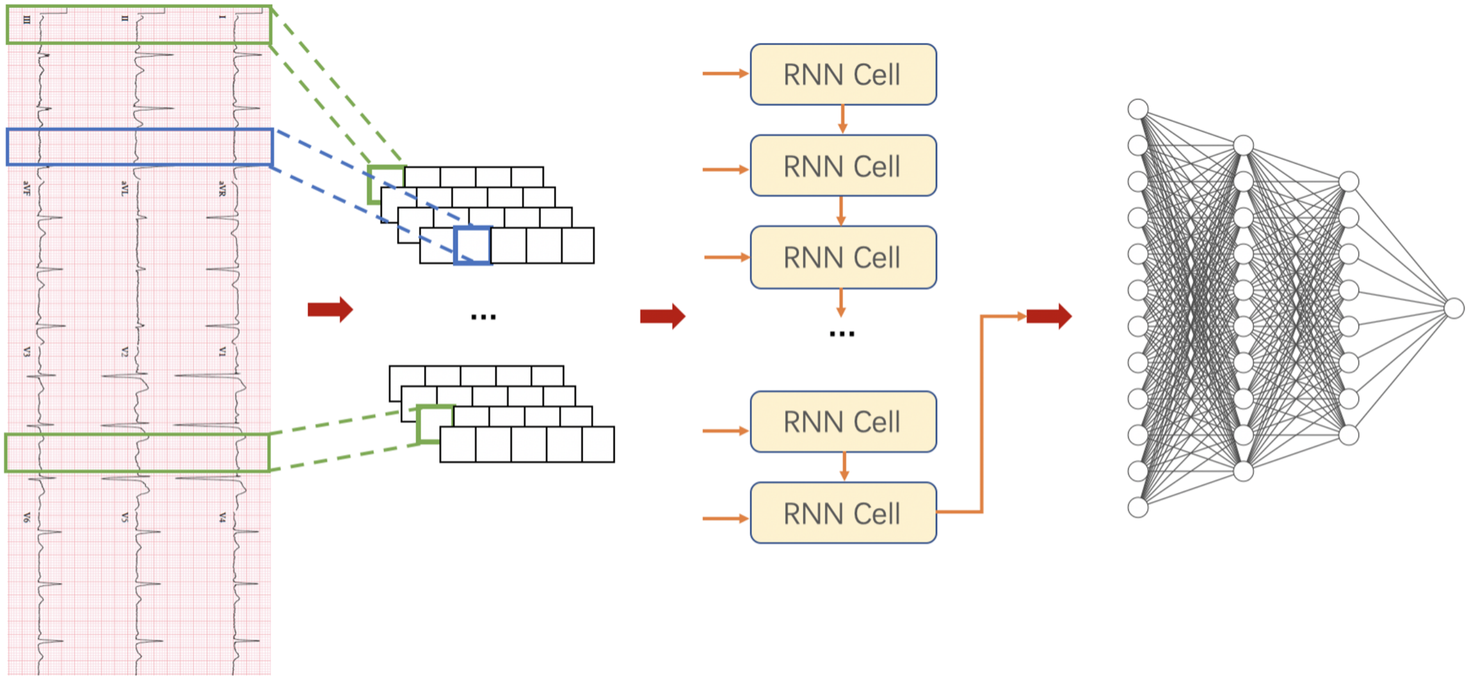
RNN - Transfer Learning
Results for Real Data





	Validation Accuracy	AUC
Best	0.77	0.82

Convolutional Recurrent Neural Network for ECG



Convolutional Layer **Recurrent Layer** **Fully Connected Layer**

Input: 2500×12 raw waveform Convolution in the time domain

CRNN - Model Performance

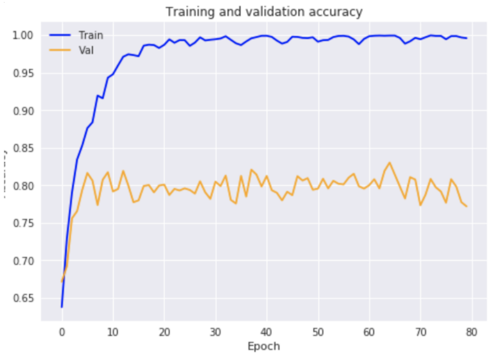
Compared with Baseline 2D CNN model (Goto et al, 2020)

	Validation Accuracy	ROC AUC Score	# Model Parameter
Baseline	80.95%	0.84	~49,000,000
Adjusted RNN	81.91%	0.86	~6,400,000
CRNN	83.14%	0.86	~909,000

CRNN outperforms baseline model with a much lower model complexity!

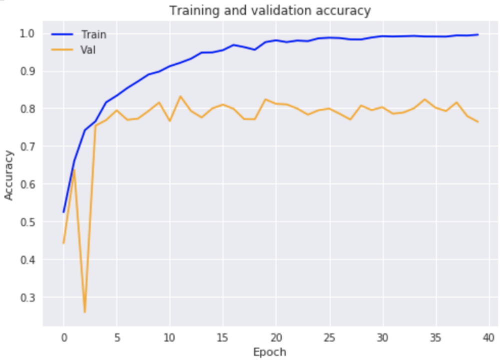
CRNN - Ablation Study

	Validation Accuracy	ROC AUC Score
CRNN w/ LSTM	0.8031	0.7956
CRNN w/ GRU	0.8300	0.8430
CRNN w/ GRU & Dropout	0.8314	0.8578
CRNN w/ GRU & Dropout & regularization	0.8295	0.8564



Model w/ low Dropout rate (0.2)

⇨



Model w/ high Dropout rate (0.5)

Handling overfitting is very important in our task

Hyperparameter Tuning

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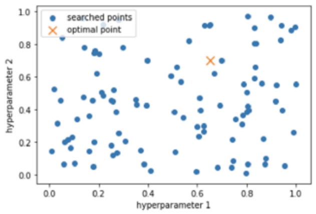
PyTorch Ignite Framework + Optuna

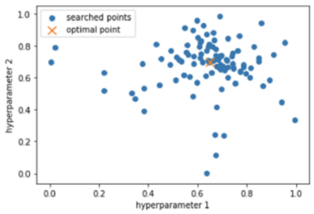
PyTorch Ignite is a high-level library for PyTorch that helps you write compact, but full-featured, code in less lines.

Optuna is a hyperparameter optimization library applicable to machine learning frameworks .

Combining the two of them allows for automatic tuning of hyperparameters to find the best performing models.



Random search

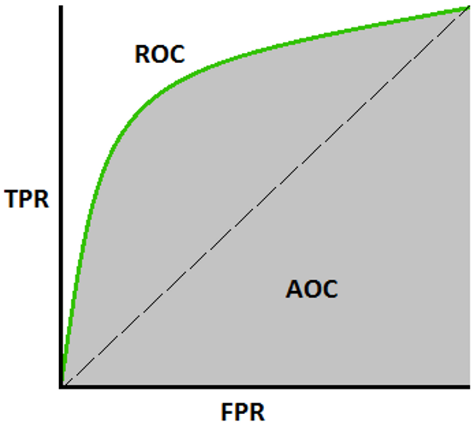


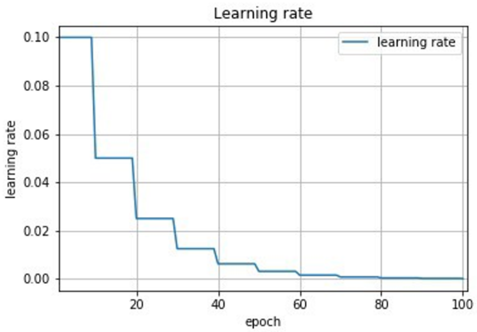
Sequential Model-based Optimization (TPE)

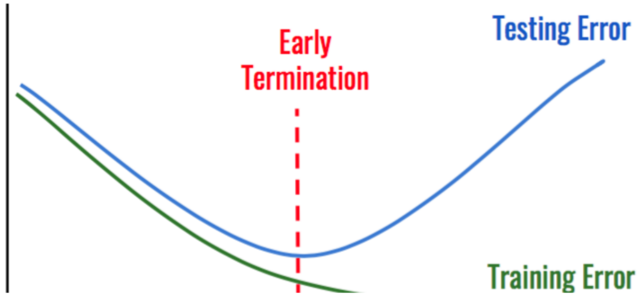
Tuning Design Choices

- Key Parameters
  - Kernel Number
  - Dropout Rate
  - Optimizer
  - Initial Learning Rate

- Other Considerations
  - Validation AUC
  - Early Stopping
  - Learning Rate Scheduler

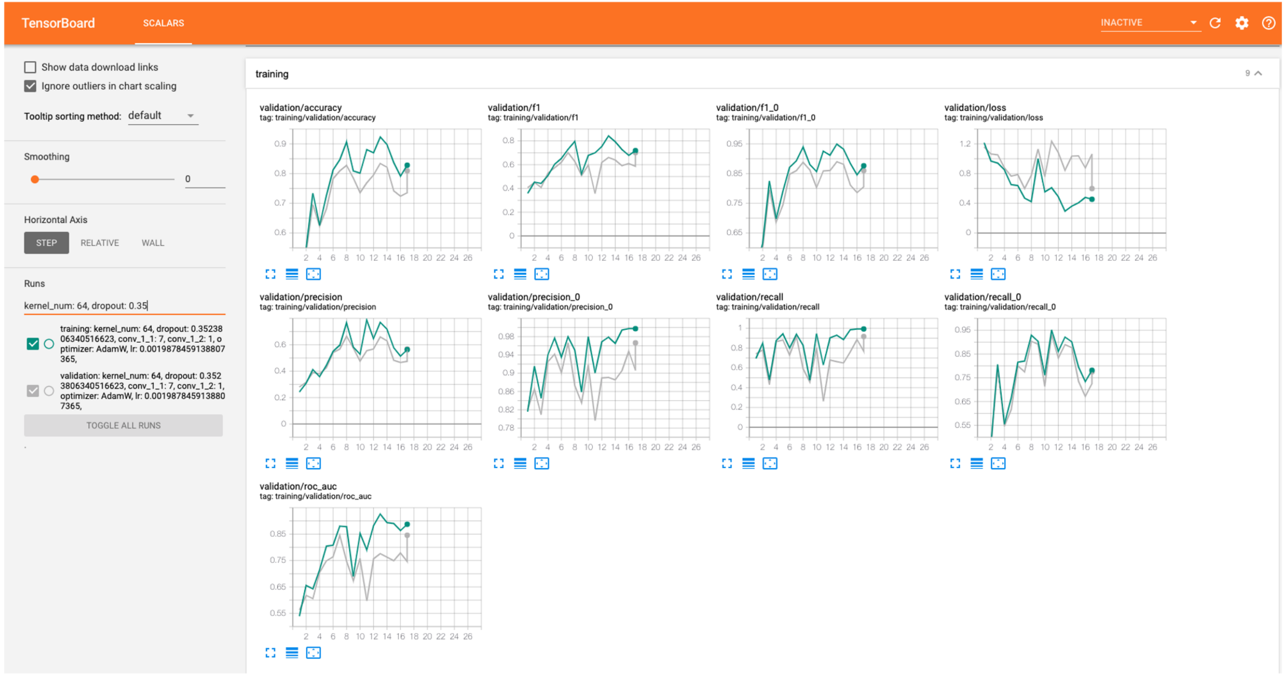






Automatic Tuning 2DCNN on Real Data

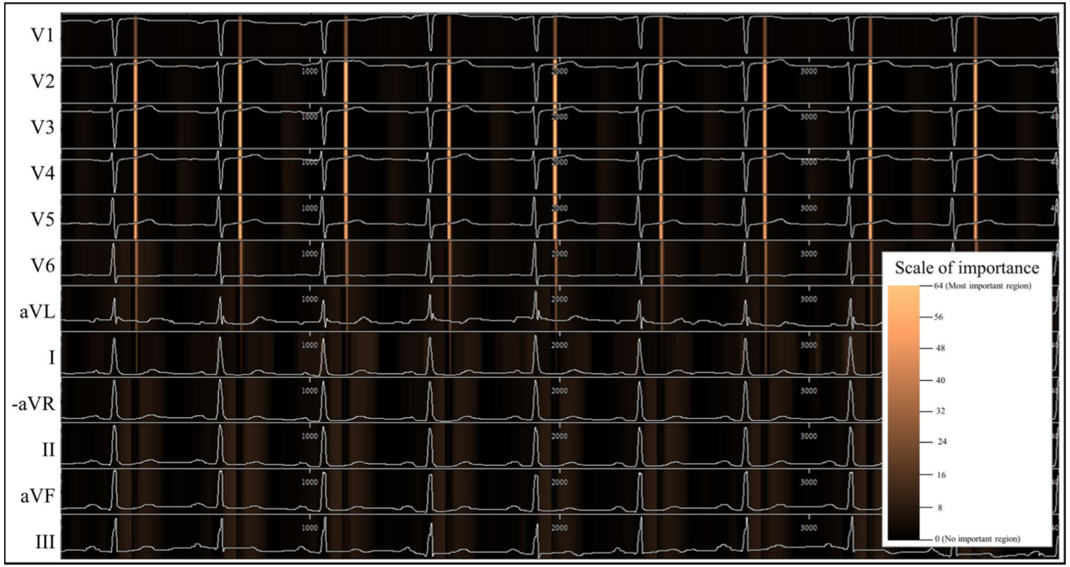
Best Params	Conv1_1: 7 Conv1_2: 1 Kernel #: 64 Dropout: 0.35 Opti: AdamW Lr: 0.00199
Best Validation Accuracy	0.8340
Best Validation AUC	0.8457



Possible Future Work

Model Visualization Using CAM (Class Activation Map):

Using the FINAL convolution feature map followed by Global Average Pooling (GAP) and softmax activation function.



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Thank You