成都理工大學 中英合作办学

CDUT Sino-British Collaborative Education

OXFORD BROOKES UNIVERSITY

Deep Learning Based Multi-Label Heart Disease Classification

Multimodal Trained Using ECG Signals and Images

Presenter : Wyatt (Yong Wang)

Student ID: 202018020232

Supervisor: Dr Happy Nkanta Monday

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Introduction

- Heart disease is the leading cause of death worldwide. Electrocardiogram (ECG) is crucial for diagnosing various cardiac conditions. This project utilizes deep learning technology to develop diagnostic tools.
- **Aim:**
- Develop specialized CNN models and data processing methods for ECG signals and images, and providing transparent model decision-making for cardiologist. Building edge devices and GUI for model reality deployment
- **Objectives:**
- 1. Implement Model 1 ResECANet for verifying 1D ECG signal dataset.
- 2. Implement Model 2 VGG16 for verifying 2D CWT feature map dataset.
- 3. Implement Model 3 ResDSCNet for verifying 2D ECG images dataset with multi labels classification experiment.
- 4. Implement GUI deployment and Raspberry Pi diagnostic device deployment

Motivation

- Why I chose this project?

- Heart health issues have a huge impact on people's lives
- Artificial Intelligence helps Medical Development

- What is the problem?

- Manual recognition of ECG pathological features by cardiologists is slow and inefficient
- The lack of interpretability in ECG classification deep learning models
- The multi label classification problem of heart disease needs to be addressed

- Why it is interesting?

- Programs could become doctors
- AI could help doctors diagnose heart disease

01 Background Review

Background Review

◆ Traditional ECG single label classification

- Small dataset such as MIT-BIH
- Complex ECG signal preprocessing and Heartbeat segmentation
- 1D signal direct training model, perform feature extraction or convert into 2D images

◆ Newly developed multi label classification

- Complex dataset like 12 lead multi-label PTB-xl
- Diverse model choices such as Graph neural network, Transformer based NN, CNN and ensemble learning
- Special feature extraction methods, including visual and non visual methods

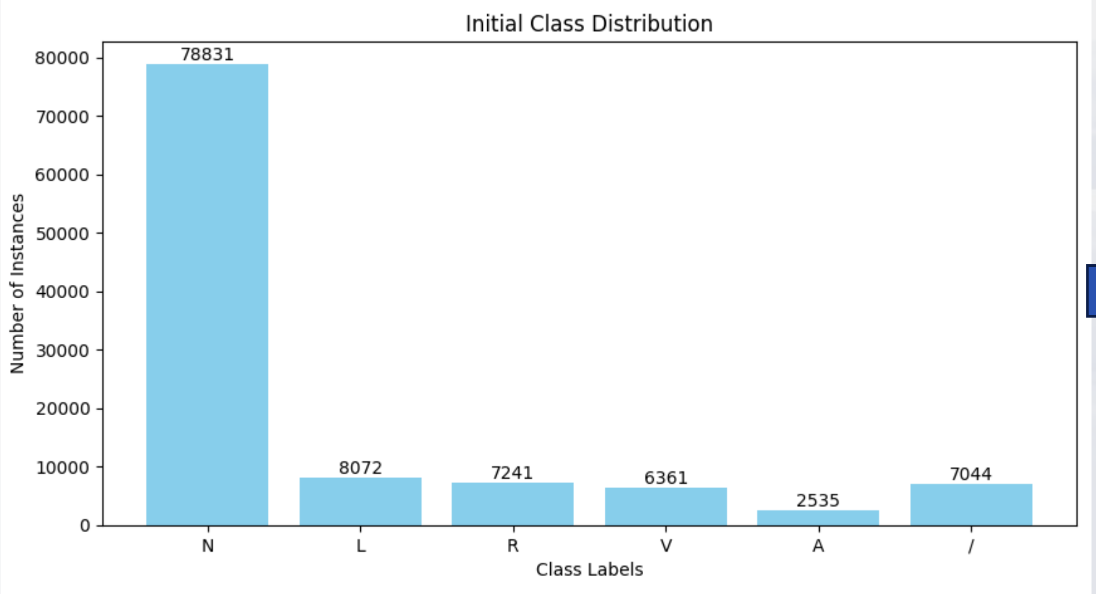
Background Review

Researchers	Techniques	Performance
Zvuloni et al. [1]	Feature engineering with modern neural networks; Combined LSTM networks with a feature-based SVM classifier.	Achieving 98.9% accuracy
Rahman et al. [2]	Deep CNN transfer learning Inception-V3, correction, image resizing, z-score normalization.	Five-class classification: 97.83%
Zhang et al. [3]	Spatial-temporal Residual Graph Convolutional Network (GCN)	Accuracy of 76.6%, F1 of 63.3%, AUC of 89.1% (multi label classification)
Cai et al. [4]	Multi-ECGNet neural network with convolutional layers, attention mechanisms, ResNet, Squeeze-and-Excitation Module, Depthwise Separable Convolution	Micro-F1 score of 0.863 (multi label classification)

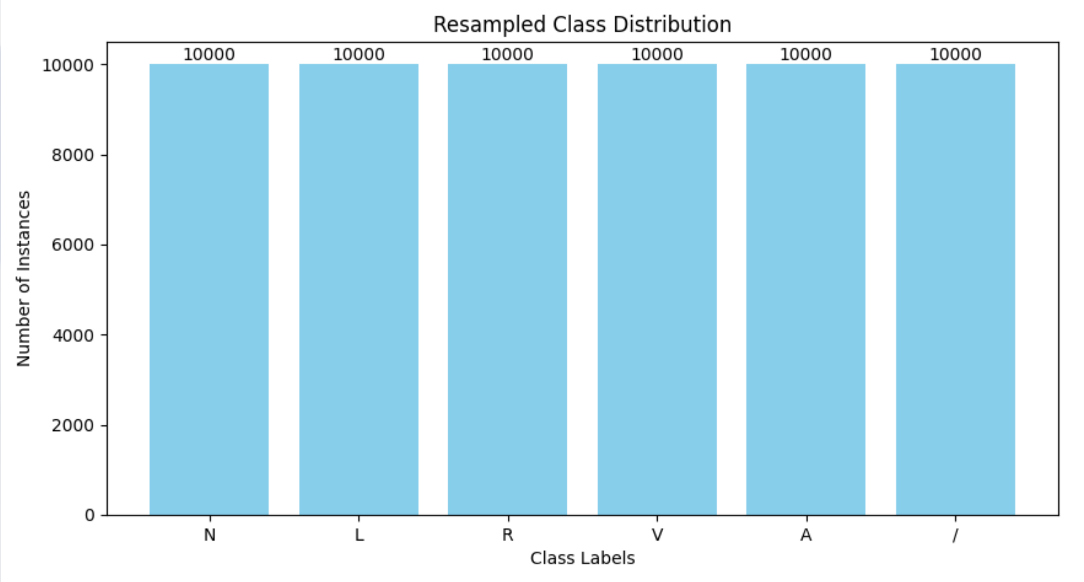
02 Methodology

Dataset MIT-BIH

- The MIT-BIH Arrhythmia Database [5] includes 48 recordings, each 30 minutes long, collected from 47 patients. Over 110,000 annotations were made on these recordings.

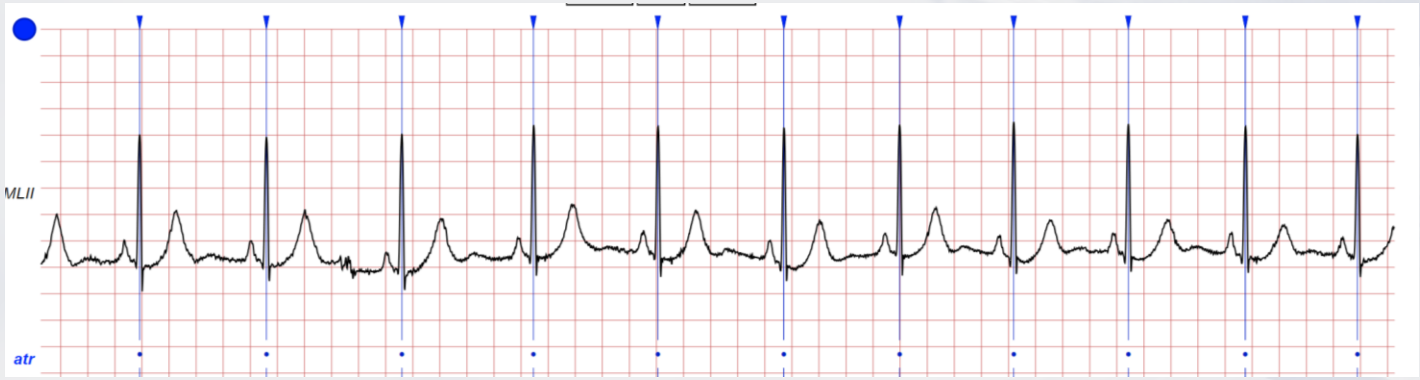


Original data distribution

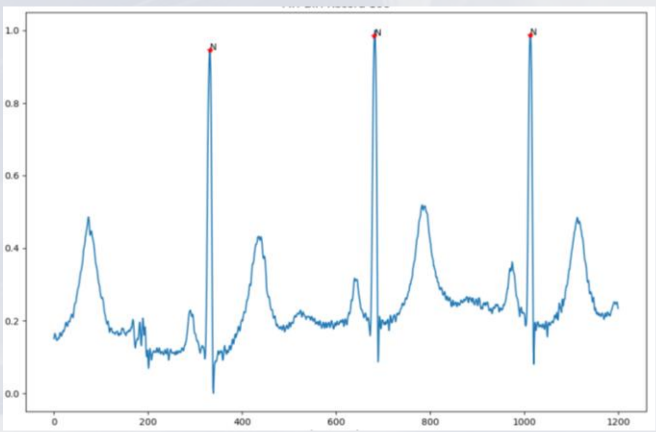


The distribution after applying SMOTE to solve the problem of data imbalance

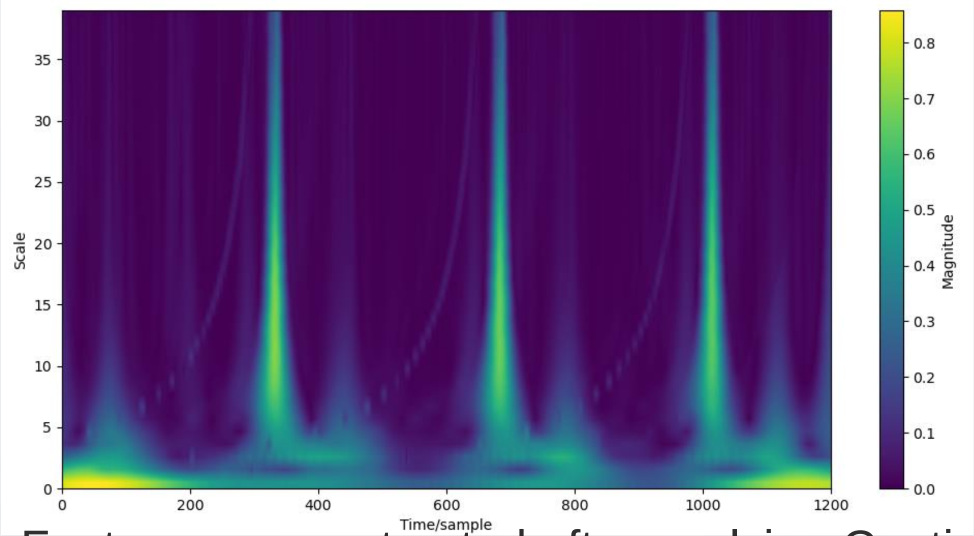
Dataset MIT-BIH processing



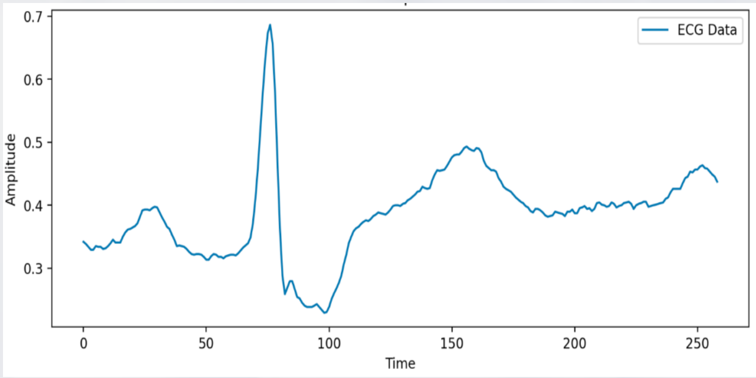
Waveform from MIT-BIH



Local plot waveform



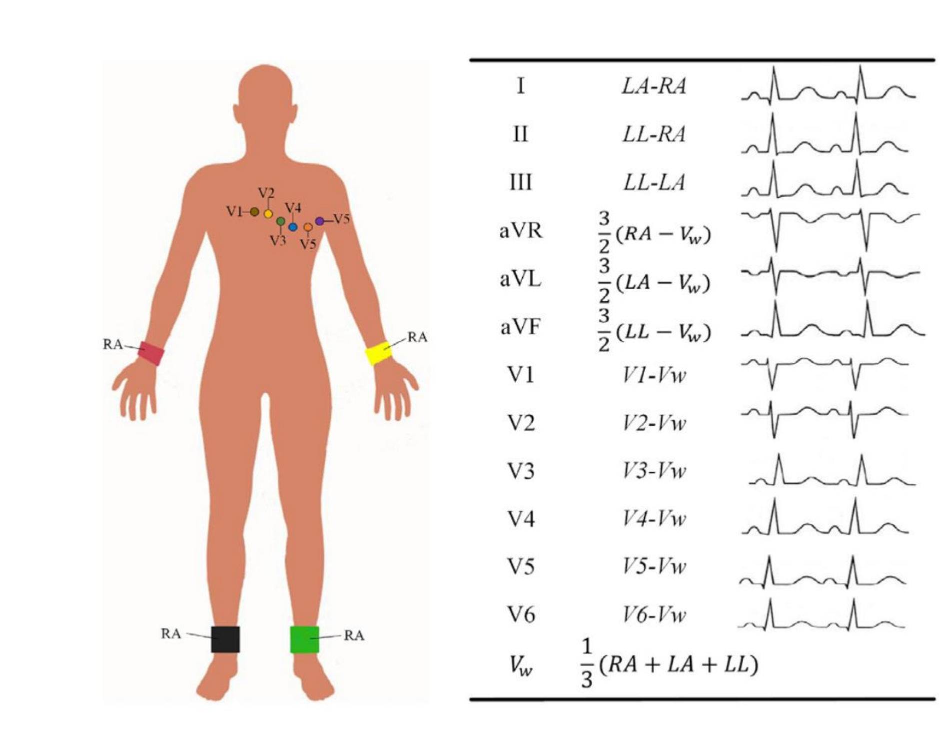
Feature maps extracted after applying Continuous Wavelet Transform (CWT)



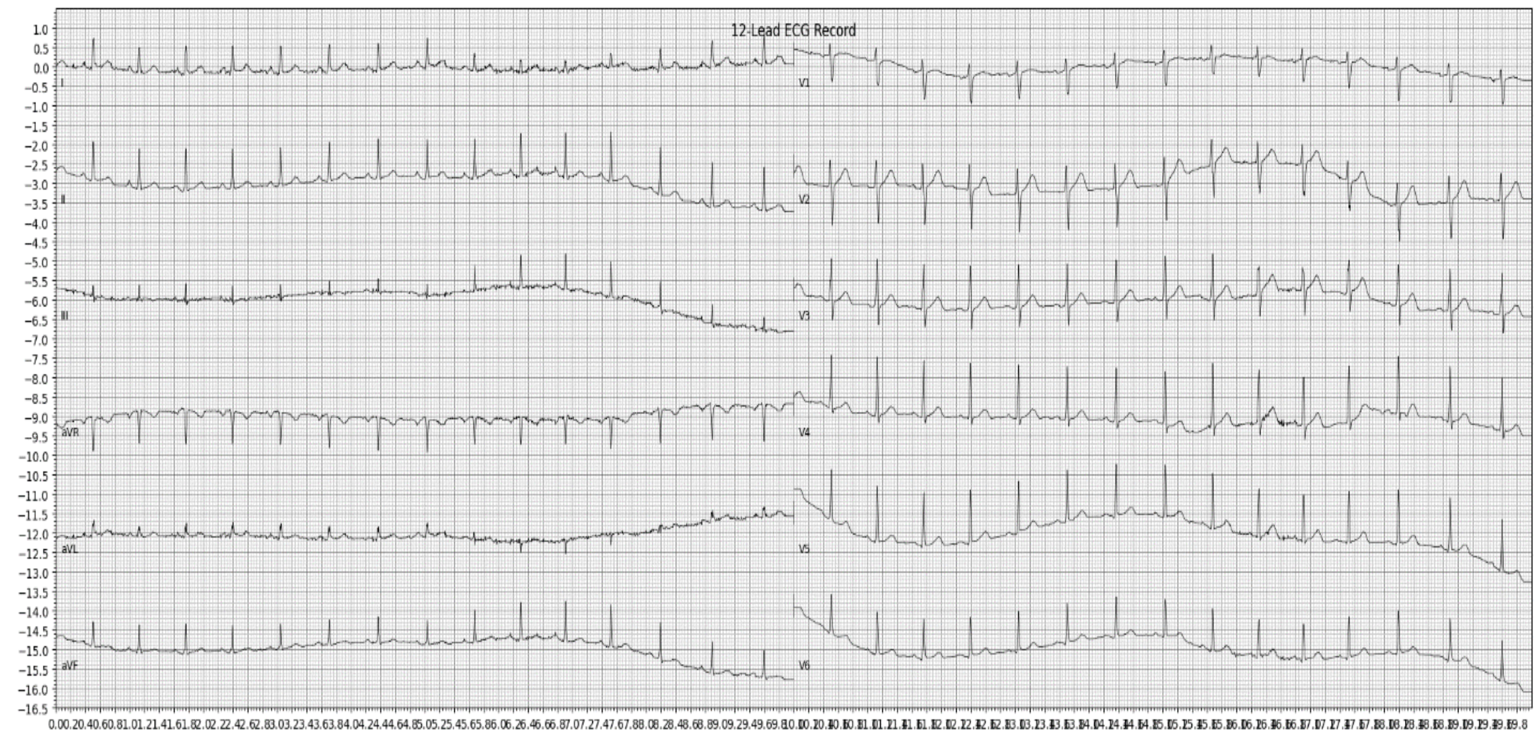
Sample after applying Pan Thompkins algorithm and Heartbeat segmentation

Dataset PTB-XL

- The PTB-XL ECG dataset [6] is a large dataset of 21799 12-lead ECGs from 18869 patients of 10 second length. 71 different ECG statements in total, This study focuses on five superclass.

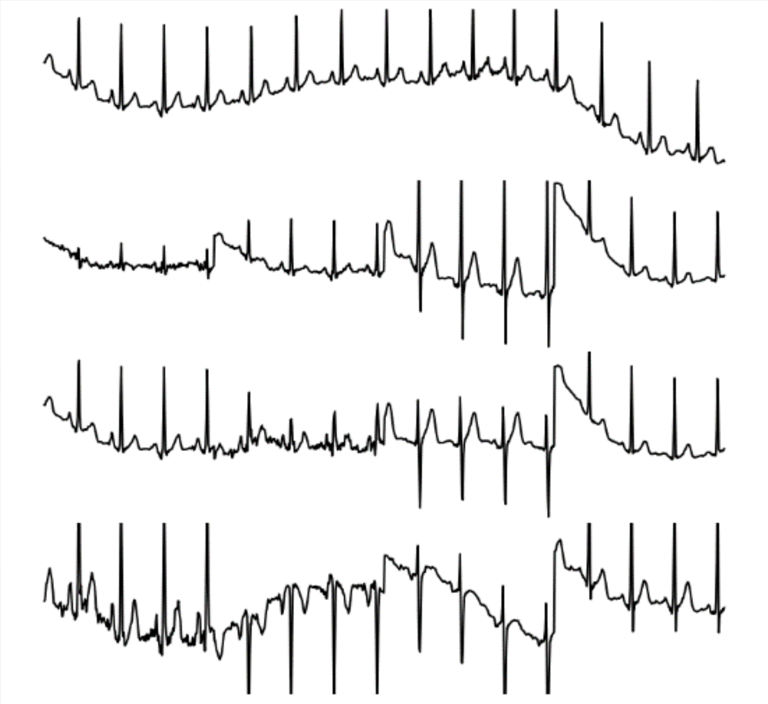


12 lead ECG data

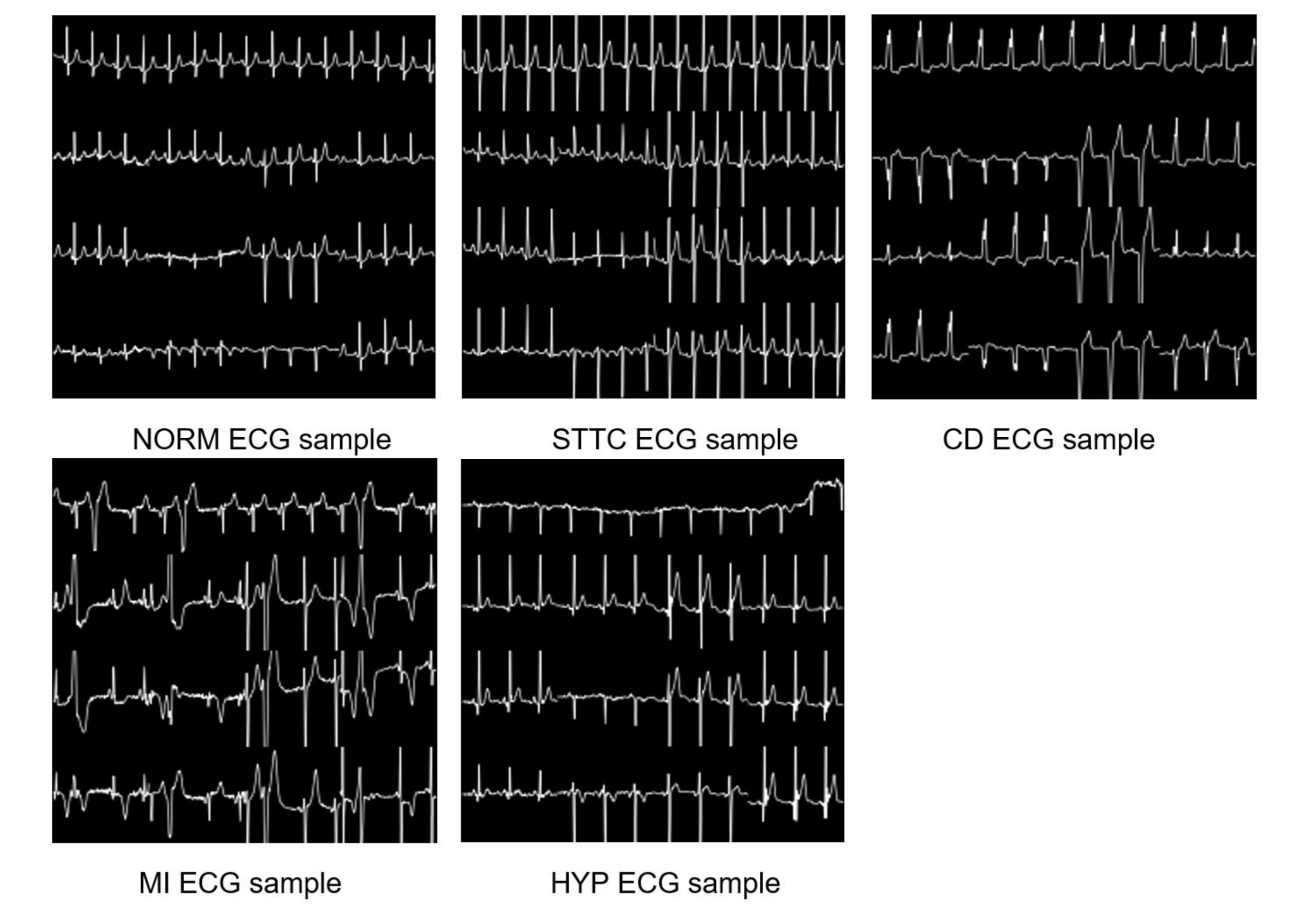


Complete samples that doctors often see

Dataset PTB-XL processing

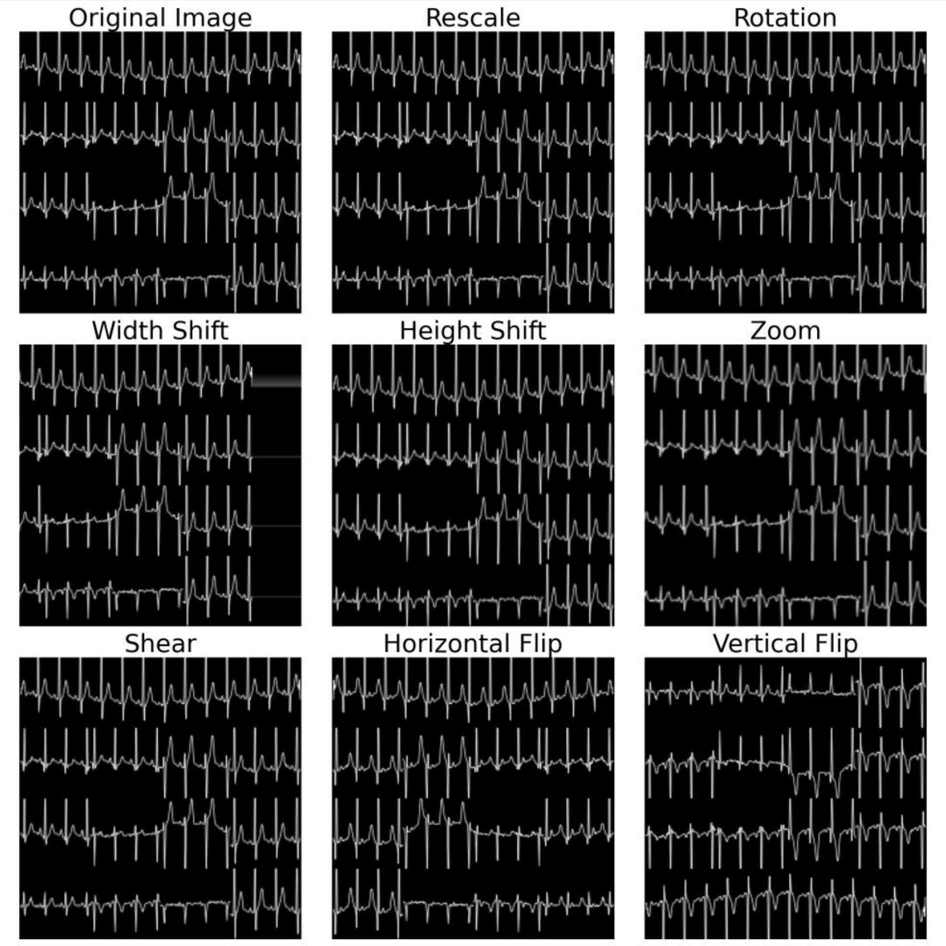


224X224 grayscale samples after segmentation and reconstruction

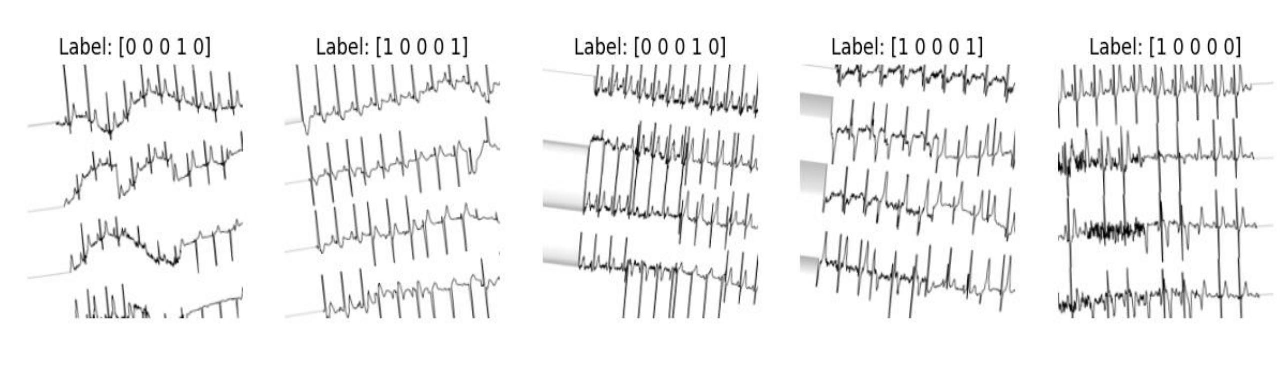


Five superclass invert colors samples

Dataset PTB-XL processing



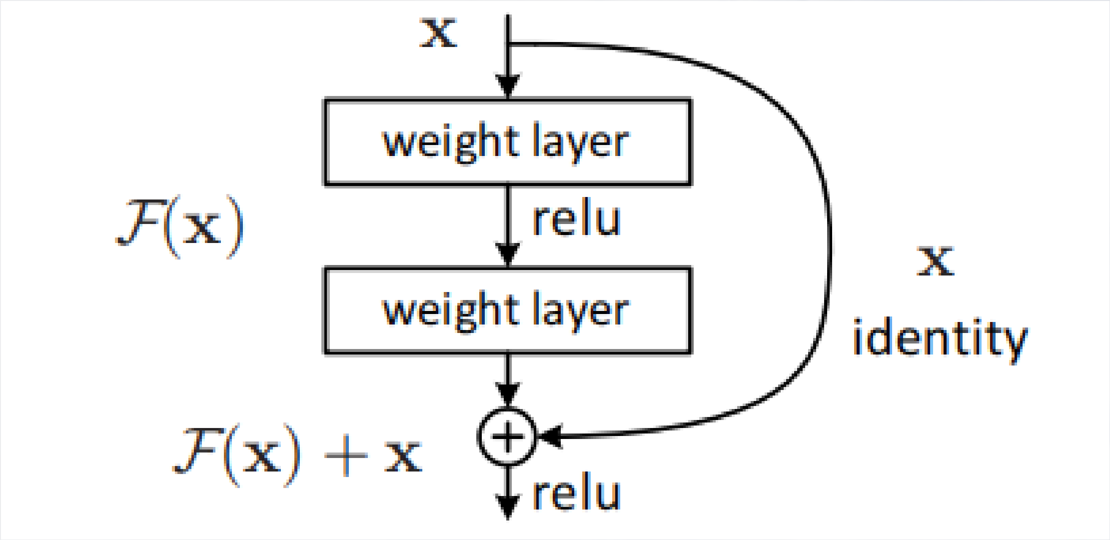
Different data augmentation effects



Multiple data augmentation stacking effects and multi label forms

Model Components

- ResNet: [7] Ensure that the original features could be effectively transmitted to deep layer neural networks



Residual block

Model Components

- Efficient Channel Attention (ECA) [8]: It is a lightweight attention mechanism, which focuses on local cross-channel interactions and adjusting the importance of each channel in CNNs.

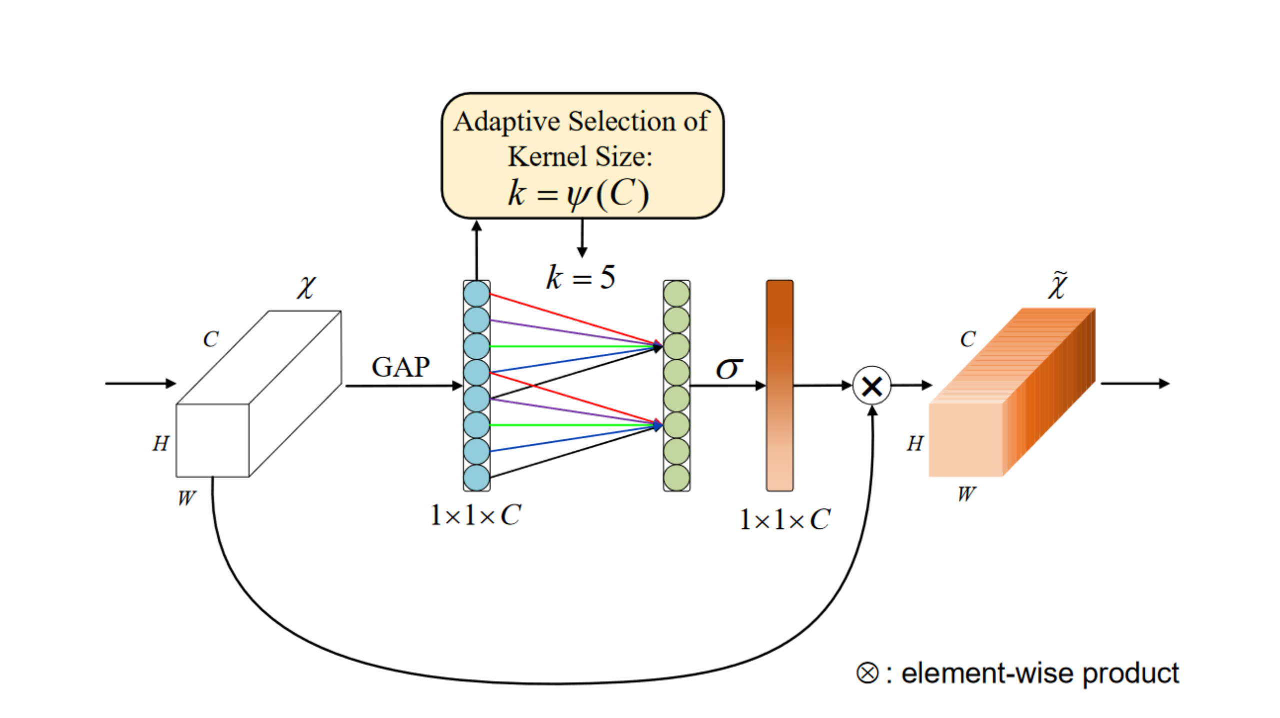
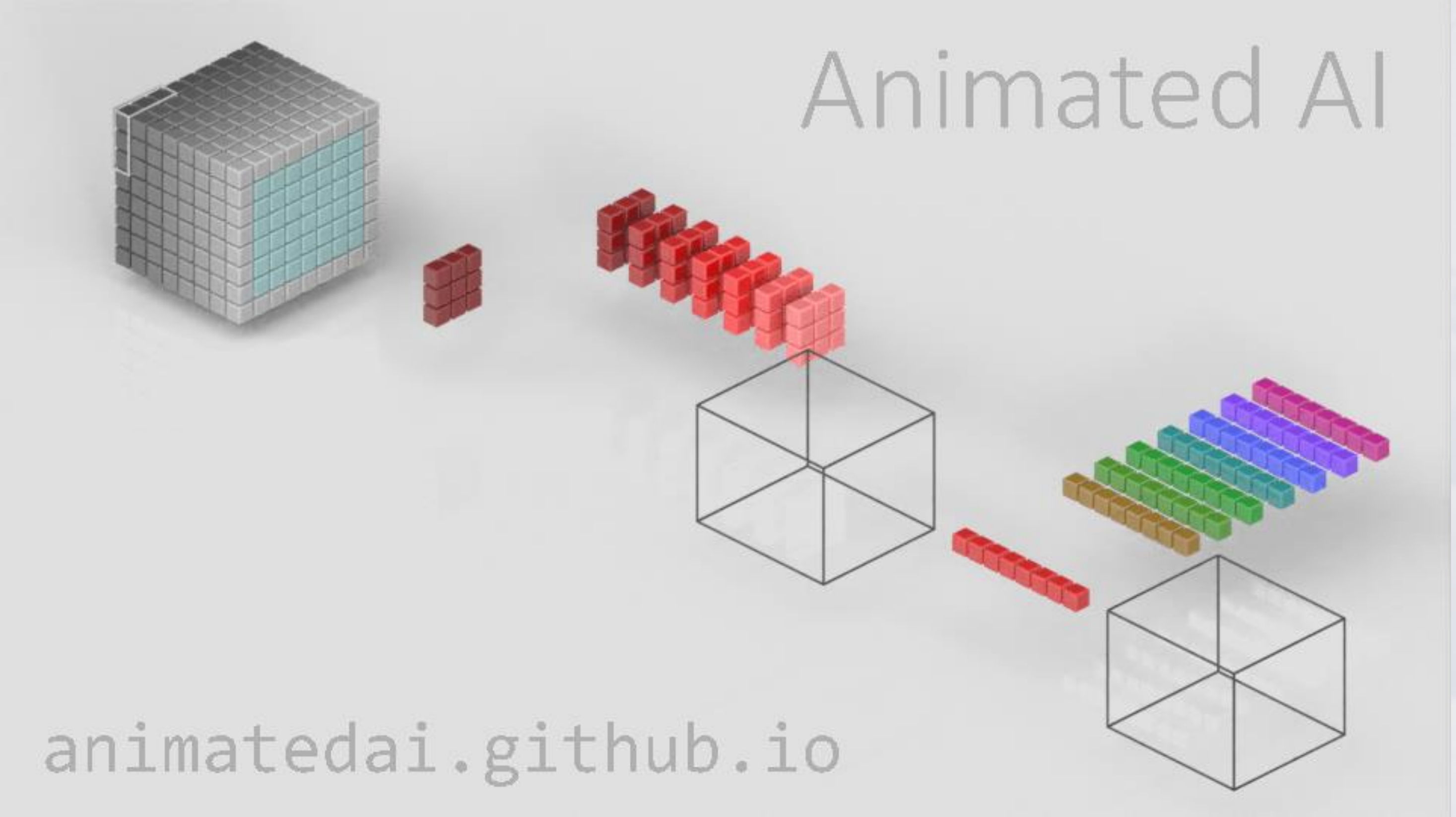


Diagram of efficient channel attention (ECA) module

Model Components

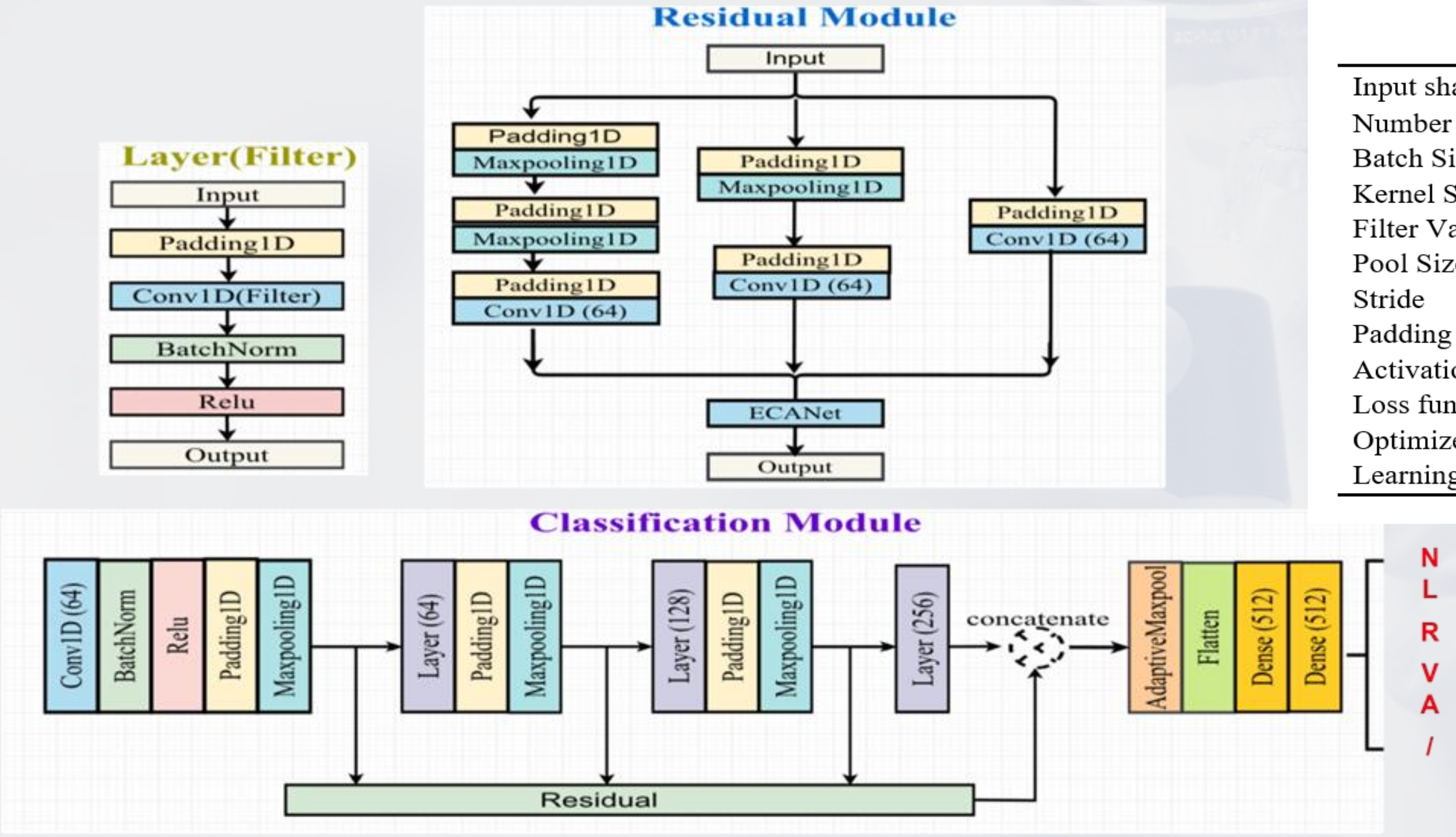
- Depthwise-Separable Convolution [9]: Reduce model parameter requirements while maintaining accuracy.



DSC demonstration animation

03 Project Implementation & Results

Model 1 ResECANet for verifying 1D ECG signal dataset



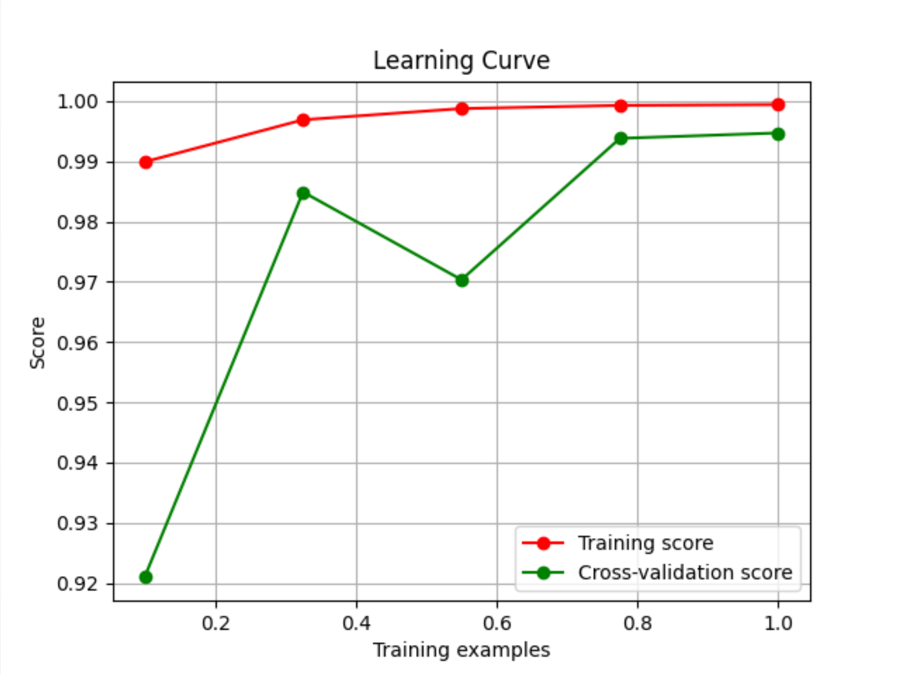
Model 1 architecture

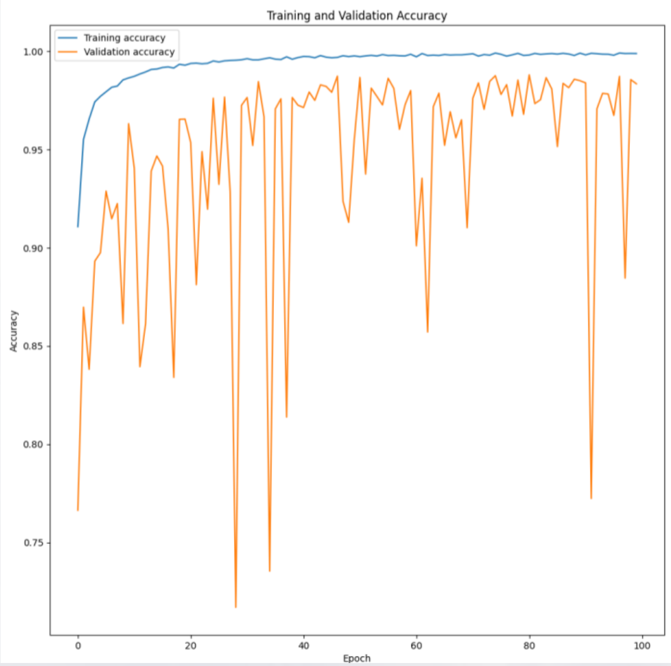
Hyperparameter Setting

Input shape	(259,1)
Number of classes	6
Batch Size	64
Kernel Size (convolution)	15 (first layer), 7 (other layers)
Filter Values	32 to 512
Pool Size	3
Stride	2
Padding	"same"
Activation	Relu, Softmax(last dense)
Loss funcation	Category crossentropy
Optimizer	Adam
Learning Rate	0.0004

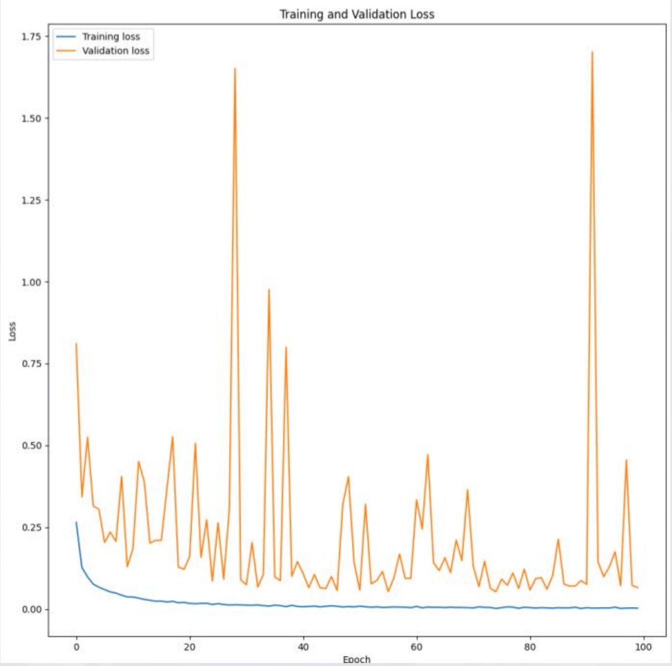
Hyperparameter Setting

Model 1 Train and Validation performance





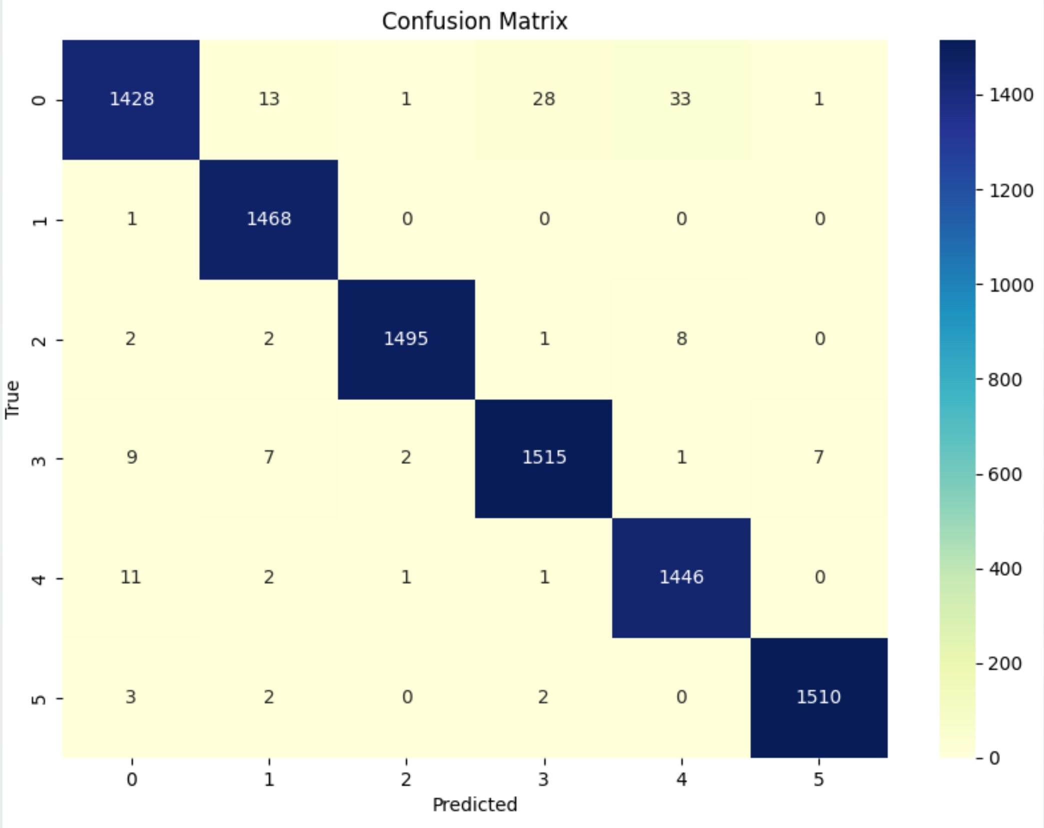
Training and Validation Accuracy



Training and Validation Loss

K-fold cross validation curve (K=5)

Model 1 Testing performance



Confusion matrix

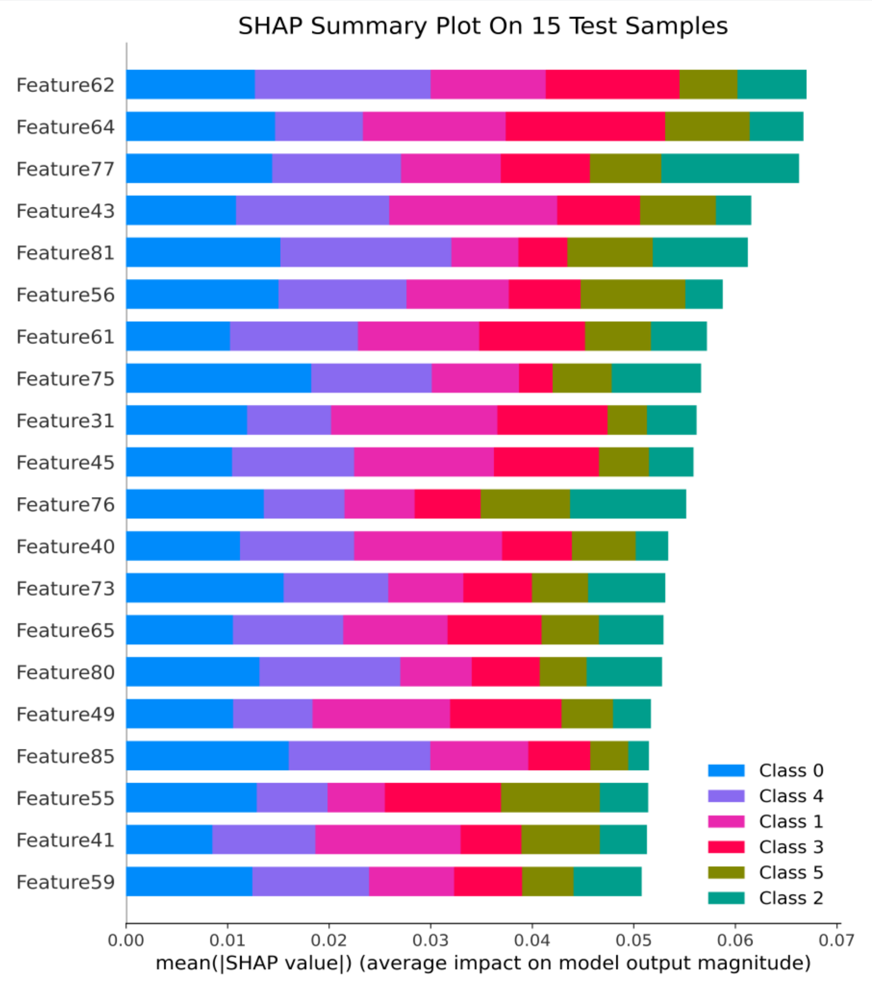
Classification Report On Test Set

Class	Precision	Recall	F1-score	Support
0	0.98	0.95	0.97	1504
1	0.98	1.00	0.99	1469
2	1.00	0.99	0.99	1508
3	0.98	0.98	0.98	1541
4	0.97	0.99	0.98	1461
5	0.99	1.00	1.00	1517
macro avg	0.98	0.98	0.98	9000
weighted avg	0.98	0.98	0.98	9000
Test loss			0.0518	9000
Test accuracy			0.9892	9000

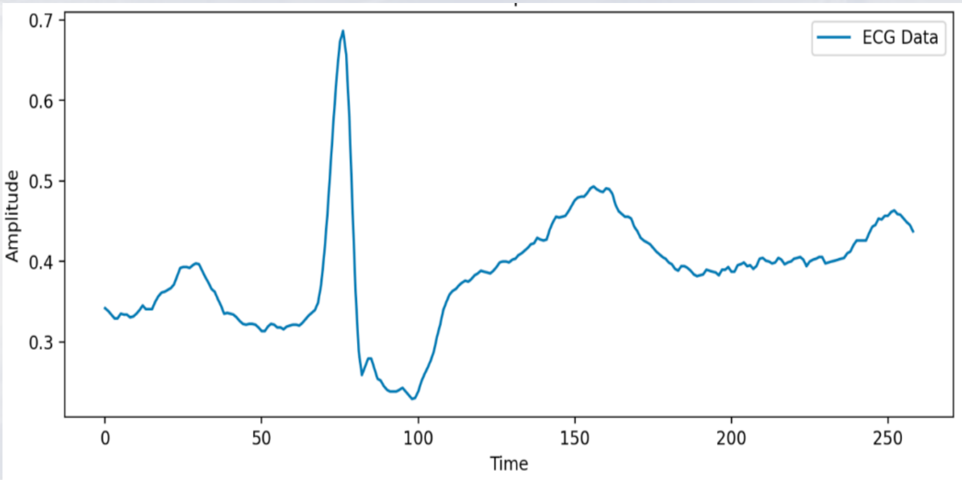
Detailed test results

Model 1 Interpretability analysis

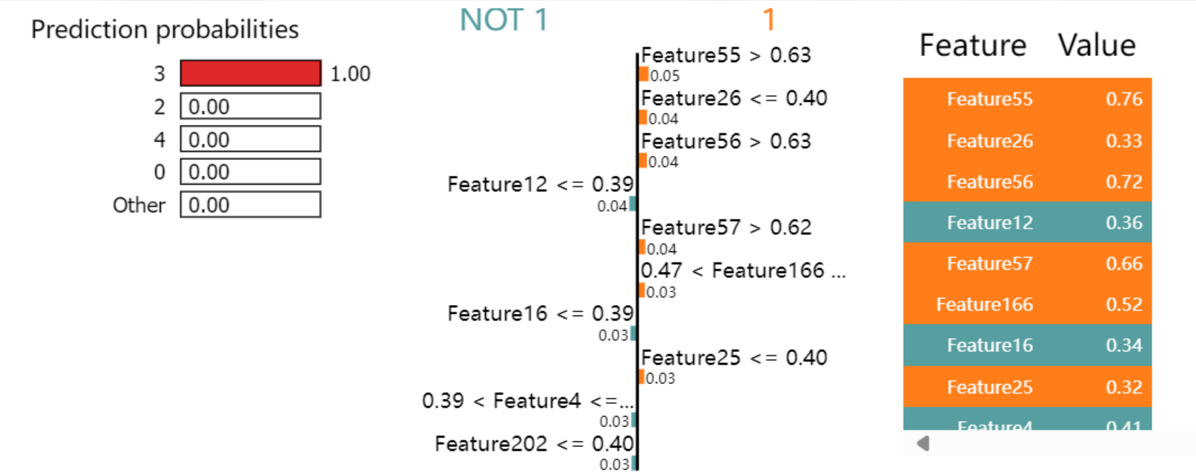
- SHAP and LIME are two popular methods provide explanations for the predictions of complex models.



SHAP (SHapley Additive exPlanations)

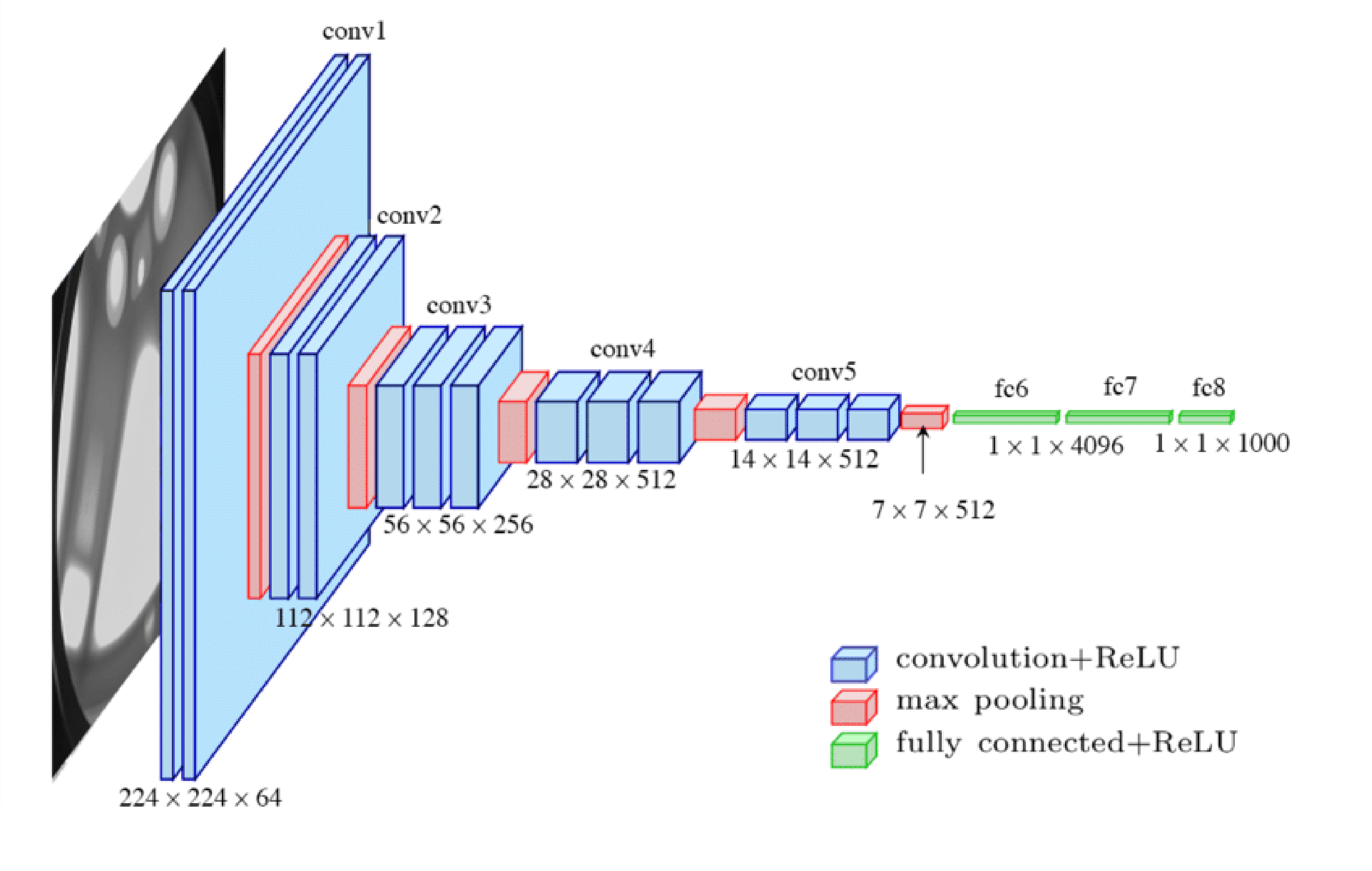


ECG sample



LIME (Local Interpretable Model-agnostic Explanations)

Model 2 VGG16 for verifying 2D CWT feature map dataset

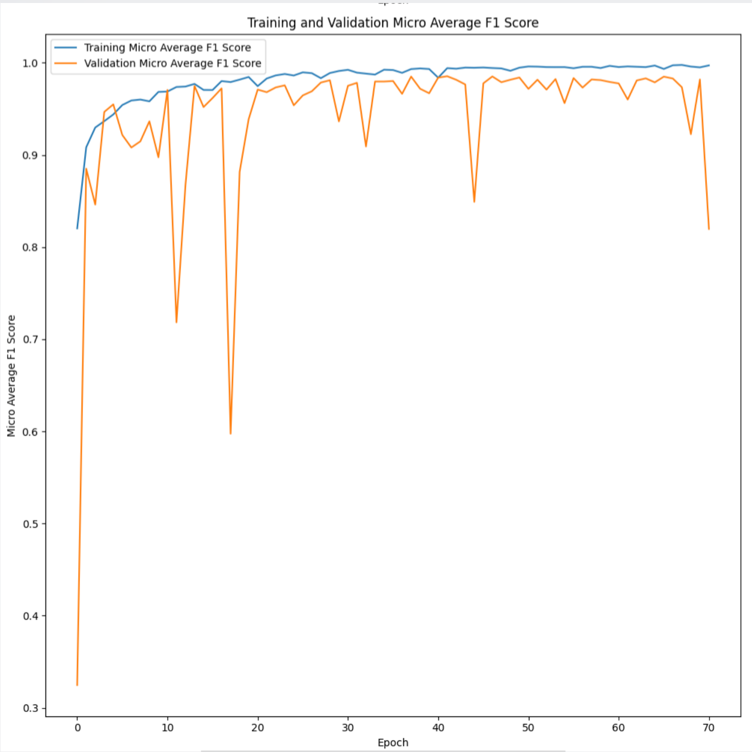


VGG16 architecture

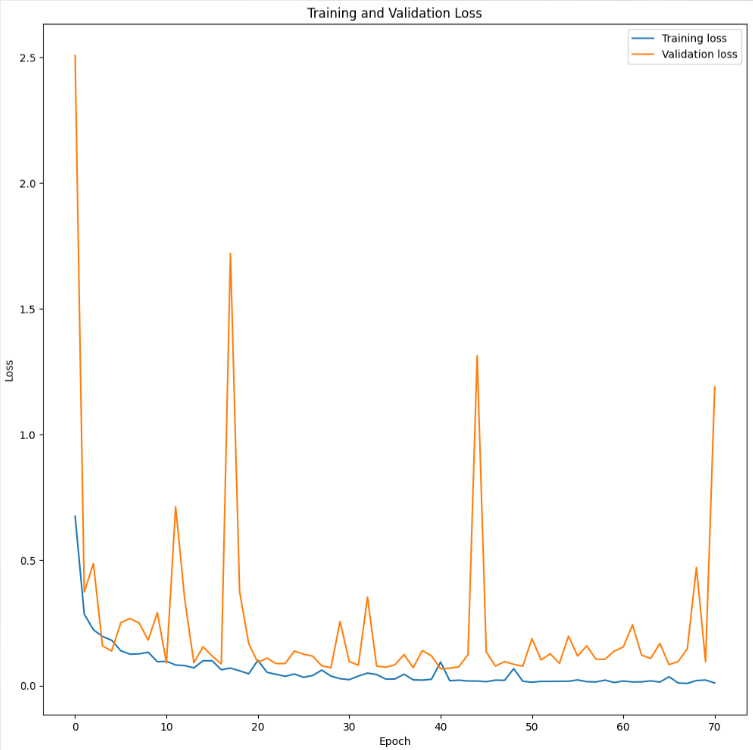
Hyperparameter Setting	
Input shape	(38, 259, 1)
Number of classes	6
Batch Size	64
Kernel Size (convolution)	3
Filter Values	64 to 512
Pool Size	2
Stride	2
Dropout rate	0.5(first dense), 0.2(other denses)
Padding	"same"
Activation	Relu, Softmax(last dense)
Loss funcation	Category crossentropy
Optimizer	Adam
Learning Rate	0.0004

Hyperparameter Setting

Model 2 performance



Training and Validation F1 Score



Training and Validation Loss

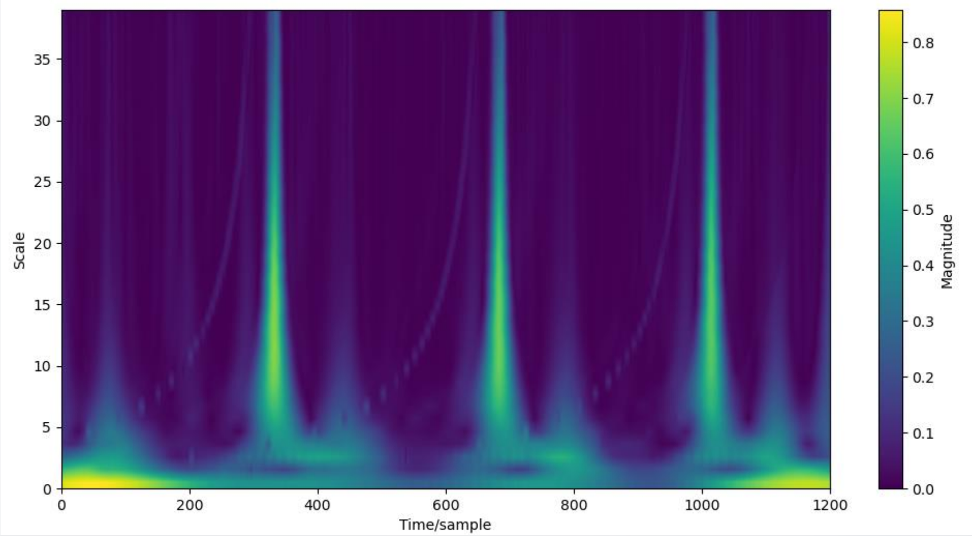
Classification Report On Test Set

Class	Precision	Recall	F1-score	Support
0	0.97	0.96	0.96	1504
1	1.00	1.00	1.00	1469
2	0.99	1.00	1.00	1508
3	0.98	0.99	0.98	1541
4	0.98	0.98	0.98	1461
5	0.99	1.00	1.00	1517
macro avg	0.99	0.99	0.99	9000
weighted avg	0.99	0.99	0.99	9000
Test loss			0.0628	9000
Test accuracy			0.9856	9000

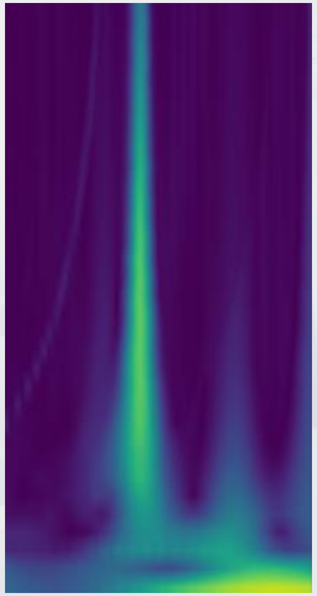
Detailed test results

Model 2 Interpretability analysis

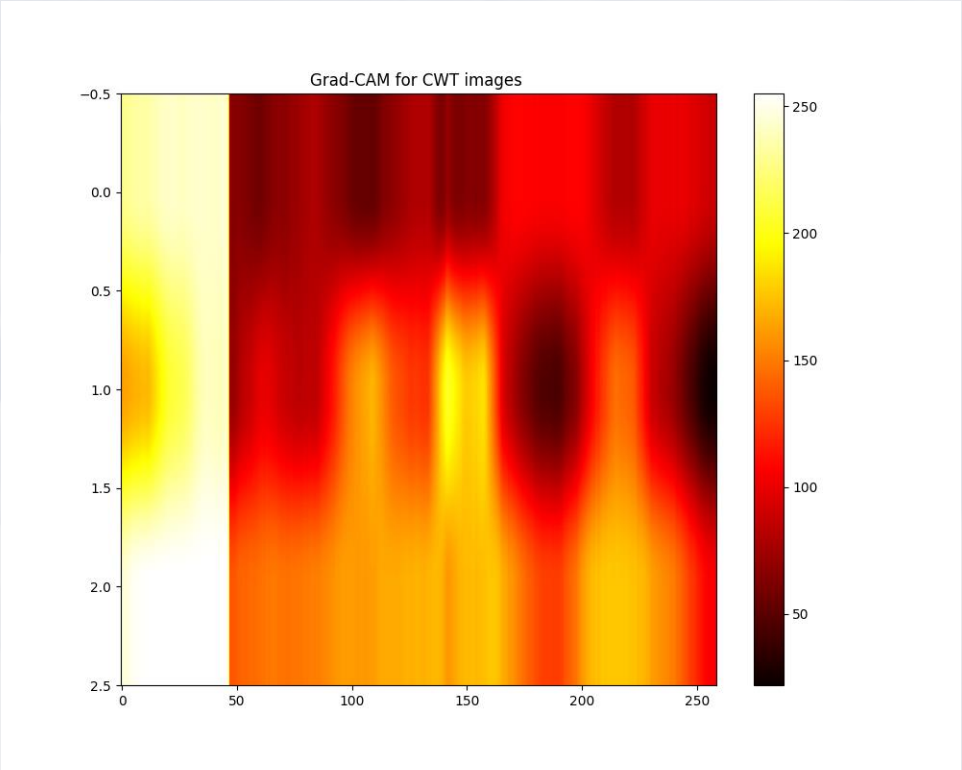
Gradient Weighted Class Activation Mapping (Grad-CAM): Using decision outputs flowing into convolutional layers to generate localization maps that display important area of the input



A series of CWT feature maps



Single heartbeat CWT feature map



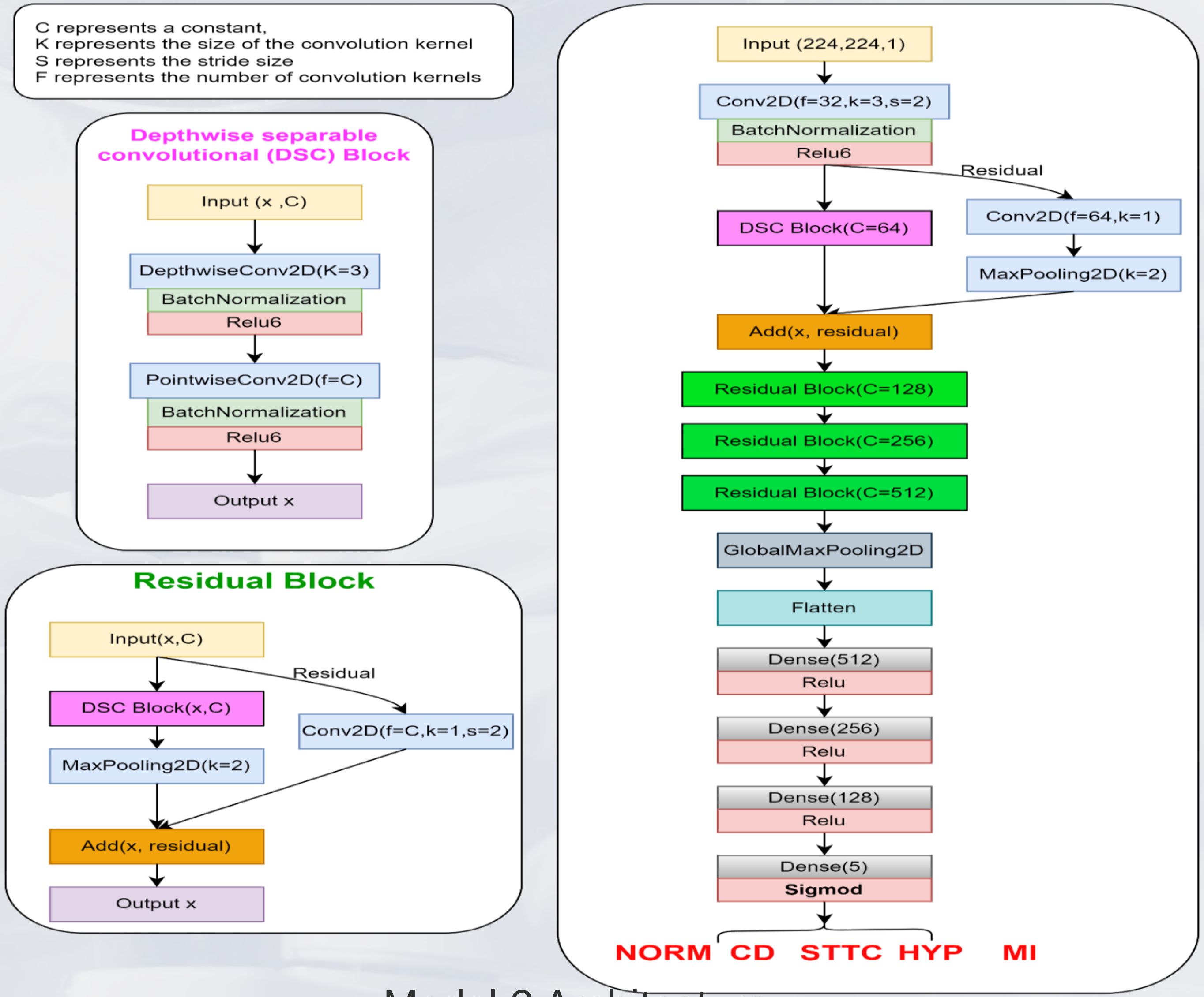
Grad-CAM

Model 3 ResDSCNet for verifying 2D ECG images dataset

Hyperparameter Setting

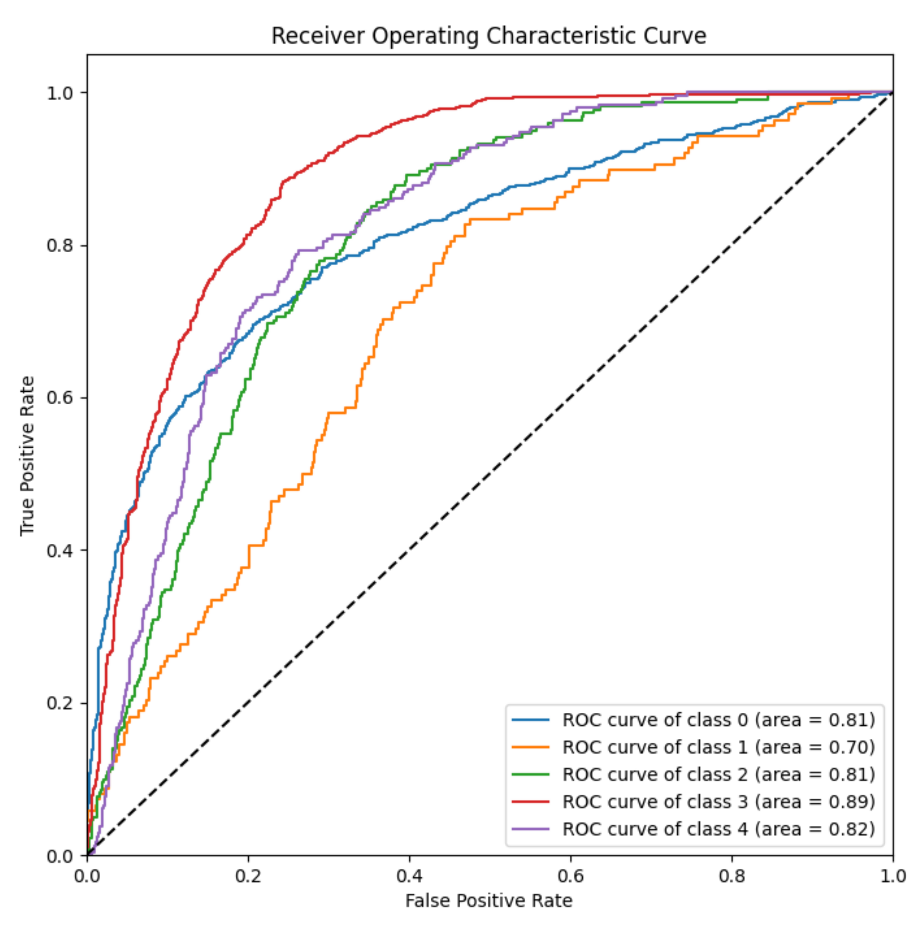
Input shape	(224, 224, 1)
Number of classes	5
Batch Size	16
Kernel Size (convolution)	3(Conv2D), 1 (Residual and Pointwise)
Filter Values	32 to 512
Pool Size	2
Stride	2
Padding	"same"
Activation	Relu6, Relu, Sigmoid(last dense)
Loss funcation	Binary crossentropy
Optimizer	Adam
Learning Rate	0.0001

Hyperparameter Setting



Model 3 Architecture

Model 3 performance



ROC curve and AUC score

Multi label classification report

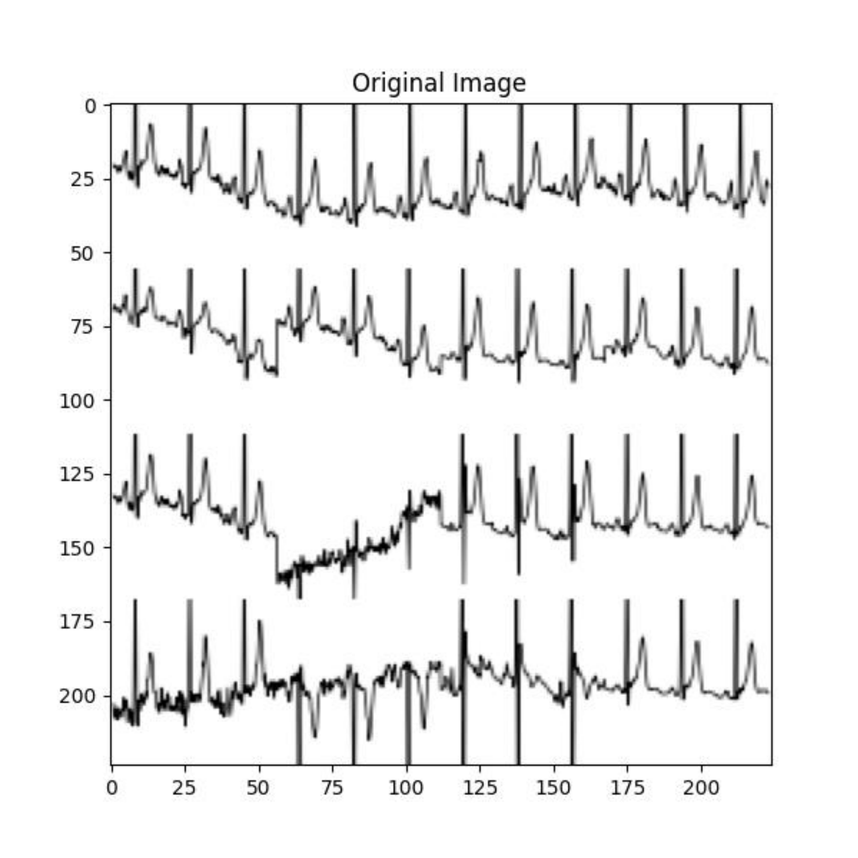
Class	Sensitivity	Specificity	F1-Score	AUC
CD	0.46	0.99	0.61	0.89
HYP	0.05	1.00	0.09	0.83
MI	0.37	0.95	0.36	0.82
Norm	0.88	0.76	0.85	0.89
STTC	0.65	0.82	0.42	0.79
Macro avg	0.482	0.904	0.466	0.84
Test loss				0.3278
Test accuracy				0.6731
Micro avg AUC				**0.89**

Detailed test results

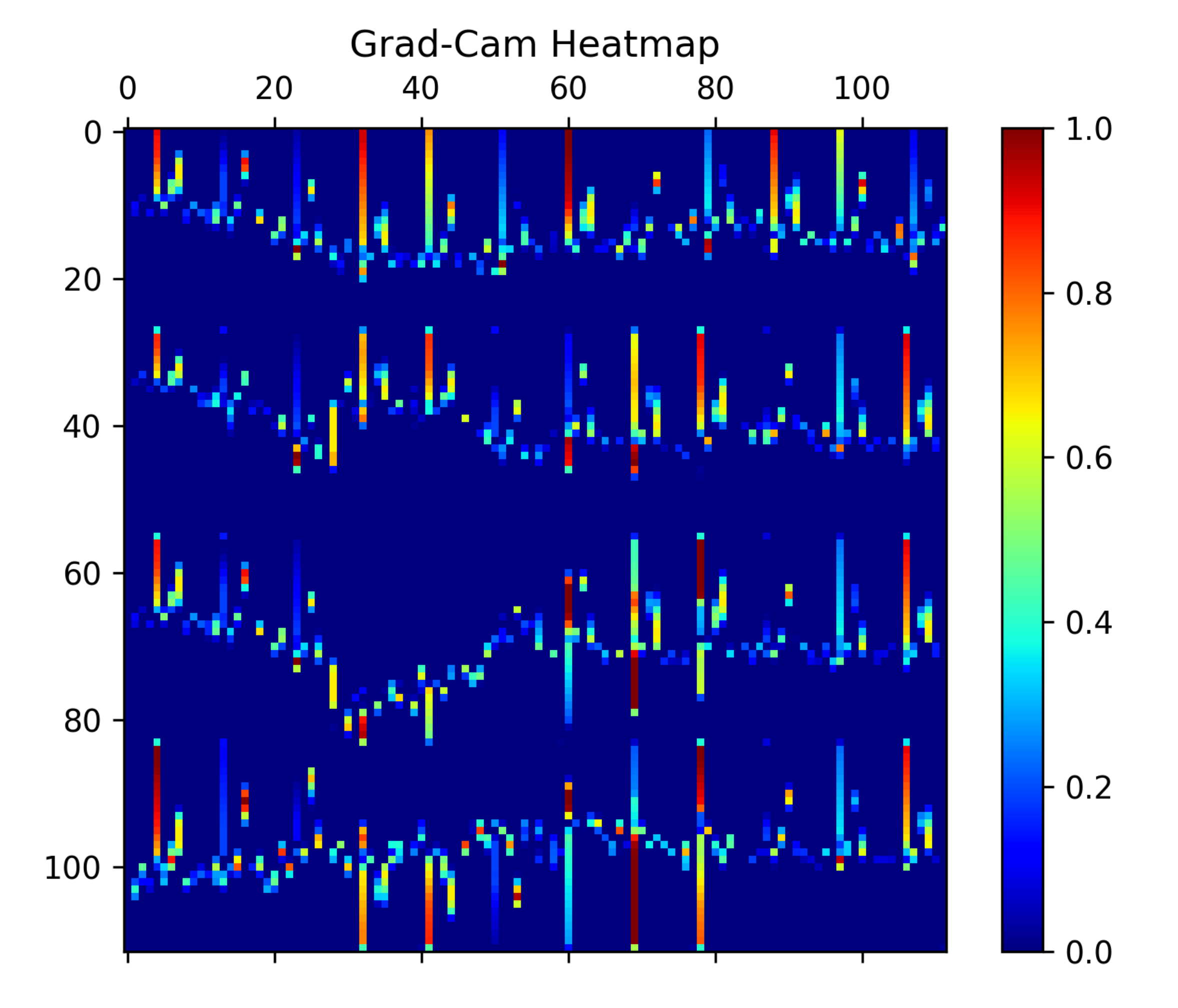
AUC	Guidelines
0.5-0.6	No discrimination
0.6-0.7	Poor discrimination
0.7-0.8	Acceptable discrimination
0.8-0.9	Good discrimination
0.9 - 1	Excellent discrimination

AUC interpretation guidelines

Model 3 Interpretability analysis



12 lead ECG iamge sample



Grad-CAM

Raspberry Pi deployment

Main components of the equipment

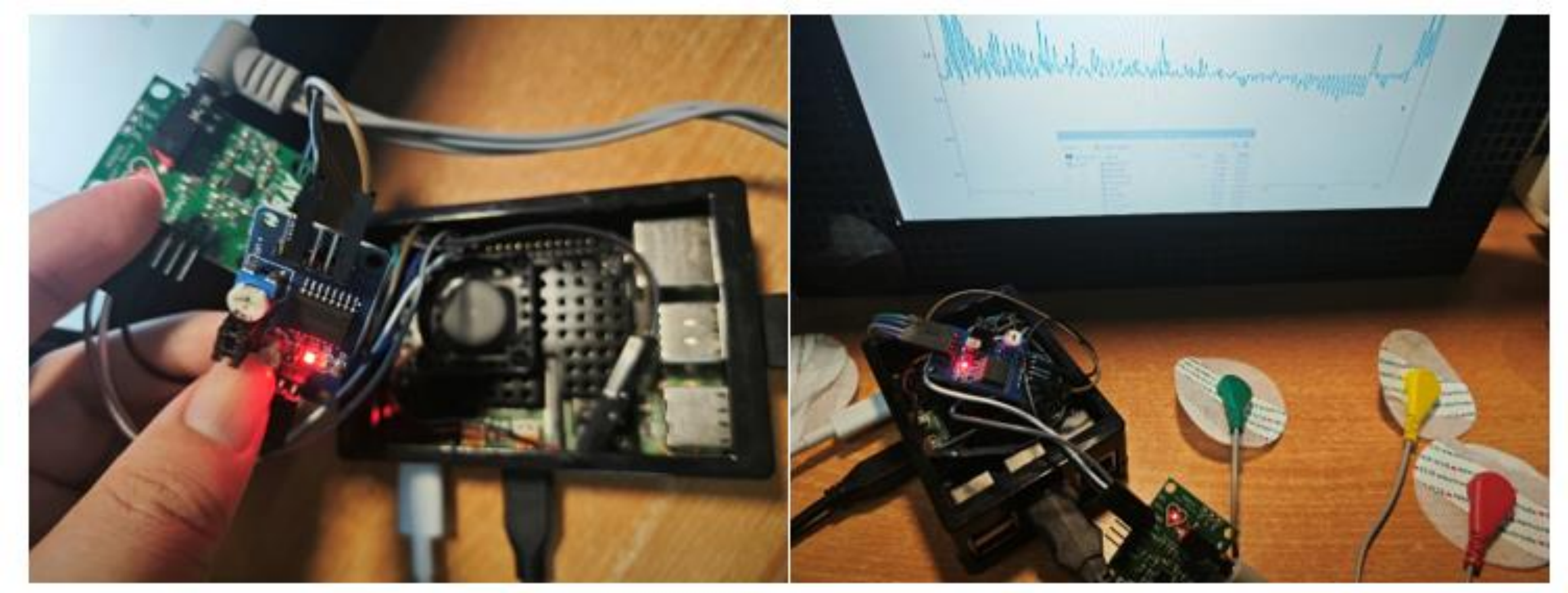
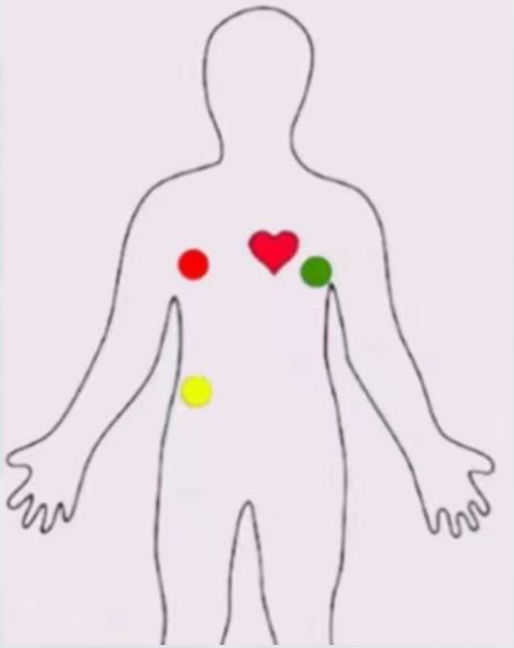
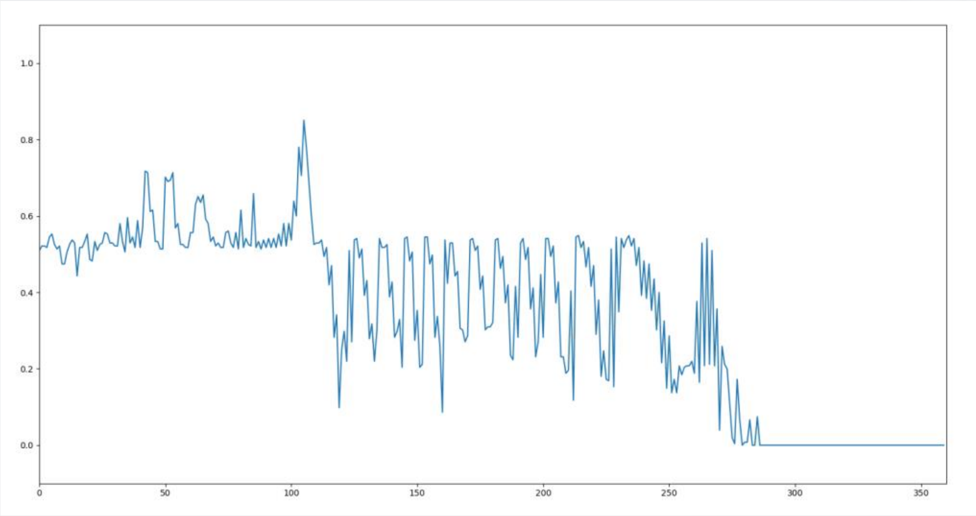


Photo of equipment assembly and power on

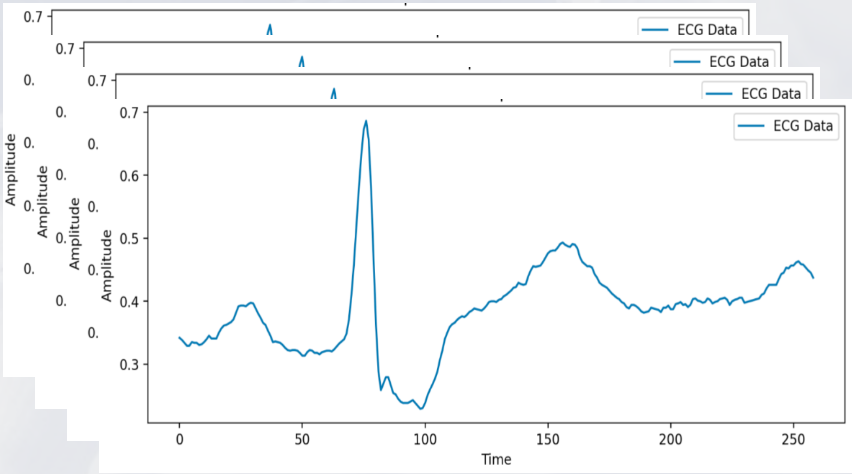


Lead connection position

Raspberry Pi deployment



The visualization of the acquisition results of a 10s 360Hz ECG signal



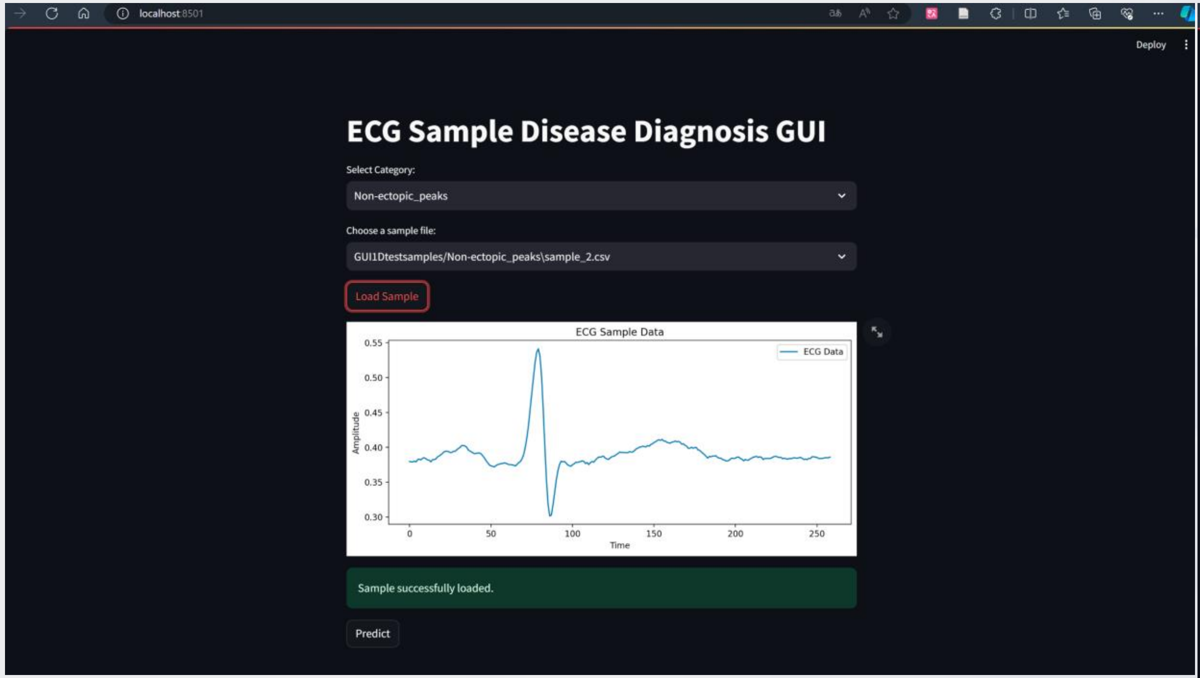
Samples after signal processing and segmentation

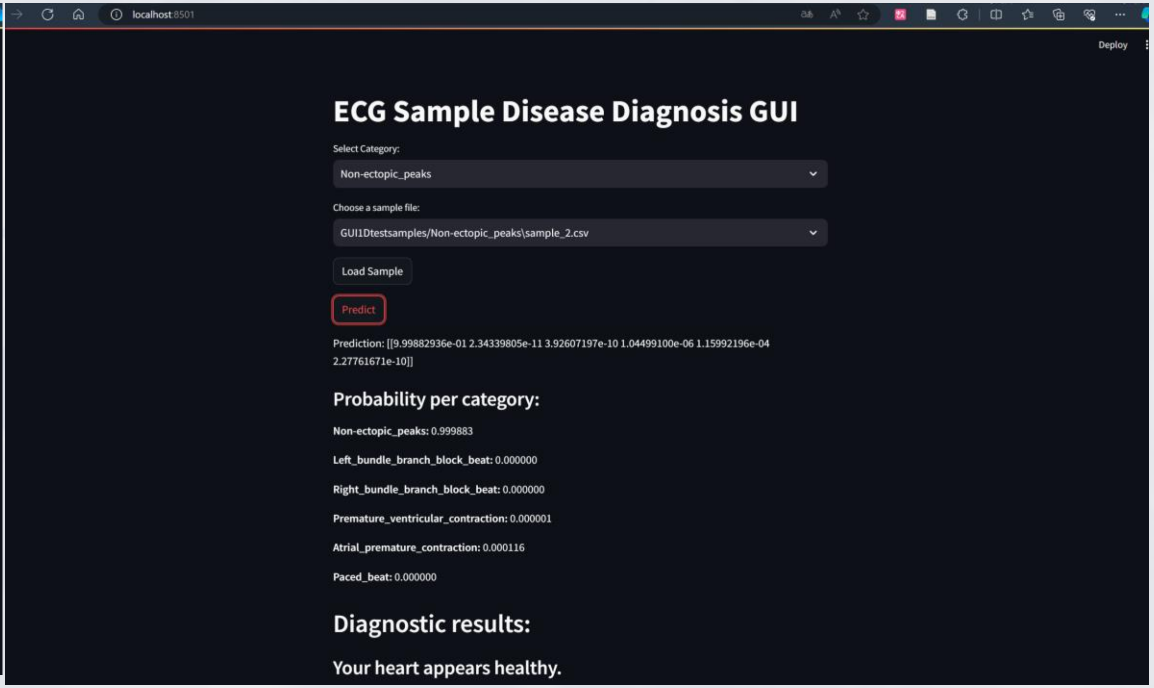
ResECANet model converted to TensorFlow Lite format

```
INFO: Created TensorFlow Lite XNNPACK delegate for CPU.
Predicted labels for all beats: ['N', 'N', 'N', 'N', 'N', 'N', 'N', 'N', 'N', 'N
', 'N', 'N', 'N', 'A']
The heartbeat appears to be normal. Occurrences: 13
Atrial premature contraction detected. Occurrences: 1
```

Model inference executed on Raspberry Pi

GUI





GUI web page

04 Conclusion

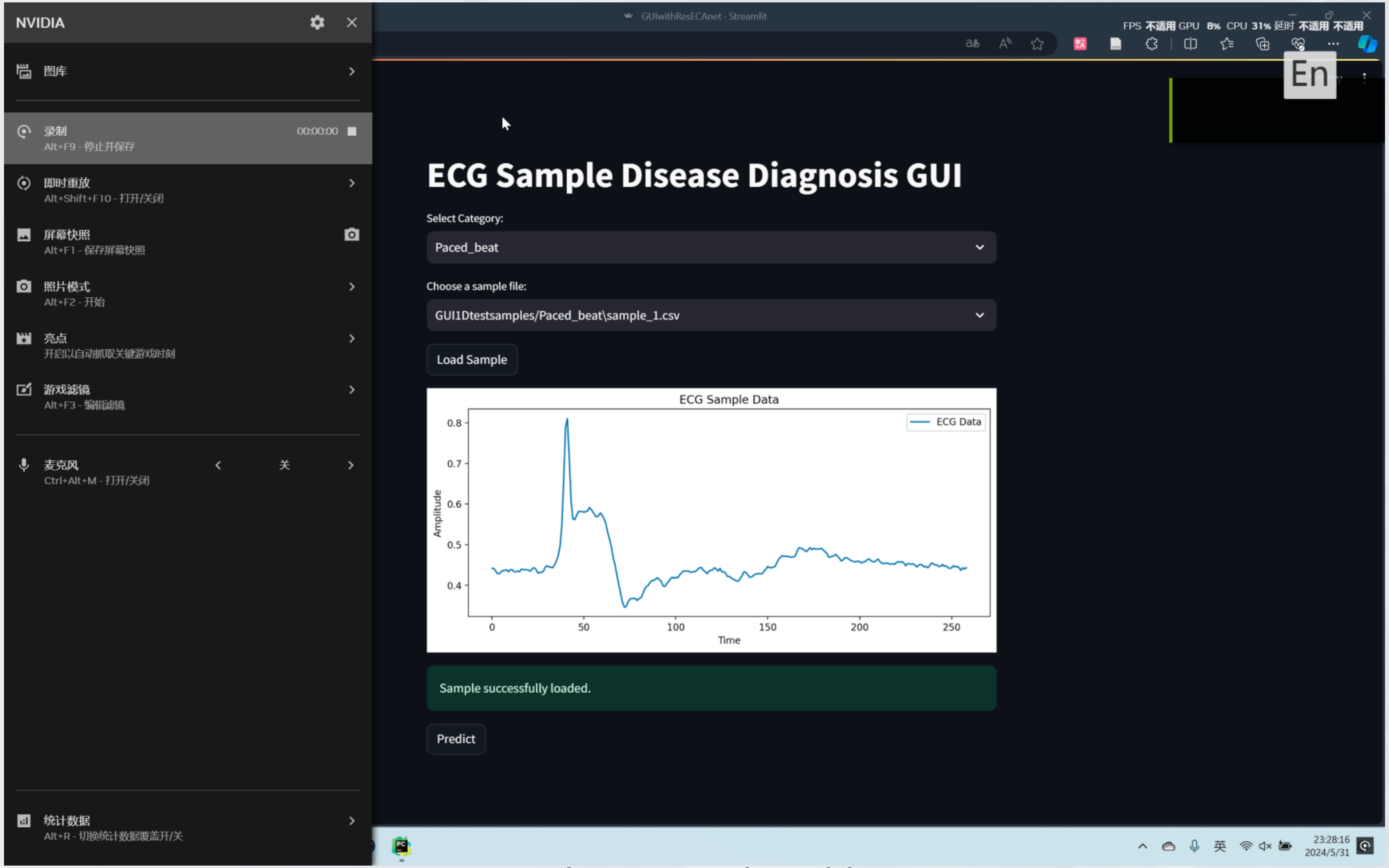
Conclusion

- **Achievement:**
- To sum up, all the Objectives have been achieved

- **limitations:**
- The diversity of heart diseases and the inevitable bias and noise in ECG data
- Model architecture and components may not be the most suitable for ECG classification
- For interpretable analysis, the depth of explanation for the decision-making process of the model is insufficient

- **Future job:**
- Explore diversity and less biased datasets
- Further progress in exploring more powerful model architectures and optimization methods for accuracy and robustness.
- Optimizing the computational cost of diagnostic equipment to make automated ECG disease detection easier to obtain

GUI



GUI demonstration video

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Thanks for listening!