# AI and Machine Learning for Detecting Myocardial Infarction

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# Contents

- **Objectives**:to infer 5-year incident AF risk using 12-lead ECGs in patients receiving longitudinal primary care at Massachusetts General Hospital (MGH).
- **Method**:Convolutional neural network (ECG-AI)
- **Innovation Point**:
  - Artificial intelligence–based analysis of 12-lead ECGs has similar predictive usefulness as an established clinical risk factor model for incident atrial fibrillation (AF), and both are complementary.
  - An ECG–artificial intelligence model for AF had predictive usefulness across independent study samples, discriminated risk in patients with heart failure and stroke, and was applicable to single-lead ECG tracings.

Circulation,Q1,B1,IF35.5,2022,DOI: 10.1161/CIRCULATIONAHA.121.057480,PMID: 34743566

- **Input**:a single 12-lead ECG containing a time series of 5000 voltage measurements for each of 12 leads sampled at 500 Hz and lasting 10 seconds
- Rather than binary classification, ECG-AI used an encoding and loss function
- the ECG-AI encoding divided time into discrete bins

Circulation,Q1,B1,IF35.5,2022,DOI: 10.1161/CIRCULATIONAHA.121.057480,PMID: 34743566

- The encoding quantizes the total follow-up time into $n$ bins.
- The censoring vector, $V_{CENSOR}$, is 0 for every time bin in which the individual was censored and 1 for time bins during which they remained in the risk set.
- The event vector, $V_{AF}$, is 1 if an AF diagnosis falls within that time bin, otherwise it is 0.
- ECG-AI emits a vector, $V_{PREDICT}$, of length n representing AF survival probability at each time bin.
- The loss function minimizes the negative log likelihood of ECG-AI' s predictions. The likelihood is factored into contributions from time bins survived and time bins with events.

$$L = -\sum \log(L_{\text{survival}} + L_{\text{event}})$$

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# ECG-Based Deep Learning and Clinical Risk Factors to Predict Atrial Fibrillation

- minimize

$$L = -\sum \log(L_{\text{survival}} + L_{\text{event}})$$

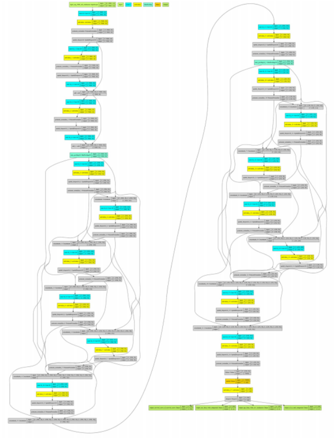
where

$$L_{\text{survival}} = 1 - (V_{\text{AF}} * V_{\text{predict}})$$

$$L_{\text{event}} = (V_{\text{censor}} * V_{\text{predict}}) + (1 - V_{\text{censor}})$$

- In this way, censored individuals do not contribute to the loss at time bins after censoring (e.g., earliest of death or last follow-up).

Circulation,Q1,B1,IF35.5,2022,DOI: 10.1161/CIRCULATIONAHA.121.057480,PMID: 34743566



- Briefly, the model takes 10 seconds of continuous 12-lead ECG waveform data as input into the first convolutional layer. The fully-connected layers take convolved ECG waveform data only to produce an estimate of time to AF (primary) as well as predictions of age, sex, and presence of AF in the diagnostic statement (secondary).
- Conv1D = one-dimensional convolution, MaxPooling1D = one-dimensional maximum pooling

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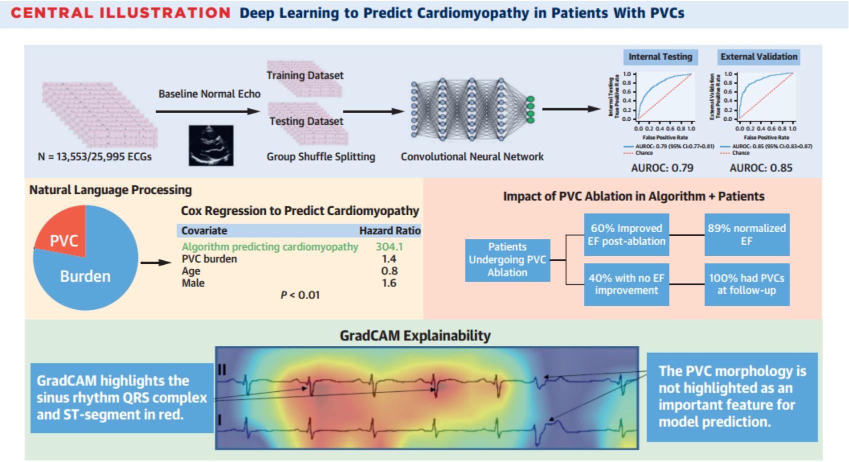
# A Novel ECG-Based Deep Learning Algorithm to Predict Cardiomyopathy in Patients With Premature Ventricular Complexes

- **Objectives**:aims to assess a deep-learning model to predict cardiomyopathy among patients with PVCs.
- **Method**:the largest available pretrained ResNet model (ResNet-152)
- ECG data consists of XML files containing waveform data for leads I, II, and V1V6. The remaining leads (III, aVF, aVL, and aVR) are called "derived leads" in that they only contain information present within other leads.
- ECG waveforms were subject to noise reduction by applying the Butterworth Bandpass filter, followed by a median filter.
- Resulting waveform data were plotted to images to allow use of 2-dimensional convolutional neural networks.

JACC Clin Electrophysiol,Q1,B1,IF8.0,2023,DOI:10.1016/j.jacep.2023.05.025,PMID: 37480862

# A Novel ECG-Based Deep Learning Algorithm to Predict Cardiomyopathy in Patients With Premature Ventricular Complexes



- We selected the largest available pretrained ResNet model (ResNet-152) as the starting point for our analyses.
- Using models pretrained on natural images allows for better performance with less data, while also requiring less time to achieve an optimal solution.
- Data were split based on group shuffle splitting which removes the potential for data leakage by ensuring that no patients are present in both the training and testing groups.
- We used gradient-weighted class activation mapping (GradCAM) methodology for generating class activation maps.

JACC Clin Electrophysiol,Q1,B1,IF8.0,2023,DOI:10.1016/j.jacep.2023.05.025,PMID: 37480862

- **Major Contributions**:
  - the signals of each patient are grouped to ensure that they can only be assigned to one of the partitions
  - a different combination of Principal Component Analysis (PCA) and Discrete Wavelet Transform (DWT)
  - By utilizing end-to-end deep neural networks, we are able to build efficient models that require only few steps to detect and localize MI from the raw signals.
- **Method**:
  - a classic ECG processing method with a novel configuration including a shallow neural network (NN)
  - an end-to-end convolutional neural network

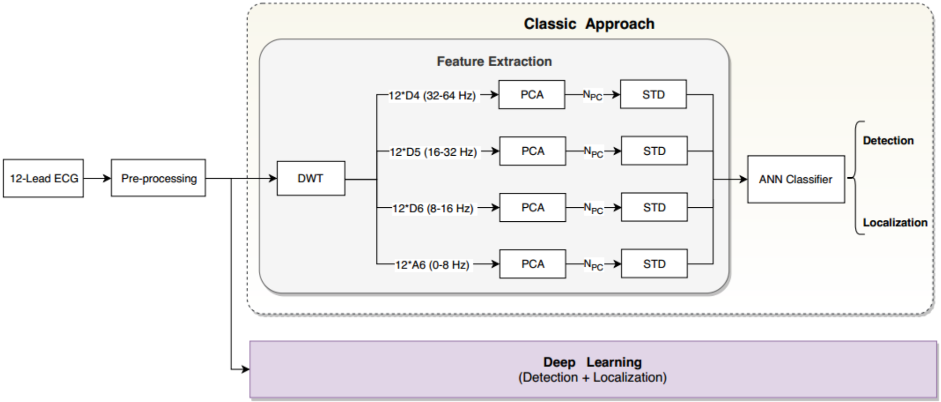
Applied Soft Computing,Q1,B1,IF7.2,2020,DOI: 10.1016/j.asoc.2020.106383

# Automating Detection and Localization of Myocardial Infarction using Shallow and End-to-End Deep Neural Networks



| Features | | Research Studies | [25] | [29] | [30] | [31] | [21] | [32] | [33] | [34] | [35] | [36] | [37] | [38] | [39] | [40] | [41] | P.M. 1 | P.M. 2 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Study Characteristics | Study type | Detection | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| | | Localization | ✓ | | | | | ✓ | | | | | | ✓ | ✓ | | ✓ | ✓ | ✓ |
| | Data types & preparation | Number of leads | 12 | 1 | 1 | 3 | 12 | 12 | 1 | 1 | 3 | 3 | 1 | 8 | 12 | 12 | 1 | 12 | 12 |
| | | Beat analysis | ✓ | | ✓ | | | ✓ | ✓ | | | ✓ | ✓ | | ✓ | | ✓ | | |
| | | Record analysis | | | | ✓ | ✓ | | | ✓ | ✓ | | | ✓ | | ✓ | | ✓ | ✓ |
| | | Intra-information segmentation | – | – | – | ✓ | ✓ | – | – | No | – | ✓ | No | No | No | ✓ | – | ✓ | ✓ |
| | Morphological analysis | ST, QRS, P wave segmentation | | | | | ✓ | | | | | | | | | | | | |
| Transformation & decomposition methods | | DWT | ✓ | | | | | | | | | | ✓ | | ✓ | | ✓ | ✓ | |
| | | FAWT | | | ✓ | | | | | | | | | | | | | | |
| | | DFT | | | | | | | | | | ✓ | | | | | | | |
| | | EWT | | | | | | | | | | | | | | ✓ | | | |
| Feature Extraction | | Statistical feature investigation | ✓ | | | | ✓ | | | | | | | | | ✓ | | | |
| | | PCA | | | | | ✓ | | | | | | | | | | | ✓ | |
| Classification methods | Traditional ML | ANN | | | ✓ | | | | | | | | | | | | | ✓ | |
| | | Random Forrest | | | ✓ | | | | | | | | | | | | | | |
| | | SVM | | | ✓ | | ✓ | | | | | | | | | | | | |
| | | Logistic Regression | | | | | | | | | | ✓ | | | | | | | |
| | | kNN | ✓ | | | | | | | | | | ✓ | | | | | | |
| | Deep learning | Deep Neural Network | | | | | | | | | | | | | | ✓ | | | |
| | | Decision Tree | | | | | | | | | | | | | | | ✓ | | |
| | | CNN | | ✓ | | ✓ | | ✓ | ✓ | ✓ | ✓ | | | ✓ | ✓ | | | | ✓ |
| | | RNN | | | | | | | | | | | | ✓ | | | | | |
| | | LSTM | | | | | | | ✓ | | | | | ✓ | | | | | |

# Automating Detection and Localization of Myocardial Infarction using Shallow and End-to-End Deep Neural Networks



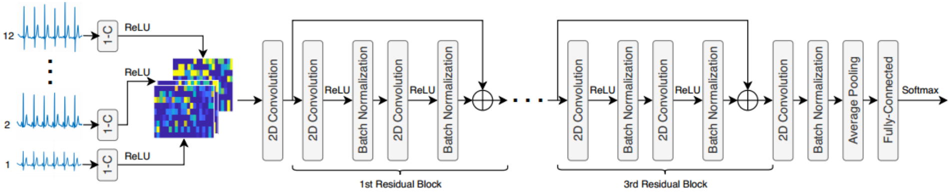

Applied Soft Computing,Q1,B1,IF7.2,2020,DOI: 10.1016/j.asoc.2020.106383

- After the pre-processing phase, a set of DWT and PCA transformations are performed to extract distinctive features from the signals.
- After de-noising ECG signals, signals are decomposed into the wavelet coefficients. Wavelet transform (WT) is a mathematical convolution of a signal with a specific wavelet function to represent the timefrequency characteristics of a signal.
- After decomposing the signals, PCA is used to extract the temporal deviations of ECG signals. PCA serves as a dimension reduction method to represent underlying variations of the data in a fewer linearly independent features

Applied Soft Computing,Q1,B1,IF7.2,2020,DOI: 10.1016/j.asoc.2020.106383

# Automating Detection and Localization of Myocardial Infarction using Shallow and End-to-End Deep Neural Networks



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# Deep Learning for Premature Ventricular Contraction-Cardiomyopathy: Are We Digging Deep Enough?

- SHOULD THE MODEL INPUT BE MATRICES OR IMAGES ?
    - Lampert et al did start out with ECG waveform data but later plotted them as images.
    - Though this conversion facilitates human comprehension, it is an extraneous step that inadvertently confines the AI to human-like processing.
    - Liberating the AI from such human-oriented constraints could potentially lead to more optimal outcomes.
    - The conversion introduces an unnecessary restriction in the form of image resolution and generates an excess of superfluous white pixels surrounding the ECG tracing.
    - Consequently, it can be questioned whether this is worth the additional computational currency.

JACC Clin Electrophysiol,Q1,B1,IF8.0,2023,DOI:10.1016/j.jacep.2023.07.003,PMID: 37611994

# Deep Learning of Electrocardiograms in Sinus Rhythm From US Veterans to Predict Atrial Fibrillation

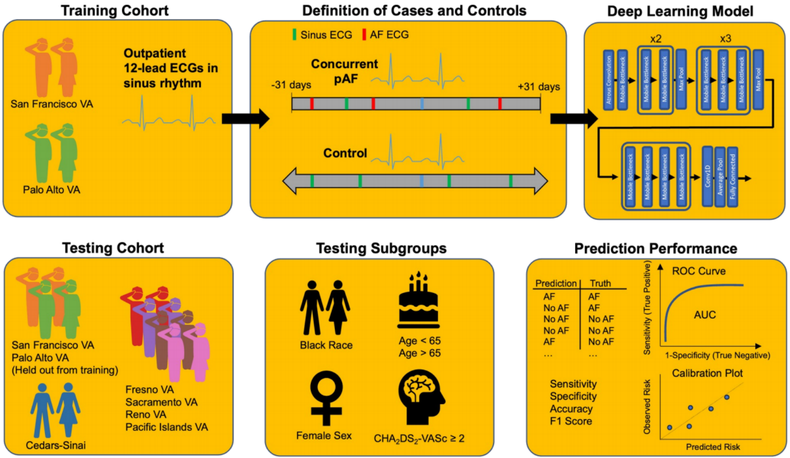


- **Input**:ECG waveform data was acquired at 250 Hz and extracted as 10 second, 12 x 2500 matrices of amplitude values, stored as base64 text. ECGs underwent baseline wander correction using median filtering at 200ms and 600ms intervals and z-score normalization.
- **Method**: an atrous convolutional neural network

JAMA Cardiol,Q1,B1,IF14.8,2023,DOI:10.1001/jamacardio.2023.3701,PMID: 37851434

# Deep Learning of Electrocardiograms in Sinus Rhythm From US Veterans to Predict Atrial Fibrillation






JAMA Cardiol,Q1,B1,IF14.8,2023,DOI:10.1001/jamacardio.2023.3701,PMID: 37851434

- **Limitation**:
  - there was site-to-site variability in the average number of ECGs per patient, and we might expect that this study' s patient population with ECGs has a higher prevalence of cardiovascular disease and AF.
  - While we used all data from the ECG database and electronic health records to identify cases of AF, it remains likely that there were patients in the control group who had undiagnosed AF.

JAMA Cardiol,Q1,B1,IF14.8,2023,DOI:10.1001/jamacardio.2023.3701,PMID: 37851434

# Development and validation of machine learning algorithms based on electrocardiograms for cardiovascular diagnoses at the population level

- **Objectives**: while existing studies have mainly concentrated on individual labels, there hasn't been any prior research developing a predictive system for the simultaneous detection of these specific conditions.
- **Method**: ResNet-based deep learning (DL) using ECG tracings and extreme gradient boosting (XGB) using ECG measurements.

NPJ Digit Med,Q1,B1,IF12.4,2024,DOI:10.1038/s41746-024-01130-8.PMID: 38762623

## Development and validation of machine learning algorithms based on electrocardiograms for cardiovascular diagnoses at the population level

- The goal of the prediction model was to output calibrated probabilities for each of selected 15 conditions.
- These learned models could use ECGs that were acquired at any time point during a healthcare episode. When training the model, we used all ECGs (multiple ECGs belonging to the same episode were included) in the training/development set to maximize learning.
- However, to evaluate our models, we used only the earliest ECG in a given episode in the test/ holdout set, with the goal of producing a prediction system that could be employed at the point of care, when the patient' s first ECG is acquired during an ED visit or hospitalization (See section 'Evaluation' below for more details).

NPJ Digit Med,Q1,B1,IF12.4,2024,DOI:10.1038/s41746-024-01130-8.PMID: 38762623

# Development and validation of machine learning algorithms based on electrocardiograms for cardiovascular diagnoses at the population level

- (a) ECG only (DL: ECG trace);
- (b) ECG + age, sex (DL: ECG trace, age, sex [which is the primary model presented in this study]);
- (c) XGB: ECG measurement, age, sex.
- gradient-boosted tree ensembles (XGB) models
- deep convolutional neural networks for the models with ECG voltage-time series traces.

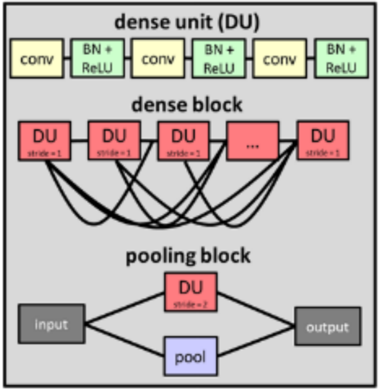
NPJ Digit Med,Q1,B1,IF12.4,2024,DOI:10.1038/s41746-024-01130-8.PMID: 38762623

## A deep learning algorithm for detecting acute myocardial

- **Objectives**: aim to develop a deep learning model (DLM) as a diagnostic support tool based on a 12-lead electrocardiogram.
- **Innovation Point**:
  - Integration of a DLM may assist frontline physicians in recognising AMI in a timely and precise manner to prevent delayed diagnosis or misdiagnosis of AMI and thereby provide prompt reperfusion therapy.
  - The diagnostic power for STEMI and NSTEMI by the DLM and conventional cardiac troponin I (cTnI) was also evaluated.

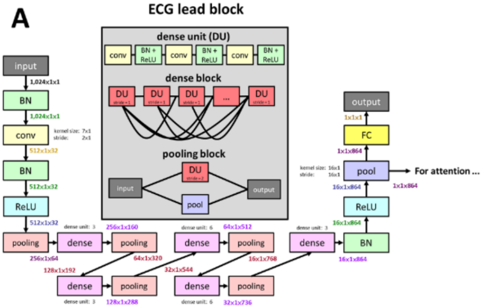
EuroIntervention,Q1,B1,IF7.6,2021,DOI:10.4244/eij-d-20-01155,PMID: 33840640

- We defined a "dense unit" as a neural combination as follows:
- (1) a batch normalisation layer to normalisation.
- (2) a rectified linear unit (ReLU) layer for non-linearisation.
- (3) a 1×1 (3×1) convolution layer with 4K filters to reduce the dimensions of the data (extract features).



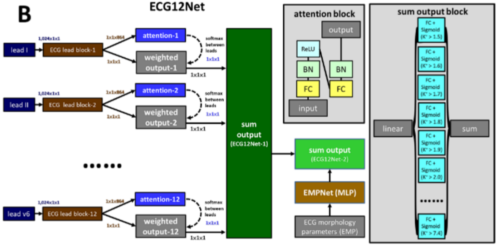

EuroIntervention,Q1,B1,IF7.6,2021,DOI:10.4244/eij-d-20-01155,PMID: 33840640

- Dense blocks cannot be concatenated when the size of the feature maps changes. Thus, a pooling block was used to concatenate each dense block for downsampling in our architecture.Each dense block was concatenated by the pooling block to integrate the features of the previous blocks.



## A deep learning algorithm for detecting acute myocardial

- ECG12Net comprised 12 ECG lead blocks corresponding to lead sequences. They designed an attention mechanism based on a hierarchical attention network to concatenate these blocks, increasing the interpretive power of ECG12Net.

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$$\text{MultiLogLoss} = -\frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{m} y_{i,j}\log(p_{i,j})$$

EuroIntervention,Q1,B1,IF7.6,2021,DOI:10.4244/eij-d-20-01155,PMID: 33840640

# Machine learning for diagnosis of myocardial infarction using cardiac troponin concentrations

- **Objectives**: to identify patients with an adjudicated diagnosis of type 1, type 4b or type 4c myocardial infarction during the index hospital admission.
- **Methods**: Four statistical methods
  - Logistic Regression
  - Naive Bayes
  - Random Forest
  - Extreme Gradient Boosting (XGBoost)

Nature Medicine,Q1,B1,IF58.7,2023,GSID: nWVNwATkyUAJ

## Machine learning for diagnosis of myocardial infarction using cardiac troponin concentrations

- The output of the XGBoost model is a probability that is computed by performing an inverse logit transformation of the sum of the weights of the terminal nodes of the trained model.
- The mathematical formula for the gradient boosting model can be described as

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i), f_k \in F$$

- XGBoost optimizes an objective function of the form

$$Obj = \sum_{i=1}^{N} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k)$$

Nature Medicine,Q1,B1,IF58.7,2023,GSID: nWVNwATkyUAJ

# Machine learning for diagnosis of myocardial infarction using cardiac troponin concentrations



- In brief, gradient boosting employs an ensemble technique to iteratively improve model accuracy for regression and classification problems.
- An XGBoost model was the best-performing model
- These XGBoost models were combined within a single clinical decision support system called CoDE-ACS, which computes a score (0–100) corresponding to an individual patient’s probability of myocardial infarction

Nature Medicine,Q1,B1,IF58.7,2023,GSID: nWVNwATkyUAJ

# Machine learning for ECG diagnosis and risk stratification of occlusion myocardial infarction



- **Objectives**:
  - identify the most important ECG features driving the classifications
  - OMI risk score provides enhanced rule-in and rule-out accuracy
- **Methods**: fit 10 machine learning classifiers
  - regularized logistic regression
  - linear discriminant analysis
  - support vector machine (SVM)
  - Gaussian naive Bayes
  - Random Forest
  - gradient boosting machine
  - extreme gradient boosting
  - stochastic gradient descent logistic regression
  - k-nearest neighbors
  - artificial neural networks

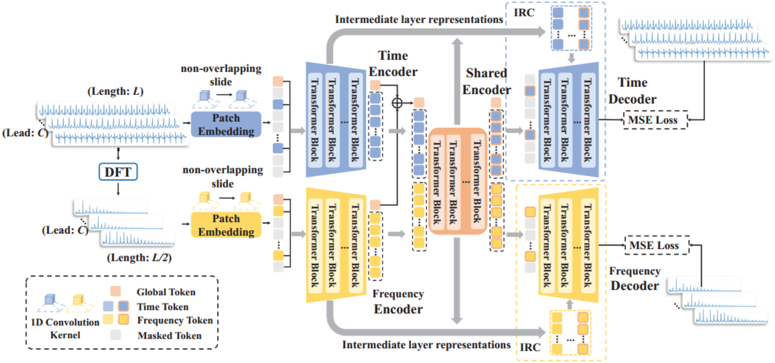
Nature Medicine,Q1,B1,IF58.7,DOI:2023,10.1038/s41591-023-02396-3,GSID: dqWsaQy_DA8J

## Bimodal Masked Autoencoders with Internal Representation Connections for Electrocardiogram Classification

- **Background**: the majority of methods concentrate solely on time domain information, overlooking the information originating from additional modalities or perspectives.
- **Method**: a novel bimodal masked autoencoder framework (BMIRC)
- **Innovation Point**:
  - a novel bimodal masked autoencoder framework for time-frequency joint modeling
  - internal representation connections (IRC) from the encoder to the decoder

# Bimodal Masked Autoencoders with Internal Representation Connections for Electrocardiogram Classification






- $ECG(Time) \xrightarrow{DFT} ECG(Frequency)$
- $ECG(T\&F) \Rightarrow Encoder(T\&F) \Rightarrow Encoder(Shared) \Rightarrow Decoder \Leftarrow IRC$

- The tokens of T and F can be expressed as

$$Z_t = [z_t^1, z_t^2, \dots, z_t^{\frac{L}{S}}] \in \mathbb{R}^{\frac{L}{S} \times D}$$

$$Z_f = [z_f^1, z_f^2, \dots, z_f^{\frac{L}{2S}}] \in \mathbb{R}^{\frac{L}{2S} \times D}$$

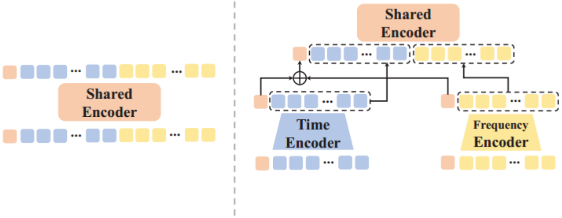
- learnable position embeddings $\mathrm{PE} \in \mathbb{R}^{N \times D}$ are integrated into the patch embeddings

$$\tilde{I}_m = Z_m + \mathrm{PE}_m$$

$$I_m = \mathrm{Concat}(z_g^m, \tilde{I}_m)$$

- a random masking strategy, meaning that each token has the same probability of being masked.

# Bimodal Masked Autoencoders with Internal Representation Connections for Electrocardiogram Classification



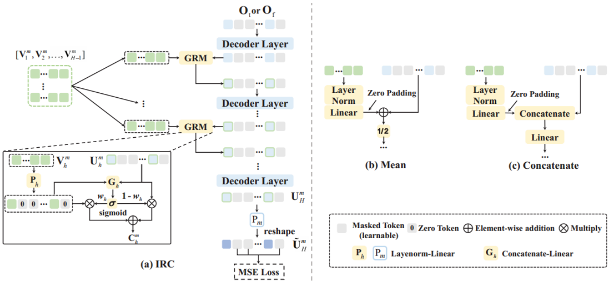

(a) All Shared (b) Specific-Shared(Ours)

- the global tokens of time and frequency modalities are added and inserted at the first position of the sequence, with the other tokens concatenated sequentially.

$$\tilde{O}_m = LN(O_m) = [\tilde{o}_g^m, \tilde{o}_1^m, \tilde{o}_2^m, \dots, \tilde{o}_n^m]$$

$$O_0^s = [o_g^t + \tilde{o}_g^f, \tilde{o}_1^t, \tilde{o}_2^t, \dots, \tilde{o}_n^t, \tilde{o}_1^f, \tilde{o}_2^f, \dots, \tilde{o}_n^f]$$

$$O_s = \Theta(O_0)$$




- gated representation mixer called GRM

$$\hat{V}_h = P_h(V_h)$$

$$w_h = \sigma(G_h(\hat{V}_h, U_h^m))$$

$$C_h^m = w_h * \hat{V}_h + (1 - w_h) * U_h^m$$

$$U_{h+1}^m = \Lambda_{h+1}(C_h^m)$$

# Limitation

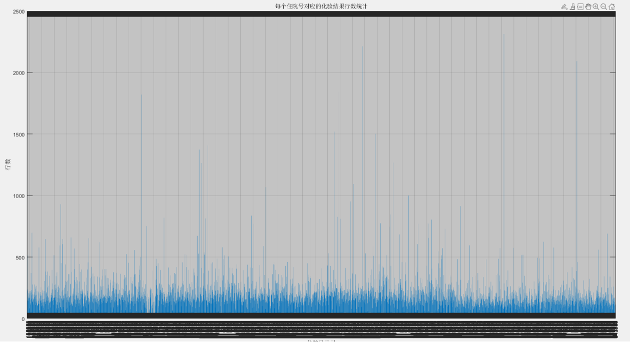


- Multimodal Data
- Missing
- Data Leakage
- DWT
- Matrices or Images

# Dataset-化验结果——全院



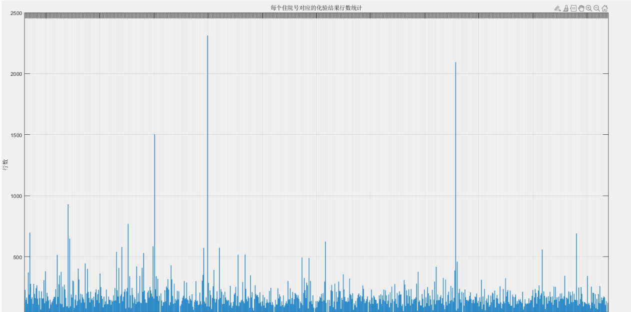
- number of samples: 608217
- number of patients: 3022
- max samples of patients: 2313
- average samples of patients: 201



# Dataset-全院记录中有心电图的人员记录

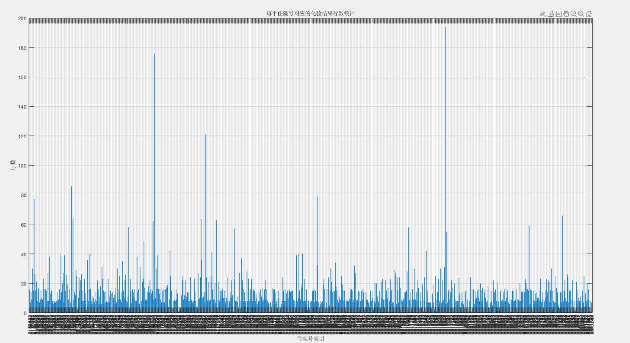


- number of samples: 137996
- number of patients: 748
- max samples of patients: 2313
- min samples of patients: 8
- average samples of patients: 184



# Dataset-筛选有心电图检查的人指标数据

- number of samples: 10419
- number of patients: 738
- max samples of patients: 194
- average samples of patients: 14



# Dataset-心脏超声



- number of samples: 3341
- number of patients: 2422
- max samples of patients: 11
- average samples of patients: 1.38