Application of Contrastive Learning on ECG Data: Evaluating Performance in Japanese and Classification with Around 100 Labels.

Junichiro Takahashi, JingChuan Guan, Masataka Sato, Kaito Baba,
Kazuto Haruguchi, Daichi Nagashima, Satoshi Kodera, Norihiko Takeda

Summary: ・Matching similar performance on medical reports compared to before ・With more labels ・Apply to non-English (Japanese)・ Contrastive learning on Electrocardiogram is effective even with model dependent on past inputs

Electrocardiogram (ECG):

- Reports to detect heart disease
- Easy to obtain -> widely used

But

・Complex interpretation
・Result depend on expertise level

12-lead ECG
shape of (12, 5000)

Previous research:
1. AI application on ECG overly simplified labels
2. The models did not depend on past inputs like BERT
3. Only English

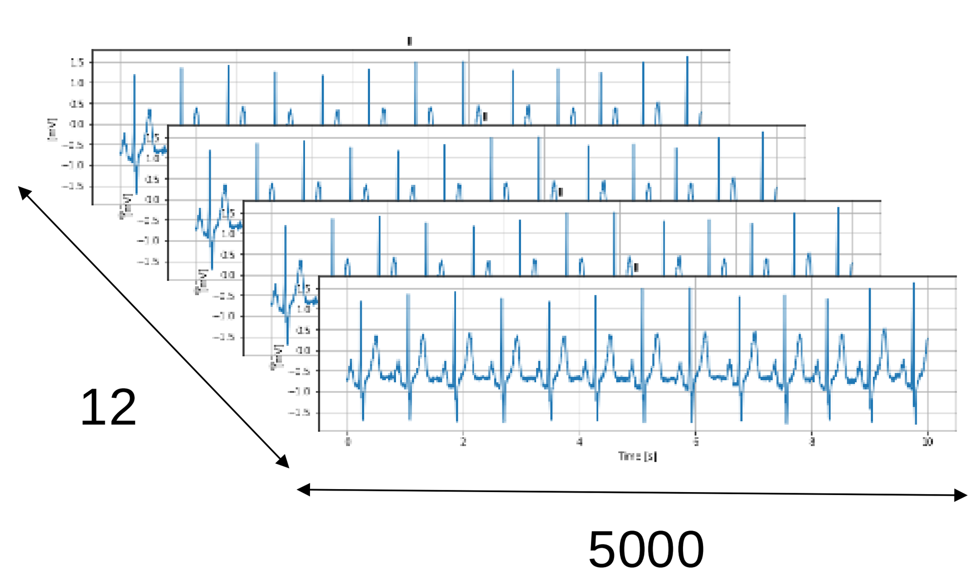
Motivation:
Develop AI system to assist in the interpretation of ECG
Bridge the gap in expertise

Method:

ECG auto-interpretation Datasets

- Timeseries data from 12 ECG leads(a 10-second interval with a sampling rate of 500 Hz) (5,000 matrix).
- 38,245 ECG data in the UTokyo Hospital for train.
- Clinical data, not research data
- No patient overlap

ECG Data



ECG auto-interpretation Datasets
- ECG reports interpreted by Fukuda Denshi.
- About 100 labels selected by two cardiologists out of 157 ECG's labels.

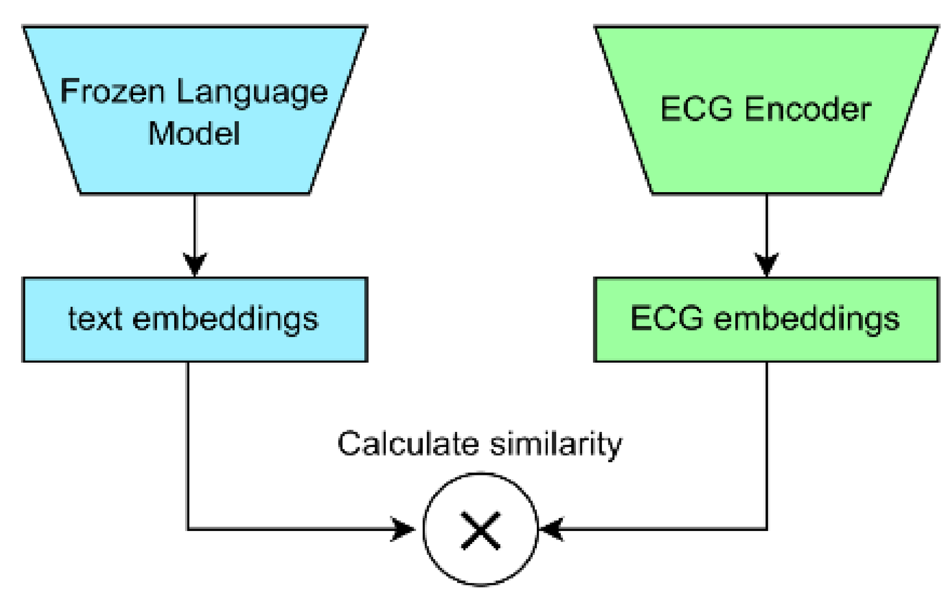
ECG reports

This ECG shows {reports}.
e.g.
This ECG shows Left Anterior Fascicular Block.

Contrastive Learning for ECG

- Extract ECG features by evaluating the similarity between medical representations and ECG waveforms.
- Autoregressive language model with medical knowledge
- ResNet1d18 as an ECG encoder.
- Learning rate: 1e-3, Weight decay: 1e-3, Global batch size: 32, Epoch: 200

Contrastive learning by using MedLlama3-JP-v2text and ResNet1d18



Result:

Results with the top 5 scores (excluding results with fewer than 10 labels)

Results with the top 5 scores		
Labels	Top-1 Accuracy	Top-5 Accuracy
Pacemaker Rhythm	89.41%	93.73%
Left Anterior Fascicular Block	88.00%	88.00%
Normal	78.40%	90.45%
Ventricular Couplet	77.78%	77.78%
Ventricular Bigeminy	76.92%	84.62%

Examples of diagnosis predictions ordered by logits

label: Short Run of Supraventricular Premature Contractions
predict: This ECG shows Ventricular Premature Contractions Couplets.
predict: This ECG shows Frequent Supraventricular Premature Contractions.
predict: This ECG shows Supraventricular Bigeminy.
predict: This ECG shows Supraventricular Premature Contractions.
predict: This ECG shows Short Run of Supraventricular Premature Contractions.

label: Suspected Inferior Wall Infarction
predict: This ECG shows Suspected Inferior Wall Infarction.
predict: This ECG shows Suspected Anterior Wall Infarction.
predict: This ECG shows Suspected Lateral Wall Infarction.
predict: This ECG shows Suspected High Posterior Wall Infarction.
predict: This ECG shows Suspected Acute Inferior Wall Infarction.

・High scores about Pacemaker Rhythm, Left Anterior Fascicular Block, Normal, Ventricular Couplet and Ventricular Bigeminy
・Competitive with previous research for ECG
・Semantic understanding of medical reports from top1-5 output

Discussion:

- Scores below criteria for productization
  - Score on echocardiography is especially lower
  - High score on Normal ECG classification but classification for Normal ECG is difficult for non experts
- Human doctors perform multimodal processing AI should follow this trend too.

Future Application

・Multimodal medical models due to our results of autoregressive language model widely used in recent large multimodal model
・Build multimodal medical models making diagnoses as doctors do
・Contribute to the development of ECG models for wearable devices

The University of Tokyo