# **Fairseq-Signals Results:**

# a. Summary of the paper:

- ECG is a widely used method for assessing heart health without invasive equipment.
- Deep learning models have been used to address heart issues like arrhythmia and myocardial infarction using ECG data.
- Two main challenges: limited labeled data and difficulties in adapting models to different ECG leads.
- A proposed method focuses on generalizing ECG data regardless of lead combinations.
- The paper introduces two key contributions: local and global contextualization of raw ECG inputs and masking tokens in the input stage.
- The method improves local representation power with a module called "wav2vec" and enhances global context with "Contrastive Multilead Self-Supervised Learning (CMSC)".
- The network optimization involves using two loss functions, one for masked time steps and another for global features.

## b. Setup:

- The transformer model is pretrained on the Physionet2021 and PTB-XL dataset by the proposed policy which is referred as wave2vec-cmsc-rlm(random lead masking).
- Then the pretrained model is finetuned on cardiac arrhythmia classification and patient identification tasks.
- The github repository <u>here</u> with few changes in the code was used for both pretraining and finetuning.
- The repository provides with preset configurations for the both tasks. The changes in pretraining are mentioned on the next page.
- For finetuning except for leads to load(kept as null), every other parameter was kept same as the pretrain config.

## **Commands:**

Training:

fairseq-hydra-train task.data=/absolute/path/to/manifest/cmsc --config-dir /path/to/examples/w2v\_cmsc/config/pretraining --config-name w2v\_cmsc\_rlm

## Finetuning:

fairseq-hydra-train task.data=/absolute/path/to/manifest\_tuning/finetune model.model\_path=/absolute/path/to/checkpoint criterion.report\_cinc\_score=True criterion.weights\_file=/absolute/path/to/weights.csv --config-dir path/to/examples/w2v\_cmsc/config/finetuning/ecg\_transformer --config-name diagnosis

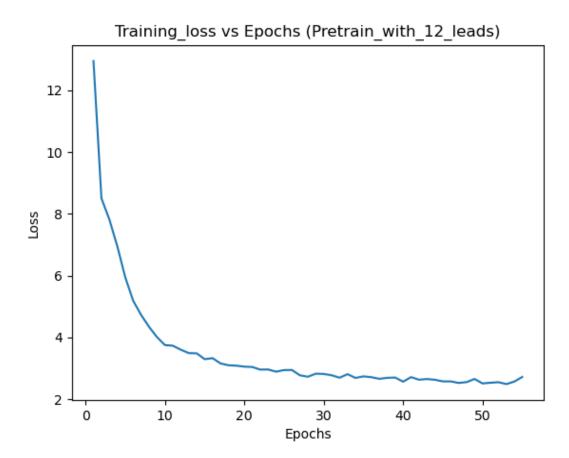
## # Pretrain Config

```
task:
  name: ecg pretraining
  data: ???
 perturbation mode: ["random leads masking"]
  p: [1.0]
  mask leads selection: random
  mask leads prob: 0.5
 normalize: false
  enable padding: true
 enable padding leads: true # Changed from false
 leads_to_load: '[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11]' #Changed
dataset:
 num_workers: 1 #Changed from 6
 max tokens: null
 batch size: 16 #Changed from 128
 valid subset: ""
 disable validation: true
distributed training:
  distributed world size: 1 #Changed from 4
criterion:
  name: wav2vec2 with cmsc
  infonce: true
 log keys: ["prob perplexity", "code perplexity", "temp"]
  loss_weights: [0.1, 10]
optimization:
 max_epoch: 55 # Changed from 200
  lr: [5e-5]
 update_freq: [2]
```

# c. Results:

## 1. Pretrain results:

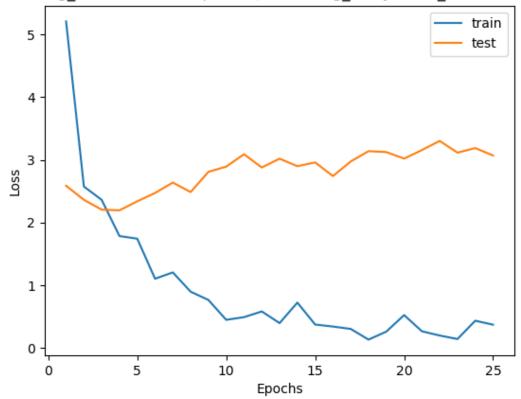
- As mentioned in the config file above, the model was trained until 55 epochs were completed.
- The training loss was equal to 2.552 with accuracy close to 61% on train split.
- The trajectory of the loss can be seen below in the "epoch vs loss" plot.

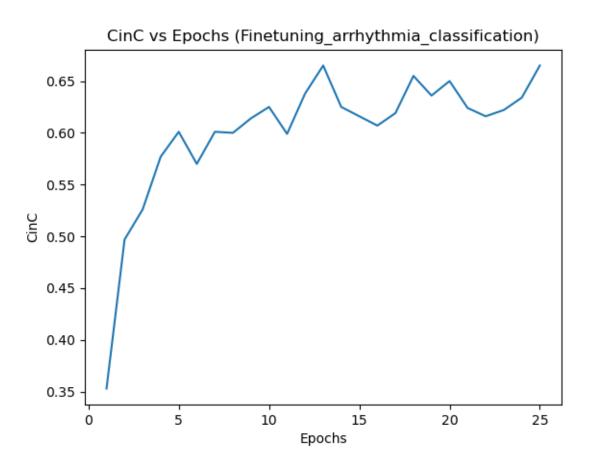


## 2. Finetune results:

- The checkpoint model that was trained for 55 epochs was used as the backbone for finetuning on arrhythmia classification task.
- It was finetuned for 25 epochs, and the loss was equal to 3.072 with CinC score equal to 0.665 on the test set.
- The results are summarized below with plots.

Training\_loss vs Test vs Epochs (Finetuning\_arrhythmia\_classification)





# d. Comments:

- The test loss stays moderately flat and marginally increases in the end. This can be a case of overfitting.
- The CinC score also increases, this maybe, because the model is performing on majority of the test datapoints, and the increase in loss is due to the minority ones.
- The paper reports a CinC score of  $0.732 \pm 0.004$  on arrhythmia classification task but here the score is 0.665 which is 0.06 units below the former value.
- The exact reasons need to be researched further.