Presenting MATE: Machine Approach To Ecg

MATE Team

Università degli Studi di Pavia

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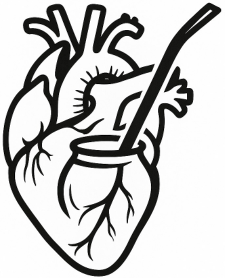


The Team

- Emirhan Kayar, Lead AI specialist;
- Lodovico Cabrini, Head of legal department;
- Alessandro Longato, Project coordinator;
- Libero Biagi, Communication manager and comic relief.

Scoping and Addressed Problem

- Since ECG analysis is still done mainly on paper by medical doctors, we chose to address the issue by introducing automation into the process.
- We settled on developing a deep learning based medical device to classify different types of arrhythmia given a 12-lead ECG signal.
- The real-life use case would be to integrate the system in ECG machines, both for hospital and home use, to have a fast and reliable first diagnosis in real time.

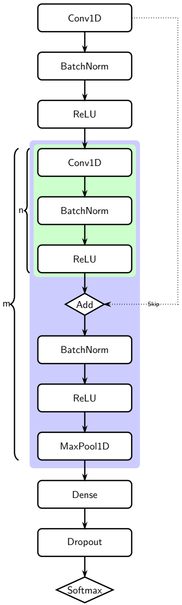
Internal Data

- We started from a dataset containing 10646 denoised and labeled 12-lead ECG signals, sampled at 500 Hz for 10s, created by Chapman University and Shaoxing People's Hospital.
- The labels are 11 rhythm types grouped into 4 approximately balanced classes (AFIB, GSVT, SB, SR).
- We settled on using denoised ECG signals as input, which we divided into training set (70%), validation set (15%), and internal test set (15%).
- We applied binning to shorten the sequences.
- The key issue that kept us from reaching the top performance was normalization. Once we realized that per-sample Min-Max normalization was the correct choice, we significantly improved our model performance.

External Data

- Since no study on AI applied to medicine is meaningful without testing on external data, we searched far and wide for it.
- We used 10834 samples from the PhysioNet/Computing in Cardiology Challenge 2020, filtered to have labels compatible with our internal data. We used data from 3 different centers (US, China, and Germany).
- We denoised the external data following the same procedure that the authors of the paper have used for the internal data. Then we applied binning and normalization as in the internal data.

Architecture



Key Architecture Features

- **Residual Learning**: Skip connections facilitate training of deeper architectures.
- **Hierarchical Processing**: Multiscale feature learning at different temporal resolutions.
- **Regularization**: BatchNorm throughout and Dropout prevent overfitting.

Performances

True \ Pred	0	1	2	3
0	0.85	0.12	0.00	0.02
1	0.14	0.86	0.00	0.00
2	0.01	0.00	0.96	0.04
3	0.05	0.04	0.13	0.78

Table: Confusion Matrix on External Data

Performances

Class	Precision	Recall	F1-Score	Support
0	0.65	0.85	0.74	1008
1	0.28	0.86	0.42	229
2	0.27	0.96	0.42	456
3	1.00	0.78	0.88	9141
Accuracy			0.80	10834
Macro Avg	0.55	0.86	0.61	10834
Weighted Avg	0.92	0.80	0.83	10834
AUC	0.9615			

Table: Classification Report on External Data

Fairness & Explainability

- Fairness analysis between genders shows no notable bias, with performances only slightly worse for males.
- Analysis between centers shows notable variations in performances, probably due to heavily unbalanced class distribution and different machines or acquisition protocols.
- Explainability is implemented using Signal GradCam, which plots the signal highlighting the most interesting sections according to the model. However, to be truly useful to clinicians, it needs refinement.

Risk Classification

- Coherently with the EU AI Act (Article 6.1), our software is classified as high risk, due to it being substantially a medical device.
- The classification as medical device software of our AI system comes, in fact, from the Medical Device Regulation (Article 2 (1)).
- Moreover, according to the Medical Device Regulation (Annex VIII, article 6.3), our device is classified as IIb, since its outputs are used for decisions which may cause a serious deterioration of a person's state of health or a surgical intervention.

Regulatory Requirements

Which requirements did we address?

- **General safety and performance requirements**, as per MDR Annex I.
- **Technical documentation**, as per MDR Annex II.
- **Technical documentation on post-market surveillance**, as per MDR Annex III.
- **Assessment List for Trustworthy Artificial Intelligence**.

And, in addition:

- Articles 9, 10, 14, 15 of the EU AI Act.

Final Notes

- For more information refer to the technical documentation.
- The code is publicly available at `https://github.com/Emirhankayar/ECGclassification` and `https://github.com/Emirhankayar/MATECG-UI`.
- We really enjoyed working on this project!

References

[1] Erick A Perez Alday et al. *Classification of 12-lead ECGs: the PhysioNet/Computing in Cardiology Challenge 2020*. Vol. 41. Physiol. Meas. IPEM, 2020.

[2] A. Longato, E. Kayar, L. Biagi, and L. Cabrini. *Machine Approach To ECG*. 2025.

[3] Samuele Pe, Tommaso Mario Buonocore, Nicora Giovanna, and Parimbelli Enea. *SignalGrad-CAM*. Version 0.0.1. 2025. URL: https://github.com/bmi-labmedinfo/signal_grad_cam.

[4] J. Zheng, J. Zhang, and S. Danioko. *A 12-lead electrocardiogram database for arrhythmia research covering more than 10,000 patients*. Vol. 7. Sci Data, 2020.

Thank you for your attention

And now the live demo of MATE!