Interpretable ECG Diagnosis with Deep Learning

AI in Healthcare: Project Proposal

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Objective

Electrocardiogram (ECG) analysis is a fundamental diagnostic tool in cardiology, yet the deployment of deep learning models for automated ECG interpretation in clinical settings remains limited due to concerns about model interpretability and computational requirements. While relatively recent advances in deep learning achieved impressive performance on ECG classification tasks [1], the lack of transparent explanations causes such tools to be less adopted, even in applications where they could provide a valuable preliminary assessment of cardiac health in resource-constrained environments.

This project aims to replicate and simplify ProtoECGNet [2], a recently proposed prototype-based deep learning architecture for interpretable multi-label ECG classification. Specifically, we will focus on developing a resource-efficient (i.e. smaller) version of the model that focuses only on ECG rhythm—a critical subset of ECG interpretation—classification. We will use the PTB-XL dataset [3], the largest publicly available clinical ECG dataset, for both training and evaluation.

Prototype-based learning offers an interesting approach to interpretable machine learning by grounding predictions in similarity to learned representations of real ECG segments. This enables clinicians to understand model decisions through case-based reasoning, similar to traditional medical training where doctors learn to recognize patterns by comparing new cases to previously encountered examples.

By the end of this project, we aim to demonstrate that a simplified prototype-based model can achieve acceptable performance on ECG rhythm classification tasks while providing the interpretability and computational requirements needed for practical clinical deployment.

Dataset

The PTB-XL dataset [3] will serve as the foundation for this project. PTB-XL is currently the largest publicly available clinical ECG dataset, containing 21,837 clinical 12-lead ECGs from 18,885 patients. Each ECG is annotated with multiple diagnostic labels following the SCP-ECG standard, making it ideal for multi-label classification tasks.

For this project, we will focus specifically on the rhythm classification subset (according to the assignation of the original ProtoECGNet work), which includes labels such as atrial fibrillation, sinus rhythm, sinus tachycardia, and other rhythm abnormalities. This subset was chosen primarily because the branch of the ProtoECGNet model that focuses on rhythm features is a 1D CNN, making it ideal from the point of view of computational efficiency. Additionally, rhythm disorders are among the most critical and commonly encountered cardiac abnormalities, making them particularly relevant for preliminary diagnostic applications.

The dataset, used in the original paper, is well-suited for our simplified replication for similar reasons:

- **Public availability**: Freely accessible for research purposes.
- **Clinical relevance**: Real patient data with expert annotations.
- **Compliance with research ethics**: Anonymized patient data with appropriate ethical approvals.
- **Balanced representation**: Sufficient examples across different rhythm.
- **Standardized preprocessing**: ECG signals are already filtered and standardized.

Data preparation

We will use the scripts provided in the original ProtoECGNet repository to implement the following preprocessing steps to prepare the PTB-XL dataset for our simplified ProtoECGNet implementation:

- **Baseline wander removal**: Apply a high-pass Butterworth filter with 0.5 Hz cutoff frequency to eliminate low-frequency baseline drift and wandering artifacts from ECG signals.
- **Signal standardization**: Use `scikit-learn`'s `StandardScaler` to normalize signal amplitudes across all 12 ECG leads, fitting on training data and applying to validation/test sets
- **Data reshaping**: Convert `numpy` arrays to PyTorch tensors with proper dimensions.
- **Multi-label encoding**: Transform SCP diagnostic codes into binary label vectors.
- **Stratified data splitting**: Use PTB-XL's predefined fold structure for data stratification (training (folds 1-8), validation (fold 9), and test (fold 10)) to ensure consistent evaluation.
- **Class balancing**: Compute inverse frequency-based class weights to handle imbalanced datasets and implement weighted random sampling.

Methodology

In this project, we will replicate only the rhythm-based branch of the ProtoECGNet model proposed in the original work. This branch is designed to classify rhythm-related ECG abnormalities by analyzing global temporal patterns in 12-lead ECG signals.

The model branch employs a 1D ResNet18 backbone to process ECG inputs of shape (12×1000) sampled at $100\,Hz$. The extracted features are compared against a set of learnable class-specific prototypes within the latent space. Each prototype corresponds to a rhythm diagnosis and is optimized to resemble representative training examples.

This simplified project will follow a methodology inspired by that of the original work, consisting of the following stages:

1. Train the model using only the 16 rhythm-related labels from the PTB-XL dataset.
2. Use a prototype-based classification layer with a composite loss function that includes binary cross-entropy, clustering, separation, diversity, and contrastive loss terms.

3. Evaluate performance using a held-out test set (fold 10) from PTB-XL.

The training process in particular will follow the three-stage process described in the original paper:

1. **Joint Training:** Simultaneous optimization of the feature extractor and prototype layer.
2. **Prototype Projection:** Each prototype is updated to match the most similar latent patch from training samples of its class.
3. **Classifier Training:** A linear classifier is trained on the prototype similarity scores to produce final predictions.

Evaluation metrics

Model performance evaluation will be done using the **Macro-AUROC** (Area Under the Receiver Operating Characteristic Curve), calculated across the 16 rhythm-related labels, in order to properly compare the results with the original ProtoECGNet work. Macro-AUROC provides a balanced assessment by computing the unweighted mean of per-class AUROC scores. This is particularly appropriate for multi-label ECG classification tasks where label imbalance is common.

We might also consider additional metrics regarding other aspects of the model's performance, such as its interpretability (based on the diversity and separation of the learned prototypes) and computational efficiency (e.g., inference time, memory usage).

Expected Output

By the end of this project, we expected to have the following outputs: (1) a simplified ProtoECGNet model capable of rhythm classification with sufficient performance on the PTB-XL dataset, (2) an interpretability analysis demonstrating the model's ability to provide case-based explanations for its predictions, (3) a performance comparison between the simplified model and the original ProtoECGNet results, and (4) a codebase with clear documentation enabling reproduction and extension of the work.

All findings will be summarized in a final report that will be submitted along with the code generated during the project, as a single repository.

Timeline

The project is expected to take around eight hours of work to complete. In order to be able to track progress, we have established a timeline for the main tasks and time estimation as detailed in table 1.

References

[1] Hannun, A.Y., Rajpurkar, P., Haghpanahi, M., Tison, G.H., Bourn, C., Turakhia, M.P., Ng, A.Y.: Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network. Nature Medicine **25**(1), 65–69 (2019)

[2] Sethi, S., Chen, D., Statchen, T., Burkhart, M.C., Bhandari, N., Ramadan, B., Beaulieu-Jones, B.: ProtoECGNet: Case-Based Interpretable Deep Learning for Multi-Label ECG Classification with Contrastive Learning (2025)

Table 1 Project Timeline and Task Breakdown

Stage	Duration	Tasks
Initial Setup & Data Preparation	1.5 hours	Set up Python environment and dependencies (e.g., PyTorch), clone the ProtoECGNet repository, download PTB-XL dataset, extract rhythm-label subset, and apply preprocessing (e.g., high-pass filtering, normalization).
Model Adaptation	1 hour	Isolate the rhythm branch from the original ProtoECGNet codebase; configure the 1D ResNet18 model and prototype layer; set up appropriate loss functions (BCE + prototype losses).
Training	2.5 hours	Execute joint model training (Stage 1), perform prototype projection (Stage 2), and train the rhythm-branch classifier (Stage 3).
Evaluation	1 hour	Evaluate performance on the held-out test set using macro-AUROC and compare to the baseline rhythm-only ResNet18 if time permits.
Interpretability Analysis	1 hour	Visualize top activated rhythm prototypes and corresponding training/test ECG segments to qualitatively inspect model reasoning.
Reporting & Documentation	1 hour	Summarize the approach, results, limitations, and insights; prepare plots and write up the final report.

[3] Wagner, P., Strodthoff, N., Bousseljot, R.-D., Kreiseler, D., Lunze, F.I., Samek, W., Schaeffter, T.: Ptb-xl, a large publicly available electrocardiography dataset. Scientific Data **7**(1), 1–15 (2020)