Active Learning Approach for Clinical Noise Characterization in Long-Term ECG Monitoring

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Introduction: Long-term monitoring (LTM) of electrocardiogram (ECG) during several days can help identify intermittent arrhythmias that may not appear on shorter recordings. These registers are prone to noise, thereby affecting their diagnostic utility. Identifying clinically valid ECG parts can improve the performance of signal processing systems and reduce the analysis time needed for cardiologists. In this work, we compute the distortion of the ECG in terms of clinical severity, which does not rely on quantitative means but on its readability. Although we have developed various machine learning systems to characterize clinical noise, we must expand our limited data to improve the performance of our models.

Objective: The main objective is to develop an active learning methodology to increase labeled data and improve the performance of clinical noise classification models.

Database: We use a repository of LTM signals from 10 patients, labeled by a trained expert and a cardiologist based on a clinical severity criterion of noise. Our experimental database comprises 8.467 excerpts of 5-second, balanced across both clean and noisy categories.

Methods: We adopt an active learning scheme with a 1-D Convolutional Neural Network (CNN) based on an autoencoder, which provides explainability of the decision making process. This iterative process initially incorporates new examples into the training set based on their class probability and, subsequently, the CNN classifies them as either clean or noisy.

Results: The F1-score test curves illustrate that the active learning scheme outperforms sample selection at random. Additionally, the analysis of the latent spaces from the 1-D CNN reveals different distributions of mapped data across iterations of the scheme.

Conclusion: The active learning scheme can refine the models by increasing the labeled data for training, strengthen the confidence of health professionals in medical decision support systems based on learning methods, and enable its application in clinical practice.

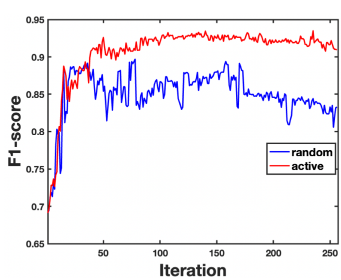

Figure 1. F1-score training with active learning strategy.