# Adaptive Long Short-Term Memory networks for classifying 12 and reduced-lead ECG arrhythmia

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**Abstract**

A heart arrhythmia classifier is proposed for continuous cardiac monitoring for signals with different signal lengths of patients, evaluated on a reduced number of leads, including twelve-lead, six-lead (I, II, III, aVL, aVR, and aVF), three-lead (I, II, V2), and two-lead (II and V5) ECG recordings. Thus, we propose a novel approach to denoise ECG signals and identify clinical diagnosis as defined in the Physionet Challenge 2021. First, a noise removal process was initially applied to the raw dataset using wavelets. Secondly, data augmentation techniques are implemented, in order to improve the generalization performance of the dataset, including y-axis shifts, filtering stages with wavelets, and adding noise-aware signals at different intensity levels which combined with the original dataset, increases its diversity. Finally, we implemented a combination of a Bi Long Short-Term Memory Recurrent Neural Network using window segmentation to reduce bias during our training model. Each signal from the dataset provided was clipped and zero-padded at 10 seconds for the training stage. The proposed methodology developed so far scored a metric challenge on the Full testing set of 0.05, 0.03, -0.01, -0.09 on the 12-lead, 6-lead, 3-lead, and 2-lead, respectively. The model was also tested using 10-fold cross-validation, yielding a challenging metric of 0.267, -0.0169, -0.055, and 0.0084 on the 12-lead, 6-lead, 3-lead, and 2-lead, respectively. Overall, the data augmentation stage can help improve the heart arrhythmia training model performance by varying the dataset measurements and helping the model to identify useful features present at the different intensity of movements. Our model keeps a high level of interpretability, demonstrating a high range of possibilities that can be configured using hybrid BI-LSTM.