

## ECG CLASSIFICATION WITH DEEP LEARNING MODELS – A COMPARATIVE STUDY

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### Abstract

The electrocardiogram (ECG) is the most common cardiological procedure to monitor non-invasively the electrical activity of the heart (Kachuee et al., 2018). It is a complex and non-linear signal, which is the first option to preliminary identify specific pathologies/conditions (e.g. arrhythmias) (Yadav & Ray, 2016). However, its processing is frequently performed manually, making it operator dependent. A multitude of algorithms to automatically process the ECG were presented. Recently, Artificial Intelligence (AI), namely deep learning models, were proposed, showing state-of-the-art results (Acharya et al., 2017). However, these models are frequently trained/tested in one specific database, not evaluating its result in other sources, as expected in the clinical practice (Baloglu et al., 2019).

In this study, we intend to study the robustness of the already described DL methods to the variation of data source. Moreover, we intend to evaluate the performance of these methods to classify different classes of pathologies. Three public databases of ECG signals were chosen, namely: MIT-BIH Arrhythmia Database (D1), European ST-T Database (D2), PTB Diagnostic ECG Database (D3). Three methods were considered for this study, namely: Convolutional Neural Network 1D paired with a Multilayer Perceptron (CNN 1D+MLP), Dense Model, Convolutional Neural Network 1D (CNN 1D). The performance of the selected methods in terms of accuracy was assessed.

Overall, only the CNN 1D+MLP architecture demonstrated high robustness to the variation of the data accuracy, with similar accuracy to the databases D1 and D2. The remaining methods achieved unsatisfactory results when changing the database. No method was considered successful to the D3, namely, failing to perform patient's diagnosis based on the full signal analysis.

As a conclusion, further studies to really evaluate the performance of state-of-the-art AI networks in real clinical situations are required.

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