A machine learning-derived electrocardiographic algorithm for the detection of cardiac amyloidosis

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Background: The diagnosis of cardiac amyloidosis (CA) requires advanced imaging techniques. Typical surface ECG patterns have been described, but their diagnostic value is limited.

Purpose: The aim of this study was to perform a comprehensive electrophysiological characterization in CA patients and to develop a robust, easy-to-use diagnostic tool.

Methods: First, we applied electrocardiographic imaging (ECGI) to generate detailed electroanatomical maps in CA patients and controls. Then, a machine learning approach was used to generate a surface ECG-based diagnostic algorithm from the complex dataset.

Results: Areas of low voltage were localized in the basal inferior regions of both ventricles and the remaining right ventricular segments in CA. The earliest epicardial breakthrough of myocardial activation was visualized in the right ventricle. Potential maps showed an accelerated and diffuse propagation pattern. We correlated the results from ECGI with 12-lead ECG recordings. Ventricular activation correlated best with R-peak timing in leads V1 to V3. Epicardial voltage showed a strong positive correlation with R-peak amplitude in inferior leads II, III, aVF. Ten blinded cardiologists were then asked to identify CA patients by analyzing 12-lead ECGs before and after training for the defined ECG patterns. Training resulted in significant improvements in the detection rate of CA with an AUC of 0.69 before and 0.97 after training (Figure).

Conclusion: Using a machine learning approach, a robust ECG-based tool was developed to detect CA from detailed electroanatomical mapping of CA patients. The developed tool proved to be a simple and reliable diagnostic tool to suspect CA without the aid of advanced imaging modalities.

Figure: A machine learning-derived ECG algorithm for the detection of cardiac amyloidosis