Left Bundle Branch Block Detection in 12-Lead ECG using End-to-End Deep Learning with Explainability

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Cardiac resynchronization therapy (CRT) improves left ventricular function, especially in patients with left bundle branch block (LBBB). Machine learning (ML) with expert-extracted features and deep learning (DL) with automated feature extraction from raw ECG data have transformed LBBB detection. However, concerns over DL's opaque nature necessitate efforts to enhance trust in these models with explainability.

Using data from a 2018 competition organized by ISCE and THEW, we compared feature-based ML and end-to-end DL models for LBBB detection. Training data (LBBB=174, non-LBBB=126) underwent randomized and stratified splits, with a separate test dataset (LBBB=156, non-LBBB=146). The random forest (RF) model used Philips DXL to automatically extract 17 features (comprised measurements of duration, amplitude, area, axis, etc.) from 12-lead ECGs based on their importance for LBBB detection. In contrast, the end-to-end DL model (ResNet) employed both the 10s ECG (RawECG) signal and the corresponding 1.2s average representative beat (RepBeat) signal automatically extracted by Philips DXL. ResNet trained with data augmentation (cutout, dropout, and scaling) using RandAugment for improved robustness. To understand why our ResNet model detects LBBB, we used SHAP (SHapley Additive exPlanations), a method that explains model decisions. We highlighted feature importance using normalized SHAP values for the influential ECG patterns in the model's classifications.

ResNet on RawECG data outperformed the feature-based RF model in LBBB detection, with an accuracy of 0.93 (RF: 0.83), sensitivity of 0.96 (RF: 0.88), specificity of 0.85 (RF: 0.78), PPV of 0.87 (RF: 0.81), and F1 of 0.91 (RF: 0.84). SHAP analysis of the ResNet revealed key ECG features for LBBB detection; QS pattern in lead V1, QRS notch in leads V5 and V6, and wide QRS duration, all aligning with established LBBB criteria (Figure 1).

AI-powered DL with explainability provides clinicians a powerful tool for accurate LBBB diagnosis, enabling them to understand better how the algorithm made its decisions.

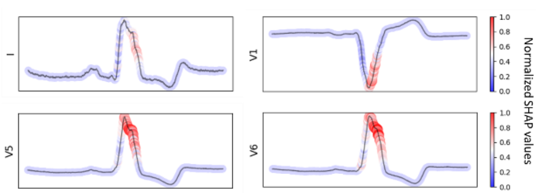

Figure 1. SHAP-based feature importance with RepBeat inputs for explainability