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Background: Conduction system pacing (CSP) in the form of left bundle branch area pacing (LBBAP) is emerging as a more physiological pacing modality than conventional myocardial pacing. Determining when capture of the left bundle branch area is present on 12-lead ECG remains a challenge for consistent, widespread uptake of the approach. Automated detection of LBBAP from ECGs would reduce complexity of implants, accelerate procedural learning curves and facilitate follow-up.
Aim: We aimed to automate discrimination of LBBAP capture from non-LBBAP capture in natively digital 12-lead ECGs acquired during implant procedures using artificial intelligence.
Method: 12-lead ECGs of individual paced-beat QRS complexes were isolated and extracted from continuous digital ECG recordings acquired during device implants using a custom semi-automatic beat segmentation pipeline comprising a QRS segmentation module and a pre-QRS spike detector. A 1D convolution autoencoder was trained to learn beat-level embeddings. To condense the high volume of paced ECG data from each case for labelling, these beat-level embeddings were clustered per patient using HDBSCAN to form compact groups of beats with similar QRS morphology. Each QRS complex cluster was assigned, by manual expert application of the 2025 EHRA CSP consensus statement criteria, a binary label of either LBBAP or non-LBBAP. A beat-level convolutional classifier was trained to predict these labels, with cluster-level optimisation to align learning with expert labels. The model was trained on ECGs acquired at a tertiary centre in the UK and externally validated on ECGs from a tertiary centre hospital in China.
Results: The UK training set comprised 244,787 beats forming 2,593 clusters from 225 patients. Although this set was imbalanced, with non-LBBAP clusters outnumbering LBBAP 1.7:1, the model demonstrated strong cluster-level performance across 10-fold cross-validation. Accuracy was 0.93 (Confidence Interval: 0.92–0.94), F1-score was 0.89 (0.87–0.91) with AUROC 0.95 (0.94–0.96) and AUPRC 0.92 (0.91–0.94), indicating robust discriminative ability. External validation on the independent Chinese dataset (67 patients, 643 clusters; class ratio 1:0.9) demonstrated similarly strong generalisation: ensemble model accuracy 0.92, F1-score 0.92, AUROC 0.97, AUPRC of 0.96. Receiver-operator and precision–recall curves further illustrate the model's high discriminative performance and reliability across a broad range of decision thresholds.
Conclusion: LBBAP can be reliably detected from individual-beat 12-lead ECGs using a convolutional neural network.

Figure 1: Example clusters

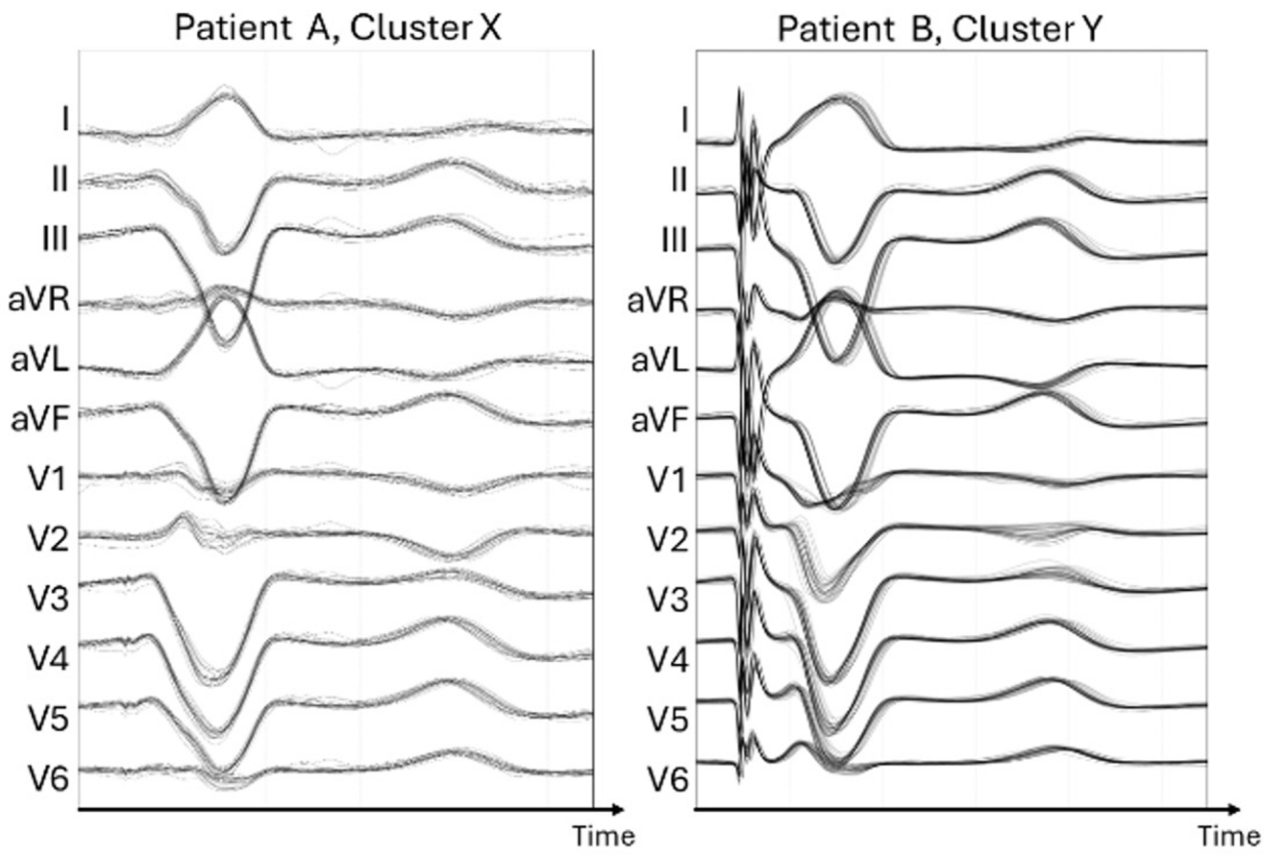

Figure 2