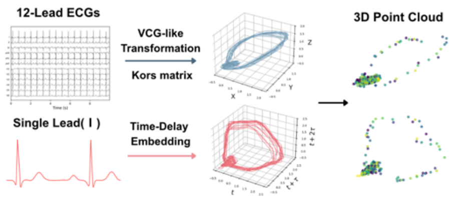
EchoPoint: Geometric Representation of ECG Signals Improves Structural Heart Disease Prediction

Motomu Nonogaki*, Osamu Muto, Daisuke Takeyoshi,
Takamichi Kuwahara, Rui Yamaguchi

Nagoya University School of Medicine, Nagoya, Aichi, Japan



Aims: Structural heart disease (SHD) can be diagnosed using echocardiography. However, its cost and limited accessibility restrict widespread screening. Therefore, simpler screening methods are needed. ECG-based approaches for SHD prediction are promising. A previous study (EchoNext, Nature 2025) demonstrated that SHD can be predicted from 12-lead ECGs using a 1D convolutional neural network (1D-CNN). Although ECGs are recorded as temporal waveforms, they implicitly encode spatial and structural information about cardiac electrical activity. In this study, we represent ECG signals as 3D point clouds and aim to improve SHD prediction by explicitly extracting global geometric features independent of temporal order.

Methods: We used the EchoNext dataset of 12-lead ECGs with paired SHD labels derived from echocardiography to perform 12-class multi-label classification of SHDs (e.g., valvular diseases). The training, validation, and test sets comprised 72,475, 4,626, and 5,442 samples, with SHD prevalence of 52.4%, 43.0%, and 42.6%, respectively. ECGs were transformed into a vectorcardiogram-like representation and converted into 3D point clouds. These were input into a PointNet-based model, which was fused with the baseline (1D-CNN) for performance evaluation. Furthermore, to extend applicability for screening, we evaluated the model in a single-lead setting. Similar 3D point clouds were constructed from lead I based on Takens's embedding theorem.

Results: The fusion model using 12-lead achieved AUROC of 83.5% and F1 score of 71.6% for SHD prediction, improving performance by 1.5% and 2.6% compared to the baseline. Under the more challenging single-lead task, our model achieved AUROC of 81.1% and F1 score of 70.0%.

Conclusion: We propose a novel SHD prediction model that represents ECGs as 3D point clouds. Results suggest that spatial and geometric features complement temporal waveform features and improve prediction performance. The method also performs well even in a single-lead setting, indicating its potential for wearable ECG devices and large-scale screening.