An Explainable Framework for Systolic Murmur Classification Using Graph Attention Network

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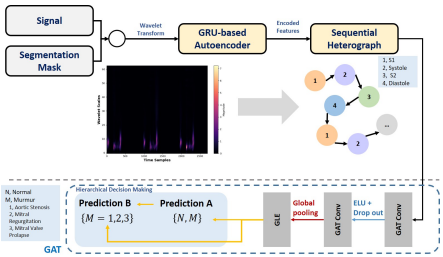
Aim: Despite recent significant advances, deep learning for computer-aided diagnostics using heart sound is still limited in clinical transparency. Graph-based methods offer a promising alternative by accommodating variable input lengths while preserving the critical spatio-temporal features of phonocardiogram (PCG) signals. This study presents a Graph Attention Network (GAT) approach designed for an explainable clinical expert system, providing both automated diagnosis of cardiovascular disease and clinically relevant characterization of systolic murmurs.

Methods: The proposed framework integrates raw PCG signals with an automated segmentation step to achieve precise temporal localization of cardiac cycles (S1, Systole, S2, Diastole). Wavelet-derived time-frequency mappings are encoded via an attention-enabled Bi-dimensional Gated Recurrent Unit (Bi-GRU) and subsequently transformed into sequential heterographs. This architecture enhances resolution in systolic and diastolic regions, optimizing the characterization of spectral anomalies. A hierarchical GAT system performs murmur detection followed by multi-class classification (Aortic Stenosis, Mitral Regurgitation, Mitral Valve Prolapse). The pipeline was validated using the Yaseen dataset and incorporates a dedicated explainability module.

Results: The model achieved 100% accuracy in detecting systolic murmurs and 98% accuracy in subsequent multi-class classification. The attention-derived explanations include the description of the murmur type based on spectral content and shape for each cycle based on established pathological descriptions and a majority voting for the final decision, which can be cross-validated against the classifier prediction.



Conclusions: Combination of these explanations with classification confidence scores facilitates more reliable clinical decision-making. Future work will assess the framework's robustness across metadata-rich CirCor/Digiscope dataset.