A Hybrid CNN-LSTM Model for Heart Failure Detection Using Raw ECG Signals

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Heart failure (HF) imposes a considerable burden on global healthcare systems, affecting over 64.3 million individuals and contributing to approximately 7 million deaths annually. This syndrome comprises three distinct classes based on left ventricle ejection fraction (LVEF): preserved (HFpEF), mid-range (HFmEF), and reduced (HFrEF). Early and accurate subclass diagnosis is vital for effective management and prognosis. This study focuses on utilizing raw electrocardiogram (ECG) signals, without feature engineering, for precise HF class detection. The data for this study (n = 303 patients) were sourced from the PRESERVE EF study and the archives of the Intercity Digital Electrocardiography Alliance (IDEAL) study of the University of Rochester Medical Center Telemetric and Holter ECG Warehouse (THEW). Ethical approval was obtained for both studies, and all participants provided consent. Patients were classified based on EF level following ASE/EACVI recommendations, resulting in 129 HFpEF, 92 HFmEF, and 82 HFrEF patients. Raw 24-hour Holter ECG recordings were obtained using three pseudo-orthogonal lead configurations sampled at 200 Hz, normalized to start from hour 12 AM using the Cosinor analysis approach. ECG data were filtered using the SDROM-ADF filter, resulting in a 1 × 720,000 matrix per ECG.

The proposed model comprises 11 layers, beginning with three sequential convolutional blocks extracting high-level features via 1-dimensional convolutional layers with ReLU activation functions. Max-pooling layers condense feature dimensions, leading to Long Short Term Memory (LSTM) layer input, known for managing long-term dependencies. Dropout layers mitigate overfitting, while dense fully connected layers alter vector dimensions. The final layer utilizes softmax activation for multi-class classification. Leveraging a deep learning architecture combining Convolutional Neural Network (CNN) and LSTM layers yielded promising results, achieving an overall accuracy of 86%, with accuracies of 89%, 80%, and 84% for HFpEF, HFmEF, and HFrEF, respectively. Integration of deep learning with raw ECG data from remote sensing and wearable devices enables early diagnosis and personalized HF management, enhancing patient outcomes and enabling real-time monitoring.