Enhancing Deep Learning in Detecting Acute Myocardial Infarction via Anatomically Informed 12-Lead ECG

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Background. According to the World Health Organization, cardiovascular disease (CVD) is the leading cause of death worldwide, claiming around 17.9 million lives annually and representing approximately 30% of all global deaths[1]. Acute myocardial ischemia/infarction (AMI) is an acute manifestation of CVD that occurs when oxygenated blood flow to the heart muscle is blocked or severely reduced, and timely diagnosis and treatment are crucial to salvaging myocardium and improving patient outcomes. The 12-lead electrocardiogram (ECG) is the initial screening tool for patients with suspected AMI, but its diagnostic accuracy remains limited. Deep learning has shown great potential in improving the accuracy of AMI detection using 12-lead ECG, but existing models have treated all leads equally, potentially limiting performance. Our study proposes a novel deep-learning model that incorporates underlying myocardial wall information measured by each of the 12 ECG leads to enhance performance. By integrating the anatomically informed 12-lead ECG, our study joins a growing body of research that incorporates clinical domain knowledge (i.e., anatomical location) to bolster the performance of machine learning applications in healthcare[2-4].

Methods. Our model (see Figure 1) incorporated anatomical information from 12 ECG leads by employing four regional learners that learn cross-lead spatial information in inferior leads (II, III, and aVF), septal leads (V1 and V2), anterior leads (V3 and V4), and lateral leads (I, aVL, V5, and V6), as well as a global learner that learns from all 12 leads to capture the global information. All learners were composed of a 1D convolutional layer that maps the original channel dimension to a higher dimensional space (i.e., 20) to learn spatial information at both regional and global levels for every sample point. The model then stacked them into a 100-feature space as input for the xResNet model architecture[5], to learn the combined information and outputs the classification probability of AMI. We compared the performance of our proposed model with a baseline model that was trained directly using 12-lead ECG as input for the same xResNet architecture. The study adopted a publicly accessible dataset, the PTB-XL, which includes 21,837 recordings of 10s 12-lead ECG (sampled at 500 Hz), with 5,486 for AMI and 16,351 for non-AMI[6, 7]. The study followed an 80%-10%-10% split for training, validations, and test sets. The model was trained with 50 epochs with a batch size of 128. We selected the binary cross entropy as the loss function.The final model was determined by the one with the least validation loss. We reported classification performance using the area under the receiver operating curve (AUROC) and conducted a performance comparison using DeLong's test.

Results. Our proposed anatomically informed 12-lead ECG model achieved an AUC of 93.7%, which is significantly higher than the baseline model with an AUC of 91.4% ($p<0.001$). When selecting the optimal cutoff probability based on Youden's index, the proposed model achieved a sensitivity of 85.5%, a specificity of 86.7%, an accuracy of 86.4%, a positive predictive value (PPV) of 68.4%, a negative predictive value (NPV) of 94.7% and an F1 score of 76.0%.

Conclusion. Our deep learning model showed significant improvement in the detection performance of AMI when incorporating existing clinical domain knowledge (i.e., anatomical location) in the model design. Our next steps will involve validating the generalizability of the model to other datasets, exploring the relationship between information learned from different regional learners and locations of occluded coronary arteries, and incorporating other data modalities through multimodal learning for further performance improvement.

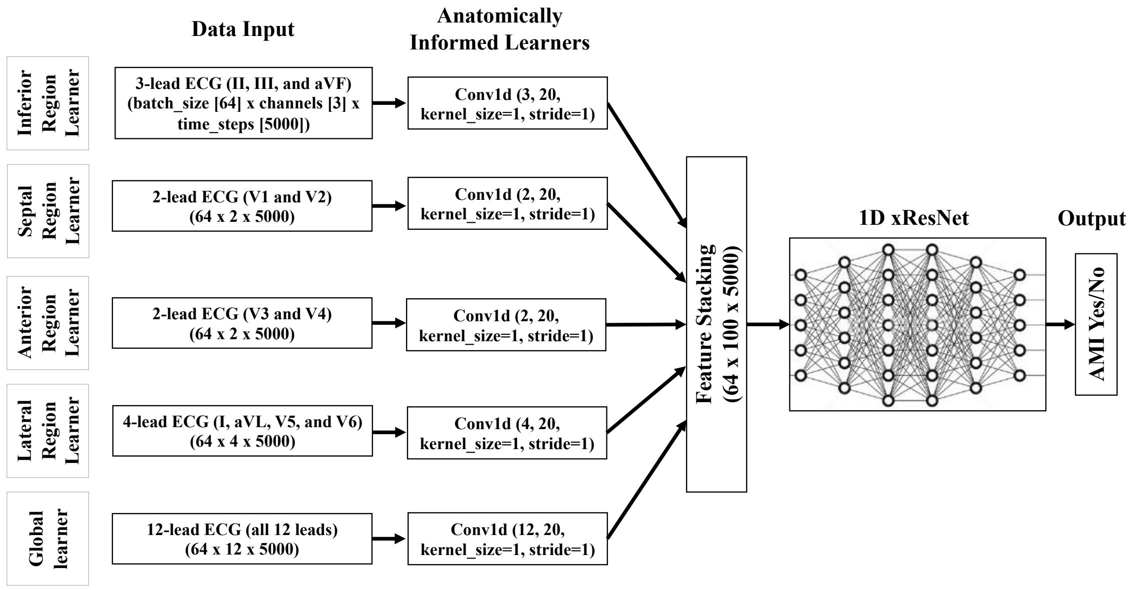

Figure 1. Model architecture for the Anatomically Informed 12-Lead ECG deep learning model

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