ABSTRACT

Automatic arrhythmia detection is commonly performed by analyzing electrocardiogram (ECG) signals, which are recordings of the heart's electrical activity. This study aims to evaluate the effAZqect of window length variation on ECG-based arrhythmia classification performance, compare the performance of GRU and BiGRU architectural variants, and analyze the impact of hyperparameter configurations on model performance. The scope of this study is limited to gated recurrent unit (GRU)-based models and their implementation in ECG signal classification using the MIT-BIH Arrhythmia dataset.

The methodology includes segmenting ECG signals using a sliding window based on R-peak counts (3R, 5R, and 10R), training GRU0–GRU3 and BiGRU0–BiGRU3 models, and tuning three key hyperparameters: number of units (32, 64, 128), dropout rates (0.2, 0.5), and learning rates (0.001, 0.0001). The models were trained using the categorical crossentropy loss function with the Adam optimizer and evaluated using accuracy, ROC AUC, precision, recall, and F1-score metrics.

The results show that the 3R window length provides the best classification performance. The GRU0 model, representing the conventional GRU architecture, outperformed other variants. The optimal configuration—128 units, 0.2 dropout, and a 0.001 learning rate—achieved an accuracy of 95.99%, an F1-score of 0.9599, and a final validation accuracy of 96.72%. These findings indicate that a simple GRU architecture, when properly tuned, can yield highly effective performance in arrhythmia classification based on ECG signals.

Kata Kunci: *Arrhythmia, BiGRU, ECG, GRU, Hyperparameter Tuning, Sliding Window*