Master Thesis Proposal

Single-lead ECG classification based on Transformer models

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1 Abstract

The accurate classification of electrocardiogram (ECG) signals is crucial in diagnosing various cardiovascular diseases such as atrial fibrillation and to provide cardiologists with reliable predictions. With the recent advancements in deep learning models, Transformer-based architectures have emerged as powerful tools for processing sequential data. This master thesis will explore the potential of applying Transformer-based models to single-lead ECG classification. A lot of research has been putted recently on accurate Transformer-based single-lead and multi-lead ECG classification [1] [2] [4] [9] [8] [11] [12] [13]. Multi-lead ECGs provide a view from different angles of the heart's electrical activity and can localize abnormalities more reliable. They are a standard in clinical monitoring. However, the accurate single-lead ECG classification is an attractive research field when it comes to continuous processing of single-lead ECGs through remote monitoring systems, for instance wearable devices such as Apple watches [8], for continuous monitoring of the conditions of an individual to give early suggestions for a doctor visit. Most recently proposed Transformer-based ECG models focus on short-term ECGs and combine the encoding block from a Transformer model with a Convolutional Network [1] [2] [4] [9] [11] [13]. CNNs have a limited receptive field, preventing them from learning distant dependencies and are designed to extract local patterns. In contrast, Transformers are better suited for learning long-range dependencies through their attention mechanism. The combination of both can capture spatiotemporal information from the ECG signal [13]. However, none of the recently developed ECG Transformer-based architectures investigate a decoder-only based approach. While the Transformer encoder-block takes into account the bidirectional contextual representation from the entire ECG signal to capture temporal dependencies from the past and the future, the decoder-block sequentially processes the signal from left to right and only focuses the attention on past states. Thus can a decoder-only based approach be a more suitable solution for both cases, short-term ECGs (monitored over a few minutes) and long-terms ECGs (monitored over several hours), to classify the occurence of atrial fibrillation related symptoms in short-term ECGs and to forecast the prediction for the next AF episode in long-term ECGs, or in worst case to recognize and prevent impending stroke and heart failures [5]. The objective of this work is to investigate and compare the effectiveness of different Transformer-based architectures for the classification of atrial fibrillation related heartbeat types focusing on varying sequence lengths (short-term ECGs vs. long-term ECGs): an encoder-only based approach like BERT vs. a decoder-only based approach like GPT vs. an encoder- and decoder-based approach. For this, the work will investigate different encoding strategies for single-lead ECG data, by using extracted conventional features, i.e. the RR-interval, or by using other embedding strategies to learn a latent representation and to keep most of the valuable information from the ECG signal. The findings of this study will provide insights into the application of Transformer models in the field of signal processing and help further research in improving Transformer-based single-lead ECG classification

accuracy of atrial fibrillation, such as the general classification of normal sinus rhythm, atrial fibrillation or other rhythm. The model developed for this thesis could be applied in remote monitoring systems, where patients ECG data can be continuously or intermittently sent to healthcare providers for analysis.

The master thesis plan is divided into the following steps:

First, a general mathematical background of Transformer models will be researched. Next, a comprehensive literature review is conducted to discuss existing Transformer-based methods for ECG classification. This review will highlight the challenges and limitations of previous approaches. Based on this the different Transformer-based models are designed and implemented. The models are trained utilizing public available datasets provided by the PhysioNet 2017 challenge [3] and the EASTAF study [10] for short-term single-lead ECG. To investigate longer single-lead ECG data, the MIT-BIH [6] and Icentia11k [7] will be used. The labels from this datasets also categorisize between atrial fribillation and normal sinus rhythm beats. The datasets differ, as they contain continous long-term ECG signals monitored over several minutes up to days, while the datasets provided from the PhysioNet 2017 challenge and the EASTAF study provide ECGs with around 30-60 seconds in length. Although, Transformer models are capable of capturing relationships between distant data in a sequence due to the self-attention mechanism, there can still be challenges in capturing very long-range dependencies effectively, leading to diminishing attention and affecting the quality of the model. In the experimental setup various hyperparameter configurations, including the number of stacked encoder-/decoder-blocks, the attention mechanisms and positional encodings are systematically explored to optimize the model's performance. To evaluate the proposed approach, extensive experiments are conducted using the developed models. The performance of the models are assessed using standard metrics such as accuracy and F1. Additionally, to benchmark the performance, comparative analyses are conducted against state-of-the-art [3] [6] single-lead ECG classification methods. The obtained results from the experiments will demonstrate the potential of the own proposed Transformer-based approach in single-lead ECG classification for the presence of AF related types.

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