Artificial Intelligence in Industry Project

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Abstract

This project focuses on the detection of anomalies within ECG data, highlighting the potential of advanced deep-learning techniques for identifying irregular heartbeat patterns indicative of heart conditions. By preparing and analyzing time series data, our project explores the performance of various model architectures, including Autoencoders and LSTM Autoencoders, in understanding the complex nature of ECG signals. These models work well to distinguish between normal and abnormal heart activity, showcasing the value of deep learning in augmenting diagnostic processes for cardiovascular diseases. Furthermore, we use a deep Neural Network model and a XGBoost model, which showcase a high success rate in anomaly classification. The outcomes of these models highlight the critical role of deep learning in medical data analysis.

1 Introduction

In this project, we focus on the application of deep learning to identify anomalies in ECG data, focusing on four principal methodologies: Autoencoders, LSTM Autoencoders, Traditional Neural Networks, and the XGBoost Model.

LSTM Autoencoders are particularly good at handling sequential data, making them highly suitable for ECG signal processing. Their strength lies in capturing both immediate and distant dependencies within heartbeat sequences, thereby learning to recognize normal rhythm patterns through data reconstruction. Anomalies are flagged when there is a strong deviation between the reconstructed output and the original input, indicating potential abnormalities in heart activity. This temporal-focused analysis ensures that LSTM Autoencoders excel in thorough examinations of heart rhythms over time.

Autoencoders, while conceptually similar to LSTM Autoencoders in leveraging data compression and reconstruction to unearth normal patterns, do not exclusively target sequential data. This flexibility allows Autoencoders to be applied across various types of data, including ECG signals. By detecting significant reconstruction errors, Autoencoders serve as effective indicators of anomalies, thus contributing to the early identification of potential cardiac issues. Additionally, we explored the capabilities of the XGBoost Model and traditional Neural Network models for classifying heart rhythms into normal and abnormal categories. These models, through their precision in classification, considerably expand our analytical framework for ECG data. The Neural Network classifiers, with their deep learning architecture, and XGBoost, an ensemble method renowned for its efficiency and predictive power, have both demonstrated remarkable performance in our analysis, rivaling that of the autoencoder-based approaches.

By integrating these advanced deep learning and machine learning techniques, our project showcases the potential of such technologies in the field of healthcare analytics. The insights derived from this study aim to enhance diagnostic processes for heart diseases.

2 Background

The motivation behind this project comes from the need for enhanced techniques in the analysis of ECG data for anomaly detection. Electrocardiograms (ECGs) are instrumental in cardiology, providing key insights into the heart's electrical activity and assisting in the diagnosis of various cardiac conditions. However, the traditional manual interpretation of ECGs poses challenges, being both time-consuming and susceptible to inaccuracies due to the inherent complexity and variability of heart rhythms. Minor deviations in ECG signals could indicate significant underlying health issues, emphasizing the necessity for automated, accurate, and efficient methods of anomaly detection. In addressing these challenges, deep learning models such as Autoencoders, LSTM Autoencoders, and traditional Neural Networks, alongside advanced machine learning techniques like the XGBoost Model, emerge as comprehensive solutions. These models excel in identifying complex patterns and temporal dependencies within ECG data, thus facilitating significant strides in early diagnosis and intervention. The integration of these diverse analytical techniques showcases a new approach to healthcare analysis.

3 System Description

Our project used LSTM Autoencoders, traditional Autoencoders, Neural Networks, and the XGBoost algorithm to detect anomalies in ECG data, utilizing the cloud-based environment of Google Colab for effective collaboration and computational efficiency. The insights for our methodology were from a several sources, including blog posts, YouTube tutorials, and academic papers, ensuring a well-rounded understanding of the applied machine and deep learning techniques.

LSTM Autoencoder Architecture: Tailored for sequential data, the LSTM Autoencoder is ideal for ECG signal analysis. It comprises:

Encoder: Two LSTM layers compress the input sequence, with the first layer mapping the input to a hidden layer double the embedding dimension and the second layer further reducing it to the embedding dimension size. Decoder: Mirrors the encoder's process in reverse, utilizing two LSTM layers and a linear output layer to reconstruct the original sequence from its compressed form.

Traditional Autoencoder Structure: Unlike the LSTM Autoencoder, the traditional Autoencoder does not specialize in sequential data. It features:

Encoder: A series of linear layers and ReLU activations compress the input. Decoder: Reverses the encoding process to expand the compressed data back to its original dimensionality, ending with a Tanh layer for output normalization.

Neural Network Classifier: A sophisticated model with six hidden layers designed for binary classification, employing ReLU activations for non-linearity and a sigmoid output layer for binary classification. XGBoost Model: A gradient boosting framework configured for binary classification with parameters fine-tuned for optimal ECG signal analysis, demonstrating the model's prowess in handling tabular data efficiently.

These diverse architectures collectively form our comprehensive approach to ECG anomaly detection, showcasing the potential of machine learning and deep learning techniques in medical data interpretation. By employing a variety of models, we aim to leverage the specific strengths of each to improve the accuracy and efficiency of diagnosing heart conditions.

4 Data

Our dataset comprises of 5,000 time-series examples, each representing a single heartbeat captured via ECG from a patient with congestive heart failure. These sequences span 140-time steps, reflecting the heart's electrical activity and the subsequent muscle contractions. Within this dataset, heartbeats are categorized into five classes: Normal, R-on-T Premature Ventricular Contraction (PVC), Premature Ventricular Contraction (PVC), Supraventricular Premature or Ectopic Beat (SP or EB), and Unclassified Beat (UB), providing a comprehensive overview of heart rhythm variability. This dataset is essential for training our models to distinguish between normal and anomalous heartbeats.

In our project, the pre-processing stage involved several steps to prepare the data for our models. Initially, the data was loaded from ARFF files into Pandas Data Frames. These were then randomized to ensure diverse training samples. To improve our analysis, we encoded the 'target' column for easier reference and employed a stratified split to organize the data into training, validation, and test sets. We focussed on normalizing the data, ensuring that each input feature had a consistent scale. This pre-processing ensures our models learn from a well-structured and representative sample of heart activity, improving their ability to generalize from training data to real-world ECG recordings

5 Summary

Anomaly detection within the provided ECG dataset was initially perceived as straightforward due to the high accuracy achieved by both our traditional neural network classification model and XG-Boost model, both nearing 100 percent. However, challenges arose when attempting to reconstruct the data utilizing an autoencoder. Identifying the precise regions contributing to anomalies necessitates the autoencoder's ability to predict a normal sample and apply this prediction to an anomalous sample, presenting inherent complexities.

Our initial assumption posited that conventional autoencoders employing traditional perceptron neurons would suffice, especially considering the fixed length of all input data. However, through experimentation with LSTM autoencoders, we discovered the notable advantages of employing such architecture. This revelation underscores the importance of leveraging recurrent neural networks, even in scenarios where input sequences possess fixed lengths, thereby enhancing anomaly detection capabilities and providing deeper insights into data reconstruction processes.