BSCI- ECG Arrhythmia Diagnosis AI Model

Team TacoBell Coding Inc

Team Members:
Fatima Hassan
Hoang Tran
Kien Le
Premal Patel
Oanh Dinh
Ariya Ansari

Final Report

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Introduction:

Boston Scientific, a global medical device company, tasked our team with creating an internal tool to analyze electrocardiogram (ECG) data and diagnose arrhythmias using machine learning. ECG signals represent the heart's electrical activity, and clinicians use the waveforms to diagnose heart conditions. However, manual ECG interpretation is time-consuming and requires expertise. Automated ECG analysis using machine learning can improve diagnosis speed and accuracy.

Our initial goal was to train a model to predict rhythms from ECG images, but this approach required extensive preprocessing. We pivoted to developing a tool that reads raw ECG data in CSV format and uses classification or time series models to predict the diagnosis. We utilized public ECG databases and designed a data processing pipeline with steps like noise removal, heartbeat detection, feature extraction, and model training/evaluation.

Project Goals:

The primary objective of the project was to develop a machine-learning system capable of accurately predicting arrhythmia rhythms from raw ECG data. We were tasked with creating a training model that could read ECG signals in CSV format and classify them into different arrhythmia categories.

To achieve this, we planned to explore two different modeling approaches: a classification model and a time series model. Classification models, such as Convolutional Neural Networks (CNNs), are well-suited for ECG analysis due to their ability to automatically learn discriminative features from the raw signal. CNNs have been successfully applied to arrhythmia detection, demonstrating high accuracy in classifying different heartbeat types.

On the other hand, time series models like Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) are designed to capture temporal dependencies in sequential data. These recurrent architectures have shown promise in ECG classification tasks, as we can effectively model the dynamic patterns and long-term dependencies in ECG signals.

We compared the performance of these two modeling paradigms to determine the most effective approach for our specific dataset and problem sets. This comparative analysis would provide valuable insights into the strengths and limitations of each model type for arrhythmia prediction.

In addition to the core machine learning models, we also planned to develop a user-friendly front-end interface. This interface would allow users to input their own ECG data in CSV format and receive the model's predicted rhythm as output 1. By providing a seamless and intuitive user experience, the tool could be easily adopted by healthcare professionals and researchers for rapid arrhythmia screening and analysis.

To ensure the robustness and generalizability of our models, we trained and validated them on diverse ECG datasets. Publicly available databases like the MIT-BIH Arrhythmia Database and the Shaoxing People's Hospital (SPH) database 5 contain a wide range of ECG recordings from patients with various arrhythmias. Training on these datasets would expose the models to different heartbeat morphologies, noise levels, and patient characteristics, improving their ability to handle real-world ECG data.

Moreover, we also considered techniques to address the class imbalance often present in ECG datasets, where certain arrhythmia types are significantly underrepresented compared to normal beats. Strategies like oversampling minority classes, undersampling majority classes, or using weighted loss functions could help mitigate the impact of imbalanced data on model performance.

Overall, the project goals encompassed the development of accurate and robust arrhythmia prediction models, the exploration of different modeling approaches, the creation of a user-friendly interface, and the consideration of real-world challenges like diverse datasets and class imbalance. By achieving these objectives, we aimed to contribute to the advancement of automated ECG analysis and improve the early detection and management of arrhythmias in clinical practice.

The expanded section provides a more detailed and technical discussion of the project goals, drawing from the key points in the original passage 1 and the additional information in the search results. It explores the rationale behind the choice of classification and time series models, the importance of a user-friendly interface, the need for diverse training datasets, and the challenges posed by class imbalance.

Project Accomplishments:

We achieved several significant milestones in developing an AI-based ECG arrhythmia diagnosis system. A key accomplishment was training and testing an XGBoost classifier model to predict ECG rhythms from raw ECG data. XGBoost is a powerful gradient-boost algorithm known for its strong performance and interpretability 2. Our XGBoost model achieved an impressive accuracy of around 91% in classifying arrhythmias.

This high accuracy demonstrates the model's ability to reliably detect abnormal heart rhythms, which is crucial for timely diagnosis and treatment. We also explored a more advanced deep learning approach by training a Timesnet model. Timesnet is a neural network architecture designed for time series data like ECGs. While the current Timesnet model achieved 11% accuracy, we recognized that it requires further training and optimization to reach its full potential 1. This highlights the iterative nature of machine learning projects and the importance of continuous improvement.

To make the arrhythmia detection system accessible and user-friendly, we built a web application. The app allows users to input their own ECG data in CSV format and receive the model's predicted rhythm as output. This streamlines the diagnosis process and enables healthcare professionals to leverage the power of AI without needing technical expertise.

Lastly, we implemented a database to store the history of all previously processed ECGs. This database serves as a valuable resource for future model improvements, research, and auditing purposes. It ensures that the system can learn from past predictions and facilitates long-term data tracking.

Project Challenges:

We encountered several significant challenges throughout the project that tested our skills and resilience. One major hurdle was the steep learning curve associated with the complex domains of ECG analysis and AI modeling. Team members had to dedicate substantial time to self-study and research to gain the necessary background knowledge. This included understanding ECG waveforms, arrhythmia types, signal processing techniques, and machine learning algorithms suitable for time series data.

Another challenge was the time-consuming nature of certain critical tasks. Denoising the raw ECG signals to remove baseline drift, high-frequency noise, and muscle artifacts was a particularly lengthy endeavor. We had to experiment with different filtering approaches like discrete wavelet transforms to clean the data while preserving key features. Training the machine learning models, especially the deep learning Timesnet architecture, also required long computation times. The computational cost of training models, particularly Timesnet, imposed a financial burden on us. We ended up spending nearly $100 on cloud computing resources to train this model, which achieved a much lower accuracy of 11%. Balancing model complexity, training time, and cost was a difficult trade-off.
Lastly, we had to adapt to changing project goals and requirements later in the semester. This forced us to re-evaluate our approach, discard some work, and quickly adjust our plans. Effectively managing these moving targets added to the overall challenge.

General Team Experiences and Challenges:

Our journey throughout the project was marked by significant growth and learning. Initially, we struggled with disorganization and lack of focus, hindering our progress. However, a turning point came when the sponsor introduced an AI professor, Dr. Elham Buxton, to provide guidance and support. This addition, coupled with an adjustment of project goals, catalyzed a dramatic improvement in our productivity and collaboration. The AI professor brought valuable expertise and insights, helping us refine our approach and align our efforts more effectively. By clarifying project objectives and providing a clearer roadmap, we were able to channel our energy and skills more productively. This highlights the importance of expert guidance and well-defined goals in complex, interdisciplinary projects.

Conclusion:
The increasing vitality of AI in fields like medicine underscores the transformative potential of this technology. This project provided valuable exposure to the cutting-edge approaches used by innovative companies to tackle complex, real-world problems. It required the team to rapidly learn new domains, master emerging technologies, and collaborate effectively to deliver a functional product - essential skills for successfully transitioning from academia to industry.

In healthcare, AI is revolutionizing areas like disease diagnosis, drug discovery, and personalized medicine. Our work on ECG arrhythmia detection demonstrates how machine learning can augment human expertise, improving the speed and accuracy of critical medical tasks. By automating the analysis of complex ECG signals, our tool could potentially aid clinicians in the early identification and management of heart conditions, ultimately enhancing patient outcomes.

Despite our hurdles, the project's success in developing accurate arrhythmia prediction models and a user-friendly interface showcases the immense potential of AI in advancing medical diagnosis. It also highlights the importance of interdisciplinary collaboration, as we had to bridge the gap between medical domain knowledge and technical AI expertise to deliver an effective solution.

In conclusion, while the journey of integrating AI into complex domains like medicine is challenging, the potential benefits are immense. By embracing a mindset of continuous learning, collaboration, and adaptability, the team has positioned itself to be at the forefront of this exciting technological revolution. Our work serves as a testament to the power of AI in solving real-world problems and improving human lives, paving the way for a future where intelligent systems and human expertise seamlessly converge.