Development of a Novel Machine Learning-based Methodology for the Differential Diagnosis of Wide QRS Complex Arrhythmias Using Automated Analysis of 12-Lead ECG

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Abstract

This study aimed to advance the differential diagnosis of wide QRS complex arrhythmias by developing a machine learning-based methodology. Utilizing a comprehensive dataset with over 58,253 ECG recordings from composite unified database we trained and validated a convolutional neural network (CNN) model. The model was rigorously tested for its ability to accurately classify arrhythmias, focusing on the differentiation between ventricular tachycardia (VT) and supraventricular tachycardia (SVT), among other arrhythmia types.

The robust architecture of the CNN model was demonstrated by its high diagnostic accuracy across various arrhythmias, achieving more than 90% for all arrhythmias and over 97% for LBBB, RBBB, WPW, LAFB, LPFB, and nonspecific IVCD. Our results indicate that machine learning can significantly enhance the precision and efficiency of arrhythmia diagnosis in clinical settings.

This research underscores the potential of AI in cardiology, suggesting a future where AI-assisted tools are seamlessly integrated into routine clinical practice to improve patient outcomes.

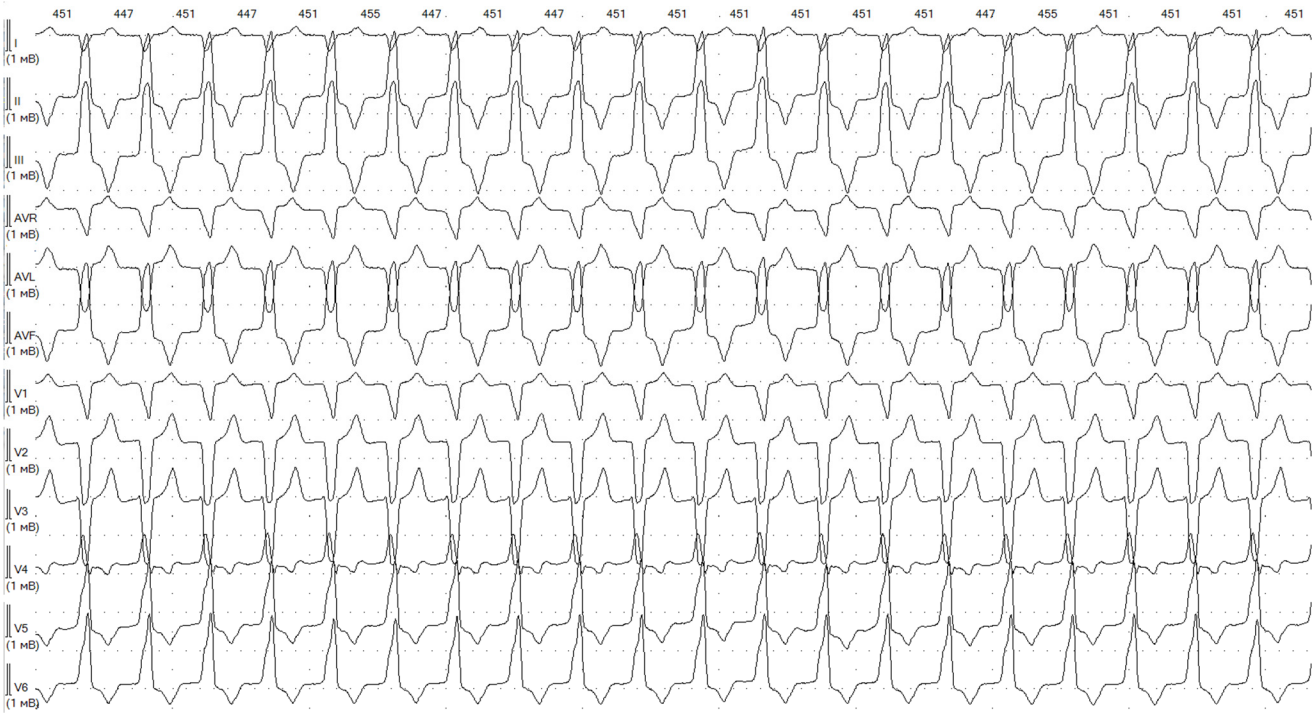

Figure 1. An Example of Wide QRS Complex Tachycardia.

1. Introduction

The diagnosis of wide QRS complex arrhythmias remains one of the most challenging scientific and practical tasks in electrocardiology and arrhythmology. Despite over six decades of study, the issue is far from resolved; however, it continues to be highly relevant as cardiologists frequently encounter the need to differentiate wide QRS tachyarrhythmias in their daily practice.

The cornerstone of diagnosis of wide QRS arrhythmias involves a detailed analysis of the ECG and the detection of atrial activity, particularly its relationship with the QRS complex. Yet, identifying P waves on a surface ECG can be extremely difficult due to their low amplitude and their tendency to overlap with the ST-T interval during premature ventricular complexes (PVCs). Moreover, during atrial flutter or fibrillation, it may become impossible to discern which atrial electrical waves are being conducted to the ventricles.

Under these circumstances, an alternative approach is necessary, focusing on the morphology of wide QRS complexes. Various scientific groups have proposed multiple morphological criteria and algorithms for this differential diagnosis, often centering on the amplitude and timing parameters of wide QRS complexes in leads V1 and V6. However, the diagnostic accuracy of these methods is not consistently high due to the inherent subjectivity in assessing the shape of wide QRS complexes by researchers and the heterogeneity of patient groups, some of whom may have structural heart disease after previous myocardial infarction. The presence of scar and myocardial fibrosis can significantly change the pathway of excitation through the ventricular myocardium, reducing the efficacy of these diagnostic algorithms.

Furthermore, individual anatomical differences in body structure and heart positioning within the chest are significant factors that can affect the morphology of the QRS complex, adding another layer of complexity to the diagnosis of wide QRS arrhythmias.

The differential diagnosis of Wide QRS Complex Tachycardias (WCT) primarily lies in dividing them into two groups: ventricular (VT) and supraventricular (SVT) origins, and this is a critically important clinical task. The urgency of distinguishing between these groups lies in the completely different therapeutic approaches each requires, and the potential for life-threatening outcomes if VT is misdiagnosed or inadequately treated. VT frequently results in the chaotic and ineffective contractions of ventricular fibrillation (VF), leading to sudden cardiac death. Such events contribute to over half of all cardiac-related deaths, underscoring the need for prompt and precise diagnosis of WCT.

While ECG is the frontline tool for capturing the electrical signatures of these arrhythmias, the interpretation of ECGs is highly variable and inherently subjective, depending greatly on the clinician's expertise. Traditional computer-generated ECG interpretations, though helpful, are limited by rigid algorithms and manual feature recognition that may not fully capture the nuances of the ECG. In contrast, artificial intelligence (AI), especially deep learning with convolutional neural networks (CNNs), heralds a new era of ECG interpretation (Figure 2). Initially applied in fields like computer vision and speech recognition, CNNs are now being harnessed to analyze routine 12-lead ECGs, with the potential for higher diagnostic accuracy and operational efficiency than ever before.

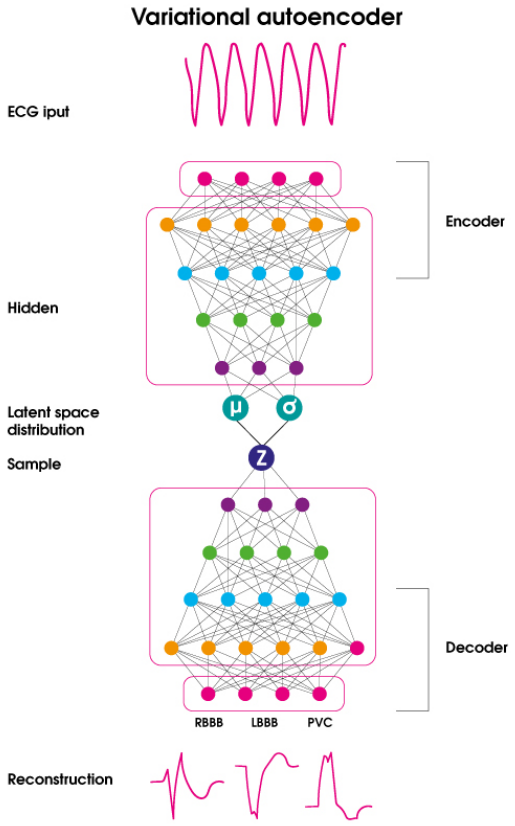

Figure 2. Schematic Structure of a Variational Autoencoder as an Example of Deep Learning with Convolutional Neural Networks

In recent publications, the potential of AI-based techniques for diagnosing complex arrhythmias like WCT has been brought to light [1]. Clearly, AI's role in ECG analysis is momentous, promising interpretations that mirror human analysis without the susceptibility to human error. The development of an AI-based diagnostic system capable of discerning the subtleties of WCT could signal a significant advancement in cardiac care, facilitating the early detection of potentially fatal arrhythmias and ensuring that life-saving treatments are not only available

but also applied judiciously and effectively.

2. The aim of the study

This study was initiated with the objective of establishing a robust machine learning protocol specifically tailored for the differential diagnosis of wide QRS complex arrhythmias. Our primary focus was on the development of a deep CNN architecture to meticulously discern and accurately classify WCT into their correct categories: VT or SVT. During the study, it became clear that we may not only differentiate between these two main classes and diagnose life-threatening arrhythmias like VT but also provide more detailed analysis to diagnose and differentiate various classes of wide complex arrhythmias such as LBBB, RBBB, WPW, PVCs and a few others. By leveraging the capabilities of this AI-driven diagnostic approach, we sought to enhance the precision of arrhythmia classification and improve the quality and effectiveness of decision-making based on real-world ECG databases to be able with further implementation of our solutions into routine clinical practice.

3. Materials and methods

3.1. Data used for ML Model Development

The size of the database is critically important for creating a robust neural network model, as many available datasets include only a very limited number of ECG recordings. Therefore, for the training and validation of our CNN model, we utilized three of the largest distinct 12-lead ECG datasets: those from Chapman University [2], the PTB-XL dataset [3], and the dataset from Shandong Provincial Hospital (SPH) [4]. These datasets, sourced from various clinics, feature a diverse array of labels and records. For our study, we merged these databases, which led to a total of 58,253 ECG recordings, including Normal ECGs as presented in Figure 3.

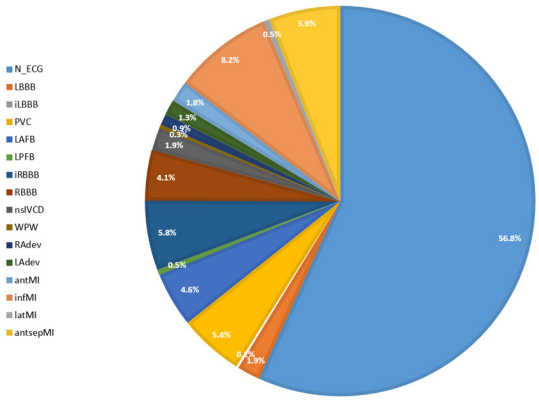

Figure 3. Pie Chart Representation of the Composite Database Structure Utilized for ML Training Algorithms.

A significant challenge in classification arises from the notable data imbalance present within them. The labels selected for analysis included normal ECG, left bundle branch block (LBBB), incomplete left bundle branch block (ILBBB), premature ventricular complexes (PVCs), left anterior fascicular block (LAFB), left posterior fascicular block (LPFB), incomplete right bundle branch block (IRBBB), right bundle branch block (RBBB), non-specific intraventricular conduction disturbance (NICD), and ventricular preexcitation (WPW), as shown in Figure 4. Additionally, labels for non-infarcted ECGs and various myocardial infarctions—anteroseptal, lateral, inferior, and anterior—were also included. The final size of the combined database was 41,170 ECG recordings. We allocated the ECG data into training and validation sets at a ratio of 0.8 to 0.2, respectively.

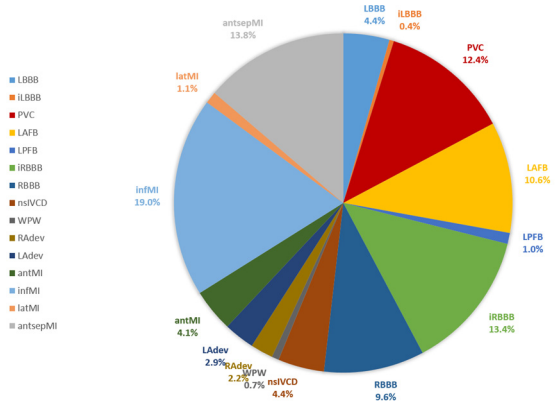

Figure 4. Detailed Pie Chart Depicting the Composition of the Unified Database for Machine Learning Training Across Various Arrhythmias.

3.2. Data Processing and Feature Classification with Deep Learning

The initial phase of our study involved stringent filtering of the ECG data to discard unsuitable signals. The remaining signals were then meticulously processed to eliminate baseline wander and other noise interferences, such as power line noise, muscle contractions, and respiratory effects. The determination of the QRS complex boundaries within the ECG signals was carried out using the Hamilton-Thompson algorithm, ensuring that only the signals encompassing the QRS complex were retained for further analysis.

To facilitate the feature extraction process, we employed a Convolutional Variational Autoencoder (CVAE). The CVAE operates as a feature converter, transforming raw ECG signals into a compressed, essential set of features within a latent space. This technique allows for a more focused analysis by distilling the ECG data into

its most characteristic elements.

The architecture of the CVAE is composed of three principal components, each with a critical role in the feature extraction and reconstruction process as shown on Figure 1. The encoder is the first step in the CVAE architecture, responsible for receiving the input ECG signals data. The encoder's output is then funneled into the latent space (bottleneck) a compressed representation that encapsulates the critical information needed to reconstruct the input data. Finally, the decoder mirrors the encoder's structure but in reverse, working to reconstruct the input data from the compressed form in the latent space.

Ultimately, an ensemble of these machine-learned models was put to the test, with their diagnostic accuracy rigorously evaluated against a separate validation dataset. This ensemble approach provided a robust assessment of the potential clinical applicability of our deep learning model in real-world diagnostic settings.

4. Results

The results of the ensemble of machine learning models demonstrated high diagnostic accuracy across various arrhythmias. Notably, LAFB, WPW and incomplete LBBB were diagnosed with an outstanding accuracy of 99%. The lowest accuracy was observed in the diagnosis of incomplete RBBB at 91%. Collectively, these findings indicate that for all types of WCT, the diagnostic accuracy of the models exceeded 90% as shown on Figure 5.

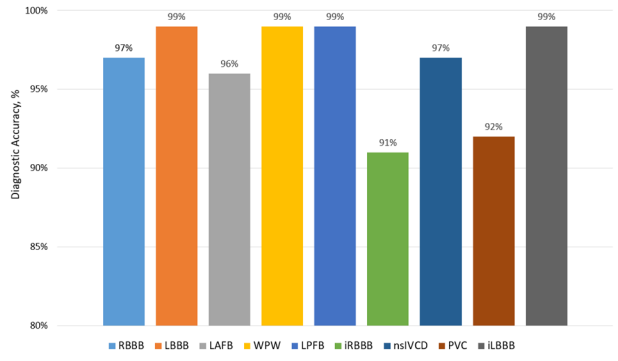

Figure 5. This column plot as categorized histogram shows the diagnostic accuracy of the final ensemble machine learning model for various types of arrhythmias characterized by wide QRS complexes.

5. Discussion and Conclusions

Machine learning is revolutionizing the diagnosis of wide QRS complex arrhythmias, providing consistent and objective analysis that surpasses the capabilities of traditional manual methods. This study introduces a methodology based on machine learning that not only enhances the precision of WCT diagnosis but also accelerates the clinical decision process for clinicians.

The uniqueness of this study lies in its use of the largest available ECG dataset and the latest developments in CNN technology. This innovative approach aims to standardize ECG interpretations for complex arrhythmias like WCT across diverse clinical settings, thereby potentially improving patient outcomes with rapid accurate diagnoses. The findings suggest that such AI-based technologies could soon be fundamental to arrhythmia diagnosis, combining advanced AI with clinical expertise to boost efficiency and diagnostic accuracy of complex arrhythmias with the prospect of integrating these technologies into routine clinical practice.

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