AI DRIVEN PERSONALIZED SLEEP PATTERN CLASSIFICATION FOR SLEEP APNEA DETECTION

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Introduction

Our project delves into the intricate fusion of electrocardiography (ECG) signals with polysomnography (PSG) to enhance the efficacy of sleep apnea detection and management. We aim to refine diagnostic precision and customize treatment protocols, prioritizing ethical standards and privacy. Our multifaceted objectives include the development of an adaptable model for personalized detection, poised for widespread integration within healthcare infrastructures.

We focus on refining classification strategies, adapting advanced detection models for resource-constrained devices, and exploring the clinical relevance of ECG signals in patient outcomes. Furthermore, we prioritize integrating machine learning algorithms for personalized detection and leveraging ECG signals to enhance accuracy, aligning with the need for precision and personalization in sleep apnea identification.

Motivation

In our quest to combat sleep apnea, we aim not just for accuracy, but for personalized precision in diagnosis. With each nuanced adaptation of our AI model, we pave the way for a healthcare landscape where every individual's sleep patterns are understood and addressed with utmost care and privacy, ushering in a new era of patient-centered medicine

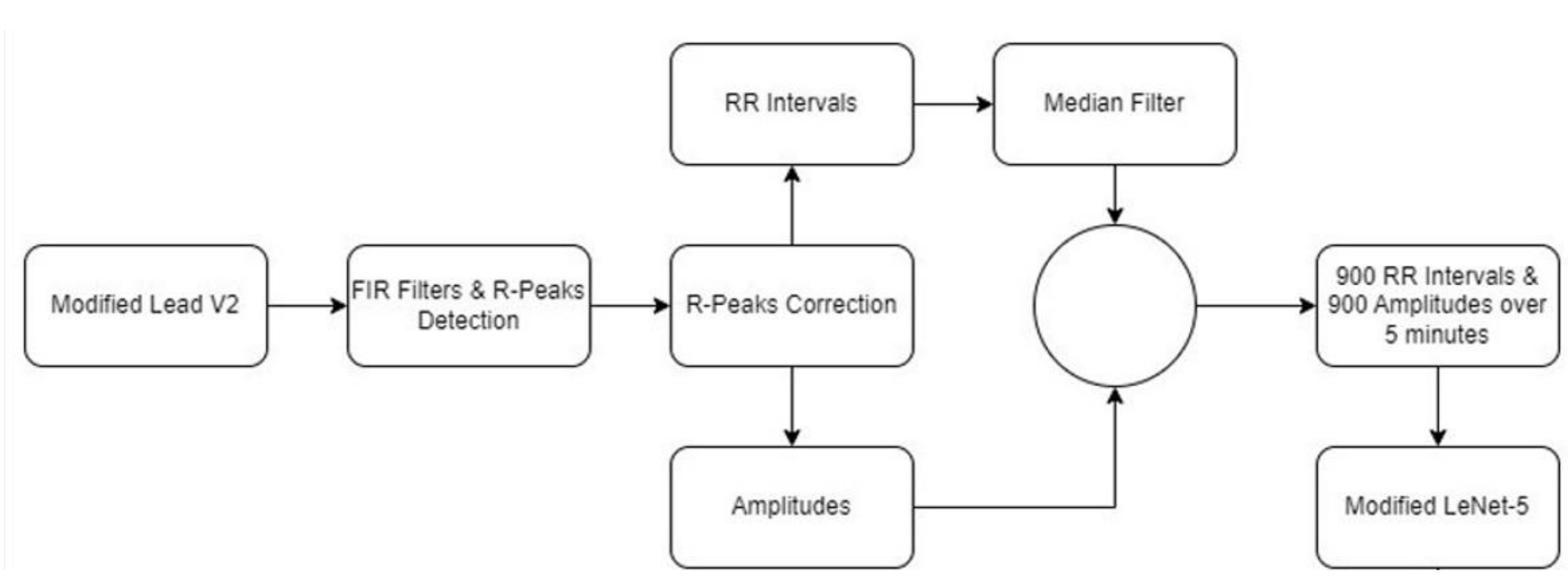
Scope of the Project

This project thoroughly reviews existing literature on using ECG signals in PSG for sleep apnea detection, assessing their role in identifying breathing events and evaluating cardiovascular health impact. It also explores machine learning techniques to enhance diagnostic accuracy and personalize treatment strategies, aiming to advance sleep apnea diagnosis and management.

Methodology

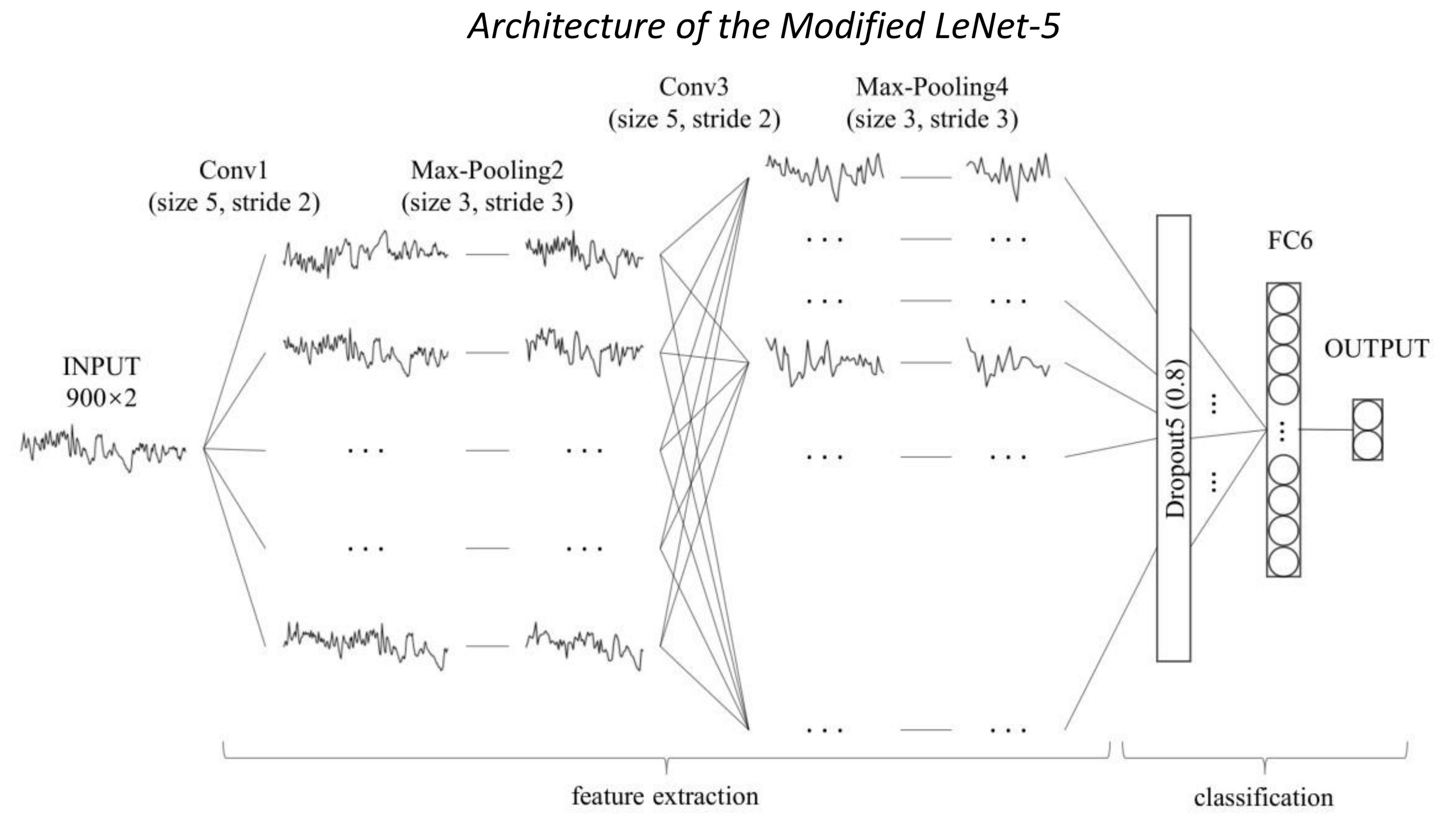
We intricately adapt the LeNet-5 architecture to specifically analyze one-dimensional electrocardiogram (ECG) data, departing from its conventional role in character recognition. This tailored modification involves meticulous adjustments, including the implementation of one-dimensional convolution operations aimed at capturing the nuanced temporal patterns inherent in ECG signals. Additionally, strategically introduced dropout layers serve to mitigate overfitting, thereby enhancing the model's capacity to generalize effectively from limited data samples. Moreover, the fine-tuning of fully connected layers enhances the extraction of meaningful features critical for the accurate classification of SA instances. These refined adaptations result in our customized LeNet-5 model demonstrating enhanced efficacy in interpreting intricate ECG data.

PhysioNet Apnea-ECG dataset preprocessing scheme



Our modified LeNet-5 architecture processes ECG signals by first detecting R-peaks and extracting RR intervals and amplitudes during the preprocessing step. These features are then normalized using min-max normalization to ensure uniform scaling. Subsequently, informative features related to RR intervals and amplitudes are extracted to capture relevant patterns indicative of SA presence. The model is trained using these features and validated using evaluation metrics such as specificity, sensitivity, and accuracy. By employing one-dimensional convolution, dropout regularization, and other adjustments, our model enhances its ability to generalize from limited data samples and effectively distinguish between normal and SA recordings.

Architecture of the Modified LeNet-5

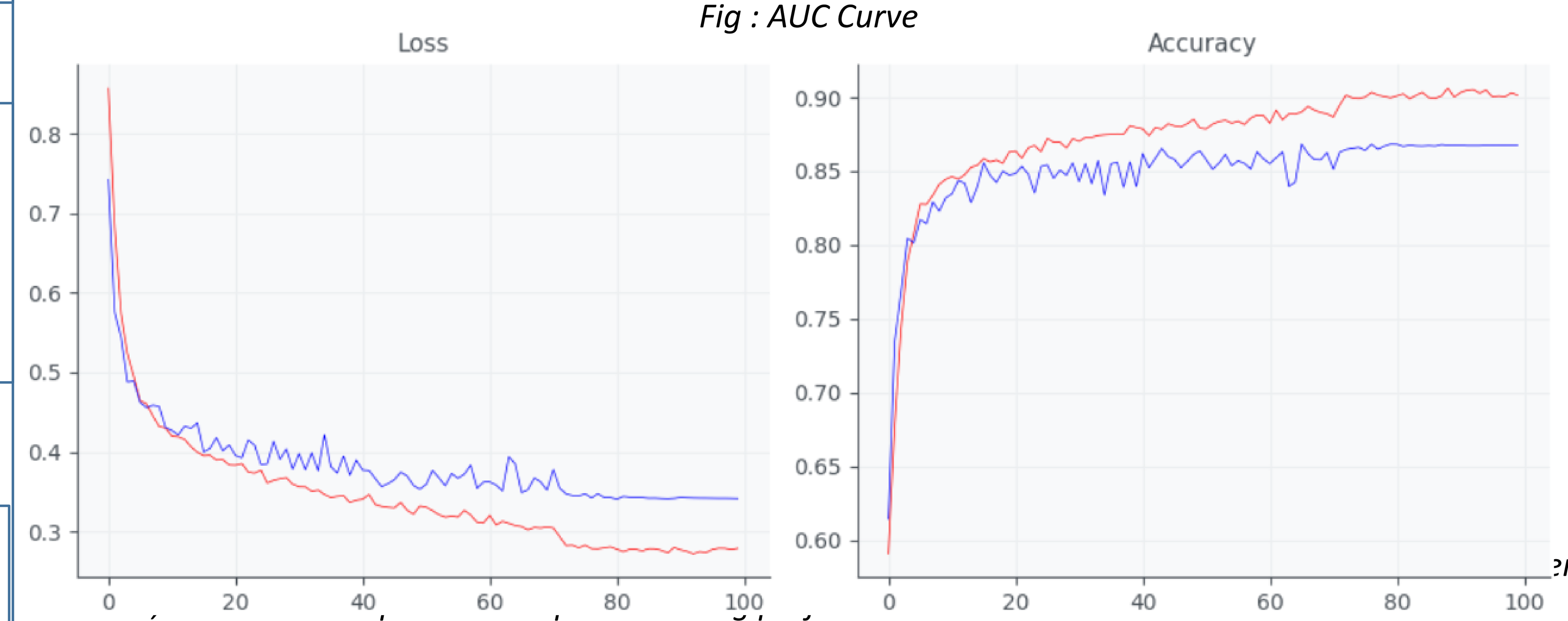


Results

In this project, PhysioNet Apnea-ECG dataset was used as a benchmark data to evaluate our proposed method's performance. The model, equipped with automatic feature extraction, demonstrates impressive performance in accurately predicting the presence of sleep apnea (SA) based on electro-cardiogram(ECG) segments, analyzed on a minute-by-minute basis. The classification was conducted based on the Apnea-Hypopnea Index (AHI), where an AHI greater than 5 indicates SA and otherwise normal. The AHI for each recording was calculated using the number of obstructive sleep apnea (OSA) segments detected per hour, obtained from per-segment SA detection results. The withheld set evaluation showcases the robustness of our model, with notable metrics including a specificity of 90.3%, sensitivity of 83.1%, accuracy of 87.6%, and an area under the receiver operating characteristic curve (AUC) of 0.950. These metrics highlight the model's ability to effectively distinguish between individuals with and without SA, providing reliable diagnostic support.

Comparative analysis against SVM, the second-highest performing method, reveals substantial improvements across all evaluation metrics. Specifically, our model outperforms SVM by margins of 6.0% in specificity, 6.2% in sensitivity, 6.2% in accuracy, and 0.063 in AUC, respectively.

Fig : AUC Curve



The convolution operation transitioned from two-dimensional to one-dimensional, aligning with the nature of the sequential data being analyzed. Additionally, a dropout layer was introduced to mitigate overfitting by randomly deactivating connections during training, promoting the learning of more robust features. Moreover, the complexity of the network was reduced by consolidating to a single fully connected layer, streamlining the architecture for improved training efficiency and generalization. Lastly, fine-tuning of convolution layer strides and fully connected layer nodes was conducted to optimize model performance.

Modifications made to the standard LeNet-5 Convolutional Neural Network.

Layer	Parameter	Output Shape	Number
Input	-	(None,900,2)	0
Conv 1	32*5*2, stride 2, pad 0	(None,448,32)	352
Max Pooling 2	3, stride 3, pad 0	(None,149,32)	0
Conv 3	64*5*2, stride 2, pad 0	(None,73,64)	10304
Max Pooling 4	3, stride 3, pad 0	(None,24,64)	0
Dropout 5	0.8 rate	(None,24,64)	0
FC 6	32, ReLU	(None,32)	49184
Output	2, SoftMax	(None,2)	66

Conclusion

Our study presents a promising method for sleep apnea detection utilizing modified LeNet-5 with ECG segments, exhibiting superior performance over traditional approaches. While our approach shows potential for clinical and home healthcare applications, limitations in dataset segmentation and event annotation highlight areas for further refinement. Future research will focus on addressing these challenges to enhance the method's accuracy and applicability in detecting various types of sleep apnea events.

References

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