

Electrocardiogram Signal Preprocessing Based on the SG-HP Filter for Sleep Apnea Detection Using Convolutional Neural Network (CNN)

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Abstract

Sleep is one of the first behaviors that is disturbed due to the change of environmental conditions. Sometimes, those environmental discomforts that cause anxiety and disturbance or cause the failure of desires and failure to satisfy the basic needs of a person disturb his sleep. Sleep apnea is known as one of such disorders in scientific societies. So far, many researches have been conducted in this field, which are associated with advantages and disadvantages. In this article, an efficient method based on the use of Savitzky-Gulai (SG) and Hodrick-Prescott (HP) filters is presented in order to improve the electrocardiogram signal pre-processing for the accurate detection of sleep apnea. In this paper we use PhysioNet apnea-ECG database. The extracted features are subsequently used to train, test and validate a deep artificial neural network. The training and testing sets are obtained by randomly dividing the data until good performance is achieved using k-fold cross-validation (k=10). According to the results, the CNN classification has sufficient accuracy to detect and diagnose sleep apnea (99.1%), which proves the good performance of the proposed method.

Keywords: Electrocardiogram, Apnea, Savitzky-Gulai (SG), Hodrick-Prescott (HP), CNN

1. Introduction

To effectively diagnose sleep apnea, it is essential to first understand normal sleep patterns and how they differ from sleep disorders. A key characteristic of normal sleep is a significant reduction in response thresholds to external stimuli. Sleep disorders are characterized by deviations from these typical patterns, where an individual fails to demonstrate the expected reductions in response thresholds and may exhibit irregular or heightened reactions. Such disorders can arise from various factors, including poor habits or medical conditions that disrupt the sleep cycle, leading to inadequate rest and persistent fatigue despite extended sleep durations. This inadequacy poses a growing threat to an individual's health and safety [1].

Breathing, an automatic physiological process during sleep, is influenced by numerous anatomical and physiological factors. Various sleep-related disorders arise from these influences, with over eighty recognized types of sleep disorders, most of which negatively impact health and diminish quality of life.

Research has categorized sleep disorders into two main types: localized insomnia and absolute insomnia [2]. Chronic sleep deprivation can lead to significant daily impairments, including increased risk of accidents, communication difficulties, emotional and social issues, decreased job performance, memory problems, and mood disorders. Recent studies have also linked sleep disorders to severe conditions such as cardiovascular disease, obesity, and diabetes.

Currently, the diagnosis of sleep apnea, a prevalent cause of excessive daytime sleepiness in both children and adults, relies primarily on polysomnography. This method, while effective, is costly and complex, often involving cumbersome equipment. Sleep apnea is characterized by intermittent cessation or significant reduction of

breathing during sleep, with pauses varying from 10 to 30 seconds or more. To enhance diagnostic accuracy and patient comfort, there is a growing need for advanced, automated techniques to predict and monitor sleep apnea.

Severe cases of sleep apnea can result in up to 400 breathing interruptions per night. Statistics indicate that over 18 million people in the United States suffer from sleep apnea, with approximately 10 million of these cases remaining undiagnosed. This disorder is often associated with fluctuations in heart rate and alterations in ECG waveforms, which can correlate with breathing disruptions. Obstructive Sleep Apnea (OSA) is a prevalent sleep-related respiratory disorder that poses significant health risks.

A critical issue is that individuals may experience breathing difficulties for years before seeking medical attention, often due to daytime fatigue, memory decline, and other complications. Long-term oxygen deprivation can lead to severe health problems, including cardiovascular issues. Currently, diagnosing sleep apnea typically relies on costly and cumbersome polysomnography. Additionally, sleep spindles—short bursts of 12-14 Hz waves occurring at 2–5-minute intervals during stages 1-4 of sleep—are crucial for reducing brain sensitivity to sensory input and maintaining sleep. In elderly individuals, these spindles are less prominent, leading to more frequent nighttime awakenings. Overall, sleep spindles are key transient waveforms in EEG signals during sleep.

Numerous automatic devices for detecting sleep spindles have been proposed, with some methods relying on pattern matching. These approaches compare the similarity between recorded signals and predefined patterns, but their accuracy can be compromised because patterns may vary between individuals. Other methods include spectrum analysis, which can struggle to distinguish spindles from other frequency components. Additionally, techniques such as matched tracking and wavelet transform have been employed.

This research introduces a method based on wavelet transform for automatically identifying sleep spindles in EEG signals. By extracting frequency features, the study compares sleep spindles in individuals with obstructive sleep apnea before and after treatment with a CPAP machine, evaluating the device's effectiveness. Wavelet transform offers advantages over Fourier transform, including time-frequency representation, multi-resolution filtering, and enhanced time-frequency analysis, which are essential for analyzing non-stationary signals like EEG. The wavelet transform identifies short bursts of 12-14 Hz waves during stages 1-4 of sleep, occurring at intervals of 2-5 minutes, which help maintain sleep by reducing the brain's sensitivity to sensory information. The study compares frequency characteristics such as median and average frequency, modified median and average frequency, and the high-to-low frequency ratio of spindles before and after CPAP treatment, assessing the device's impact on sleep apnea recovery.

Sleep spindles: these are short bursts of brain activity with a frequency range of 12-14 Hz, occurring every 2-5 minutes during sleep stages 1-4. These waves help decrease the brain's sensitivity to sensory input and are essential for maintaining sleep continuity. In older adults, sleep spindles are less pronounced, leading to more frequent awakenings throughout the night. Overall, sleep spindles are crucial transient waveforms in the EEG signal during sleep.

Detection Devices: Several automated devices have been developed to detect sleep spindles. Some methods use pattern matching, comparing recorded signals to predefined patterns, although their effectiveness can be limited by individual variability in these patterns. Other methods, such as spectrum analysis, face challenges in distinguishing spindles from other frequency components. Techniques based on matched tracking and wavelet transform have also been employed to address these issues.

Sleep Breathing Parameters: Sleep breathing parameters include several key definitions: Hypopnea is defined by a 50% reduction in airflow during sleep for at least 10 seconds, accompanied by a 3% decrease in blood oxygen saturation or arousal. Arousal refers to a sudden shift from sleep to lighter stages or wakefulness, ending apnea and hypopnea events.

The Apnea Index (AI) measures the number of apneas per hour of sleep, while the Apnea-Hypopnea Index (AHI) includes both apneas and hypopneas per hour, also known as the Respiratory Disturbance Index (RDI). The Respiratory Arousal Index (RAI) quantifies the number of arousals per hour of sleep. Obstructive sleep apnea is

diagnosed when the AHI exceeds 5, and Obstructive Sleep Apnea Syndrome is diagnosed when the AHI is greater than 5 with associated symptoms such as snoring, witnessed apneas, excessive daytime sleepiness, or fatigue.

Central sleep apnea syndrome is characterized by having more than 50% of identified apneas being of the central type. Diagnosis of sleep apnea syndrome is typically made by a physician based on evaluations of sleep breathing parameters.

In 1997, the American Sleep Disorders Association (ASDA) defined obstructive sleep apnea syndrome as a condition involving obstruction of the upper respiratory tract (URT) during sleep, often accompanied by decreased oxygen levels. The prevalence of this condition ranges from 1 to 5 percent. Despite the known risk factors, which are comparable to those for diabetes and bronchial asthma, the precise pathophysiology of these obstructions remains incompletely understood. Generally, "sleep Apnea" is defined as a cessation of breathing lasting at least 10 seconds. This disruption often leads to frequent nighttime awakenings, disturbed sleep quality, excessive daytime sleepiness, and increased pulmonary artery and arterial PCO₂ pressure. Sleep Apnea predominantly affects premature infants, adult men, and postmenopausal women [3]. It is a common disorder marked by interruptions in breathing, with Apnea typically lasting between 10 and 30 seconds and, in severe cases, occurring hundreds of times per night.

Each apnea event can last up to 2 minutes. Obstructive sleep apnea, the most common type of sleep apnea, is a serious condition where individuals experience repeated short interruptions in breathing during sleep. After falling asleep, affected individuals may briefly wake up feeling short of breath due to airway obstruction. Normal breathing typically resumes with snoring or a hoarse sound. Loud snoring is a frequent symptom of sleep apnea. Sleep apnea is generally classified into three types: central, obstructive, and mixed [4].

Electromyography (EMG) is used to observe and record electrical activity in muscles, with EMG signals spanning frequencies from 10 to 5000 Hz. Electrooculography (EOG) tracks eye movements based on the electrical activity of muscles around the eyes. Thermal resistance sensors measure airflow through the nose to detect obstructions in the upper respiratory tract. Microphones capture and record snoring sounds, while a special tape around the chest records the expansion and contraction of the chest to monitor breathing patterns.

SpO₂ is a signal that indicates the oxygen concentration level in the blood. Using a PPG device, changes in blood oxygen levels following breathing are analyzed. Additionally, statistical analysis of various signals, including tracheal airflow, speech-related audio signals, brain electrical activity (EEG), and cardiac electrical activity (ECG), is another method used for identifying sleep apnea [5].

This article is organized into four main sections. The second section covers the foundational aspects of the research. The third section details the proposed method, along with simulations and results. The final section presents the conclusion.

Spectral density is a technique used to develop models for predicting future behavior of dynamic systems and to diagnose hidden periodicities in time series data. This method is crucial for identifying cyclical patterns and understanding the fundamental dynamics of a system, especially when fitting seasonal ARIMA models. Spectral analysis has applications across various fields, including forecasting sales in production companies, predicting geological developments in geophysics, studying stars in astronomy, forecasting weather in meteorology, and predicting traffic flow in transportation or short-term traffic patterns [6].

In 2016, Dariusz and Paul developed estimation and prediction methods and compared classical and advanced forecasting tools, assessing the influence of spectral analysis on the prediction model parameters. In 2015, Kovach introduced the Demodulated Band Transform (DBT), a new method for spectral estimation that minimizes susceptibility to spectral loss. Their conclusion was that the DBT efficiently estimates both stationary and non-stationary spectral and cross-spectral statistics. Over the past decades, many studies have proposed the Hodrick–Prescott (HP) filter to optimize time series prediction, particularly in financial and economic contexts. The HP method is popular among economic researchers due to its detailed methodology for stationary situations. Researchers aim to apply it to non-stationary data without modeling the non-stationarity, typically by decomposing the observed variable into trend and cycle components [7].

Furthermore, the HP method has been used for business cycle analysis to decompose time series into trend and cyclical components. Some decomposition procedures have added refinements over time. Additionally, the Beveridge-Nelson decomposition is a popular method. As discussed in [8], “it is likely that the HP filter will remain one of the standard methods for detrending,” although Harvey and Jaeger (1993) identified some issues with the HP filter. One difficulty is its low performance at certain limits, unlike trend and cycle estimation. In the 1990s, the HP filter gained popularity, particularly after an econometricians’ article published in 1997. Harvey and Trimbur in (2003) provided a primary application in their work, and the software was designed to yield cycle estimates based on trend-cycle output. Marlon et al. in 2007 introduced the Hodrick-Prescott (HP) filter, suggesting the estimation of a topical linear trend that defines the bandwidth endogenously and is mechanically corrected at boundary points for short-range dependence 4. Agustin and Ana introduced several criteria, such as the HP decomposition for different levels of aggregation, which yields consistent results. They used a standard method to preserve the frequency period with a gain filter of 1/2; this method is theoretical and simple to apply.

Due to the importance of electricity forecasting, numerous studies have reviewed the techniques and methods used, as discussed by [9]. These reviews cover the most common approaches and categorizations for forecasting techniques. From these studies, it can be concluded that a key property of spectral analysis is its ability to identify hidden cycles, which is crucial for constructing models for stationary time series through precise frequency domain analysis. Therefore, spectral analysis is particularly useful in physical and natural sciences, such as acoustics, communications engineering, geophysics, and biomedical sciences. In contrast, the Hodrick–Prescott (HP) filter is a significant procedure applied in the field of macroeconomics.

2. The basics of research

To create a suitable platform for presenting the proposed method, this section is dedicated to discussing the tools used. The first tool discussed is the Savitzky-Golay filter, which is integrated with a deep convolutional neural network and then Hodrick–Prescott (HP) filter. The Savitzky-Golay filter is a well known method; Therefore in the following, the HP filter is described in more details.

2.1. Savitzky-Golay (SG) filter

The Savitzky-Golay filter was proposed by Savitzky and Golay in 1964[10]. One of the most common and widely used filters in the fields of science and technology, especially used for signal processing, is a smoothing filter. This filter can be used to reduce the high frequency noise in the signal due to its smoothing property and reduce the low frequency signal using differentiation.

2.2. Hodrick–Prescott (HP) filter

The HP filter is a mathematical approach that is used in analyzing economic data to extract the cyclical component and trend from a time series. This approach considers that a time series can be divided into a nonlinear growth or trend component. The series Y_t denotes the interest time series variable that is made up of a trend component τ_t , a cyclical component c_t and an error component e_t , such that:

$$Y_t = \tau_t + c_t + e_t \quad 1$$

However, any decomposition is ought to be based on a conceptual artefact, as there is no guaranteed observation of the trend and cycle parts. Before these elements can be estimated from the data, there must be a definition of what is a trend and a cycle. Therefore, the solution of the following standard penalty program derives the trend from a time series by using the HP filter method:

$$\min_{\tau} \sum_{t=1}^T (Y_t - \tau_t)^2 + \lambda \sum_{t=1}^{T-1} [(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2 \quad 2$$

where λ is the positive smoothing parameter as a penalization of the trend component variability. The series to be filtered will be called the input sequence τ and the output sequence Y_t . In order to solve this problem, it is important to identify some related information; any economic time series will be described as a sequence of real numbers, where each observation is an element of the sequence process. The above equation has an intuitive explanation. The HP filter decomposes two components for a time series: a stationary cycle and a long-term trend,

which needs the previous description of the parameter λ , which setting the smoothness of the trend and determines the major period of the cycle that will produce the filter. However, when it uses the similar λ for a series at various.

2.2. Deep Convolutional Neural Network

Deep convolutional neural networks (CNNs) are among the most widely used structures in recent signal processing researches. These networks consist of layers with specific functions, following consistent principles and rules. Generally, a CNN is composed of three basic layers: the convolutional layer, the pooling layer, and the fully connected layer. Each of these layers has a specific task.

The training process for this class of neural networks includes two main stages: the forward pass and the backpropagation stage. In the forward pass, the input is fed into the initial layer of the network, where pointwise multiplication occurs between the input and the components of each neuron, followed by the convolution process in each layer. Finally, the network's output is calculated.

To adjust the network parameters, or in other words, to train the network, the obtained output is used to measure the network error. The network's output is compared with the correct answer using an error function, and the error rate is calculated. In the next step, error propagation begins. At this stage, algorithms such as gradient descent are used to calculate the derivative of the error function with respect to each parameter according to the chain rule. All parameters are then updated based on their contribution to the network's error. After updating the parameters, the backpropagation stage is repeated. Finally, after a suitable number of iterations, the network training is completed.

In the testing phase, after inputting the test data into the pre-trained neural network, the degree of belonging of each data point to different classes is determined at the output of the fully connected layer.

3. Proposed method

Our proposed method for this paper focus on preprocessing stage in Fig.1 you cand find detail of this stage.

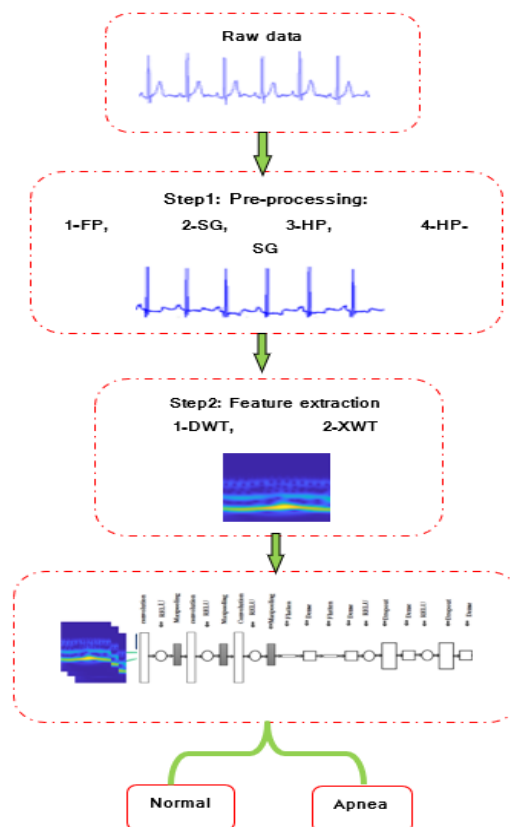


Fig.1 block diagram of proposed method

According to Fig.1 we have 4 scenarios in this paper:

- 1- Raw data and using full pass filter classification based CNN
- 2- Preprocessing using SG filter and classification based CNN
- 3- Preprocessing using HP filter and classification based CNN
- 4- Preprocessing using HP filter and SG filter and classification based CNN

So first part of proposed method is dataset:

In the related researches in the field of machine vision and pattern recognition, different criteria are used to validate the model and evaluate the results. Among these criteria, we can mention accuracy, which that is an important component for evaluating the result of a two-mode or binary classification like this research.

The classification efficiency is defined as the proportion of negative cases that the test correctly flags as negative. The accuracy rate measures the performance of the classifier on both categories simultaneously. calculate four components in necessary :

True positive: the data of the apnea class is correctly recognized in the same class.

False positive: the Normal data are recognized as the apnea.

True negative: the Normal is correctly recognized as the same class.

False negative: the data of Apnea is recognized as Normal.

The correctness component is the most common, basic and simple measure of the quality of a category, and it is the amount of correct recognition of the category in the total of two categories. This quantity actually indicates the amount of correctly recognized patterns and is formulated and defined in the form of the following relationship based on the matrix presented above.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad 4$$

4. Simulation

The simulation of this paper has been coded in a system with CPU Core i7 RAM: 32GB GPU: 6GB in the environment of MATLAB. will also be raised. In this section, the simulation of the proposed method is evaluated step by step in details.

4.1. Dataset

University College Dublin (UCD) Sleep Apnea Database [10], includes overnight PSG records from 25 people with sleep-disordered breathing, with 14 different types of signals from each patient in the middle-aged category, of which 21 patients died and 4 patients is a woman It has labels of sleep stages and different types of sleep apnea. 10 of these patients have all three types of Apnea. Each ECG record contains a continuous single-lead ECG signal and annotation of the onset time and duration of apnea/hypopnea events. The patients of this database did not have any previous history of heart diseases or other diseases. The records of these patients have three channels of heart rate along with other signals, including electro-oculography, electromyography, electroencephalography with two different channels, oxygen saturation, patients' snoring, air flow, abdominal and chest breathing signals. The length of each ECG signal is between 6 hours and 10 hours. It can be said that this database has all the necessary signals to diagnose apnea and the information needed by each patient. The input data used in this research is related to this sleep apnea database of University College Dublin, which includes 25 data with specific dimensions and labeled as normal or apnea for 60 second intervals of each of the signals. In fig1 you can find sample of raw data.

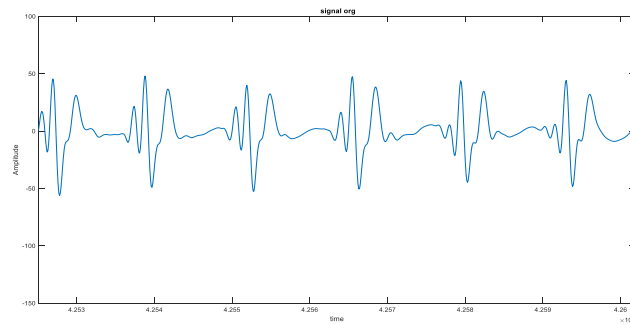


Fig1. raw data

4.2. Pre processing

The preprocessing techniques for ECG signals are highly varied and can generally be categorized into two main groups: filter-based approaches and machine learning-based methods. Filters are among the most widely used and longest-established techniques introduced for preprocessing ECG signals. Machine learning-based methods exhibit significant diversity and are further classified into adaptive and non-adaptive approaches. Research works such as those by Sharma and Sharma [11], Song et al. [12], and Varun et al. [13] have focused on methods centered around feature engineering. Conversely, studies by Wang et al. [14], Hong Yu Chang et al. [15], Singh and Majumder [16], and Li et al. [17] have proposed feature learning methods that leverage neural networks to automatically learn the features of ECG signals or RR intervals.

Notably, the apnea detection system by Singh and Majumder [16] employs a two-dimensional CNN model, necessitating the use of continuous wavelet transform to convert one-dimensional ECG signals into two-dimensional scalogram images during the preprocessing stage. This two-dimensional CNN model demands more parameters and incurs higher computational costs compared to a one-dimensional CNN model. Other studies have required the identification of R peaks and the calculation of RR intervals. Methods such as the median filter [11, 14, 17] and R peak correction [13] are frequently applied to eliminate physiologically meaningless points. Additionally, QRS complex extraction and EDR extraction have been highlighted in the works of Sharma and Sharma [11], Song et al. [12], and Varun et al. [13], respectively.

We have 4 scenarios that each one led to discriminate results. Result of These scenarios are as follow:

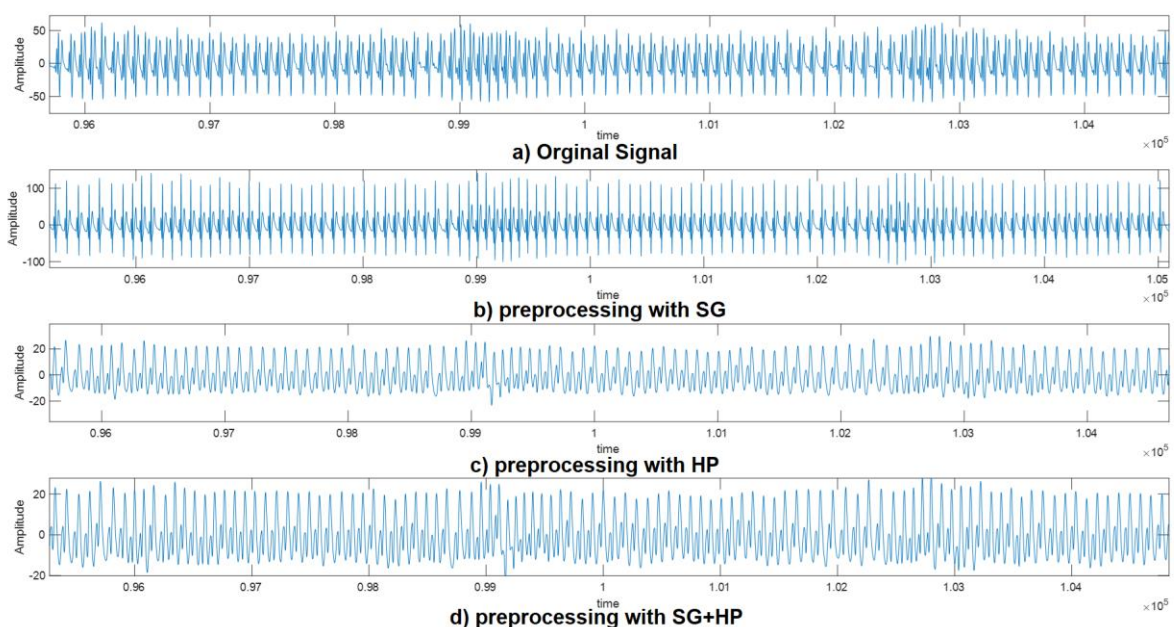


Fig2. various scenario for preprocessing a)Original signal b)SG c)HP d)SG+HP

In this figure, you can find the impact of the SG filter and HP filter and the combination of these states and raw data using a full pass filter. We can find out from this figure that a combination of the SG filter and HP filter could provide better discrimination for R picks in comparison with other scenarios.

4.3. Classification

In [18], four different classifiers—random forest (RF), k-nearest neighbor (KNN), logistic regression (LR), and support vector machine (SVM)—were evaluated to identify the most suitable model for this research. Feng et al. [19] proposed a sleep apnea diagnosis approach utilizing unsupervised feature learning and single-lead ECG signals, achieving per-segment classification results of 85.1% accuracy, 86.2% sensitivity, and 84.4% specificity. Pombo et al. [20] employed an artificial neural network (ANN) for sleep apnea diagnosis, obtaining 82.12% accuracy, 88.41% sensitivity, and 72.29% specificity. Bai et al. [21] utilized convolutional neural network (CNN) classification, reporting 94% accuracy and 88% sensitivity for diagnosing sleep apnea syndrome. Additionally, Karunakaran et al. [22] used a Grid Search optimization method with an SVM classifier, achieving 89% accuracy in detecting obstructive sleep apnea from ECG signals.

It should be noted that two approaches have been adopted in the implementation of this paper. In the first approach, the classification process was implemented using CNN classifier, and in the first approach, Autoencoder was not used, and in the next approach, it was used and then the data was classified using CNN classifier. You can find structure of proposed CNN in Fig.3.

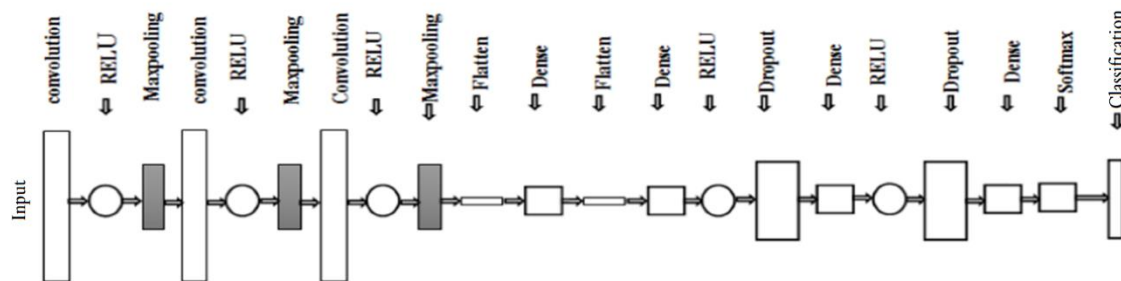


Fig3. Structure of CNN in proposed method.

The accuracy and error curve for the learning stage of the first approach is as follows. It should be noted that 70% of the data of ten classes were randomly selected as training and 30% as testing. Fig4. Shows the final results for training and validation of proposed method.

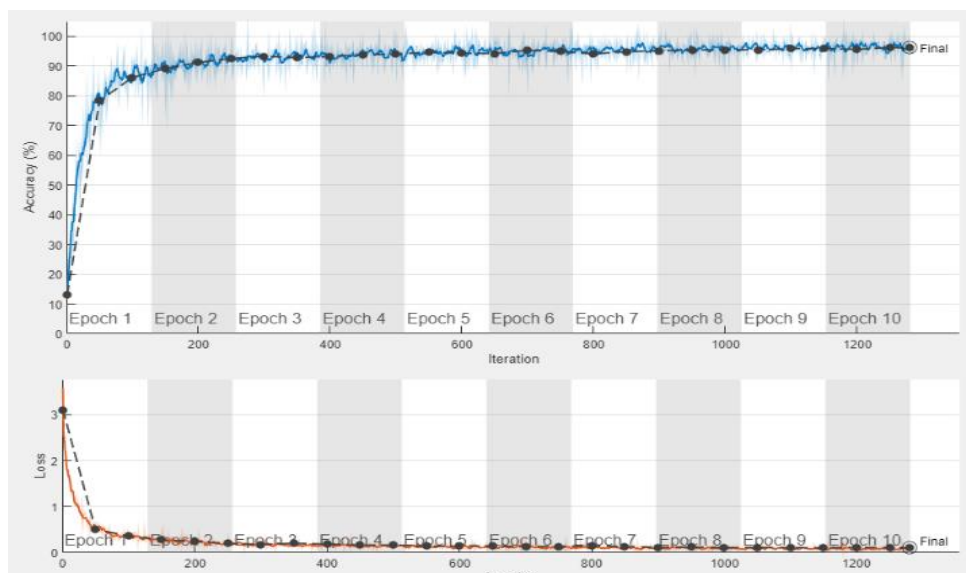


Fig4. train and validation results for final proposed method.

5. Results

Finally for comparison the results for this thesis you can find average of all results in Table1.

Table 1 average of accuracy and loss for models

Method	Accuracy	Loss
MLP	65%	0.69
LSTM	75%	0.53
MLP with filter SG+HP	69%	0.68
LSTM with filter SG+HP	77%	0.67
Proposed method	%99.1	0.61

For better comparison in second part of this thesis we extract some features from segmented signals. This feature contains min, max, average, std and var. With these features we train a CNN like first part of simulation and traditional classifiers like SVM and decision tree. We split data to the 2 categories Apnea and normal class in each category. If each segment classified as Apnea.

Table 2 average of accuracy and loss for compared methods

Method	accuracy
Mostafa et al., 2020 CNN	94.24%
Cen et al.,2018 CNN	91.28%
Liu et al., 2023 CNN+transformer	88.2%
Proposed Method	99.1%

In comparison with the previous methods (the method presented in the basic paper) our proposed method in this paper has better performance. In such a way that we see an improvement of approximately 5% compared with of the best method according table 2 and and more than 29% compared to the conventional methods according table1.

6. Conclusion

In recent years, due to the significant increase in the Apnea in various societies, we have seen a significant increase in usage AI methods to detect it. The safety of patients in the hospital and the issues and should be of particular interest. There has been a lot of research so far, each of which has benefits and disadvantages. This study uses conventional machine learning methods that are often not highly accurate in diagnostic processes. however, is significant increase when compared with classical methods such as a support vector machine. We could reach 99.1% accuracy in Physionet dataset that shows our method is efficient in new real clinical data.

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