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Detection and Classification of Obstructive Sleep Apnea Disorders: A Comparative Analysis of Various Deep Machine Learning Classifiers

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ABSTRACT

Obstructive Sleep Apnea (OSA) is a respiratory sleep disorder labeled by a temporary cessation of breathing that will last more than 10 seconds while sleeping. Generally, OSA is caused by in-adequate oxygen levels in the human body. It causes daytime fatigue, if goes unchecked results in number of serious health diseases. In general, a Polysomnography (PSG) screening test is used to diagnose Sleep Apnea (SA), but this test is highly expensive, requires constant supervision of a healthcare expert. So, PSG test beyond the reach of general public. In recent years, to overcome these issues, several cost-effective methods are proposed by several healthcare researchers like automatic SA detection methods with the help of emerging Artificial Intelligence (AI). Primary objective of this paper is to analyze the recent advances in SA and review novel approaches, algorithms that have been implemented using AI techniques like ANNs, Machine Learning and Deep Learning. A comprehensive search was performed on many indexing portals, yielding 633 published original research articles and 27 papers. With the promising potential many diagnostic tools, methods are tabulated. Further, how these techniques can be used to detect and diagnose Sleep Apnea in a more convenient way with accuracy as well as economical is discussed.

1. INTRODUCTION

Sleep Apnea (SA) disorder is mainly caused by blockage of the upper respiratory tract. It is a common respiratory disorder now-a-days. SA condition is primarily characterized by loud disruptive snoring during sleep. It also causes brief repeated cycles of cessation of breathing. It is very common among the adults but a small percentage existing children's. Recent studies reveal that it is becoming common in children's as well. The signs and symptoms of SA disorder includes loud excessive snoring, choking or gasping for air, restless sleep during night, excessive daytime sleepiness, early morning headaches, falling asleep during routine activities during daytime. A low sleep quality can affect several vital functions which includes temporary cessation of breathing. It may occur sometimes for more than 10 seconds or minutes. During this period, hundreds of times SA events may occur and if these events get repeated over a long time it can lead to depression, memory loss, asthma, low blood oxygen levels, daytime fatigue, a lack of energy and serious health issues like high blood sugar levels, high blood pressure levels, weakened immune system, neurological issues, liver problems and cardiovascular complications.

Human brain instructs the breathing muscles to take a breath during the sleep.

This paper is organized as follows: section 2 describes about various types of Sleep Apnea. Section 3 details the process used for diagnosis of Sleep Apnea and also about presence of OSA in children. Section 4 presents the literature survey of articles used for detection and diagnosis of Apnea related problems. Section 5 describes how ECG can be used for detection of Sleep Apnea with Deep Learning. Section 6 details about Apnea ECG database and how the features of ECG are extracted for data processing. Section 7 presents the discussion of various ML, DL classifier models used for diagnosis of Apnea with their accuracies.

2. TYPES OF SLEEP APNEA

Sleep Apnea can be divided into three primary forms which depends on: a) presence of breathing effort b) measuring the thoracoabdominal movement c) contributions to the total respiratory volume.

2.1 Obstructive Sleep Apnea (OSA)

OSA is a necessary and important category of SA. Mainly, this happens during the sleep when throat muscles relax and block the throat air passage. When the air passage is blocked, oxygen does not reach the brain. Then the brain signals the body to wake up and resume breathing [1]. This can happen semi-occasionally a night or frequently a night (in severe cases). Primarily, Obesity is one of the most common causes of obstructive SA in adults. This can mainly be a problem with older adults as throat muscles become looser after 40. So, the young people are less likely to have OSA than the older adults. Furthermore, women and children are less likely to be affected by SA than men, though it is not uncommon in the last two population groups.

2.2 Central Sleep Apnea (CSA) or Cheyne–Stokes Respiration

Cheyne-Stokes caused mainly when the brain is inconstant and fails to signal the breathing muscles. These are responsible mainly for controlling breathing. In this scenario, breathing repeatedly ceases for several seconds. The sleep-er may not even be aware that they are awakening many times during the night because of the breathing. Unlike OSA, which is considered mostly as a mechanical problem, the Central Sleep Apnea (CSA) is more like a communication problem. CSA is much less common than OSA, comprising less than 20 per-cent of all SA cases.

2.3 Complex sleep apnea syndrome

This is mainly caused when someone has disorders OSA and CSA of SA. It is also known as "*Treatment-Emergent Central Sleep Apnea*" or "*Mixed Sleep Apnea*". This phenomenon was noticed long back in sleep labs but not previously researched. This was first diagnosed as a SA condition in 2006 from the study conducted by Mayo Clinic on 223 SA patients and researchers noted that about 15% of patients who were believed to have OSA were treated with Continuous Positive Air Pressure (CPAP) machines.

3. DIAGNOSIS OF SLEEP APNEA

The global occurrence of SA disorder has increased over the past few decades. Now it is important and required to diagnose because in short-term it can lead to poor quality of life due to lack of restful sleep. On the basis of patient's medical history, diagnosis of SA often will be suspected, but there are several others tests to confirm the SA disorder.

3.1 Polysomnography (PSG) screening test

Brian Sun and Sally Sun [2] describes that Polysomnography test plays a significant role for the diagnosis of disorder namely Obstructive SA. In many countries Polysomnography (PSG) is widely used as a Sleep Apnea diagnosis method and tool to detect sleep dis-orders. PSG screening test also called as *gold-standard procedure* used to diagnose the SA is performed in well-equipped hospital laboratories by using the PSG signal. The primary objective of this test is to measure and analyze sleep signals at various stages [3]. During attended PSG screening test, a healthcare expert physically observes a person sleeping in the sleep laboratory setting. As part of PSG test, several sensors are used to measure and record the brain, cardiopulmonary, respiratory signals and muscle, blood oxygen saturation (SPO_2), breathing airflow, patient body position that includes.

An electro-encephalogram (EEG) screens, detects and measures the continuous electrical activity in diagnosing brain related disorders.

- Electro-oculogram screens eye movement – EOG
- Electrocardiogram screens and checks the heart's rhythm and electrical activity – ECG
- Measurement of airflow - via mouth and nasal
- Chest and abdominal movement's measurement
- Loudness of snoring audio recording
- Blood oxygen Saturation levels (SPO_2)
- Video monitoring of the patient
- Muscle activity monitoring using Electromyogram (EMG).

PSG screening test provides an objective measurement of sleep related ailments which includes details on flow of air, breathing effort. These ailments can be used to predict Sleep Apnea disorder. The PSG screening test records cardio-respiratory (CR) signals and also electro-physiological (EP) signals throughout the sleep night. This is one of the difficult situations for any patient to stay in Hospital's Sleep Lab for the whole night to run the PSG screening test depicted in Figure 1. Once laboratory screening test are completed, all the recorded signals are manually examined by an expert health consultant. Finally, after cross-checking all the information with patient symptoms a diagnosis is reached but it is a time-consuming, labour intensive and error-prone. Screening is also an expensive and complex process as it needs to be performed in Sleep-lab and also requires the trained health expert's effort. Negative side of this PSG screening test is forcing patient to stay in an laboratory environment with multiple sensors attached to the body which directly impacts the sleep quality of the patient. Therefore, under these circumstances, there is a requirement for a smart diagnostic system which uses less signals, examines maximum patients quickly.

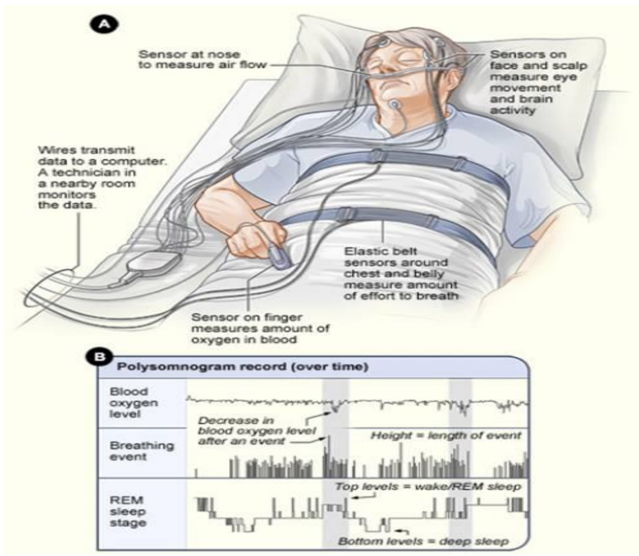

Figure 1. Sleep test – polysomnography /image: World chronicle polysomnography market research report analysis

Brian Sun and Sally Sun [2] described that Apnea-Hypopnea Index (AHI) was computed mainly by considering the patient's *electro-encephalography* or EEG test record, *electro-oculography* or EOG test record, *electro-myography* or EMG test record, and also *electro-cardiography* or ECG test records or activities.

- Apneic event - above 90% drop of airflow measurably for 10 seconds.
- Hypopneic-event - in between 30–90% drop of airflow which lasts minimum of 10 seconds.

3.2 Obstructive sleep apnea in children

Typically, in children's group OSA occurs up to 2 to 5% and it may occur at any age. Mostly it is observed between the ages of 2 and 6years old. The common reason of OSA in children is inflamed *tonsils* and *adenoids* that block the air flow and breathing during sleep. For the categorization of OSA in children, as tabulated in Table 1, AHI scale is adjusted [4]. Some of the literature work also uses the Respiratory Disturbance Index (RDI) to diagnose the movement of OSA.

Table 1. Apnea-Hypopnea Index (AHI), RDI severity rating chart for pediatric & adult OSA

AHI	AHI for Pediatric OSA	RDI	OSA or RDI severity
<5	-	<5	Normal
5-15	1-5	5-15	Mild
15-30	5-10	15-30	Moderate
>30	10	>30	Severe

4. LITERATURE SURVEY

In this paper, a comparative performance analysis based on the study in the application of Deep Learning techniques is done. The search was conducted using the IEEE Explorer, Science Gate, ScienceDirect, PubMed, Web of Sciences, www.sleepdata.org, referred literature in the included journals. As shown in Figure 2, the published papers distribution along with the year of publication. This survey was carried on the research papers that were published from the year 2000 through 2021.

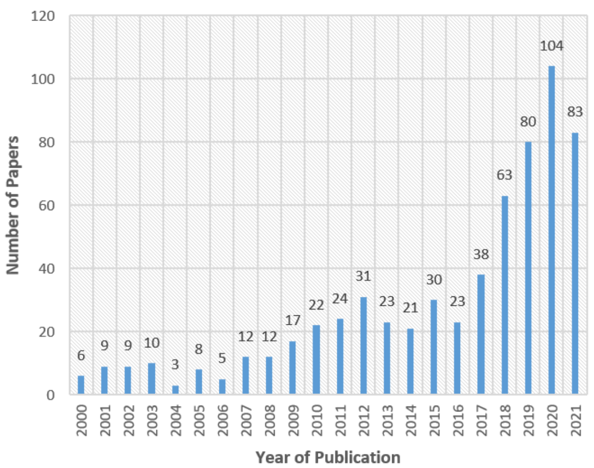

Figure 2. Literature research work published according to the year

The focus of this survey includes on following aspects of OSA detection with database extracted from a PSG performed in a Sleep-lab:

(i) what type of electrodes, signals used for database collection,
(ii) pre-processing implemented on database,
(iii) feature selection and extraction methods applied on the data, and
(iv) assessment of different types of DL and ML classification techniques used for detection of Sleep Apnea.

By choosing these criteria numbers of research papers available are plenty in numbers. Here, a total of 27 original research articles are chosen as part of this literature survey with the highest results.

Our initial electronic search identified 633 articles were gathered for this comparative analysis. After the initial screening, 566 records were excluded because they did not match the pre-determined eligibility criteria of our research. Many of these excluded records/papers were not related to AI/Machine learning techniques but related to Sleep Apnea survey and analysis reports. Only reports related to AI/Machine learning based Obstructive Sleep Apnea detection/diagnosis methodologies were included. In inclusion criteria, the keywords Sleep Apnea, Machine Learning, ECG and Deep Learning, Deep Neural Network, CNN and LSTM were used to identify the relevant article that is relevant to this research.

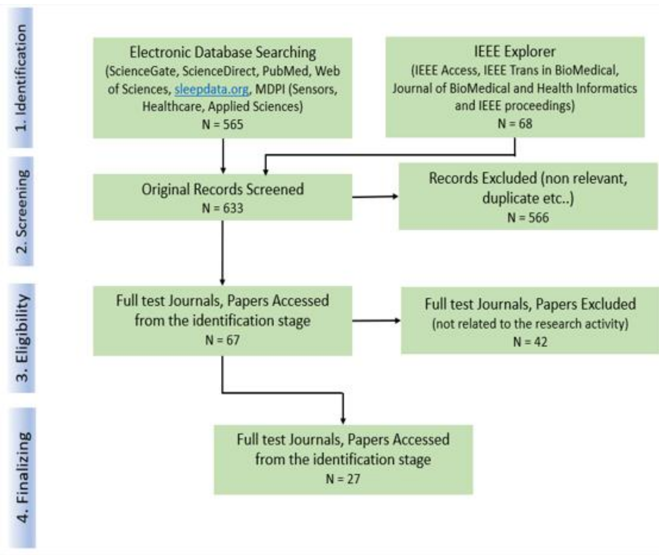

Figure 3. Flowchart (PRISMA flow diagram) of the comparative study research papers selection and exclusion procedure

In total, 27 research articles were selected for survey. It is found that most of the research is done on ECG related source signals and most commonly used ML and DL classifiers: CNN (Convolutional neural network) and LSTM (long short-term memory). Figure 3 shows flowchart (PRISMA flow diagram) of the comparative study research papers selection and exclusion procedure, where N indicates the total number of research articles selected as part of this study survey. It depicts Preferred Reporting Items for Systematic Reviews and Meta-Analyses criteria (PRISMA) flow structure for this literature survey.

5. ECG SIGNALS - OBSTRUCTIVE SLEEP APNEA DETECTION WITH DEEP LEARNING ARCHITECTURE

In recent years, various research and development approaches have been suggested for detection and diagnosis of OSA disease. For PSG screening test, an exhaustive data-collection is required which is fused by multiple sources of data as discussed in the above Section-2 such as ECG, *electro-encephalogram* (EEG), *electro-oculogram* (EOG), *electro-myogram* (EMG), oxygen-saturation (SpO_2) and many other signals will be recorded with multiple electrodes and sensors attached to the patient. From the screening test results, it is obvious that the PSG test is typically more robust in detecting the SA [5]. But it requires significant amount of effort, time of trained professionals towards completing the screening test process. PSG screening test also has severe impact on the patient's sleep quality as the patient may be forced to sleep for longer durations in hospital's Sleep Labs. Due to these circumstances, complicated examination has limited the usage of PSG screening test in clinical execution and practice.

For identification of Obstructive SA, various researchers have developed new techniques over the decades. Due to the low cost, ECG signals are used as feature rich and powerful sensor signal to diagnose, detect various cardiac disorders. Moreover, it is a well-defined method which can simulate, measure the electrical activity of the heart over a period by using a set of electrodes [6]. They are used to detect the small electrical changes on the skin of human body that arise during each heartbeat.

Table 2. Main components of ECG signal

Wave name	Description
P	Depolarization of the atria.
Q	Produced due to septal depolarization.
R	First up-ward deflection after the P-wave and part of the QRS complex.
S	First down-ward deflection of the QRS complex which occurs after the R-wave.
T	Repolarization of the ventricles.
P-R Segment	Distance between P wave and QRS complex.
R-R Interval	Distance between two successive R peaks.
QRS complex	Movement of electrical impulses through the lower heart chambers.

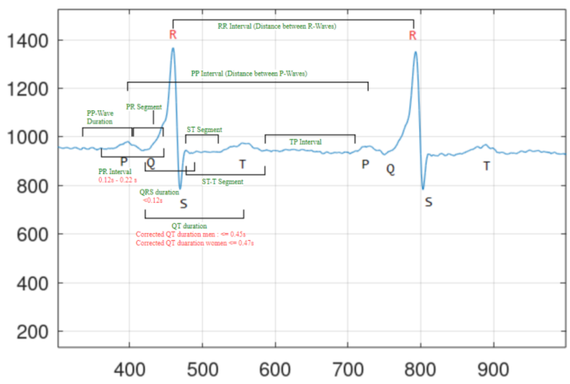

Figure 4. Classical ECG signal characteristics

Several Bio-Medical researchers have already done deep dive into the usage of ECG signals to diagnose and to detect Sleep Apnea disorder. Several methods which uses a single channel ECG signal for Sleep Apnea diagnosis have been proposed to reduce costs. This has become one of the most popular methods because of physiologically relevant signals of Sleep Apnea [7]. Its occurrence can be easily recorded. Several research papers have already discussed the necessity of examining the ECG signals for determining the Sleep Apnea disorder [8]. ECG signal can be efficiently used to examine the patient's heart condition because it has a low amplitude typically ~0.5 mV -- 1.0mV range with a frequency range of 0.05 --150 Hz. Every ECG signal consist of 6 set of waves i.e. P, Q, R, S, T, U and also several intervals such P-R, R-R, S-T and Q-T which are used to calculate duration and amplitude levels [9]. From the ECG signal it is possible to identify different waves and intervals as described in Figure 4 and each component details are tabulated in Table 2.

During literature survey and study, it was found that most of the research articles proposed a Deep Learning/Machine Learning algorithm architecture. It is a common schematic representation of the Machine Learning system architecture to detect Obstructive Sleep Apnea event is shown in Figure 5.

For classification of the Obstructive Sleep Apnea the Deep Learning architecture is segmented it to 6 stages that includes:

(1) Single channel ECG database collection
(2) Input signal pre-processing
(3) Applying Deep Leaning techniques for feature extraction and selection
(4) Classifier stage
(5) Post-processing and OSA severity.

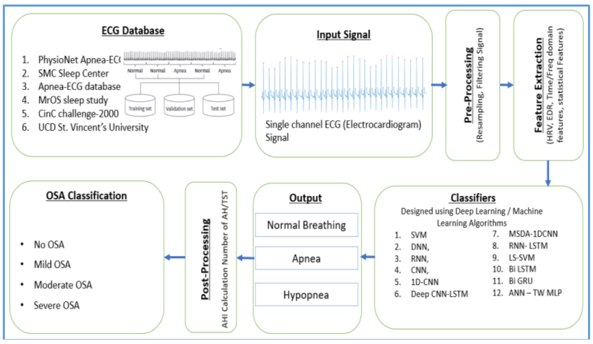

Figure 5. Generic block-diagram: ECG signals based OSA disorder classification using different AI/ML classifiers

5.1 Description of ECG database

For analyzing the ECG signals, Apnea-ECG Database [10] is one of the most commonly used data bases by several researchers. Philipp's University, Marburg, Germany provided 70 ECG recordings with one-minute annotations which are freely available. These ECG signals were sampled at 100 Hz sampling rate and the length of the recordings varies between 401minutes and 587 minutes. In this paper, research articles that used Physionet's CinC challenge-2000 database which is a another widely used public ECG database for Sleep Apnea research [10] were also analyzed. This CinC challenge-2000 database contains total of 70 records but are separated as training database and test vectors of size with 35 records. The main objective of CinC challenge-2000 data base is to check the regular ECG events with 1 minute duration along with the apneic events, if any, that are labeled as normal and OSA affected.

5.2 Preprocessing

After copying the raw ECG signals from well-known "*The Apnea-ECG database*" improve the quality of ECG signal. Therefore, a filtering process should be applied as these signals are noisy. So before building the ML training database it is necessary to remove noise. Typically, these noises are 60 Hz power line interference. The type of filtering operations can be done using Digital Signal Processing (DSP) filtering applications. Most of the researchers have applied an IIR filtering process to remove the noise.

5.3 Feature extraction

As described in the block-diagram of Figure 5, after completion of filtering on ECG signals, the next general methodology used in most of the research is extracting features from filtered ECG signal [11]. These set features will be used to determine the presence of OSA from the test signal.

Therefore, feature extraction techniques have been mostly applied in AI/Machine Learning applications related to Sleep Apnea detection.

Totally 11 features are used/extracted from ECG data signal. They are viz. Average heart rate, mean R-R interval distance, Root means square distance of successive R-R interval, Number of R peaks in ECG that differ more than 50 millisecond, percentage NN50, Standard deviation of R-R series, Standard deviation of heart rate, Sample entropy, Power spectral entropy, Average heart rate variability, Heart rate variability.

5.4 Neural networks - deep learning classifiers

Machine learning is one of the best alternate options because from the provided raw input data it can automatically learn and extract features. As described in section 2, it was found that most of the Sleep Apnea detection research area is happening around various deep machine learning techniques. The major difference between the classical neural networks and the deep learning algorithm techniques are the latest computing techniques. It enables deep machine learning to build networks with a large number of layers so that deep learning algorithms can explore more complex data and increased volumes of data. During the comparative analysis of various ML, Deep learning classifiers course, we have come across several Machine-Learning classifiers like SVM, DNN, RNN, CNN, 1D-CNN, CNN-LSTM, multi scale dilation attention 1-D convolution neural network (MSDA-1DCNN), RNN-LSTM, LS-SVM, Bi-LTSM, Bi-GRU and ANN-TW MLP. Especially convolution neural networks (CNNs), Long Short-Term Memory (LTSMs) classifiers are the well designed, developed classified and also most commonly used classifiers to achieve excellent performance. Further, these two ML and DL networks (CNNs, LSTMs) have gained lot of success due to its complex data processing and excellent outputs in various domains.

5.5 Post-processing

CNNs, LSTMs Deep Learning algorithm was used to determine Sleep Apnea events from classifier’s output. After getting the classification as output, the very next step is performing post-processing. In this step Apnea-Hypopnea Index (AHI) is calculated and if the AHI index values vary between 5 to 15 shows a mild OSA symptom. Moderate OSA can be diagnosed with 15 to 30 AHI index and above 30 or more AHI events per hour can be treated as severe OSA as shown in Table 1.

6. MATERIALS AND METHODS - ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN SLEEP APNEA

In today’s world, Machine Learning is the most important field of Artificial Intelligence. Recent advances in artificial intelligence, Machine Leaning and Deep Learning techniques have solved the many limitations that were seen in the conventional SA diagnosis methodologies. These studies elaboratively discussed on the enablement of PSG database. The PSG database has the massive volume of signals derived from an *electro-cardiogram* and *electro-encephalogram* (EEG) signals which are well suited for AI/Machine Learning-based tools development. Numerous well authored articles, literature studies mentioned and highlighted the capability to apply ML and DL in detecting SA. CA, Goldsteine et al. [12] discussed the advantages of ML in sleep medicine. Since ML can identify characteristics that predict progression from prodromal symptoms to full disease expression and therefore guide, study participant selection to improve power of clinical trials. The use of AI to stage sleep and score respiratory movement events could reduce the time sleep. These are required to devote to PSG scoring, enabling them to provide greater assistance with patient. Additionally, ML techniques may allow the sleep medicine provider to efficiently distil vast amounts of data from multiple sources and patient generated data from wearable and mobile devices.

A comprehensive description of AI/ML based classification for detection of Sleep Apnea is beyond the scope of this paper. However, the following discussion of different methods implemented in Sleep Apnea will help to explain the relevance of using ML and Deep Leaning technology for sleep medicine.

7. DISCUSSION

In sleep medicine, many researchers have used modern deep learning algorithm techniques to detect sleep related disorders from the vast databases. In order to categorize the new Sleep Apnea data and its events Machine Learning, Deep Learning methods outputs a well-trained model on a given predefined database. In the previous sections, the most commonly used Machine Leaning and Deep Learning Architecture and a set of common parameters or features that are used to detect obstructive sleep apnea events have been explained. The set of extracted features using ECG signals that are used for sleep apnea detection are also discussed. Here, the main focus is on *electro-cardiogram* (ECG) sensors-based ML and DL techniques.

In this section, application of classical machine learning and deep learning techniques by researchers to recognize and detect obstructive Sleep Apnea disorder was discussed. Conventional machine learning methods are often classified into two: - Supervised and Un-supervised Learning. Support Vector Machines (SVM) is a popular and most important method of conventional classification. SVM is a supervised ML algorithm which is used for both regression and classification challenges. From the past many years, DL have become the best ML technique for most of AI type problems. It has over shadowed the conventional machine learning. The vivid reason is that Deep Learning methods have achieved great accuracies. These accuracy values are far beyond that of classical ML methods. It includes many important domains like: speech, vision, natural language and even in Bio-medical field. In many important tasks, conventional ML can’t even compete. So next question comes to our mind is what deep learning is. Generally, Deep learning is a sub-field of machine learning. However, there is major difference in the manner Deep learning can learn by applying different feature engineering, applying neural network algorithms in layers to produce an "Artificial Neural Network” and make intelligent-decisions on its own.

Most of the researchers used ML/DL techniques with the single-lead ECG as input signal to classify OSA disorder. For example, Pombo et al [13] implemented an efficient alternative technique to the conventional PSG, based on a single ECG signal. Xie and Minn [14] used various ML classifiers with a set of different combinations to detect sleep apnea. On the other hand, Li et al. [15] proposed a hybrid model to detect Obstructive Sleep Apnea based on Hidden Markov Models (HMM) and Deep Neural Networks (DNNs) as classifiers (SVM and ANN) and achieved 85% accuracy and 88.9% for the sensitivity.

Zhang et al. [16] designed a OSA event detection method based on CNN techniques. The advantage of this method is, based on the ECG signal database, it detects the start and end of the OSA events. The accuracy and specificity of this model reached to 96.1% and 96.20%, respectively.

Yet another example of novel Deep Learning classifier technique is proposed by Varon et al. [17] to detect sleep apnea events based on the extracted novel features from ECG signal. This approach showed excellent performance in detecting SA events. One-dimensional (1D) CNN model is the latest CNN based classifier proposed by Chang et al. [18] to detect OSA events and this approach showed a good accuracy of 87.9%. As discussed earlier, most of the researchers used ECG signals to detect OSA. Similarly, Urtnasan et al. [19] developed a new algorithm for the detection of OSA using a convolution neural network (CNN) classifier. CNN network was designed using six convolution layers and it showed 96% accuracy, sensitivity, and specificity. The same authors [20, 21] proposed a novel algorithm using recurrent neural network (RNN), achieved 98.5% and 99% accuracy by using LSTM and GRU networks.

Based upon a deep learning technique by employing convolution neural network which is an automated OSA detection method. It has high accuracy and was proposed by Dey et al [22]. The main advantage of proposed method is OSA detection accuracy enhancement when compared to the existing methods. This method eliminates the separate feature extraction module requirement and classification algorithms.

Table 3. Summary of comparative analysis of machine learning and deep learning classifiers

Reference Paper	Year of publication	Database & Recordings	Classification type	Performance measurement		
				Accuracy	Sensitivity	Specificity
[3]	2021	CinC challenge-2000 database	CNN-LSTM	86.25%	88.79%	95.10%
[10]	2021	PhysioNet database,70 ECG recordings	Deep CNN-LSTM Model	96.10%	96.10%	96.20%
[15]	2018	Apnea-ECG database	SVM, HMM, ANN (DNN), Decision Fusion	84.7%	88.9%	82.1%
[17]	2015	Apnea-ECG database, Sleep Laboratory, UZ Leuven	LS-SVM	84.74%	84.71%	84.69%
[18]	2020	Apnea-ECG database	1D Deep CNN Model	87.9%	81.1%	92.0%
[19]	2018	Sleep Center of Samsung Medical Center (SMC)	CNN + DNN (FC Layer)	96%	96%	96%
[20]	2018	Apnea-ECG & Sleep Center of Samsung Medical Center (SMC)	LSTM GRU	98.5% 99.0%	98.0% 99.0%	98.0 99.0%
[21]	2020	Apnea-ECG & Sleep Center of SMC	CNN	99%	-	-
[22]	2017	Apnea-ECG dataset	CNN	98.9%	97.8%	99.2%
[23]	2017	Apnea-ECG database	LSTM-RNN	92.1%	84.7%	99.5%
[24]	2021	PhysioNet database,70 ECG recordings from 32 subjects	TDCS utilizing HMM and Meta-Cost algorithm	85.10%	86.20%	84.40%
[25]	2018	MrOS sleep study	CNN + LSTM + DNN	79.45%	77.60%	80.10%
[26]	2018	PhysioNetApnea-ECG	SVM Classifier	88.2%	80%	93.9%
[27]	2021	Apnea-ECG database	MSDA-1DCNN	89.4%	89.8%	89.1%
[28]	2020	Apnea-ECG database	SVM	87.23%	90.14%	89.34%
[29]	2020	Apnea-ECG database	1D-CNN	88.23%	82.74%	91.62%
[30]	2008	Apnea-ECG database	RNN- LSTM	82.1%,	85.5%	80.1%
[31]	2020	Apnea-ECG database	1D-CNN	93.77%	97.05%	97.25%
[32]	2019	Apnea-ECG &SUMS hospital	RNN- LSTM	-	100%	100%
[33]	2020	PSG & ROBIN Device data	Classification stage -two-phase LSTM	72.8%	58.4%	76.2%
[34]	2021	UCD St. Vincent's University Hospital's Sleep Apnea database	1D-CNN	99.56%	96.05%	99.66%
[35]	2017	Physionet, CinC database [36]	LSTM-RNN	99.99%	99.9%	100%
[37]	2016	Apnea-ECG database [38]	ANN: Feed-Forward NN	82.12%	88.41%	72.29%
[39]	2019	Apnea-ECG database	ANN – TW MLP	97.1%	100%	91.7%
[40]	2012	Apnea-ECG database	SVM	96.5%	92.9%	100%
[41]	2021	Apnea-ECG database	Bidirectional LSTM Bidirectional GRU	91.7% 90.4%	86.9% 87.0%	91.7% 92.7%

In this comparative analysis and study of Deep Machine Learning Classifiers for Identification of OSA Disorders, we briefly summarized, outlined the recent research advances in sleep medicine and compared various Deep Machine Learning classifier techniques and algorithms to diagnose and detect the SA. A summary of comparative analysis of ML and DL classification techniques for the detection of OSA using ECG signal's features is presented in the below Table 3.

8. CONCLUSION

This paper briefly discussed into the application of various ML, DL methods and algorithms for the detection and diagnosis of Sleep Apnea. From the selected 27 original research articles, major advantages of these machine learning classifiers and each classification advantages were also discussed. It was also verified that a large number of Sleep Apnea investigation were published in various renowned journals. Of all the methods CNN and LSTM classifier are best suited for Sleep Apnea with improved performance accuracy. But still the comparison between various deep learning techniques and clarification parameters a choice of Deep Neural Networks is still a matter of ongoing research topic.

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