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Deep Learning Based Approach for Obstructive Sleep Apnea Detection Using EEG Signals

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Abstract— *Obstructive sleep apnea, the most prevalent type, is characterized by abnormal breathing patterns or intervals of difficulty breathing while sleeping. The most frequent ailment is obstructive sleep apnea (OSA). All ages are affected, however older persons are the most typically impacted. The regular sleep cycle is dramatically altered by OSA, which results in numerous heart-related problems. The traditional way of diagnosing sleep problems is polysomnography (PSG), although over the past few decades, various alternatives have been offered to replace traditional approaches due to their complexity and time commitment. This study proposes a deep learning-based obstructive sleep apnea detection system that uses the power of convolutional neural networks (CNN), artificial neural networks (ANN), and logistic regression algorithms to detect sleep apnea patterns from electroencephalogram (EEG) signals.The hybrid classifier technique used by the system successfully recovers spatial and temporal information from EEG data, increasing the precision and efficacy of sleep apnea detection. The study's methodology involves data collection, preprocessing, feature extraction, and model training using a labeled dataset of EEG signals from patients with obstructive sleep apnea. The deep learning-based classifier's performance is assessed using a different test dataset to determine accuracy, sensitivity, specificity, and area under the curve (AUC). The results show that the suggested method surpasses existing state-of- the-art techniques in identifying sleep apnea, giving a more accurate and efficient diagnosis. However, the system's dependability is strongly dependent on the correctness and completeness of EEG data, and more validation with varied datasets is required to establish its generalization abilities.*

Keywords— **Obstructive Sleep apnea, EEG, ECG, Deep Learning**

I. INTRODUCTION

Quality sleep is crucial to maintaining physical and psychological well-being throughout the life cycle. It has a significant impact on brain functions as well as human body renewal and restoration (Jayanthy et al., 2020). Sleep is necessary, but nearly 40% of Americans suffer from sleep problems, such as insufficient sleep time, respiratory problems, such as obstructive sleep apnea (OSA), neurological disorders related to sleep, difficulty falling or staying asleep (insomnia), and circadian rhythm problems (Roebuck et al., 2014). There are anticipated to be 425 million people aged 30-69 with moderate to severe obstructive sleep apnea, making up about 936 million people with mild to severe OSA (Benjafield et al., 2019). When a person is sleeping, their breathing can become disrupted, known as sleep apnea. If left untreated, this significant sleep condition can cause major health issues, including high blood pressure and heart difficulties. Generally, sleep apnea comes in three forms. Obstructive sleep apnea (OSA) is the first form resulting from a physical upper airway blockage. The majority of cases of this kind of sleep apnea are seen in overweight men over 35 who have big tonsils, a small jaw, and a narrow airway opening. Approximately 84% of those with sleep apnea have OSA (Benjafield et al., 2019). Secondly, sleep apnea is caused by an inability to breathe, known as central sleep apnea (CSA). The chest and diaphragm muscles, which regulate respiration, do not receive signals from the brain for a limited period while this condition is present. Around 0.4% of those with sleep apnea have CSA(Aurora et al., 2012). Sleep apnea can also occur as mixed sleep apnea, resulting from alternating extended stretches of OSA and short bursts of CSA. Mixed sleep apnea is thought to affect 15% of all sleep apnea sufferers(Aurora et al., 2012).

Due to the significant risk of arrhythmia, hypertension, heart attack, and stroke, it is crucial to identify and treat sleep apnea early on. However, it is challenging to physically monitor a patient for extended periods since it requires much knowledge and effort. Nowadays, sleep apnea is diagnosed using polysomnograms (PSG) and home sleep tests (HST). The most popular sleep study/test for identifying SAs is polysomnography. Various physiological signals are simultaneously recorded during sleep as part of polysomnography (Jacobs et al., 2004). ECG, eye tracking, EEG, jaw muscle tone, chest and stomach activity, oxygen saturation (SpO2), and ankle movements are examples of these signals (EMG). The patient's sleep is tracked during the experiment, and the results are then assessed by a sleep expert. The diagnoses can only be made offline after the signals have been collected overnight, even though this approach gives a complete study of apnea occurrences that may be used for precise therapies. It is also obtrusive and highly costly. Therefore, it follows that the development of less intrusive and more portable technologies is crucial(Sundar & Das, 2015).

The development of sensors, low-power integrated devices, and artificial intelligence has opened the way for more intelligent healthcare that is also more economical, with automated monitoring of the subjects' vital signs.

Theidentification of sleep apnea is one use for such a technology. The latest developments in sensor technology have made it possible to continuously gather a range of essential metrics that can help with the quality of sleep monitoring. Sensors have been used to detect sleep apnea, and machine learning methods have proven reliable and accurate in identifying apneic situations. Vision-based systems, environmental sensors, or biomedical sensors can be used to collect the parameters required to identify sleep apnea, such as EEG, SPO2, and ECG, as well as their derivatives, such as ODI HRV, thoracic, BCG and abdominal signals, sound, and pressure(Roebuck et al., 2014).

The suggested electroencephalogram (EEG) signal analysis-based deep learning obstructive sleep apnea diagnosis system seeks to make use of the insightful information. The technology can recognize distinctive markers of sleep apnea episodes by recording and analyzing the intricate patterns and features contained in the EEG data. By offering a more accurate and automated way for locating occurrences of obstructive sleep apnea, this strategy has the potential to change the diagnosis of sleep disorders.

The methodology used in this study is a hybrid classifier approach that combines logistic regression, convolutional neural networks, and artificial neural networks. The system can efficiently scan and analyze the EEG signals and identify sleep apnea accurately by utilizing the strengths of these deep learning approaches.

This study has the potential to make a substantial impact on the area of sleep medicine by increasing the efficacy and accuracy of sleep apnea identification. An early diagnosis of sleep apnea can enable effective interventions and treatment plans, improving health outcomes and general wellbeing for those who suffer from this sleep disease.

The methods, findings, and discussions will all be covered in great length in the parts that follow. A thorough conclusion will then follow. The goal of the study is to show how the deep learning-based obstructive sleep apnea detection method can revolutionize the area of sleep medicine and improve the lives of those who have the condition

II. LITERATURE REVIEW

In this section, a comprehensive review of the existing literature related to OSA disclosure is provided. ScienceDirect, IEEE Xplore, PubMed, Google Scholar, and other specialized databases were employed for literature search. Nine hundred eighteen total research papers are found in all databases. Then EEG and ECG-based research are chosen among these papers, and similar documents and the same ones are removed. After then, the highly cited and most recent research papers are identified. The following is a summary of the process utilized.

Multiple classifiers, signal preprocessing techniques, and feature extraction techniques have been suggested to detect OSA according to the user signal. However, these methods have yet to be developed on a system. This section reviews the most recent and highly cited papers(ten) that have proposed algorithms based on ECG and EEG signals.

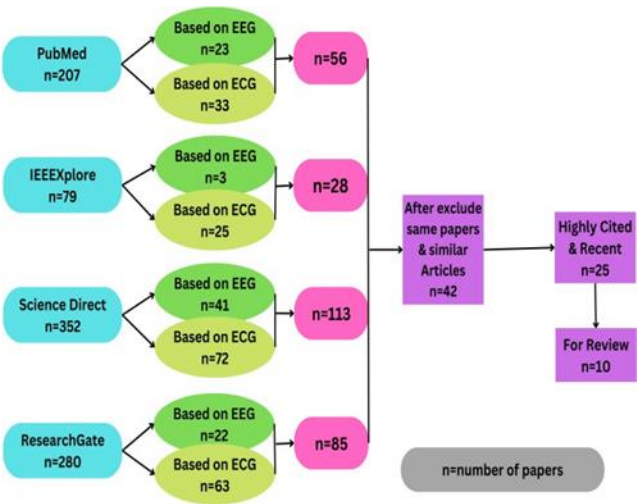

Figure 1. Literature Searching Process

Source: Author Designed

A. *Approaches/Systems which used EEG signals.*

The study of sleep EEG synchronization has recently emerged as a frontier for understanding brain functions. Numerous sleep studies have demonstrated that sleep issues may be identified and predicted using just one EEG channel. Therefore, the advancement of automated approaches results in a thorough evaluation of sleep quality.

A method used in the identification process is the analysis of EEG data.

Mahmud (Mahmud et al., 2021) devised an automated deep-learning method for identifying sleep apnea frames from EEG signals in this paper. The suggested approach divides the EEG signals into multiple modes using the variational mode decomposition (VMD) algorithm. The variations in the frequency spectrum brought on by apnea occurrences may be processed effectively, regardless of the patient, when these decomposed EEG signals for extracting features. In order to individually extract the temporal characteristics from each VMD mode in parallel while keeping their temporal relationships, a fully convolutional neural network (FCNN) is suggested. A stack of bi-directional long short-term memory (LSTM) layers is then used to determine whether the source is reliable. These parameters were retrieved from various EEG phases to explore the inter-modal temporal fluctuations further. As a result, during the assessment phase, the trained and improved system can produce forecasts of apnea frames. In contrast to other research, this one is subject-independent, meaning that different people were considered for training and testing. A semi-supervised technique is also investigated. A tiny fraction of the patient's data is used in training to gain knowledge about potential environmental fluctuations, which improves classification performance on a subject's frames. In the related cross-validation approach, extensive experiments on three publicly accessible datasets show average accuracy of 89.41%,93.25%, and 93.22%.

In this research, a single lead electroencephalography (EEG) signal-based automated apnea detection technique is suggested to distinguish between apnea patients and healthy people as well as to handle the challenging task of categorizing apnea and non-apnea occurrences of an apnea patient (Bhattacharjee et al, 2019). The feature variation structure inside an EEG frame is demonstrated to display noticeably distinct properties in apnea and non-apnea frames, leading to the development of a novel multi-band sub-frame-based feature extraction technique. Some statistical metrics and distinctive probability density functions can better depict this change in the within-frame feature. The employment of Rician model parameters coupled with a few statistical metrics has proven to provide highly resilient features in traditional performance standards. K Nearest Neighbor (KNN) classifier uses specified features for classification. The suggested technique provides higher classification results in accuracy, specificity, and sensitivity, according to thorough analyses and experiments on three publicly accessible databases.
Researchers, Shahnaz, and Minhaz (Shahnaz et al, 2016) used Empirical Mode Decomposition (EMD) method to detect sleep apnea through the wavelet reconstructed delta wave of EEG signal. The suggested strategy for detecting apnea frames consists primarily of four phases. A thirty second EEG frame's delta wave is first reconstructed using wavelets. Following that, the reconstructed delta wave is subjected to empirical mode decomposition (EMD). Then, from the Intrinsic Mode Functions (IMFs) produced by EMD, certain characteristics are retrieved. Last but not least, the performance of the suggested strategy is supported using the SVM classifier. Thirteen nightly polysomnographic (PSG) recordings from the MIT-BIH sleep apnea database are used to evaluate the suggested technique. Each patient and the whole patient population are subjected to the suggested technique. They discovered rates of 77.87%, 85.59%, and 80.43%for specificity, sensitivity, and accuracy across all patients.

Using features of two (C4-A1orC3-A2) symmetrical EEG channels Prucnal and Polak compared the accuracy of sleep apnea detection (Prucnal & Polak, 2019). To do this, the pertinent information (25 whole-night PSGs) from the PhysioBank database was employed. The exact feature matching and selection process was used for individual and combined EEG channels. Based on the city block metric and k-nearest neighbor algorithm (kNN) with k = 12, the automated classifications for breathing, hypopnea, obstructive apnea, hypopnea, and central apnea were generated for the three types of EEG epochs. For the C4-A1, C3-A2, and both EEG channels, respectively, the accuracy of kNN-based classification was64.3%, 63.8%, and 70.3%. The key outcome of this study is that using data from symmetrical channels (which are typically available) rather to just one increases the accuracy of identification of sleep apnea using only the EEG signal. This research has concentrated on the most typical scenario, where only two channels are accessible, like in the Physio Net database, even though it appears evident that adding more processed EEG channels could further enhance the outcomes of automatic apnea identification.

Using on the Electroencephalogram (EEG) data, Almuhammadi (Almuhammadi et al., 2015) proposed an effective approach that could be applied in hardware to distinguish OSA patients from healthy controls. First, Infinite Impulse Response (IIR) Butterworth band-pass filters are used to filter and deconstruct the EEG recorded datasets that were downloaded from the Phsyionet website into theta gamma, beta, delta, and alpha sub-bands for this objective. Second, from each frequency band, descriptive information like energy and variance are collected and utilized as classification input variables. In order to determine if the OSA exists or not, many machine learning methods are used. These include Support Vector Machines (SVM), Naive Bayes (NB), Linear Discriminant Analysis (LDA), and Artificial Neural Networks (ANN). The sensitivity, accuracy, and specificity of the output from various classifiers are then analyzed. According to the research observations, the SVM outperformed the competition with an accuracy rate of 97.14%.

B. Approaches/Systems which use ECG signals.

Another common factor frequently employed in the diagnosis of sleep apnea is the ECG. Rather than EEG, there are more sleep studies research using ECG signals.

Hachem (Hachem et al, 2016) analyzed ECG data from short-duration epochs and offer an automated categorization technique in this study. The automated classification method relies on the Multi-layer Perception (MLP), Radial Bases Function (RBF), and Support Vector Machines classifiers (SVM). In this analysis, 15-second ECG records from the "PhysioNet Database" were used. Patients with ages ranging from 27 to 60 and weights between 53 and 153 kg are represented by two hundred recordings (one hundred normal and one hundred apnea), captured at 100 Hz using a 12-bit resolution ADC with one sample bit representing 5 V. The acquired findings demonstrated a high level of accuracy, with a score of around 97.55 surpassing all the other classifiers previously employed in literature. Additionally, the method they created can serve as a foundation for th creation of an OSA screening tool in the future. In the future, they intend to investigate more characteristics using more classification methods and investigate the impact of combining several signals (HRV, SpO2,), which will improve the outcomes.

Researches (J and Jose, 2022) look into existing methods for detecting and forecasting obstructive sleep apnea that have not yet been implemented on technology but whose accuracy has been verified by at least one research. The current study conducts an evaluation of innovative methods for OSA prediction using the public Apnea-ECG dataset, which is published at PhysioNet. In order to determine OSA, researchers have taken a variety of ways. Around nine of the publications surveyed for this study were found to utilize SVM, and six more studies used ANN classifiers. The kNN classifier has the greatest accuracy of all the methods examined, at 98.75%. The SVM classifier has the best sensitivity of 100%, and the MLP ANN classifier showed the highest specificity of 96.87%. The overall analysis of this review identified several areas for future research, including improving OSA detection methods by putting the addressed technique into effective hardware, performing advanced research with machine learning classifiers and verifying the findings of the algorithms designed by individual research teams utilizing publicly released datasets so that outcomes might be validated.

Mendez (Mendez et al., 2010) compares two techniques for detecting obstructive sleep apnea (OSA) while you are asleep using only the ECG signal. OSA is a common sleep disorder brought on by recurrent obstructions of the upper airways, which results in a distinctive ECG pattern. QRS peak area and the Heart rate variability (HRV), two ECG features, include data that can be used to quickly, non-invasively, and easily screen for sleep apnea. They used empirical mode decomposition (EMD) and contrasted the outcomes with those from the well-known wavelet analysis (WA). Several features from the ECG signal have been recovered using these decomposition approaches, and they have been supplemented with a number of common HRV time domain measurements. Sequential feature selection (SFS) was utilized to choose the highest performing feature subset, which was then fed into the linear and quadratic discriminant classifiers. They achieved an accuracy of up to 89% with WA and 85% with EMD by using different best- subset sizes to identify the signals on a minute-by-minute basis as apneic or nonapneic.

The most effective approach for automatically identifying instances of sleep apnea (SA) from an electrocardiogram (ECG) signal was investigated by Erdenebayar (Erdenebayar et al., 2019), and this work serves as an example of deep learning techniques. Six deep learning algorithms were created and used for the automatic identification of SA events: one-dimensional (1D) convolutional neural networks (CNN), recurrent neural networks (RNN), two-dimensional (2D) CNN, deep neural networks (DNN), long short-term memory, and gated-recurrent unit (GRU). The performances of designed deep learning models were examined and contrasted. The ECG signal underwent pre-processing, normalization, and segmentation into intervals of 10 s. As a result of the signal transformation, a 2D CNN model was used to analyze it. A 99.0% accuracy rate was achieved by the best-performing model, while 99.0% recall rates were achieved by the GRU and 1D CNN models. It is possible to detect sleep apnea using deep learning algorithms such as 1D CNN and GRU in sleep apnea screening and related studies.

A single-lead ECG was used by Varon (Varon et al., 2015) to automate the detection of sleep apnea. Along with two brand-new features generated from the ECG and two well-established features in heart rate variability analysis, the serial correlation coefficients of the RR interval time series and standard deviation are employed. The primary structural components of the QRS complexes are used to address alterations in their morphology brought on by increased sympathetic activity during apnea. The second distinctive characteristic isolates the common information between respiration and heart rate using orthogonal subspace projections. Three innovative algorithms are used in this study to extract respiratory information from the ECG and are then compared. A least-squares support vector machine (LS-SVM) classifier with an RBF kernel takes all features as input. The study contained 80 ECG recordings in total. For two independent datasets that include both hypopneas and apneas together, minute-by-minute accuracy of roughly 85% is attained. With 100% accuracy, apnea and regular recordings may be distinguished.

In order to diagnose OSA from ECG data, Haifa Almutairi(Almutairi et al., 2021) used deep learning architectures. The suggested machine learning algorithms automatically extract input as features from the ECG signals. This paper presented three CNN architectures: CNN, CNN with LSTM, and CNN with GRU. These structures took as input a series of R intervals and QRS complex amplitudes. They used deep learning-based models for OSA detection with the following details: Using Convolutional Neural Networks (CNN) with three unique designs to identify OSA: CNN, CNN with two consecutive Long Short-Term Memory (LSTM) layers, and CNN with two consecutive Gated Recurrent Unit (GRU) layers. Use of 10-fold cross- validation to confirm model correctness. Comparison of the results of the proposed deep learning approaches with the results of other innovative methods. The models were evaluated using thirty-five recordings from the PhysioNet Apnea-EKG collection. CNN architecture with LSTM performed best for OSA detection according to experimental findings. In this investigation, an average of 89.11% classification accuracy, 89.91% sensitivity, and 87.78% specificity were achieved.

Table 1. Sumamry of the Research Papers

Ref. No	Paper	Feature Engineering	Classifiers employed	Signal & Dataset	Performance
[1]	Sleep Apnea Detection from Variational Mode Decomposed EEG Signal Using a Hybrid CNN-BiLSTM (2021)	Variational mode decomposition (VMD) algorithm is used for feature extraction.	Fully convolutional neural network (FCNN), Bi-directional long short-term memory (LSTM)	EEG signals (Used three publicly available datasets)	93.22%(accuracy) 93.25%(accuracy) 89.41%(accuracy)
[2]	Sleep Apnea Detection Based on Rician Modeling of Feature Variation in Multiband EEG Signal (2017)	To find the different feature variants, a multiband sub-frame-based feature extraction method is applied. Probability density functions and statistical metrics (mean and variance) were employed.	K Nearest Neighbor (KNN)	EEG signals (publicly available dataset)	provides higher classification results in accuracy
[3]	Sleep Apnea frame detection based on Empirical Mode Decomposition of delta wave extracted from wavelet of EEG signals (2016)	The Delta Wave is decomposed using empirical mode decomposition and wavelet-based reconstruction. Extrapolating characteristics from intrinsic mode functions. (Mean absolute variation and variance)	SVM classifier	EEG signals (MIT-BIH sleep apnea database)	80.43%(accuracy)
[4]	Effectiveness of Sleep Apnea Detection Based on One vs. Two Symmetrical EEG Channels (2019)	Discrete wavelets transform (DWT) and Hilbert transform (HT) are used to feature extraction. Extraction of HT attributes: amplitude (IA), frequency (IF) and amplitude-weighted frequency (WIF) Calculated statistical indexes (mean, standard deviation, skewness, kurtosis and median) of IA, IF and WIF	k-nearest neighbor's algorithm (kNN)	EEG signals ((25 whole- night PSGs) from the PhysioBank database)	70.3% (For both channels) (accuracy)
[5]	Efficient Obstructive Sleep Apnea Classification Based on EEG Signals (2015)	With the use of Infinite Impulse Response (IIR) Butterworth band-pass filters, the EEG signal was filtered and divided into the delta, theta, alpha, beta, and gamma sub-bands. Each frequency band is used to extract features like energy and variation.	Support Vector Machines (SVM), Artificial Neural Networks (ANN), Linear Discriminant Analysis (LDA) and Naive Bayes (NB)	EEG signals (PhysioNet Database)	97.14%(accuracy)
[6]	ECG Classification for Sleep Apnea Detection (2016)	14 statistical features are used. (Mean value, Standard deviation, NN50 measure (variant 1&2), Two pNN50 measures, SDSD measures, RMSSD measures, Median value, Inter-quartile range, Mean absolute deviation values, Variance of RRI, Slope of first degree polynomial model of RRI, Difference between maximum and minimum value of RRI)	Multi-layer Perception (MLP), Radial Bases Function (RBF), and Support Vector Machines classifiers (SVM).	ECG signals (PhysioNet Database)	97.55%(accuracy)
[7]	Review on Obstructive Sleep Apnea Detection using ECG Signals (2022)	Relevant characteristics were acquired and analyzed by several classifiers in order to detect OSA. Utilized include band-pass filtering, absolute thresholding for peak detection, and RR interval statistical properties.	kNN classifier	ECG signals (Physio Net Database)	98.75%(accuracy)
[9]	Deep learning approaches for automatic detection of sleep apnea events from an	Algorithms for deep learning are employed. For instance, feature maps were extracted using filter kernels from the CNN convolution layer. dimension was reduced by the pooling layer.	DNN, 1D CNN, 2D CNN, RNN, LSTM, and GRU	ECG signals	1D CNN and GRU models had 99.0%(accuracy)

III. METHODOLOGY

A hybrid classifier strategy is used for Deep learning based obstructive sleep apnea detection system in order to precisely detect sleep apnea using EEG signals. To do this, the suggested methodology uses logistic regression, convolutional neural networks, and artificial neural networks (ANN).

A. Collecting Data

Data gathering is the initial step of the approach. Patients with obstructive sleep apnea undergo electroencephalogram, which records EEG signals. The deep learning-based classifier models are trained and evaluated using this data as the basis. PhysioNet Database is used for data gathering.

B. Data Preprocessing

To get rid of noise and artifacts, the recorded EEG signals are preprocessed. The quality of the EEG data is improved and pertinent data is extracted for the identification of sleep apnea using preprocessing techniques such filtering, normalization, and feature extraction.

C. Feature Extraction and Selection

Then, a deep learning model is built utilizing the algorithms of CNN, ANN, and logistic regression. To automatically extract distinguishing features from the preprocessed EEG signals, the CNN architecture is used. It makes use of the spatial information contained in the EEG data to capture regional sleep apnea patterns. The hybrid classifier's ANN component is in charge of extracting temporal dependencies and higher-level representations from the EEG signals. Finally, depending on the learnt features, sleep apnea cases are classified using logistic regression as a decision-making layer.

D. Classification Model Training

A labeled dataset that comprises EEG data tagged with sleep apnea information is used to train the hybrid classifier model. Backpropagation and gradient descent optimization techniques are used to train the model on the dataset, which is split into training and validation sets. The performance of the model is optimized through hyperparameter adjustment.

E. Classsifiation Model Testing

A different test dataset is utilized to gauge how well the suggested solution performs. In order to evaluate the system's performance in identifying sleep apnea, the trained hybrid classifier is applied to this dataset, and performance measures like accuracy, sensitivity, specificity, and area under the curve (AUC) are computed.

The effectiveness of the proposed deep learning-based classifier is compared with current state-of-the-art techniques for sleep apnea identification in order to validate the findings. The accuracy and effectiveness of the hybrid classifier technique are established through this comparison.

The recommended approach makes sure that the deep -based obstructive sleep apnea detection system makes the most of the capabilities of CNN, ANN, and learning logistic regression algorithms to precisely identify sleep apnea patterns in EEG signals. In order to better detect sleep apnea and ultimately assist in the diagnosis and treatment of those who suffer from this sleep disease, the hybrid classifier approach was developed.

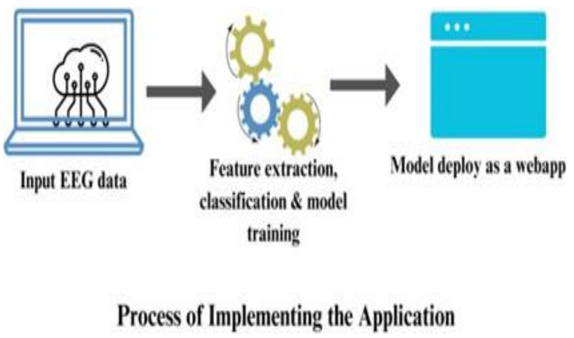

Figure 2. Experimental design Source: Author Designed

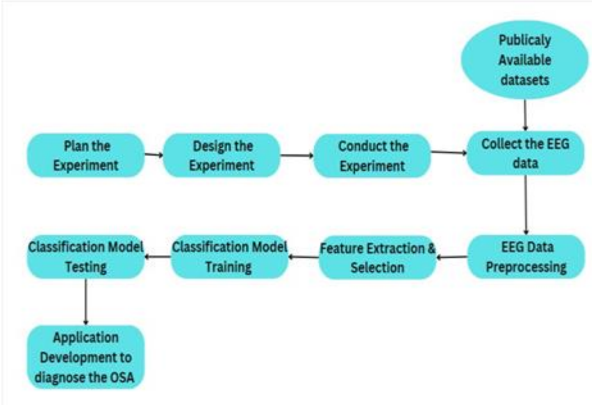

Figure 3. Experimental process
Source: Author Designed

IV. RESULTS AND DISCUSSION

The study's findings and analysis highlight the potential advantages and drawbacks of the suggested strategy. The technique required using EEG signals as input for a hybrid classifier approach that also included CNN, ANN, and logistic regression methods. The precision and efficiency of the detecting system are the main foci of the research's anticipated results. The suggested approach intends to correctly identify instances of obstructive sleep apnea, enabling prompt diagnosis and treatment, in terms of health consequences. The device has the potential to improve people's general health and well-being by accurately detecting sleep apnea.

Different performance measures were used to assess the system's performance. Calculations were made to determine the accuracy, sensitivity, specificity, and area under the curve (AUC) of the deep learning-based classifier's ability to identify sleep apnea. The results show that by utilizing the features discovered by the hybrid classifier approach, the system is capable of correctly identifying episodes of sleep apnea.

According to the research, the suggested deep learning-based obstructive sleep apnea detection system performs better than current state-of-the-art approaches. The effectiveness and potential superiority of the hybrid classifier strategy, which combines the CNN, ANN, and logistic regression algorithms, are highlighted by this comparison. The technology performs better at properly diagnosing sleep apnea because it can extract spatial and temporal information from EEG signals. It's crucial to recognize the shortcomings of the suggested strategy, though. The dependence on the accuracy and completeness of the EEG data is a key restriction. The performance of the system may be affected by inaccurate or missing data, which can produce less than ideal outcomes. The reliability and integrity of the EEG signals gathered during the data collection phase must be guaranteed.

Additionally, the system's detections may not take into consideration additional potential signs of sleep apnea since they are primarily focused on the analysis of EEG waves. The proposed system may not account for all possible individual variances or extra characteristics that may be relevant to the diagnosis of sleep apnea. Additionally, the training and validation datasets utilized have a significant impact on the system's performance. To improve the system's generalization abilities and its capacity to precisely diagnose sleep apnea in a variety of individuals, it is essential that different and representative data be made available.

Overall, the study shows how the deep learning-based obstructive sleep apnea detection system has the potential to increase the precision and effectiveness of sleep apnea diagnosis. The hybrid classifier strategy, which combines the algorithms of CNN, ANN, and logistic regression, shows promising results in correctly recognizing occurrences of sleep apnea from EEG information. To prove the system's dependability and usefulness in real-world circumstances, more analysis and validation with larger datasets and various populations are required.

V. CONCLUSION

This study proposed Using deep learning techniques, the work on "Deep learning based obstructive sleep apnea detection system" suggests a novel method for reliably identifying sleep apnea. Convolutional neural networks (CNN), artificial neural networks (ANN), and logistic regression algorithms are used in the methodology's hybrid classifier approach. The findings and discussions show the proposed system's ability to accurately detect cases of obstructive sleep apnea and outperform current state-of-the- art techniques.

The study's findings demonstrate how important it is to use EEG signals and the strength of deep learning algorithms to increase the precision and effectiveness of sleep apnea identification. The hybrid classifier strategy improves the system's efficacy in precisely identifying sleep apnea patterns by extracting both spatial and temporal information from EEG data. It's crucial to recognize the shortcomings of the suggested strategy, though. The accuracy and efficiency of the system strongly depend on how well and thoroughly the EEG data are gathered. The performance of the system may be affected by inaccurate or lacking data, which can produce less-than-ideal outcomes. Future enhancements to the suggested system could involve the addition of more varied and extensive datasets, such genetic data, to improve the detections' accuracy.

Overall, the deep learning-based method for detecting obstructive sleep apnea is promising for enhancing the precision and efficacy of sleep apnea diagnosis. The proposed method advances the study of sleep disorders and improves the field of sleep apnea diagnosis by utilizing the strength of CNN, ANN, and logistic regression algorithms. To verify the system's dependability and effectiveness in real-world circumstances, more analysis and validation are required. The suggested method may improve sleep apnea diagnosis and treatment, resulting in better health outcomes and general well-being for those who suffer from this sleep disease.

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