Predicting Sleep Disorder using Raw Multi-Channel EEG signal

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Declaration of Authorship

This is to certify that the work presented in this thesis represents our own research and intellectual contributions of Asfi Rahman, Afnan Jarif and Tasfia Tabassum Prima under the supervision of Lutfun Nahar Lota, Assistant Professor, Department of Computer Science and Engineering, Islamic University of Technology (IUT). It is also declared that this thesis has not been submitted in its whole or in part for any academic qualification. All the sources of information used and referenced from published or unpublished work of others have been duly acknowledged and cited.

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Abstract

Accurate sleep stage scoring and finding relevant feature form multi-channel EEG signal form different subject (healthy and unhealthy) is complex task. In recent years, deep learning, a type of machine learning that involves training artificial neural networks on large data sets, has shown promise for improving the accuracy and reliability of sleep stage scoring. This approach involves analyzing the pre-processed raw data and extract important feature and try to find information and based on that we predict if a person has sleep disorder or not. By using deep learning to train our model the extracted data set we reprocessed and find promising result, it is possible to develop more accurate algorithms or models for automatic prediction of sleep disorder and other abnormal activity in brain

1 Introduction

The technique of extracting information for raw multi-channel EEG is feature extraction. Then by tuning and running multiple deep learning and complex method we extract time domain and frequency domain feature. Based on that we compare and analyze the features of healthy and unhealthy person and train our model and find how our model performing based on the trained data. After by anaylzing the time domain, event domain, frequency domain or time-frequency domain features we will calculate the transition rule between different sleep stage or epochs. Then based on that we want to find transition pattern of two type of subjects(healthy and unhealthy). The sleep cycle is divided into numerous phases, including light sleep, deep sleep, and rapid eye movement (REM) sleep. Each stage is linked with distinct patterns of brain activity and physiological changes, which can be monitored by EEG signal. Different and multiple type of channel or electrodes is attached to different part of human scalp or head(frontal lobe, parietal lobe, temporal lobe and occipital lobe).

Automatic sleep disorder predicting by sleep stage scoring and feature extraction is the process of identifying the different stages of sleep based on physiological signals, such as brain wave activity, muscle tone, and eye movements. Accurate sleep stage scoring and feature extraction is important for understanding sleep patterns and for diagnosing and treating sleep disorders. Deep learning, a type of machine learning that involves training artificial neural networks on large datasets, has the potential to significantly improve the accuracy and reliability of sleep stage scoring. By analyzing the correlations between different sleep stage features and the different sleep stages, it is possible to identify patterns and features in the data that are more indicative of specific sleep stages. This information can then be used to develop more accurate algorithms or models for sleep disorder prediction.

1.1 Motivation

This thesis research on predicting sleep disorder by extracting relevant feature from different raw multi-channel EEG signal was motivated by the need for a rapid and efficient method to detect abnormality on EEG signal of a human brain. In conventional approaches, sleep disorder detection is typically conducted with convolutions neural networks (CNN's), where each pixel of the EEG wave is calculated (the downfall,spikes and continuity.[1]

The motivation for predicting sleep disorders by processing raw EEG data can be derived from several factors:

- **Increasing Prevalence of Sleep Disorders:** Sleep disorders such as insomnia, sleep apnea, and narcolepsy are becoming more prevalent due to lifestyle changes, increased stress levels, and other factors. Predicting these disorders can help mitigate their impact on public health.

- **Improving Quality of Life:** Sleep problems can have a major impact on a person's standard of living. A person's health, productivity, and well-being can all benefit from precise prognostication and preemptive action.

- **Technological Innovation:** Using prediction models built on electroencephalogram (EEG) data can help advance the field of sleep science. This method may improve our understanding of sleep's structural components and the underlying causes of sleep disorders. This may open up fresh avenues for research into diagnostic and therapeutic strategies.

  Due to the necessity for specialized facilities and skilled personnel to interpret the results, scalability becomes a difficulty in conventional sleep investigations. More widespread and cost-effective screening for sleep disorders might be possible with the help of a reliable predictive model.

1.2 Scope

The scope of our thesis research is the creation and evaluation of a sleep disorder detection by multi channel EEG signal technique. There are not enogh study to predicting sleep disorder on based on multi channel EEG signal. Single channel EEG signal gives prominent result but in case for multi channel their models dont give enough accurate results

Physical and mental health issues can both deteriorate when a person isn't getting enough sleep. Predicting sleep disorders by analyzing electroencephalogram (EEG) raw data using machine learning.Physical and mental health issues can both deteriorate when a person isn't getting enough sleep. Electroencephalogram (EEG) data analysis and interpretation using machine learning for the prediction of sleep problems has numerous intriguing applications:ers has many potential applications:

1. **Early Detection and Intervention:** The prospect of early detection and intervention of sleep disorders is a promising avenue for research. Utilizing a model trained on both healthy and non-healthy EEG data, it may be possible to predict the onset of sleep disorders prior to their escalation into more severe conditions. Timely identification may result in prompt interventions, thereby enhancing patient outcomes.

2. **Customized Treatment Plans:** The potential of artificial intelligence in delivering more accurate diagnoses and subsequently aiding in the development of personalized treatment plans is a subject of research. The potential effectiveness of a strategy that is tailored to specific situations surpasses that of a universally applicable treatment.

3. **Understanding Sleep Disorder Mechanisms:** Through the analysis of variances in electroencephalogram (EEG) patterns between individuals who exhibit normal sleep patterns and those who suffer from sleep disorders, we can acquire a deeper comprehension of the fundamental mechanisms that underlie these afflictions.

4. **Integration with Other Health Data:** Sleep data can be used in conjunction with other health data (genetic, lifestyle, mental health) for a holistic approach to health and wellness.

But there are some problems that need to be fixed, like making sure personal health data is safe, making sure AI predictions are accurate, dealing with the high dimensionality and noise of raw EEG data, and making sure the algorithm can work for people of different ages, races, and other demographic factors. Large-scale, independent studies would also need to be done to check how well the prediction model works.

1.3 Research Challenges

The task of forecasting sleep disorders through the utilization of multi-channel EEG data extracted from EDF (European Data Format) files of both healthy and unwell subjects poses a series of challenges, primarily stemming from the inherent properties of the data. Enumerated below are several noteworthy impediments that researchers may encounter:

- **Data Preprocessing:** Electroencephalogram (EEG) data is commonly affected by noise, which can originate from various sources such as muscle activity, eye movements, and other non-cerebral factors. Prior to conducting data analysis, it is imperative to identify and eliminate these elements. Preprocessing can present a significant challenge, particularly when dealing with multi-channel data.

- **Feature Extraction:** The process of feature extraction from EEG signals is a crucial step in the development of machine learning models aimed at identifying sleep disorders. The complexity, dimensionality, and noise of EEG signals make the process particularly challenging, given that these signals are time-series data. The following is a more comprehensive overview:

  1. **Time-Domain Features:** These features directly leverage the characteristics of the EEG signal as it changes over time. Common time-domain features include statistical measures such as mean, standard deviation, skewness, kurtosis, zero-crossing rate, and peak amplitude. Other time-domain features can involve autocorrelation measures or the Hjorth parameters (activity, mobility, and complexity).[**srinivasan2005artificial**]
  2. **Frequency-Domain Features:** The frequency domain analysis of EEG signals involves the use of Fourier transform or wavelet transform methods to extract features such as power spectral density (PSD) across various EEG frequency bands (delta, theta, alpha, beta, and gamma). Band power ratios, such as the ratio between alpha and delta waves, can provide particularly valuable insights.
  3. **Non-linear Features:** These things measure the complicated and wavy patterns of EEG signals. They use stuff like entropy, fractal dimension, Lyapunov exponent, and detrended fluctuation analysis. Entropy measures can tell you stuff about how complex and irregular the signals are.

- **Data Size and Complexity:** The volume and intricacy of data obtained from multi-channel EEG recordings can be substantial. This phenomenon results in a high computational burden for processing and analyzing. Efficient algorithms and robust computational infrastructure are necessary for managing large datasets. The electroencephalogram (EEG) signals exhibit significant inter-individual and intra-individual variability. The task of constructing a model that can be applied universally to individuals and is sustainable over a period of time is a formidable one.

1.4 Research Contributions

Our contribution was to pre-process raw EEG data from normal and patient who is suffering from different sleep disorder. As early studies there are various method of data pre-processing but their method wont work well for abnormal EEG signal as their EEG signal is not commonly sequential. Then by extracting information from raw data we extract 13 relevant feature. Note that we have divide each EEG signal into 5s epochs which give us more detailed information of each subjects recording. And we handled 19 channel so the extracted data set was high dimension we then to reduce dimensionality we applied feature extraction method to filter out some feature from different channels. Then compare the feature pattern and sequence of two type of subject(healthy and unhealthy) and train our model and see how it is giving result.

2 Literature Review

A literature review is a summary and evaluation of the existing research on a particular topic. In the context of sleep stage detection, a literature review might include a summary of the different methods that have been proposed for detecting sleep stages, an evaluation of their strengths and limitations, and a discussion of the current state of the field.

There are several approaches that have been proposed for detecting sleep stages, including the use of electroencephalography (EEG), electromyography (EMG), and electrooculography (EOG). These approaches can be used individually or in combination to provide a more comprehensive view of sleep stages.

Manual scoring of sleep studies is a typical approach for detecting sleep phases in which a trained expert visually inspects the EEG, EMG [2][3], and EOG data to find specific patterns that correlate to different sleep stages.

Automated methods for sleep stage detection have also been proposed, including the use of machine learning algorithms such as support vector machines (SVMs) and decision tree ensembles. These methods can be trained on manually scored sleep studies to learn the characteristic patterns associated with different sleep stages. While automated methods can be faster and more objective than manual scoring, they may not be as accurate and may be sensitive to variations in the data.

Overall, the field of sleep stage detection is an active area of research, with ongoing efforts to develop more accurate and efficient methods for detecting sleep stages.

2.1 A method for automatically classifying sleep states from a single EEG channel.[1]

Convolutional Neural Networks are a type of AI that Akara Supratak used to spot repeating patterns in EEG readings over time. To further investigate the connection between the different stages of sleep, they employed a method called bidirectional-Long Short-Term Memory to analyse the patterns. Single-channel EEGs from two publicly-available sleep datasets were used to validate the researchers' model. There were three sites on the skull where electrical activity was recorded: the F4-EOG (Left), Fpz-Cz, and Pz-Oz.[1] Variables like sampling rate and scoring indices like AASM and R&K differentiated the datasets. There have been several attempts to use EEG, EOG, and EMG signals—or even just an EEG signal alone—to automatically classify sleep stages. Using raw PSG data that has been preprocessed, the authors of Reference 6 looked into how Deep Belief Nets (DBNs) may learn probabilistic representations.

Several studies have been conducted with the aim of devising an automated approach for sleep stage scoring, utilising various signals including EEG, EOG, and EMG. [2]-[3], or single-channel EEG [4]–[5]. For instance, the authors in [6] have investigated a capability of Deep Belief Nets (DBNs) to learn probabilistic representations from preprocessed raw PSG.

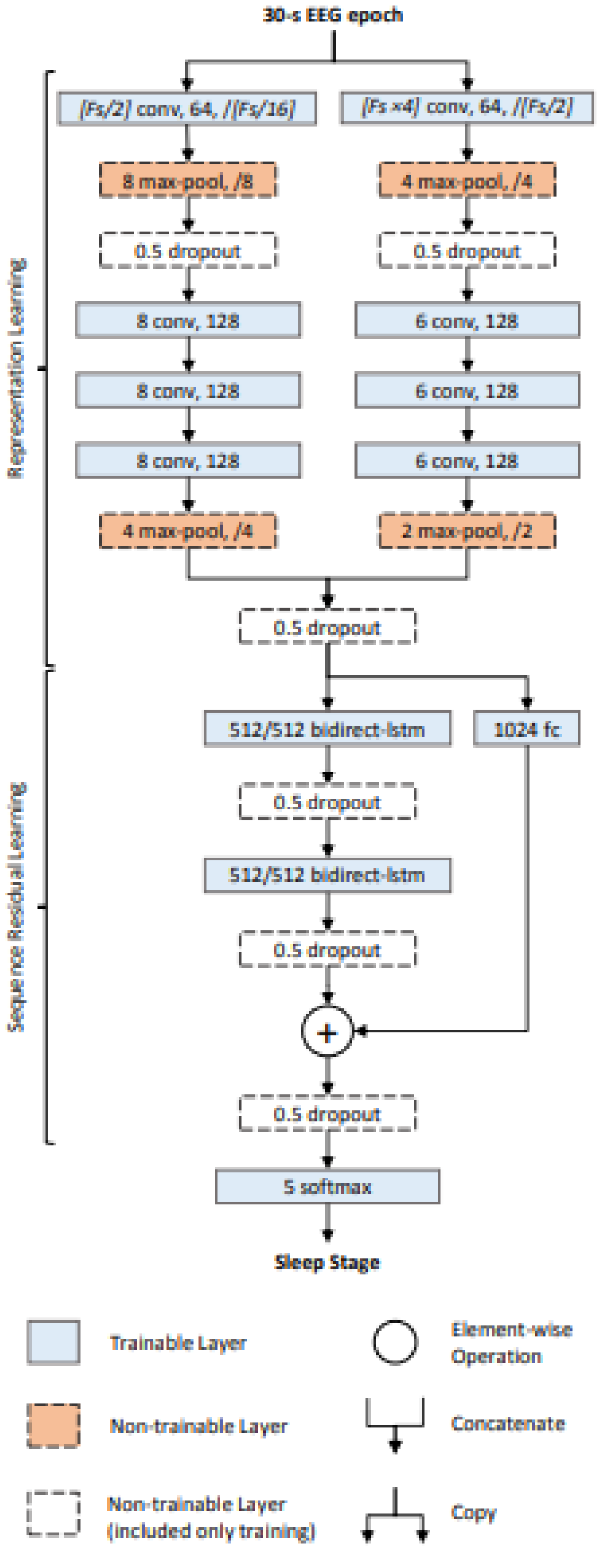

Figure 1: . An overview architecture of DeepSleepNet

In addition to showing that our model can train end-to-end via backpropagation without requiring any changes to the model architecture or training algorithm.

We feel that DeepSleepNet is a better method to remote sleep monitoring than hand-engineering since their model automatically learns characteristics from raw EEG. However,The model was only tested on a small dataset of 20 subjects The model was trained and tested on data from a single EEG channel

2.1.1 Results and discussion

CONFUSION MATRIX OBTAINED FROM 31-FOLD CROSS-VALIDATION ON THE F4-EOG (LEFT) CHANNEL FROM THE MASS DATASET USING DEEPSLEEPNET WITHOUT SEQUENCE RESIDUAL LEARNING

	Predicted					Per-class Metrics		
	W	N1	N2	N3	REM	PR	RE	F1
W	**5215**	709	94	19	190	84.5	83.7	84.1
N1	468	**2582**	747	11	916	40.8	54.7	46.8
N2	241	1846	**24140**	2435	872	93.4	81.7	87.2
N3	19	3	472	**7156**	1	74.3	93.5	82.8
REM	227	1181	383	5	**8668**	81.4	82.8	82.1

Figure 2

The DeepSleepNet model is a way to automatically learn features in sleep stage scoring from raw single-channel EEGs. This means that there is no need for humans to engineer features. To achieve this goal, we use CNNs and bidirectional LSTMs.

Datasets	#Subjects	EEG Channel	Sampling Rate	W	N1	N2	N3	REM	#Total Samples
Sleep-EDF-20	20	Fpz-Cz	100 Hz	8285 *19.6%*	2804 *6.6%*	17799 *42.1%*	5703 *13.5%*	7717 *18.2%*	42308
Sleep-EDF-78	78	Fpz-Cz	100 Hz	65951 *33.7%*	21522 *11.0%*	69132 *35.4%*	13039 *6.7%*	25835 *13.2%*	195479
SHHS	329	C4-A1	125 Hz	46319 *14.3%*	10304 *3.2%*	142125 *43.7%*	60153 *18.5%*	65953 *20.3%*	324854

Figure 3: DETAILS OF THREE DATASETS USED IN OUR EXPERIMENTS (EACH SAMPLE IS A 30-SECOND EPOCH)

Dataset	Method	Per-Class F1-score W	N1	N2	N3	REM	Overall Metrics Accuracy	MF1	κ	MGm	Avg Training time / fold
Sleep-EDF-20	SeqSleepNet [37]	87.7	43.8	88.2	86.5	84.0	84.6	78.0	0.79	85.3	2.5 hrs
	AttnSleep *(ours)*	**90.3**	**47.9**	**89.8**	**89.0**	**85.0**	**85.6**	**80.9**	**0.80**	**88.2**	**31 mins**
Sleep-EDF-78	SeqSleepNet [37]	91.8	46.0	85.0	77.5	81.0	82.6	76.3	0.76	84.3	7.3 hrs
	AttnSleep *(ours)*	**92.6**	**47.4**	**85.5**	**83.7**	**81.5**	**82.9**	**78.1**	**0.77**	**85.6**	**1.9 hrs**
SHHS	SeqSleepNet [37]	84.2	**47.3**	87.2	85.4	**88.6**	85.6	78.5	0.80	85.4	15.2 hrs
	AttnSleep *(ours)*	**88.3**	46.3	**88.7**	**87.6**	87.4	**86.6**	**79.7**	**0.81**	**87.9**	**2.9 hrs**

Figure 4: COMPARISON OF THE PERFORMANCE OF ATTNSLEEP AGAINST SEQSLEEPNET WITH 3 EPOCHS AS INPUT

The results indicated that theier method is quite stable with different number of heads.

2.2 Deep learning with sequence-to-sequence for automatic sleep stage scores [7]

Sajad MousaviI has proposed a new approach which alternate the Manual sleep stage scoring. The proposed method, SleepEEGNet, utilises a single-channel EEG input to automatically annotate sleep stages. The SleepEEGNet utilises deep convolutional neural networks (CNNs) to extract time-invariant features, frequency data, and a sequence-to-sequence model, with the aim of capturing the intricate and prolonged contextual relationships between sleep epochs and scores. The researchers utilised innovative loss functions to address the class imbalance issue present in the sleep datasets, aiming to achieve comparable misclassification errors for all sleep stages during network training.

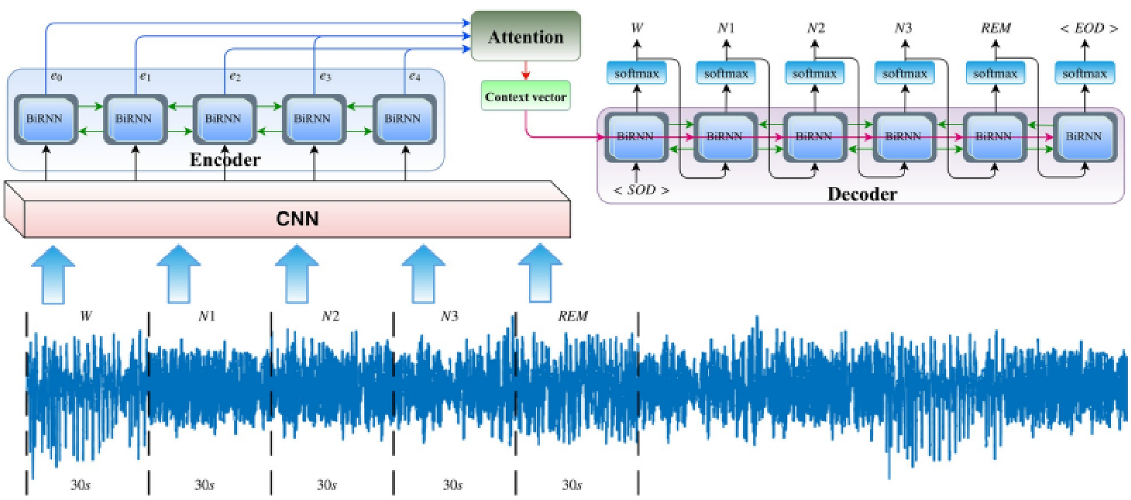

Figure 5: Illustrator of proposed sequence to sequence deep leaning network architecture

Each CNN component consists of a succession of four successive one-dimensional convolutional layers. After each convolutional layer, a rectified linear unit (ReLU) nonlinearity is applied. This thesis investigates the architecture of a convolutional neural network, which consists of a first layer, a max pooling layer, and a dropout block. Following the final convolutional layer is only a dropout block.

Bidirectional recurrent neural network (BiRNN) units have been added to the network design in place of the standard LSTM units. Standard RNNs can only use the previous input state because they can only send information in one way. This study talks about the study's limitations. BiRNN have been proposed [8]

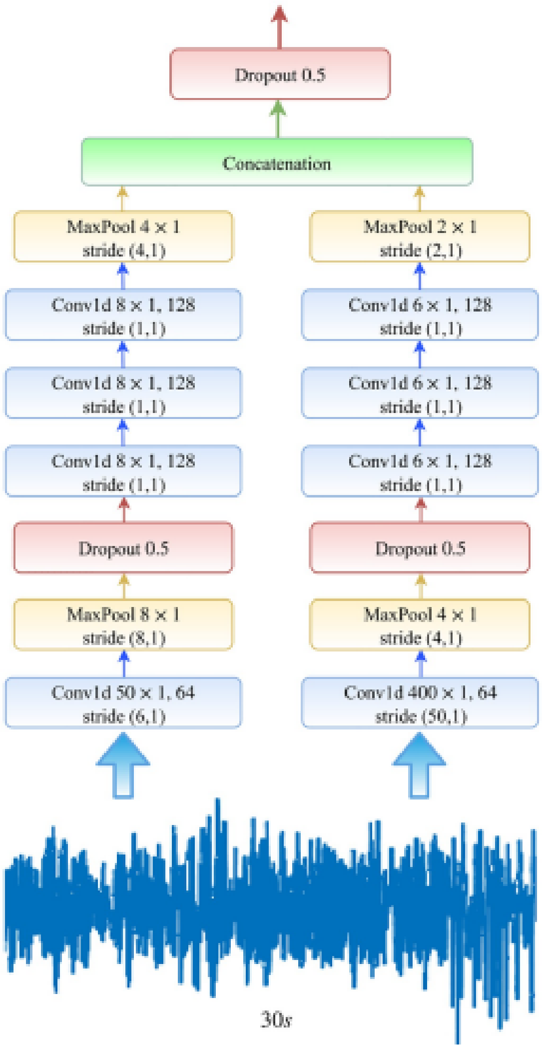

Figure 6: Detailed architecture of utilized CNN model

2.2.1 Experimental result

Table 2. Confusion matrix and per-class performance achieved by the proposed method using Fpz-Cz EEG channel of the EDF-Sleep-2013 database.

	Predicted					Per-class Performance (%)			
	W1	N1	N2	N3	REM	Pre	Rec	Spe	F1
W1	7161	432	67	27	219	87.84	90.58	96.97	89.19
N1	442	1486	364	25	409	50.05	54.51	96.08	52.19
N2	359	735	14187	1035	837	91.26	82.71	94.20	86.77
N3	37	9	560	4857	2	81.69	88.87	96.90	85.13
REM	153	307	368	2	6520	81.63	88.71	95.59	85.02

Figure 7

The principal diagonals of each confusion matrix indicate the true positive (TP) values, which represent the number of correctly scored stages. The analysis of the confusion matrices reveals that the true positive (TP) values have greater values than the other values in the rows and columns.

2.2.2 Contribution and limitaion

It is to be noted that in spite of the imbalance-class problem, their model yielded desirable performance, especially for stage N1 which is most difficult to fetch.

However, It is not ready yet to use multimodal polysomnography(PSG) signals including EEG, EOG (electrooculography) and EMG (electromyogram) to boost the performance of the sleep stage classification.

3 Methodology

- Data Collection: The first stage consisted of putting together electroencephalogram (EEG) data. The subjects of this dataset were divided into two unique groups: healthy persons and patients who had been diagnosed with sleep problems. This was a necessary stage in the process of developing a comparison analysis between the two groups, which would ultimately assist in identifying the elements that contribute to sleep disorders. In order to conduct an exhaustive investigation, a total of 28 EEG recordings saved in the.edf format were collected.

- Data Loading Using the MNE (MNE-Python) module, the gathered.edf data files were loaded into the Python environment and processed there. MNE is a piece of software that was developed specifically for the purpose of processing and visually representing multichannel EEG data. It was essential to complete this stage in order to transform the raw EEG data into a format that was able to be efficiently processed and studied.

- Preprocessing: In order to guarantee the accuracy of the results, the raw EEG data were put through a number of preparatory procedures. The data was referenced, which is a phase that includes re-referencing the EEG signals to a common reference point. The primary goal of this step was to get rid of the common sounds that were present in all of the channels. This eliminates the possibility of the data being influenced by the surrounding noise. After this step, a bandpass filter was applied such that only frequencies between 1 and 45 Hz could pass through. The elimination of frequencies that were outside of this range assisted the analysis to become more focused on the frequencies that were most pertinent to human brain activity and the stages of sleep. These frequencies were likely to correlate to noise or information that was not relevant to the study.

- Epoch Extraction: After that, the continuous EEG data was cut up into predefined segments, or epochs, with each one having a duration of five seconds and an overlap of one second. This procedure was carried out in order to regard each segment as an individual occurrence that can be linked to a specific stage of sleep. The overlapping was done in order to keep the continuity of the data and to make certain that the segmentation did not result in the loss of any important information.

- Labeling of Data One of the most significant steps in the process was to label each epoch according to the group to which it belonged, either the control group or the sick group. This was an essential part of the procedure. The labeling process is a requirement for the supervised learning process that will be used to construct a predictive model. This prerequisite must be met before beginning the supervised learning process.

- Extraction of Features: After that, features were extracted from each epoch in order to characterize the EEG signals in terms of the statistical qualities they possessed. Insights regarding the central tendency and variability of the signals could be gleaned from characteristics such as the mean, the standard deviation, the variance, and the peak-to-peak amplitude. Information regarding the EEG recordings' peak values could be gleaned from the extreme value features, which included lowest and maximum values in addition to the time points at which they occurred. The mean square, root mean square, and sum of absolute differences between consecutive data points were extracted in order to provide further insights on the magnitude and changes in the signals. These details were provided to show how the signals changed over time. In addition, the skewness and kurtosis of the EEG signals were calculated so that the researchers could gain insight into the symmetry and distribution of the signals. This exhaustive approach of feature extraction attempted to derive as much useful information as it could from the EEG epochs so that it may assist in accurate prediction of sleep problems.

- Data Organization After the data had been preprocessed and its features extracted, the final dataset was arranged as an array of features that were taken from each epoch. The following stage of the research will involve the use of a machine learning model, and one of its inputs will be this dataset, which does an effective job of capturing the important components of the EEG recordings.

4 Our Model

- **Data Pre-processing:**

  The development of machine learning models aimed at predicting sleep disorders necessitates a series of sequential procedures, including the extraction of features from electroencephalogram (EEG) signals. This phase presents a considerable challenge owing to the intricate nature of EEG signals, which are time-series data characterised by a substantial degree of complexity, high dimensionality, and a significant amount of noise. A comprehensive overview is available below:

  Time-domain features are derived from the inherent properties of the EEG signal as it evolves over time. Frequently used time-domain characteristics encompass statistical parameters, such as the mean, standard deviation, skewness, kurtosis, zero-crossing rate, and peak amplitude. Additional time-domain characteristics may encompass autocorrelation metrics or the Hjorth parameters, which consist of activity, mobility, and complexity.[9]

- **Dimensionality Reduction Techniques:** Principal Component Analysis (PCA) and t-distributed Stochastic Neighbour Embedding (t-SNE) are two methods that can be used to decrease the number of dimensions in a dataset while still keeping its essential structure or variance.
- **Feature Selection Methods:** Techniques such as recursive feature elimination, mutual information-based selection, and LASSO can be utilised to identify and select the most predictive features.

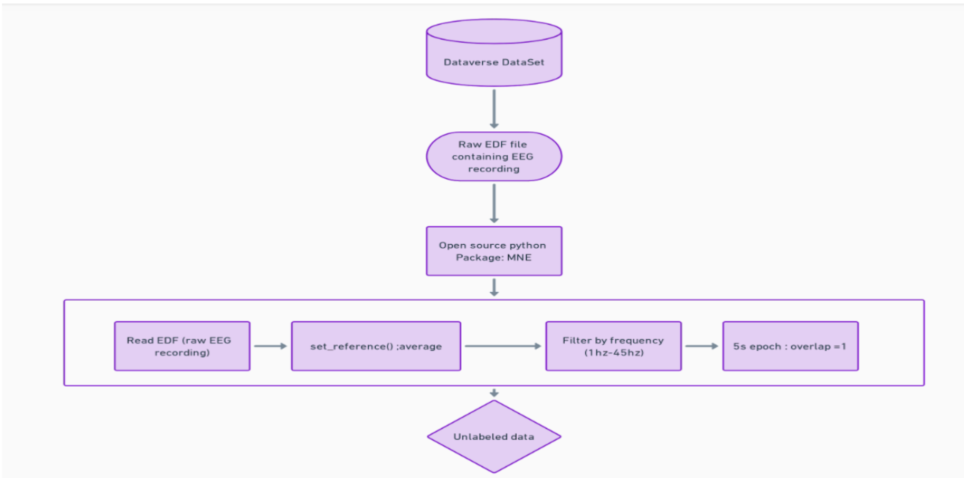

Figure 8: Label1

After the Label we extract some relavant features from the raw preprocessed data.

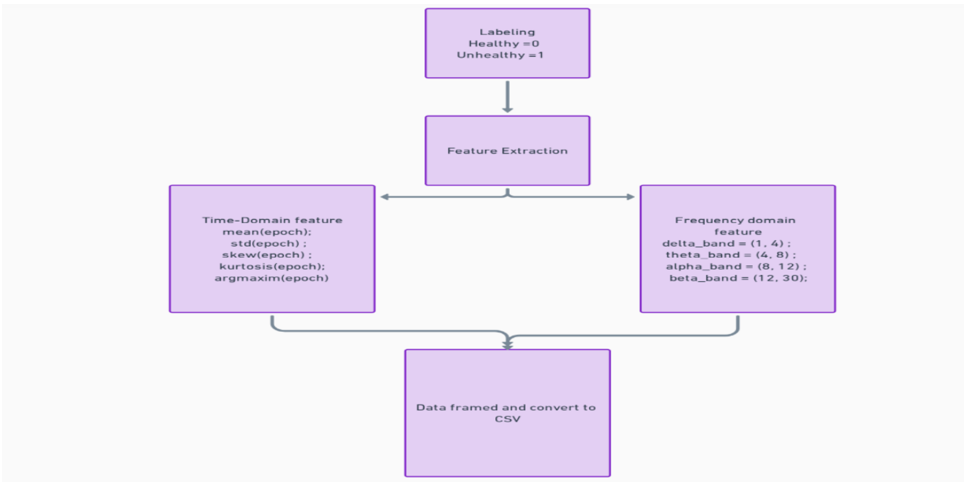

Figure 9: Label2

4.1 CNN Mode

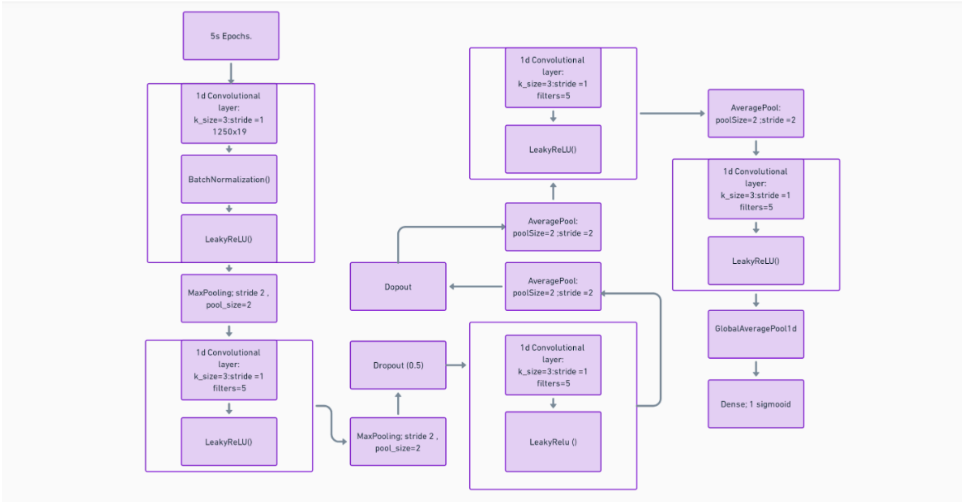

Figure 10: Caption

Data Preprocessing and Reshaping: Prior to the analysis, the data was reshaped to comply with the requirements of the following convolutional neural network (CNN) model. The reshaping process involved rearranging the axes of the data array, with the "channel" axis being moved from the second position to the last, while maintaining the other dimensions. The reshaping step ensured the data is in the correct format for the CNN model, which requires the data to be structured in the form (number of samples, length of the time series, number of channels).

Model Development and Configuration: A Convolutional Neural Network (CNN) model was constructed using the Keras API with TensorFlow as the backend. CNN was chosen due to its proficiency in handling multidimensional data and capturing temporal dependencies, which is essential for time-series data like EEG signals. The model consisted of multiple layers, including Conv1D, BatchNormalization, LeakyReLU, MaxPool1D, Dropout, AveragePooling1D, GlobalAveragePooling1D, and a Dense output layer.

Each layer served a distinct function in the network:

- Conv1D layers: Applied convolution operation to the input, passing the result to the next layer. The first layer also defined the input shape of the data.
- BatchNormalization layer: Used to normalize the activations of the neurons in the network, improving training speed and reducing the chance of getting stuck in local

optima.

- LeakyReLU layers: A type of activation function that addressed the problem of dying neurons encountered in regular ReLU function.

- MaxPool1D and AveragePooling1D layers: Performed pooling operations to reduce the spatial size of the representation, decreasing the number of parameters and computation in the network and controlling overfitting.

- Dropout layers: Regularized the model by randomly setting a fraction of input units to 0 at each update during training, which helped prevent overfitting.GlobalAveragePooling1D layer: Reduced the dimension of the data by taking the average across the time dimension, which was necessary before passing the data to the dense layer.

- Dense layer: The final layer of the model which used the sigmoid activation function, suitable for binary classification tasks.After defining the architecture, the model was compiled using the Adam optimization algorithm and the binary cross-entropy loss function, ideal for binary classification problems.

Model Training and Validation: A Group K-Fold cross-validation approach was employed to assess the model's performance, which is a suitable choice when dealing with groups or sets of related samples. This technique ensured that all samples from a group were included in the same fold during the training and validation process, thereby providing a more robust measure of the model's ability to generalize to unseen data.

Before feeding the data into the model, the training and validation data were standardized using the StandardScaler to have zero mean and unit variance. This step was crucial to ensure the model treated all features equally during the training process.

The CNN model was then trained on the training set for 100 epochs, with a batch size of 128. The validation set was used to validate the model's performance at each epoch.

Model Evaluation: The trained model was evaluated on the validation set, and the accuracy of classification was calculated. This process was repeated for all the folds in the cross-validation process, and the average accuracy was calculated, providing a comprehensive measure of the model's performance.

In summary, the methodology implemented in this study involved careful data collection, preprocessing, model building, training, and evaluation, all of which combined to create a robust model capable of predicting sleep disorders using raw multi-channel EEG signals.

5 Experiment

A series of preliminary experiments have been conducted in accordance with our initial hypothesis. The objective of our study was to address the limitations of current sleep disorder detection methods and enhance the accuracy of detection outcomes. This thesis will discuss the details of the experiments conducted.

5.1 Data Gathering and experiment

First we searched for different raw EEG recording of multiple subjects. Firstly we didn't consider the if the subject is healthy or not. We try to preprocess the raw edf file which holds the EEG recording of different subject during sleep. By :

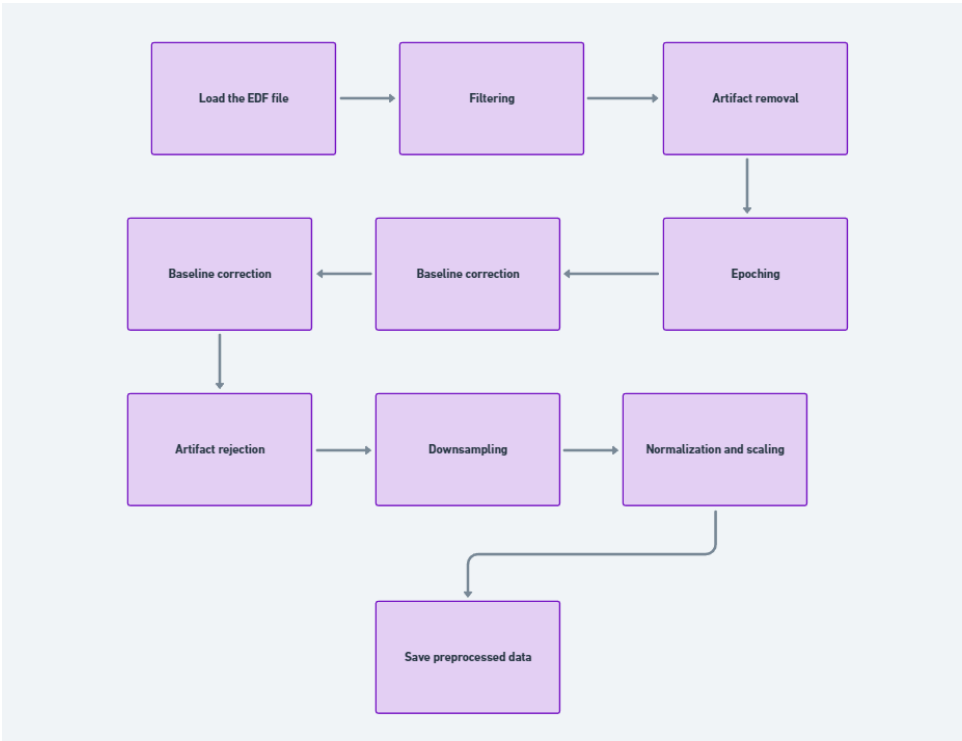

Figure 11: Method of Preprocess and experiment

Here in every step we fine tune and hyperparameter tuning in each methods and fuction. In MNE library there is a method `datax.filter(l_freq=**, h_freq=**)`

`epochs = mne.make_fixed_length_epochs(datax, duration=**, overlap=**)` We change the filter size and frequency banding overlap boundary and see the out come raw data

5.2 Labeling and Feature Extraction

The process of feature extraction from raw EEG data involves converting time-series EEG signals into a collection of characteristic features that effectively capture relevant information for future analysis or classification purposes. Common techniques for feature extraction from EEG raw data are:

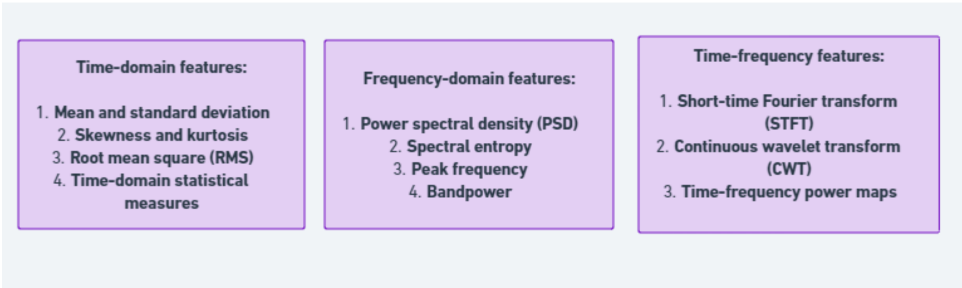

Figure 12: Techniques of Feature Extraction

5.2.1 Different Features

When analysing EEG data, you can identify various characteristics that can help differentiate between different states or conditions. These are some of the most frequently used ones:

1. **Time Domain Features:**

   - **Mean:** This is the average amplitude of the EEG signal.
   - **Standard Deviation:** This measures the variability of the EEG signal amplitude.
   - **Variance:** Another way to measure how spread out the signal is, or how much the amplitudes differ from the average.

2. **Frequency Domain Features:**

   Typically, these characteristics are derived by transforming the signal into the frequency domain using the Fast Fourier Transform (FFT) or other comparable techniques[10].

- **Power Spectral Density (PSD):** This measures the power of the signal based on its frequency. There are five frequency bands that are commonly used to classify brainwaves and the power spectrum of a signal. These are Delta (0.5-4Hz), Theta (4-8Hz), Alpha (8-13Hz), Beta (13-30Hz), and Gamma (30-100Hz). One thing that can be taken advantage of is the varying strength of each frequency band when compared to the others.
- **Peak Frequency:** This is the frequency with the highest power in the power spectral density.

3. **Other Features:**
   - **Cross-Correlation:** This determines the degree to which two EEG channels are comparable given the quantity of time delay introduced to one of the channels.
   - **Coherence:** At each frequency, the phase difference between the two signals (EEG channels) is calculated.
   - **Hjorth Parameters:** Mobility and complexity are two methods of signal measurement. Mobility measures the frequency variation, whereas complexity measures the amplitude variation.

We have extracted different feature for different training models and by those pattern for each epoch of certain subject we tried to predict sleep disorder subject by just analyzing raw EEG data nad see which features give the most accurate result.

5.3 Train different models

The EEG data was sorted into "healthy" and "unhealthy" groups using a number of different machine learning methods. Among these were:

- **Support Vector Machines (SVM)** SVMs were trained with a radial basis function (RBF) kernel to handle the high dimensional data[11]. Grid search cross-validation was used to zero in on the best settings for the various variables.
- **Random forest:**To determine whether the number of estimators had an effect on the performance of Random Forest models, different quantities of estimators were used during training.

We compared the performance of traditional machine learning models with that of deep learning models to see if the latter could produce better results. The main point of the study was to see how well Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) can handle sequence data.

- **Convolutional Neural Networks (CNN):** Convolutional neural networks were employed to acquire spatial hierarchies of features in an automated and adaptable manner[4]. Various architectures and hyperparameters were subjected to experimentation, encompassing diverse layer sizes, activation functions, and dropout rates.

- **Recurrent Neural Networks (RNN):** LSTM and GRU-based RNNs were used[12], given their ability to handle sequential data and their efficacy in remembering long-term dependencies.

We have tested these model and analyze the score and make confusion matrix by checking whether our model is good or not.

6 Result Analysis

Title	Author	Date	Publication	Model	Signal type	Accuracy
DeepSleepNet: A model for automatic sleep stage scoring based on raw single-channel EEG	Supratak, Akara, et al.	2017	IEEE Transactions on Neural Systems and Rehabilitation Engineering	CNN, BiLSTM	EEG	MASS: 86.2%-81.7, Sleep-EDF: 82.0%-76.9
An Attention-based Deep Learning Approach for Sleep Stage Classification with Single-Channel EEG	Emad Eldeen Adele, Zhenghua Chen, Chengyu Liu, Min Wu, Chee-Keong Kwoh, Xiaoli Li, and Cuntai Guan	2021	IEEE Transactions on Neural Systems and Rehabilitation Engineering	CNN	EEG	
SleepING Net: Automated sleep stage scoring with sequence to sequence deep learning approach	Mousavi, Sajad, et al.	2019	PloS one	CNN, BiLSTM	EEG	84.26%
Automatic Sleep Stage Scoring with Single-Channel EEG Using Convolutional Neural Networks	Orestis Tsinalis, Paul M. Matthews, Yike Guo, Stefanos Zafeiriou	2017	IEEE Transactions on Neural Systems and Rehabilitation Engineering	CNN	EEG	

Figure 13: Comparison between relevant papers

Dataset	Method	Per-Class F1-score W	N1	N2	N3	REM	Overall Metrics Accuracy	MF1	κ	MGm	Avg Training time / fold
Sleep-EDF-20	DeepSleepNet [20]	86.7	**45.5**	85.1	83.3	**82.6**	81.9	76.6	0.76	**86.9**	2.5 hrs
	SleepEEGNet [24]	89.4	44.4	84.7	84.6	79.6	81.5	76.6	0.75	85.3	1.5 hrs
	ResnetLSTM [43]	86.5	28.4	87.7	89.8	76.2	82.5	73.7	0.76	81.8	1.2 hrs
	MultitaskCNN [17]	87.9	33.5	87.5	85.8	80.3	83.1	75.0	0.77	83.1	2.6 hrs
	AttnSleep *(ours)*	**89.7**	42.6	**88.8**	**90.2**	79.0	**84.4**	**78.1**	**0.79**	85.5	**21 mins**
Sleep-EDF-78	DeepSleepNet [20]	90.9	**45.0**	79.2	72.7	71.1	77.8	71.8	0.70	81.6	7.2 hrs
	SleepEEGNet [24]	89.8	42.1	75.2	70.4	70.6	74.2	69.6	0.66	82.3	4.6 hrs
	ResnetLSTM [43]	90.7	34.7	83.6	80.9	67.0	78.9	71.4	0.71	80.8	3.4 hrs
	MultitaskCNN [17]	90.9	39.7	83.2	76.6	73.5	79.6	72.8	0.72	82.5	5.3 hrs
	AttnSleep *(ours)*	**92.0**	42.0	**85.0**	**82.1**	**74.2**	**81.3**	**75.1**	**0.74**	**83.6**	**1.7 hrs**
SHHS	DeepSleepNet [20]	85.4	**40.5**	82.5	79.3	81.9	81.0	73.9	0.73	82.6	14.4 hrs
	SleepEEGNet [24]	81.3	34.4	73.4	75.9	77.0	73.9	68.4	0.65	82.7	6.4 hrs
	ResnetLSTM [43]	85.1	9.4	86.3	87.0	79.1	83.3	69.4	0.76	76.4	5.2 hrs
	MultitaskCNN [17]	82.2	25.7	83.9	83.3	81.1	81.4	71.2	0.74	80.4	6.2 hrs
	AttnSleep *(ours)*	**86.7**	33.2	**87.1**	**87.1**	**82.1**	**84.2**	**75.3**	**0.78**	**84.0**	**2.1 hrs**

Figure 14: Further Comparison

The Result of different models and their confusion matrix,

- **Logistic Regression:**We trained our extracted data which has labeled in healthy and non-healthy subject and test it with logistic regression. We can see that the presicted result is low bellow 40% . The accuracy is 0.39 and the precision is 0.41, recall is 0.15 and f1 score is 0.22.

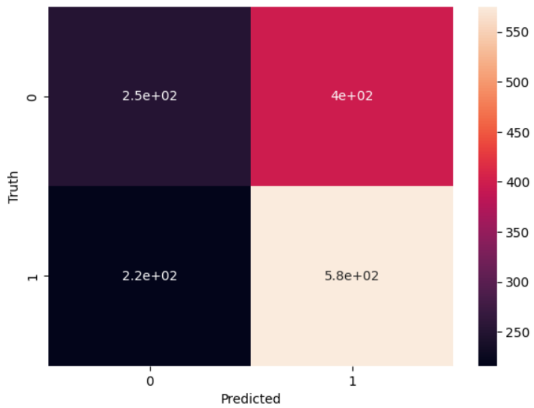

Figure 15: Logistic Regression

- **Random Forest:** We trained our extracted data which has labeled in healthy and non-healthy subject and test it with Random Forest. We can see that the predicted result is low bellow 60% . The accuracy is 0.51 and the precision is 0.45, recall is 0.35 and f1 score is 0.52.

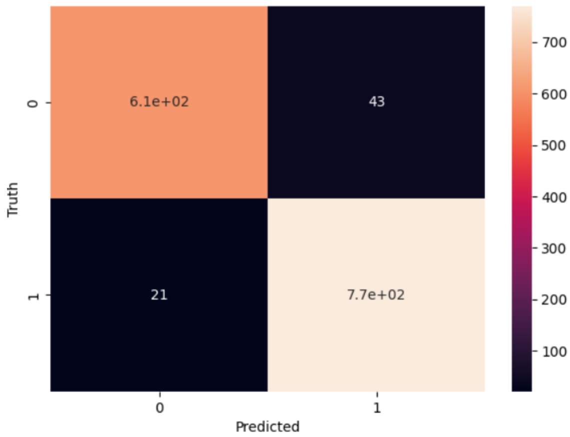

Figure 16: Random Forest

- **Support Vector Machines:** Our extracted data, which has been classified into healthy and non-healthy subjects, was subjected to training using the Support Vector Machine (SVM) algorithm. The resulting predicted outcome was observed to be suboptimal, with a value below 60%. The statistical metrics for the model's performance are as follows: the accuracy stands at 0.51, precision at 0.54, recall at 0.39, and f1 score at 0.45.

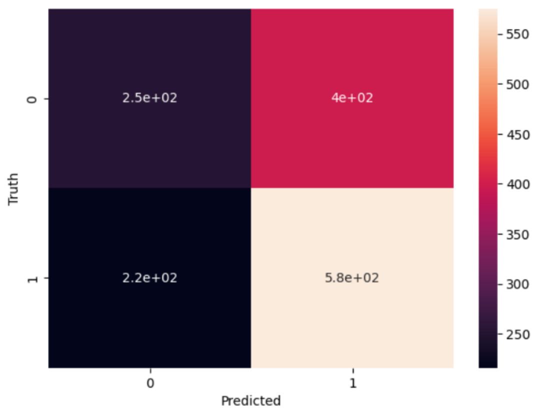

Figure 17: Support Vector Machine

From this we can assure that in those models the predicting of healthy and unhealthy the based on different feature is not precise and accurate.

ML Model	Precision	Recall	F1 Score	Accuracy
SVM	0.54	0.39	0.45	0.57
	0.59	0.73	0.65	
Logistic Regression	0.41	0.15	0.22	0.52
	0.54	0.82	0.65	

Figure 18: Table of different ML model's result

6.1 Future Goal

Improving the prediction of sleep disorder only by features extraction we have came up to know that by predicting the sequence of different sleep stage of normal and unhealthy people[13] we can predict much good result.

The analysis of the progression from one sleep stage to another can yield significant insights into potential sleep-related pathologies. Polysomnography is a diagnostic tool utilised to identify sleep disorders, which involves a comprehensive examination of various sleep stages.

An individual passes through a series of sleep stages during a standard night's sleep, including Non-Rapid Eye Movement (NREM) sleep stages (N1, N2, and N3) and Rapid Eye Movement (REM) sleep. The temporal distribution and order of sleep stages may serve as diagnostic indicators for a variety of sleep pathologies.

- **Insomnia:** Frequently distinguished by an extended duration required to shift into the more profound phases of sleep, namely N3 and REM[14]. It is possible for individuals to allocate an inordinate amount of time to the lighter sleep stages, namely N1 and N2.

- **Sleep Apnea:** Marked by frequent awakenings or shifts to lighter sleep stages due to interrupted breathing[13].

- **Narcolepsy:** Rapid eye movement (REM) sleep induction. People with narcolepsy often enter rapid eye movement (REM) sleep soon after passing out[15].

- **REM Sleep Behavior Disorder:** characterised by the presence of motor activity and behaviours associated to dream content, as opposed to the usual muscle atonia observed during REM sleep.

7 Conclusion

This study examined if our convolutional neural network(CNN) could assess EEG data and predict sleep disorders. EEG data shows promising for distinguishing healthy and unwell patients. EEG data can research sleep disorders. EEG data analysis demonstrated that data preparation and feature extraction are crucial before analysis. Time, frequency, and statistical variables were derived from the original EEG data. These traits fed models. Even though EEG data was complex and difficult to deal with, it was simplified and made easier to interpret and study. The study revealed that basic machine learning models and logistic regression may accurately identify sleep difficulties from EEG data. They discussed other enhancements. To improve predictions, researchers should examine machine learning and deep learning models. The study also found that our sleep patterns may assist diagnose certain sleep disorders. Researchers may now create transition pattern models. This study adds to the growing body of research using artificial intelligence and machine learning to identify and treat sleep disorders. The study encourages sleep medicine innovation and makes it easier to design tools that effectively detect sleep disorders and are easy to use.

References

1. Supratak, A., Dong, H., Wu, C. & Guo, Y. DeepSleepNet: A model for automatic sleep stage scoring based on raw single-channel EEG. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* **25,** 1998–2008 (2017).
2. Lajnef, T. *et al.* Learning machines and sleeping brains: automatic sleep stage classification using decision-tree multi-class support vector machines. *Journal of neuroscience methods* **250,** 94–105 (2015).
3. Huang, C.-S. *et al.* Knowledge-based identification of sleep stages based on two forehead electroencephalogram channels. *Frontiers in neuroscience* **8,** 263 (2014).

4. Tsinalis, O., Matthews, P. M. & Guo, Y. Automatic sleep stage scoring using time-frequency analysis and stacked sparse autoencoders. *Annals of biomedical engineering* **44,** 1587–1597 (2016).

5. Hassan, A. R. & Subasi, A. A decision support system for automated identification of sleep stages from single-channel EEG signals. *Knowledge-Based Systems* **128,** 115–124 (2017).

6. Längkvist, M., Karlsson, L. & Loutfi, A. Sleep stage classification using unsupervised feature learning. *Advances in Artificial Neural Systems* **2012** (2012).

7. Mousavi, S., Afghah, F. & Acharya, U. R. SleepEEGNet: Automated sleep stage scoring with sequence to sequence deep learning approach. *PloS one* **14,** e0216456 (2019).

8. Schuster, M. & Paliwal, K. Networks bidirectional reccurent neural. *IEEE Trans Signal Proces* **45,** 2673–2681 (1997).

9. Yang, S. & Deravi, F. *Wavelet-based EEG preprocessing for biometric applications* in *2013 fourth international conference on emerging security technologies* (2013), 43–46.

10. Al-Fahoum, A. S. & Al-Fraihat, A. A. Methods of EEG signal features extraction using linear analysis in frequency and time-frequency domains. *International Scholarly Research Notices* **2014** (2014).

11. Lee, H. & Choi, S. *Pca+ hmm+ svm for eeg pattern classification* in *Seventh International Symposium on Signal Processing and Its Applications, 2003. Proceedings.* **1** (2003), 541–544.

12. Roy, S., Kiral-Kornek, I. & Harrer, S. *ChronoNet: a deep recurrent neural network for abnormal EEG identification* in *Artificial Intelligence in Medicine: 17th Conference on Artificial Intelligence in Medicine, AIME 2019, Poznan, Poland, June 26–29, 2019, Proceedings 17* (2019), 47–56.

13. Zarei, A., Beheshti, H. & Asl, B. M. Detection of sleep apnea using deep neural networks and single-lead ECG signals. *Biomedical Signal Processing and Control* **71,** 103125 (2022).

14. Zhao, W. *et al.* EEG spectral analysis in insomnia disorder: A systematic review and meta-analysis. *Sleep Medicine Reviews* **59,** 101457 (2021).

15. Liu, D., Pang, Z. & Lloyd, S. R. A neural network method for detection of obstructive sleep apnea and narcolepsy based on pupil size and EEG. *IEEE Transactions on Neural Networks* **19,** 308–318 (2008).