SLEEP CLASSIFICATION USING CNN AND RNN

ON RAW EEG SINGLE-CHANNEL

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SIGNAL PROCESSING AND DIGITAL DESIGN

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I, **Satyam Mishra**, Roll No. **2K18/SPD/08** student of M.Tech. (Signal Processing and Digital Design), hereby declare that the project Dissertation titled "**Sleep Classification using CNN and RNN on raw EEG Single-Channel**" which is submitted by me to the Department of Electronics and Communication, Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of Master of Technology, is original and not copied from any source without proper citation. This work has not previously formed the basis for the award of and Degree, Diploma Associate ship, Fellowship or other similar title or recognition.

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I hereby certify that the Project Dissertation titled "**Sleep Classification using CNN and RNN on raw EEG Single-Channel**" which is submitted by **Satyam Mishra**, Roll No. **2K18/SPD/08** Department of Electronics and Communication, Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of Master of Technology, is a record of the project work carried out by the students under my supervision. To the best of my knowledge this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

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ABSTRACT

Automated neurocognitive performance assessment (NCP) of a subject is a pertinent theme in neurological and medical studies. NCP signifies the human mental/cognitive ability to perform any allocated job. It is hard to establish any certain methodology for research since the NCP switches the subject in an unknown manner. Sleep is a neurocognitive performance that varies in time and can be used to learn new NCP techniques. A detailed electroencephalographic signals (EEG) study and understanding of human sleep are important for a proper NCP assessment. However, sleep deprivation can cause prominent cognitive risks while carrying out activities like driving, and can even lead to lack of concentration in individuals. Controlling a generic unit in non-rapid eye movement (NREM), which is the first phase of sleep or stage N1is highly important in NCP study. Our method is built on RNN-LSTM which classifies different sleep stages using raw EEG single-channel which is obtained from the openly available sleep-EDF dataset. The single raw channel helps classify the REM stage particularly, because a single raw channel, human motion, and movement are not considered. The features selected constituted as the RNNs network inputs. The goal of this work is to efficiently classify the performance in sleep stage N1, as well as improvement in the subsequent stages of sleep.

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CHAPTER1

INTRODUCTION

Sleep plays a crucial function in human wellbeing. Given that modern life encroaches like every day that passes, quality sleep is crucial. Sleep is one of the most critical facets of our lives. The functions of the brain and body are not functioning normally, despite adequate sleep. This can also meaningfully lower living standards. Deprivation of sleep will affect our nervous system, our immune system, our respiratory system and our overall health and success depends on quality sleep. Sleeping eminence guarantees greater results in our everyday lives. Lack of sleep for a longer period affects our performance and the ability of the brain to take decision swiftly. Furthermore, analysis of quality sleep becomes more crucial as it helps us to comprehend our sleep much improved and here lies the catch, signals generated in human body during sleep are non-stationary signals, which are tedious to deal with. So, we take some epoch to examine sleep signals.

EEG epoching is a procedure by which the continuous EEG signal extracts specific time-windows. These time windows are termed "epochs," and an event e.g. a visual stimulus is usually time-locked with due respect. A set of signals from these sensors is called an electroencephalogram (EEG), an electrooculogram (EOG), an electromyogram (EMG), and an electrocardiogram (ECG). This PSG is divided into 30-ies epochs, which the experts further group into various sleep periods according to sleep guides such as the Rechtschaffen and Kales (R&K)[5] and the American Academy of Sleep Medicine (AASM)[6].

1.1 ELECTROENCEPHLOGRAPHY

Electroencephalography is a discipline that applies to electroencephalogram analysis and perception. Electroencephalogram (EEG) is a record of the electrical signal generated by the co-operative action of brain cells, or more accurately, the timing of the extracellular field potential generated by their synchronous action. An EEG uses electrodes to record or detect electrical activity inside the brain. EEG monitors the influx of current in several pyramidal neurons during the synaptic excitation. Cells of the neurons create electric dipoles between soma and dendrites. A large number of neurons produce electrical activity which an EEG records. Summed ionic current penetrates between the electrodes and neural cells across the blood, skull and many other types of soft tissues.

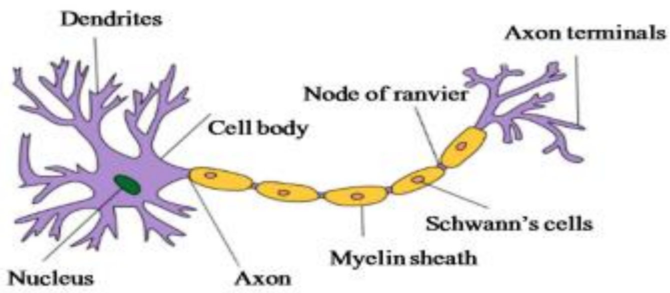


Fig 1.1 Structure of a neuron

Electrodes read the signal captured by the surface of the brain, amplify it so they can be accurately digitized. Amplification is important since the detected signals are weak and not compatible with devices like Analog-to-Digital Convertor. EEG basically works on the principle of differential amplifier. The enhanced analog signal is then rehearsed and transformed into a digital type using the Analog to Digital Converter over a fixed time period. The A / D converter interacts with the computer and preserves information in the device's storage. The electrode-captured data are EEG raw data, meaning that the electrical behavior of the surrounding muscles is not just brain but also electrode motion disturbance, which is called noise. Items are considered

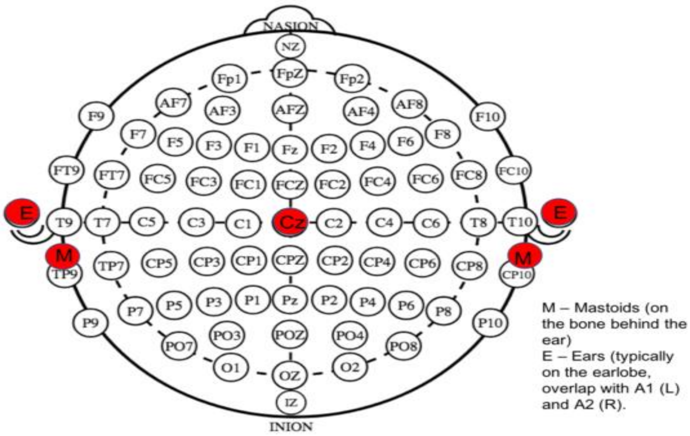


Fig.1.2 EEG electrode cap and its structure

such causes of disturbance, which contribute to distortion of signal. The analysis becomes tedious when analyzing the EEG signal, because the brain also works for other organs, so their signals interfere with EEG signals. These signals are called polysomnographic (PSG) signals, so EEG signals are basically classified into two types, i.e. single-channel raw EEG signals and multi-channel based EEG signals, which are based on analysis of only brain signals and the effect of other signals is excluded, and in multi-channel terms [18], we also consider the effect of other PSG signals.

1.2 Sleep Classification

Neurocognitive output (NCP) reflects the human mental/cognitive capacity to perform a particular task. Mathematically speaking measurement of the NCP is subject to question still unanswered in various areas, such as recovery, neurology, psychology/psychiatry, and longitudinal studies [4]. NCP results mostly depend on how correctly and precisely the information stored in EEG signals is utilized for highly efficient analysis and classification [1]. As extraction of EEG signals is mostly done manually, chances of error are high, as EEG signals are nonstationary hence extracting knowledge is cumbersome and time-consuming. Also, developing the study protocols is complicated. Human's sleep for about one third of their entire lifetime and it's of prime importance that human beings should have quality sleep. Inadequate sleep causes many disorders which are difficult to tackle as they require immense care, medical help. The brain functions constantly and effectively in our sleep too. Our brain's neural network generates such impulses that are in a specified frequency band. These ranges of frequencies are classified by ranges, and are called alpha, beta, theta and delta. Classified based on certain ranges and wave sleep generation. Sleep was generally categorized into two categories: Rapid Eye Movement (REM) and Non-Rapid Eye Movement (NREM). To summarize, in the table below, we have tabulated:

STAGES	CLASSIFICATION
W	Alpha waves (8-12 Hz) and beta waves (16-30 Hz).
N1(NREM1)	Theta wave (4-8 Hz), vertex shape may present.
N2(NREM2)	High voltage biphasic (kcomplexes), sleep spindles (12-16 Hz) and theta waves can be present.
N3(NREM3)	High amplitude (> 75μv) and delta wave (2-6 Hz)
REM	Theta and sawtooth wave (2-6 Hz) waves are evident.

Table I. Sleep Classification Based on Wave generation

CHAPTER2

LITERATURE REVIEW

2.1 DEEP LEARNING

Artificial intelligence has been key in helping people understand their behavior much better as it imitates human intelligence in a highly trained and well-programmed way. Training plays a vital role whilst programming or inserting human emotion. Artificial intelligence is based on the simple concept of training, testing and implementation, the bigger the dataset, the better the yield will be for training. Deep learning is a part of artificial intelligence, based on learning to strengthen it. Reinforcement learning is based on feedback, i.e. it evolves with the evolution of complexity.

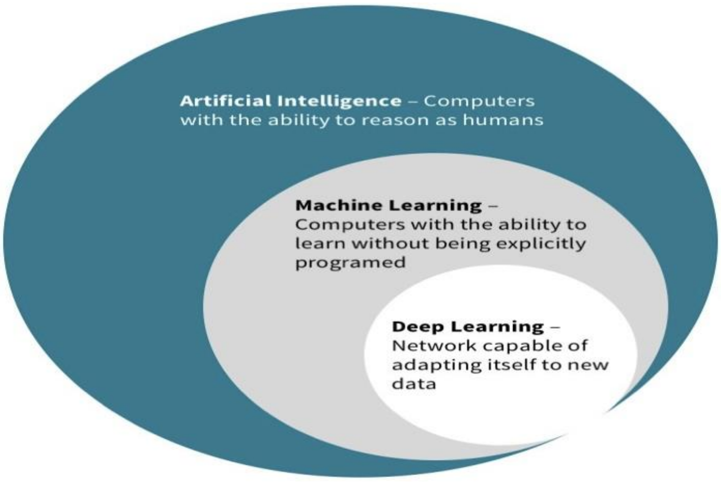


Fig 2.1. Artificial intelligence and its artifacts

Bio-medical signals and PSG signals are non-stationary in nature, so it becomes tedious to analyze their attributes, which is where deep learning becomes quite crucial. Deep learning allows one to build a network architecture that performs outstandingly well in terms of accuracy and precision.

2.2 NEURAL NETWORK

The neural network is a collection of architectures designed to explain the fundamental connections between a data set using a method which simulates the functioning of the human brain. Artificial neural network mimics human brain, i.e. it has some inputs, hidden layers and then predict or rather takes action accordingly. Neural networks in this sense refer to neuron systems, either organic or of an artificial nature. Neural networks will respond to evolving inputs. The channel then produces optimal performance without modifying the output parameters. What makes Neural Networks special is that they work on reinforcement learning. Output generated by hidden layers and propagation are iterative in nature and then it increases the precision and accuracy.

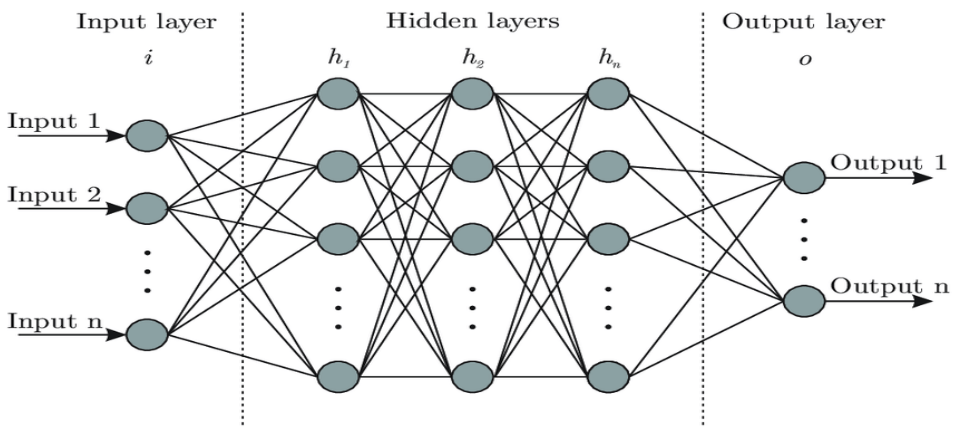


Fig2.2 Artificial Neural Network with Hidden Layers

Artificial Neural Network generally works on large data-set. Non-stationary signals are tedious for analysis as they are non-reparative, so, Artificial Neural Network predicts the outcomes with the help of hidden layers. In any neural network, while solving it, for every input we have activation function which generates corresponding output. One can understand activation function as a transfer function, in any system, it helps to find the output with its characteristic and input signal. The activation function is helpful in calculating the output of the corresponding node. There are two types of Activation function, namely:

- Linear Activation function
- Non-linear Activation function

2.2.1 LINEAR ACTIVATION FUNCTION

The linear function is linear in nature. Its output ranges from (-∞,+∞), i.e. the does not have any confined range. For example f(x) = x; it covers all the possible ranges, because of its covers all the possible range, it is not used frequently.

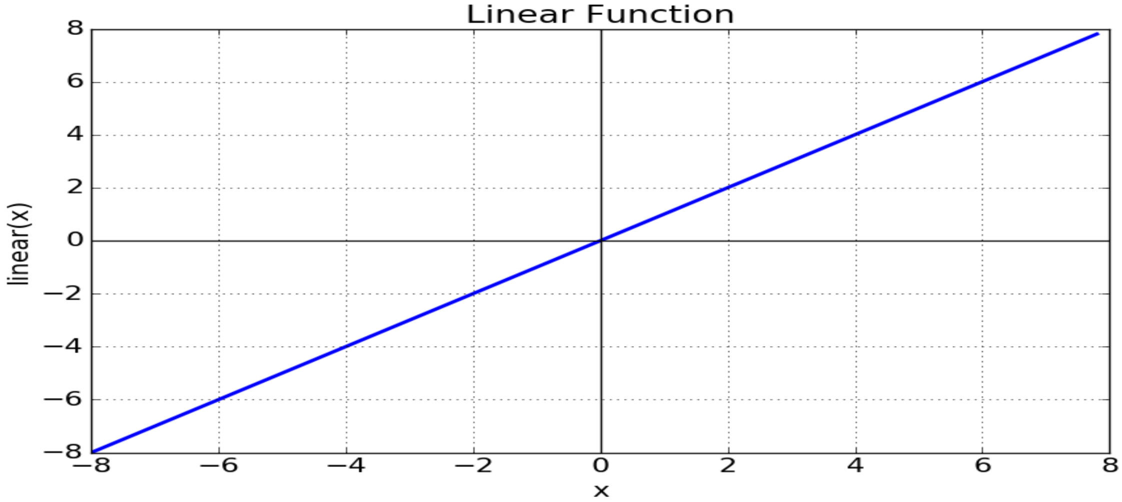


Fig 2.3 linear activation function

2.2.2 NON-LINEAR ACTIVATION FUNCTION

Non-linear activation has very confine ranges, it generally generates the probability of the distribution. Non-linear activation functions are non-linear and can be discrete also. There is a function that gives output in (0-1) range, now these signals are helpful in analysis particularly, the bio-medical signals which are non-stationary. Softmax, sigmoid is the example of a non-linear activation function. The neural network is complicated caged structured which is made easy with the help of confined ranges activation function.

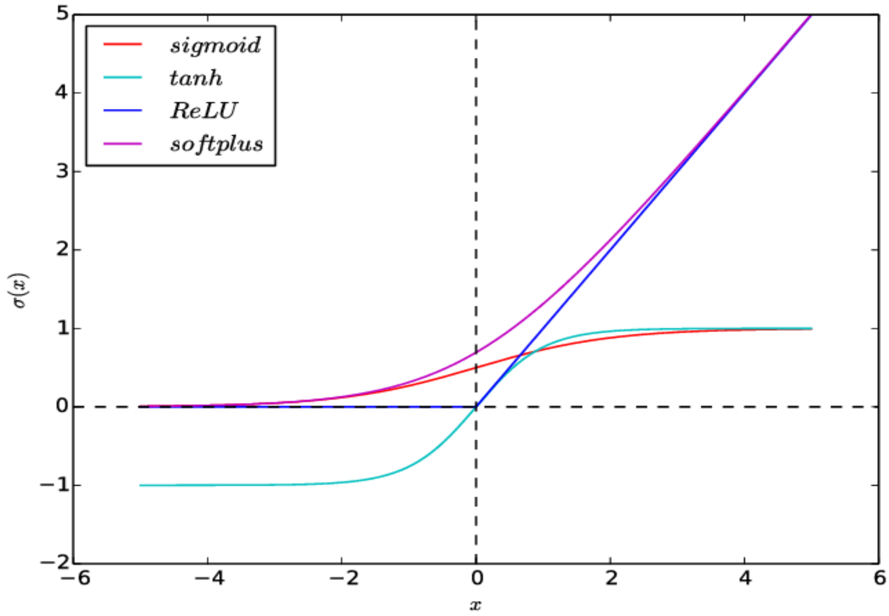


Fig2.4 Various Example of Non-Linear Activation Function

2.3 SLEEP STAGES

Human's sleep for about one third of their entire lifetime and it's of prime importance that human beings should have quality sleep. Inadequate sleep causes many disorders which are difficult to tackle as they require immense care, medical help. Sleep disorder are insomnia, dyssomnia, narcolepsy to name a few [4]. Sometimes, due to various reasons, even when we are physically and mentally exhausted sleep deprivation can occur, which impacts in many common activities like lack of concentration, or operating a standardized compute. Deep Learning enables us to extract information from a non-stationary signal like EEG, which is hard to extract manually. Deep Learning are reinforcement learning, which works on continuous feed work, so accuracy increases. The circadian cycle controls sleep, which continues to shift over the course of human life. Newborns spend around 50 per cent of their total sleep in REM sleep, usually entering REM sleep directly. Newborns also tend to sleep in short intervals at first, getting about 12-18 hours of sleep. As children age 5 to 10, their demand for sleep decreases to 10 hours. The availability continues to decline as teenagers require 8 to 9 hours, and adults require 7 to 8 hours. Our circadian rhythm also regulates the nocturnal release of adrenocorticotropic hormone (ACTH), prolactin, which are essential hormones for maintenance of good health. Sleep stages are classified in basic two category, namely:

- REM (RAPID EYE MOVEMENT)
- NREM (NON-RAPID EYE MOVEMENT)

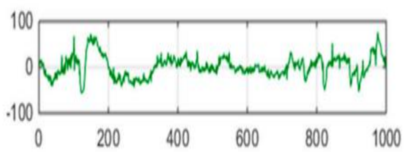
2.3.1 NON-RAPID EYE MOMENT

The division based on the movement of the eyes and deeper sleep. Sleep is never been a constant process, as we fall down there are various stages we go through as time passes. This stages are classified as NREM and REM based on their attributes. There are five sleep stages, four of them are categories in NREM and other is called REM.

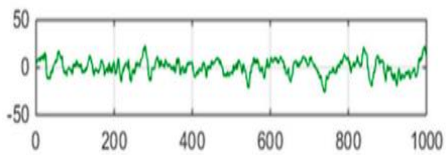
Wakefulness (stage1), N1 (stage2), N2 (stage3), N3 (stage4) and REM. Stage N1 to N3 are classified as NREM, majority sleep occurs in NREM, while progressively going into deeper sleep. Sleep is arranged in consecutive 30-second epochs, and a particular sleep stage is allocated to each of these epochs. The bulk of sleep is spent on the N2 level.

- Wakefulness (stage1): The first step is the wake period or step W, which relies on eye movement. Alpha and beta waves are existing during eye-open wakefulness, mainly gamma. As individuals get drowsy and eyes close, the alpha rhythm is the prevailing form. An epoch is called stage W when it includes more than 50 per cent alpha waves and wakefulness-related eye movements.
- N1 (stage2): It is the lightest period of sleep which begins as the low-amplitude mixed-frequency (LAMF) behavior absorbs more than 50 per cent of the alpha waves. Skeletal muscle tone is apparent, and breathing appears to occur at a regular rate. This stage tends to last 1 to 5 minutes, which is about 5 per cent of the overall cycle.

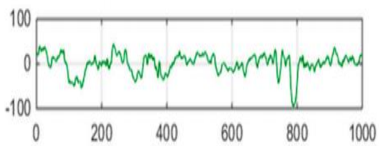
- N2 (stage3): This stage represents deeper sleep as well as a temperate drop in your heart rate and body. It is identified by the existence, or both, of sleep spindles, K-complexes. The superior temporal gyri, anterior cingulate, insular cortices and the thalamus should be stimulated by these sleep spindles. The K-complexes suggest a shift to a deeper sleep. They are single, long waves of the delta which only last a second. When the sleep grows deeper and the person transitions into N3. They'll replace all their waves with delta waves. In the initial cycle, Stage 2 sleep lasts about 25 minutes and lengthens with each successive cycle, eventually consisting of about 50 percent of total sleep.
- N3 (stage4): This is recognized to be the deepest stage of sleep and is characterized by a much sluggish frequency with high amplitude signals known as delta waves. This stage is the hardest to wake up from, and for some people, even loud noises (over 100 decibels) won't wake them up. As people grow older, they continue to spend less time in this sluggish, delta wave sleep and more time in N2 sleep. Although this period contains the highest level of anticipation, if anyone is awake at this point, they may have a brief process of mental fogginess. It's classified as night inertia.



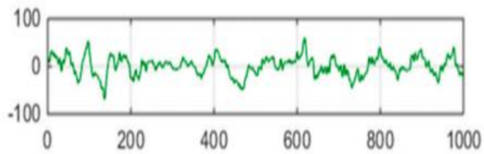
(a) Wakefulness (stage1)



(b) N1 (stage2)



(c) N2 (stage3)



(d) N3 (stage4)

Fig 2.5 EEG Waveform of NREM Sleep Classes

2.3.2 REM (RAPID EYE MOVEMENT)

During REM, the pons turn off signal to neuron in the spine, preventing us from acting out our dreams. Dreams are more vivid and frequent in REM. PGO waves are emitted during REM and may help facilitate our ability to see our dreams. Nevertheless, the pace of breathing is adjusted, becoming more rapid and sporadic. This period typically starts 90 minutes after you fall asleep, and every of the REM periods should be longer at night. The first cycle normally lasts 10-13 minutes, and the last one will last up to an hour.

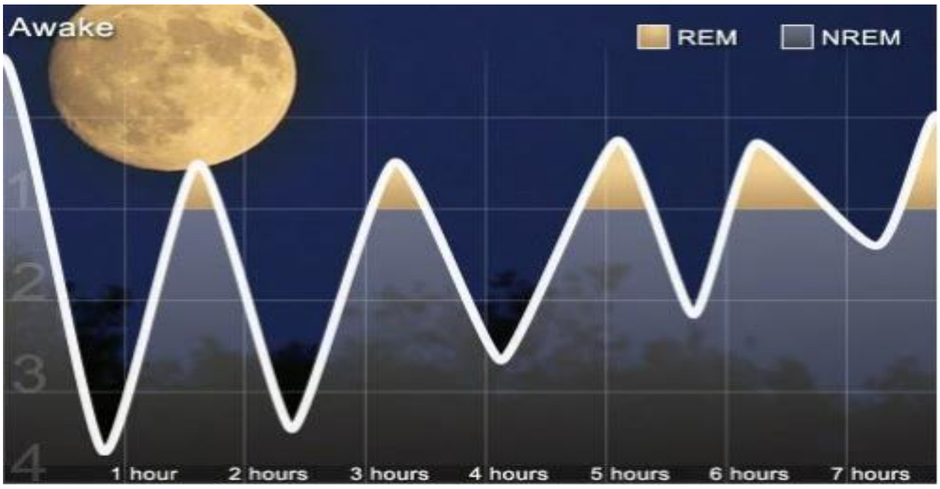


Fig 2.6. Sleep Cycle of NREM and REM

2.4 DATASET OF SINGLE CHANNEL RAW EEG

In the EEG signal, while analysis, it is important to have complete knowledge of biomedical signals and their rawness. When we record any EEG signal it is mandatory that the contribution of other organ are nullified because that can impact our accuracy and precision as well. In any signal, especially PSG signal like EEG, ECG, EMG, which are prone to the noise, we must take the dataset in its purest form, if not then the adaptive and appropriate filter should be applied to remove unwanted filters. There are generally two types of single-channel raw EEG datasets, namely, MASS dataset and SLEEP-EDF dataset. These datasets are freely available and require minimal filtering to eliminate the noise which corrupts PSG signals.

2.4.1 MASS DATASET

In MASS cohort 1, 5 subsets of audios, SS1-SS5, were actually coordinated depending on to their research study and also acquisition protocols. We used data coming from SS3, that included PSG files of 62 stable subject matters (grow older 42.5 ± 18.9). Each recording comprised 20 scalp-EEG, 2 EOG (left and right), 3 EMG and 1 ECG tracks. The EEG electrodes were put on the common 10-20 body as well as the EOG electrodes were located diagonally on the outer edges of the head. EEG as well as EOG audios were actually pre-processed along with a 60 Hz notch filter and a 0.30-100 Hz (EEG) as well as 0.10-100 Hz (EOG) band-pass filter. The same sampling price was actually 256 Hz for both EEG as well as EOG reports. Such recordings were actually personally sorted right into some of the five sleeping stages (W, N1, N3, n2 and rem) through an AASM-standard sleeping professional. At the beginning and completion of each subject's files, which were phoned number Unclear, there were actually likewise activity things. Our team checked our version utilizing the F4-EOG (Left) road, which was actually acquired through montage reformatting without further pre-processing.

2.4.2 SLEEP-EDF

There are two types of subjects that come from the research: age influence in healthy subjects (SC) and the impact of Temazepam on sleep (ST). There are 20 SC subjects (age 28.7±2.9). A PSG recording consisted of two set of channels Fpz-Cz and also Pz-Cz scalp-EEG signals, one EOG (parallel), one EMG, and one oronasal respiration signal. Both EEG and EOG displayed the very same 100 Hz tasting rate.

The dataset used for this study was the Sleep-EDF database, which is the PhysioBank is freely accessible. The other topics were omitted from the study since their observations included gestures and unreported intervals. In addition, we have combined stage 3 and stage 4 into a single stage N3, which is currently suggested by the AASM norm. Only the EEG Fpz-Cz signals were used as single-channel signals in this work because K-complexes and sleep-spindles (typical N2 stage patterns) could be recorded in the central / frontal regions and, during stage N1, sharp vertex waves, which often occur in the central / frontal brain regions, according to the AASM guidelines, may be present. The dataset is in the EEG data collection is recommended to use a digitized system at 200 SPS (Samples per second), a low pass filter of 30 Hz, and also a high pass filter of 0.1 Hz, to achieve adequate interference cancelation from SNR (Signal Noise Ratio). The effects of pressure on the skull are more likely to measure brain tissue conductivity. The other topics were omitted from the study because their observations included movements and epochs which were not recorded. As we have discussed earlier stage 3 and 4 are combined to have high accuracy as per the guidelines of AASM. This has a different impact from other studies like AASC system in which we arbitrarily select a substantial number of epochs which were identified at stage W (10 percent). Hence it becomes easy to determine as w cycle as it has comparatively little variability. Sleep-EDF dataset has excluded other movement which can hamper the accuracy and precision. The sample has taken only brain signals recorded by EEG electrode caps.

2.5 PREVIOUS METHODS

Sleep classification has been a relatively new domain as it is done mostly by machine learning and deep learning. However, from the last ten years, as machine learning has evolved, researchers are inclining towards the bio-medical field. Signals like EEG, ECG, EMG and PSG give a plethora of information, but extracting this manually is tedious and difficult too. Deep learning implementation is complex but high accuracy and precision can be achieved. Dimension reduction technique particularly, principle component analysis (PCA) is been used for data refinement as EEG signals contain various differentially amplified peaks. Linear discriminative analysis (LDA) has also shown promising results as it reduces the tedious calculation of bio-medicals using machine learning. The past researches related to sleep stage classification and analysis are described in this section. N.Michielli et al. [1], employed cascaded LSTM RNNs for automatic classification of sleep stages. Supratak et al. [2] developed a deep sleep-net algorithm using CNN and deep learning for classifying sleep stages. Gevnis et al. [3] used non-invasive human neuro-cognitive performance capability testing. Shuyuan et al.[7] classified sleep using k-means clustering. Hassan et al. [12] applied the tunable-Q factor wavelet transform (TQWT) on single channel EEG data to generate EEG sub bands. Then normal inverse Gaussian (NIG) pdf modelling was applied to extract NIG as features and finally adaptive boosting technique was applied for sleep stage classification. Boostani et al. [13] have reviewed the various classification methods for sleep stage classification of patients and healthy people. Aboalayon et al. [14] reviewed the past researches in the field of sleep stage classification and proposed a new methodology achieving a accuracy of 93.13% on the sleep EDF dataset.

However, we have found that machine learning is not quite adequate in terms of accuracy and classification of the different stages, in particular NREM sleep stage 3 and NREM sleep stage 4. So, we need a lot more robust methodology that works extraordinarily well in the NREM sleep stage classification. We know that deep learning performs almost as well as either feed forward spread-based or backpropagation-based learning. It is iterative in nature, and the neural network has many hidden layers that make it very credible and realistic. We developed a combination of deep learning techniques in which sleep classification has been performed using multilayer CNNs and RNNs. In general, the classification between N1 and REM is difficult because they possess some similarities in their wave generation. So, in order to distinguish them, the neural network plays a decisive role. It helps to differentiate between different classes as filtering (hidden layers) classify them in temporal and frequency domain both. Hence the classification between different stages is smooth and accurate.

Sleep scoring is grounded on EEG signals performed using machine learning is generally carried out using more than one technique or combination of many techniques. According to our research, the most common algorithms used for selecting features in the Automatic Sleep Stage Classification (ASSC) program are: sequential forward and reverse selection methods with minimal redundancy maximum relevance (mRMR). Automatic methods for classifying the sleep stage can be based on reinforcement learning, unsupervised or supervised learning, to name a few, k-means, bootstrap aggregation (bagging) [1], [3], support vector machine (SVM) [8], random forest classifier, artificial neural networks (ANNs). Recurrent neural networks (RNNs) [1] are used for sequencing and Convolutional neural networks (CNNs) are generally preferred for image data are the most preferred algorithm to work on EEG signals. RNN itself has many variants namely gated recurrent unit (GRU), bidirectional RNNs, and Long-short term memory (LSTM) [1].

CHAPTER 3

PROPOSED METHOD

3.1 STRUCTURE OF THE MODEL

We have performed sleep classification which is grounded on raw single-channel EEG signal and it is executed using CNNs and RNNs (bidirectional LSTM). We aim to classify sleep stages, which can be implemented by applying the feature extraction abilities of deep learning. We have developed a methodology that uses two CNNs at first layers and RNNs with separate filter sizes. CNN work better for extracting temporal information. The process requires a raw single-channel EEG signal dataset to implement our model, for which the sleep-EDF dataset which is openly accessible on Physio-Bank Data Acquisition. The dataset is in the EEG data collection is recommended to use a digitized system at 200 SPS (Samples per second), a low pass filter of 30 Hz, and also a high pass filter of 0.1 Hz, to achieve adequate interference cancelation from SNR (Signal Noise Ratio). The effects of pressure on the skull are more likely to measure brain tissue conductivity. The other topics were omitted from the study because their observations included movements and epochs which were not recorded. As we have discussed earlier stage 3 and 4 are combined to have high accuracy as per the guidelines of AASM. This has a different impact from other studies like AASC system in which we arbitrarily select a substantial number of epochs which were identified at stage W (10 percent). Hence it becomes easy to determine as w cycle as it has comparatively little variability. In classifying as occult layers the neural network helps to achieve an optimum output, as it is frequently iterated. For retrieval of temporal and frequency properties, RNNs and CNNs are useful. While choosing the attribute we were very selective as attributes needs to gives relevant information about a non-stationary signals. Temporal and spatial attributes are separated as the implementation of neural network works both on feedforward as well as backpropagation.

A selection of features and a functional transformation approach was introduced to reduce the amount of neural network input functions. Two different methods were considered: The minimum redundancy and maximum relevance (mRMR) algorithm was used for the first RNN for feature selection, while the PCA was used for dimensionality reduction for the second RNN. Finally, the two RNNs were linked in a cascade, in order to classify five different sleep stages. CNNs operates on neural network feedforward while RNNs works on neural network backpropagation. With the aid of this neural network we were able to identify different phases of sleep. Deep learning lets us produce a simple distinction between stage 3 of the NREM and stage 4 of the NREM, which has been quite challenging as they display tremendous resemblance. Other stages can be classified easily, even machine learning produces better results in other classes as compared to its own performance in NREM sleep stage 3 and stage 4. Gaussian mixture model (GMM) which is an unsupervised type of machine learning helps to classify the sleep stages[14]. GMM is a useful solving problem which require classification or implementing any boundary with different classes. Unsupervised machine learning can be used to classify between NREM and REM sleep stages, but for deeper and precise classification we need to switch for better options like deep learning. In our model, the architecture that has been followed is such that the iterative nature of the algorithm makes good accurate classification. RNNs and CNNs have their own characteristics to classify any attribute, on which further algorithm is based.

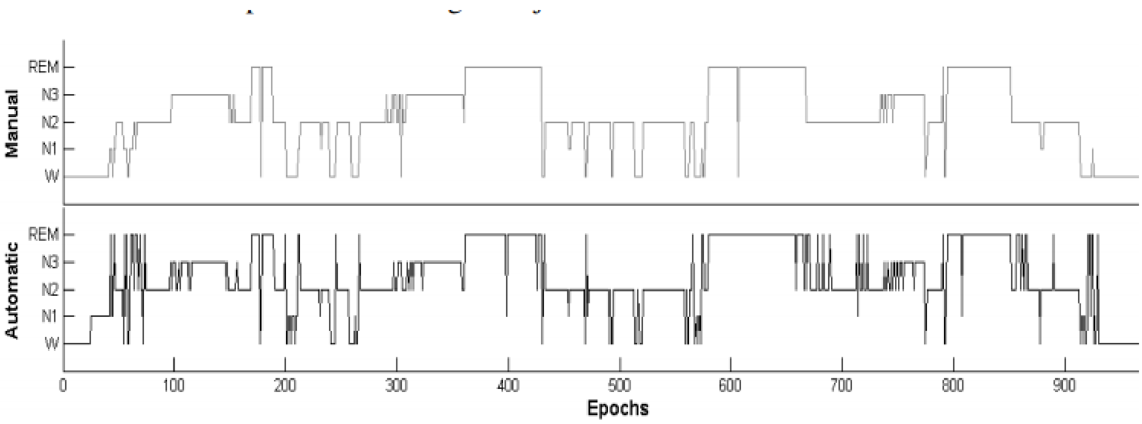


Fig3.1 Different segmented epochs

3.2 FEATURE SELECTION

Each signal has some properties that can be correlated with time, frequency and power. Although EEG signals can also be associated with time and strength, EEG signals are inherently stationary. We must remember the non-stationary nature of EEG signals when selecting any attribute or characteristic. The criteria for selecting any attribute should therefore extract both temporal and spatial information, which can help in classifying different phases.

We have classified 48 different attributes which are characteristics of EEG (Fpz-Cz) signals. For each 1s filtered epoch, both frequency and time-invariant features were determined for two reasons [10]: firstly, temporal information is extracted by forwarding feedback propagation which is CNN and secondly, as we know RNNs works better for input sequences. We have classified attributes in four different categories, which helps us to retrieve the information in a well-mannered way. These features are time, frequency, non-linear, and entropy.

3.2.1. TIME-DOMAIN FEATURES

There are many ways to extract features, mainly depending upon the dataset whether the dataset is been used for classification or prediction purposes.

Generally these parameter have been selected for sleep classification;

- Statistical parameter (mean, variance, standard deviation, skewness , minimum value and maximum value)
- Hjorth parameter (activity, mobility, complexity)
- Zero crossing

A) Statistical Parameter:

A statistical function, or population parameter, is a quantity joining a mathematical or random variable's likelihood distribution. This may be used as a predictive feature of a human community or as a mathematical pattern.

MEAN $\mu = \frac{1}{N}\sum_{i=1}^{N} Xi$ 3.1

VARIANCE $\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2$ 3.2

The average rectified value which is mathematically represented as:

ARV(x) = $\frac{1}{N}\sum_{i=1}^{N}|x_i|$

3.3

Min V = min $[X_n]$ 3.4

Max V = max $[X_n]$ 3.5

Where, $X_n = 1,2,3\ldots\ldots.n$, n is time series and N are data points.

B) Hjorth parameter:

Hjorth parameters are characteristics often utilized in the assessment of EEG signals [1], i.e. action, movement and complexity). The first and second signal derivatives are used in the calculation of the Hjorth parameter.

Hjorth complexity $HC(x) = \frac{HM(dx/\partial t)}{HM(x)}$ 3.6

Hjorth mobility $HM(\alpha) = \alpha_1/\alpha_0$ 3.7

Hjorth activity $HA(\alpha) = \alpha_0^2$ 3.8

Where, α_0 is variance, α_1 is first derivative of the variance and α_2 is second derivative of variance.

EEG signals have been segmented and they have epochs so mobility, complexity and activity gives us vital information about our signal or set of different epochs.

C) Zero Crossing:

Zero-crossing is a temporal process that is widely utilized in circuit-manipulation, algebra, imaging and signal processing. It transmits the amount of zero crossings in the segment. Null intersection happens as the signals in the measurements are variated. This function is commonly used as a random noise metric. The sum of zero crosses in EEG signals often differs through cognitive function and during various sleep cycles. ZC is related to as ($\beta n-1<0$ and $\beta n>0$) or ($\beta n-1>0$ and $\beta n<0$), or ($\beta n-1 + 0$ and $\beta n>0$, respectively).

3.2.2 FREQUENCY DOMAIN FEATURES

Certain attributes are classified for frequency domain feature, namely:

- Discrete wavelet coefficients
- Signal strength
- Mean frequency

A) Discrete Wavelet Coefficient:

Discrete wavelet transformation (DWT) is an interpretation of the data built to address the Fourier transformation shortcomings over non-stationary signals, and this approach is less noise prone and can easily be extended to non-stationary signals. With non-stationary signals, DWT is even easier as it is valid with non-periodic signals, whereas Fourier transform has a drawback by just operating on periodic signals. Also mathematically speaking, the short-term Fourier transform (STFT) does not refer to EEG signals as it is rather difficult to locate and synchronize a fitting timeframe and epoch for EEG signals at the same time. So for non-stationary, like EEG signals, DWT works better.

$$\text{DWT (j,k)} = \frac{1}{2^{j/2}} \int_{-\infty}^{\infty} x(t) \psi(t - 2^j k / 2^j)\, dt \qquad 3.9$$

X(t) is main signal while, ψ is wavelet coefficient. For the estimation, a low-pass filter is used Signal coefficient having a low frequency and a high-pass filter shall be used to make a comprehensive signal coefficient having a high frequency. In the case of DWT, which is commonly used in the study of EEG signals, it is necessary to define the correct wavelet

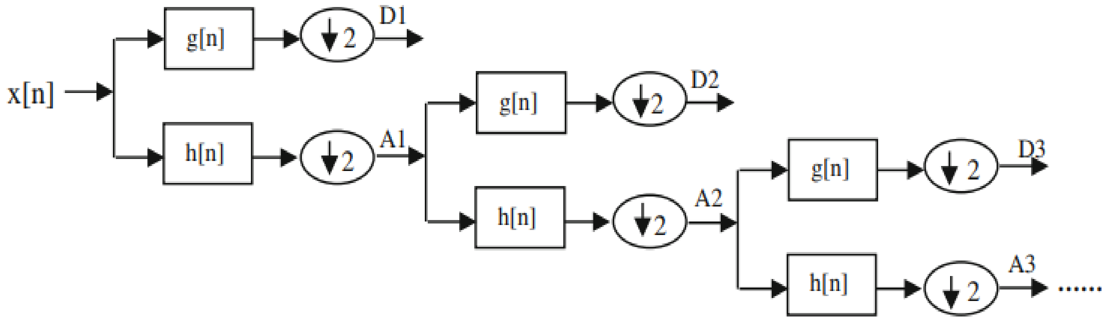


Fig 3.2. DWT implementation by decomposing sub-band

Coefficient and to evaluate the degree of decomposition. The number of stages of decay is selected on the basis of the primary frequency range of the signal. The values are selected in such a way that such parts of the signal that correspond well with the frequencies required for the classification of the signal are retained in the wavelet coefficients. EEG signals have valuable information in the range 0–30 Hz. The level of decomposition is therefore set at 5.

In the given figure h[n] is high pass filter and g[n] is low pass filter, the decimation factor is generally of factor 2, but we can decimate by any factor for example 5, 6 or 8. In choosing discrete wavelet decimation coefficient, it important to keep in mind that different level of decimation gives information accordingly. Preferably decimation factor is by 2. Experiments and their result shows that decimation factor should be optimum and can varied according ones application. The discreet X(n) signal crosses, as can be seen in the figure. The high-pass filter evidence is essential coefficients (Di[n]) and crosses the low-pass filter to obtain approximation coefficients (Ai[n]). At increasing abstraction point, half-band filters promote the creation of signals that shape part of a frequency band.

B) Signal strength or Power:

In the EEG signal, signal strength is related to the power of a particular epoch segment. Power is an important attribute which helps us distinguish the different level of the waveform generated by different sleep stages. One can simply understand that, every different NREM sleep stage and REM sleep stage generates different power, hence power plays an important role to identify different sleep stages. Specifically speaking, power is helpful in the detection of stage W (wakefulness) and NREM stage 1, because the waveform generated in these stages and their power distinguishes them.

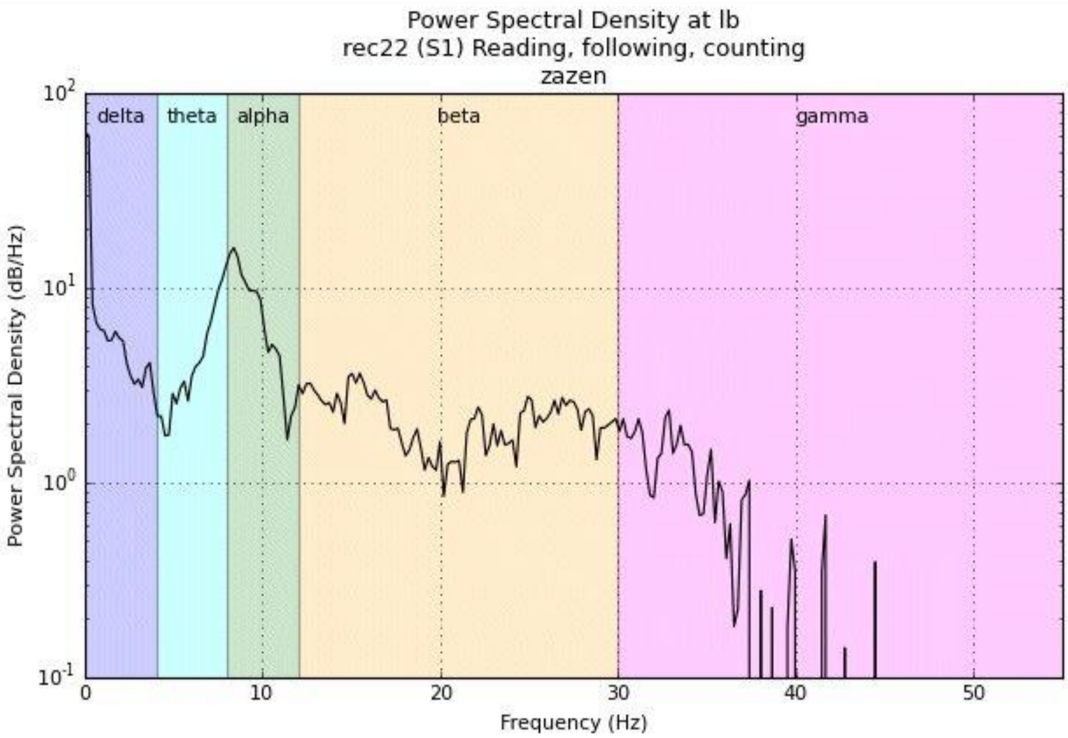


Fig3.3 Power Spectrum Density of Different Wave

C) Mean Frequency:

Mean frequency is a peak calculation that measures the power center through frequencies. Below is an indication of a medium frequency in a blackbird thrush:-The medium frequency estimation gives a smooth measurement of the spectral power distribution. It is formulated as:

$$\text{Mean frequency} = \frac{\sum_{i=0}^{n} PiFi}{\sum Pi} \qquad 3.10$$

3.2.3 ENTROPY ATTRIBUTES

Entropy can be related to the randomness of any system. As we know human-generated signals are random, be it, ECG, EEG, EMG, or any kind of PSG. Calculation of different entropy will lead us towards the Pandora of knowledge of any bio-medical signals. There are different types of entropy and it can be used for sleep classification as sleep waves are random. Some entropy-based attributes are listed as below:

- Renyi entropy
- Spectral entropy

A) Renyi Entropy (RE):

Renyi entropy, presented by Renyi, is an unique case of spectral entropy based on the idea of simplistic entropy of probability distribution. When p is a distribution of probability in a fixed number, its order r RE is:

$$RE = \frac{1}{1-r} ln \sum_{i=0}^{n} Pi^{r} \quad (r \neq 1) \qquad 3.11$$

Renyi entropy is extension of traditional Shannon entropy [15]. Even if the given order value r=1, is another case of entropy.

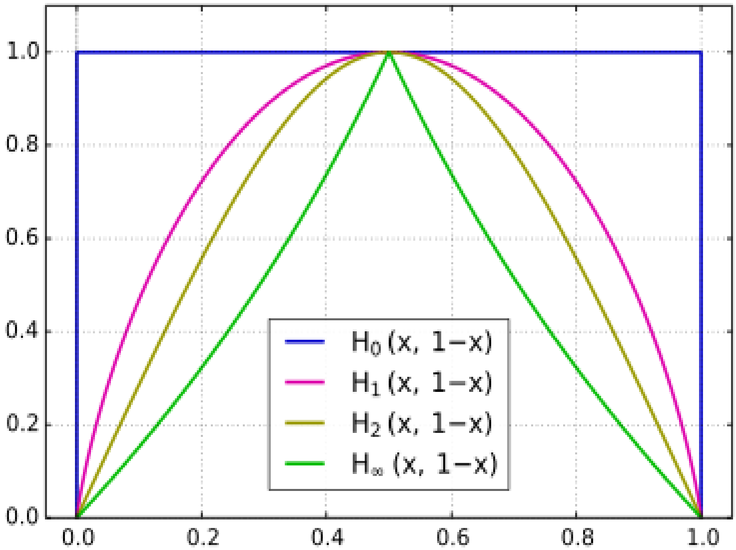


Fig3.4 Renyi Entropy

B) Spectral Entropy:

SpEn spectral entropy (SpEn) is a function define the extent of regularity of the dynamic signals. The entropy would be greater for data with normal distribution of probability. On the same line, data entropy with non-homogenous distribution of probability will be small. Unlike standard entropy figures, spectral entropy is determined using the power spectrum of the signal's likelihood values. SpEn is formulated as:

$$SpEn = -\sum Pi \log(1/Pi) \qquad 3.12$$

Here P is probability distribution.

3.2.4 NON-LINEAR ATTRIBUTES

Bio-fluctuations analyzes do an outstanding path to explore the factors that explain the preservation of an internal homeostasis, especially in response to the continuously evolving demands of the climate and illness activities. However, nonlinearity and non-stationarity limit the quality of the standard study in physiological data series. Innovative method of extracting complex information at various timescales, in particular from non-stop signals, is Hilbert – Huang transform (HHT), built on nonlinear concept. HHT has used for the study of alpha electroencephalography (EEG) waves, which in the stable topic tend frequently to fluctuate between 6 and 10 hertz but erratic or in a particular demented state. Besides, the outcome of these methods and HHT are collected by frequency analyses.

Eventually, the major applications of HHT in the qualitative and quantitative characterization of biological signals, including non-stationary, extremely rapid phase and voltage or an assessment of correlation, are demonstrated. The discrepancies between the regular and dementias brains and the nonlinear properties of the underlying processes have successively been recorded in these EEG applications.

Overall, all 48 sleep classification parameters can be classified into four basic groups, i.e. time domain, frequency domain, entropy, and non-linearity. The features are tabulated, further and it is understandable that there can be hundreds of attributes, but that attributes are classified which are most important, sleep classification is dominant in the time and frequency domain characteristics which help us to classification the most difficult stages, such as NREM sleep stage 3 and sleep stage 4.

SERIAL NO.	ATTRIBUTES	SERIAL NO	ATTRIBUTES
1	Variance	25	Amplitude (alpha sub-band)
2	Arithmetic Mean	26	Amplitude (gamma sub-band)
3	Average Rectified Value	27	Amplitude (theta sub-band)
4	Peak to Peak amplitude	28	Amplitude (sigma sub-band)
5	Skewness	29	Energy (delta sub-band)
6	Global Maxima	30	Energy (theta sub-band)
7	Root Mean Square	31	Energy (alpha sub-band)
8	Kurtosis	32	Energy (beta sub-band)
9	Median	33	Energy (gamma sub-band)
10	Hjorth Mobility	34	Energy (sigma sub-band)
11	Hjorth Complexity	35	P_{sigma}/P_{alpha}
12	Mean Frequency	36	P_{beta}/P_{gamma}
13	Spectral entropy	37	P_{gamma}/P_{beta}
14	Renyi entropy	38	Power (delta sub-band)
15	P_{delta}/P_{gamma}	39	Power (theta sub-band)
16	P_{gamma}/P_{sigma}	40	Power (alpha sub-band)
17	E_{delta}/E_{gamma}	41	Power (beta sub-band)
18	E_{delta}/E_{gamma}	42	Power (gamma sub-band)
19	E_{alpha}/E_{gamma}	43	Power (sigma sub-band)
20	Es_{igma}/E_{gamma}	44	P_{alpha}/P_{sigma}
21	E_{beta}/E_{gamma}	45	P_{alpha}/P_{beta}
22	Zero Crossing’s	46	P_{gamma}/P_{theta}

23	Amplitude (delta sub-band)	47	P_{delta}/P_{sigma}
24	Amplitude (beta sub-band)	48	P_{theta}/P_{sigma}

Table II. List of 48 Different Attributes

CHAPTER4

ALGORITHMS

4.1 FEATURE EXTRACTION ALGORITHMS

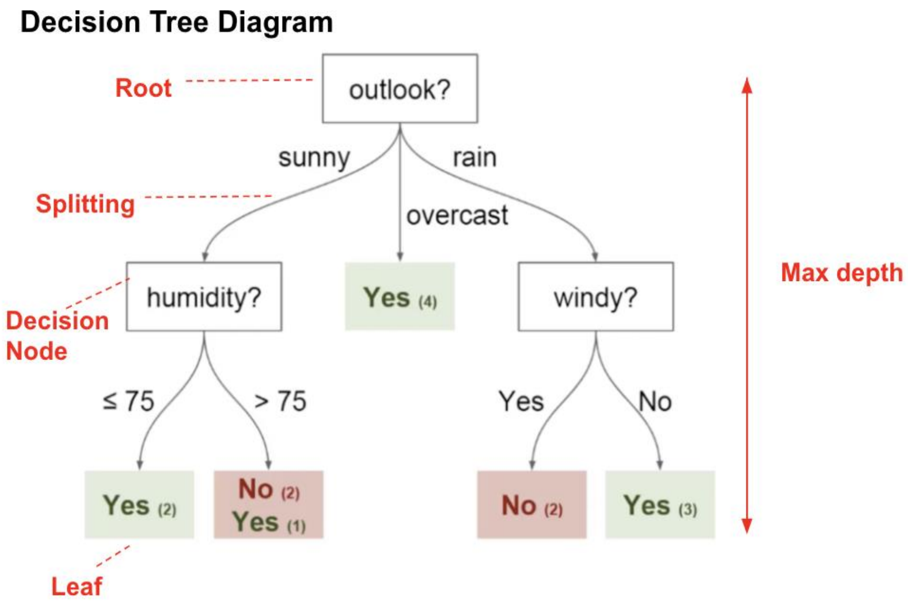
We also tested the algorithm which is consistent with raw single-channel EEG signals in depth in the implementation of sleep classification. Since we have spoken about deep learning, we need well defined extraction algorithms to enforce sleep classification. For the operation of neural networks, RNN and CNN are both included. The algorithm has been implemented with minimal redundancy and maximum relevance (mRMR). However, various forms of algorithms for feature selection are possible and described below:

- Decision Tree
- mRMR
- Fisher Score Algorithm

4.1.1 Decision Tree:

We may claim, that it functions on chance, to realize the Decision Tree function. If some occurrence is expected to occur, the odds of failure are P and 1-p. So, you will measure the impartial chance when deciding some occurrence to occur. Today, that it is more probable that the incident will take place than it will. Then we must therefore take decisions. This is the basic rule of any decision tree for a threshold to be established for all situations when a particular event passes the threshold. When we see its function we realize that the decision-making tree is perfect for classification.

Because the resolution of the classification problem is easier to structure and comprehensible compared to other algorithms. The reason this process is used extensively is because the guidelines used in trees structures are simpler and easier to understand. In



the Fig 4.1 Decision Tree Block Diagram

Classification procedure, Decision trees employ a multi-stage or consecutive approach. Choose the features with the highest rate of application of information. The procedure goes until a single class matches each branch of a tree. Subsequently the decision tree can be compiled into a series of rules.

4.1.2 Minimum redundancy and maximum relevance (mRMR)

The mRMR algorithm is a feature extraction process, with training examples, which selects the most appropriate characteristics while reducing heterogeneity among the features selected. In computing the feature and function-label similarity values, mRMR uses mutual information. For a and b characteristics, p(J) and p(K) are the functions of the marginal likelihood, and p(J, K) is the related allocation of likelihood and I(J, K) is a mutual sum of J and K information. The governing equation has been given as:

Information $I(J, K) = \sum_{l,m} P(Jl, Km) \log \frac{P(Jl,Km)}{P(jJ)P(Km)}$ 4.1

Mutual information helps us to calculate the non-linear similarity in a non-stationary signals quickly. Computational time is very less, this is the main reason for adapting, mRMR algorithm. As, EEG signals which are generated by brain's neural activity are random, non-linear. Now, minimizing the redundancy and maximizing the relevance, mathematically is given as:

Minimum Redundancy $R_d = \frac{1}{|F|^2} \sum_{a,b \in F} I(x,y)$ 4.2

Maximum Relevance $R_e = \frac{1}{|F|} \sum_{i \in F} I(z,x)$ 4.3

Here, F is set of feature, z is training class, I(x, y) is the mutual information between x feature and y feature. These two factor, R_d and R_e, are important for calculating mutual information difference and mutual information quotient.

Mutual information difference MID = $|R_d - R_e|$ 4.4

Mutual information quotient MIQ = R_d/R_e 4.5

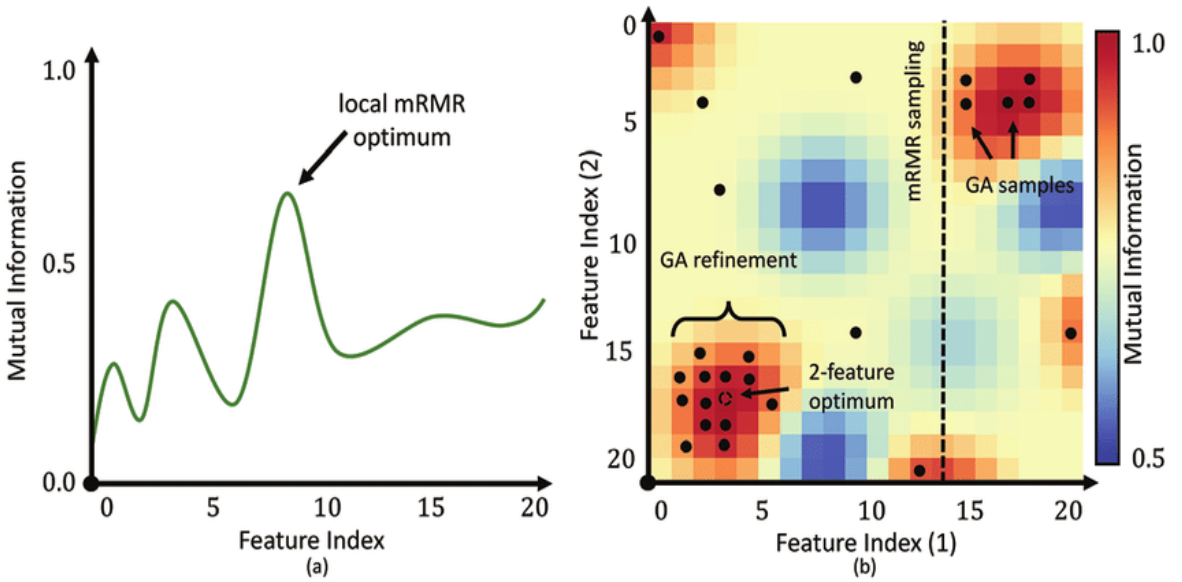


Fig 4.2 Graph of mRMR Feature Selection between two Feature Index and Mutual Information

4.1.3 Fisher Score Method:

An effective and convenient tool that calculates the difference between two groups is the Fisher value. This method measures the Fisher value for each function in the sample group according to the specification and measures the cumulative Fisher score value over all characteristics. The Fisher score value is calculated appropriately. The essential value is used in the attribute space of the sample group system if the Fisher score is larger than the base value for the system Fisher.

The estimating characteristics of Fisher's evaluation system for optimizing probability and solving approximate equations dependent on near-like characteristics are studied. Consistent evaluation of the actual vector parameter is shown important for achieving a fast convergence rate. If this is met, however, the algorithm is very appealing [16]. This connection between the productivity and adequacy of the issue modeling underlines the scoring algorithm. The consequences of linear output constraints are addressed and examples of probability calculations and almost likelihood are provided.

4.2 CONVOLUTIONAL NEURAL NETWORK

CNN is a part of deep learning, which gives the solution to complex structures like EEG signals. Multilayer perceptron generally means networks that are fully connected, that is, it is many to many mapping. Here every single node is neuron, and mapped to every other neuron of another layer, hence it is called a fully connected network. Two different sizes of the convolutional layer have been applied with one smaller and other bigger filter size to extract time-invariant features as used in [8]. The small filter works for extracting temporal information while a bigger filter size works for extracting frequency domain information. Each convolutional layer has basic three operations which need to be performed are:

- 1D-convolution with its filters
- pooling (confining the given data)

- Using an activation function (SOFTMAX, ReLU, SIGMOID etc.)

$\{X_1, X_2, X_3, \ldots X_N\}$ are EEG single-channel EEG epochs from N-30. To extract the i^{th} feature a_i from the i^{th} EEG epochs X_i, we use two CNNs as:

$$h_i^s = CNN\Phi_s(X_i) \tag{4.6}$$

$$h_i^l = CNN\Phi_l(X_i) \tag{4.7}$$

$$a_i = h_i^s \,||\, h_i^l \tag{4.8}$$

Here CNNs(x_i) is a technique that converts the 30-s EEG epoch into a feature vector hi using a CNN, in the primary layer parameters of both small and large filter sizes and is a concatenates operation that integrates two CNN outputs. These linked or concatenated functions $\{a_1, a_2, \ldots, a_N\}$ are then promoted to the sequence's remaining adaptive part.

4.2.1 1D- Convolution with its filter:

CNNs are typically used for the processing of images. The images are 2D in nature and therefore the convolution filters used are 2D (usually 3x3, 5x5, 7x7 pixels or something similar). There are, however, concepts other than images with a different dimensionality that you can process. 1D CNNs are also used in the processing of natural languages.

Now consider an image which is a combination of red, green, blue colors. Any image which consists of RGB colors can be represented by pixel values. for example, if an image is of 28x28x3 then it simply means there are 28 columns and 28 rows and 3 channels. So, to implement this image on CNN we need 2352 hidden layers. Now to get a perspective generally an image is the size of 200x200x3, so 120000 total number of hidden layers require to implement this image on CNN. now, coming back to convolutional filter, if we want to classify anything, first we need to select an attribute for that category, after that, we will make a filter and placed that filter to every center valued pixel, multiply them with their corresponding intensity value i.e. pixel value and calculate their mean and replace it center valued pixel to mean pixel value. In given figure, if we want to detect "X" symbol then convolutional filter will looks like:

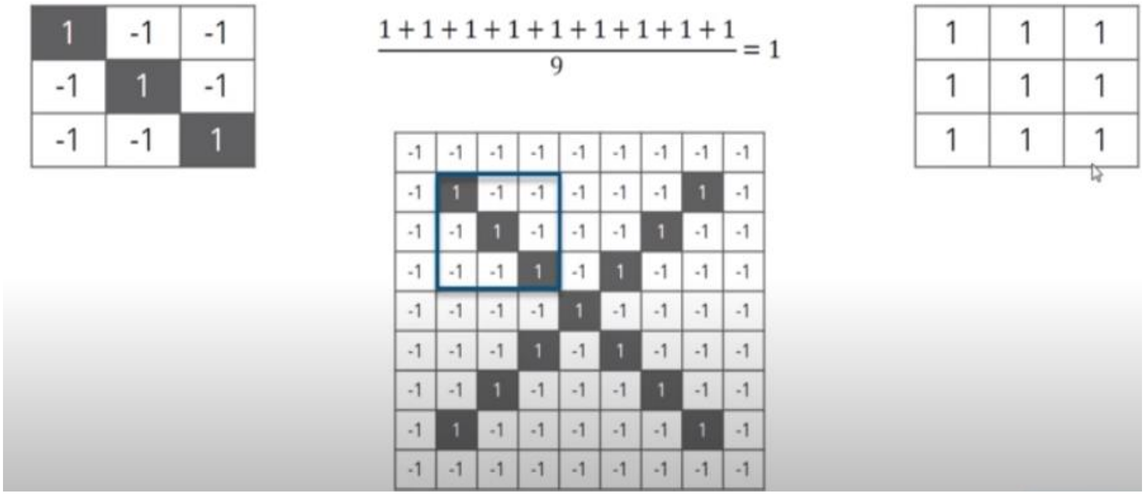


Fig 4.3 convolutional filter for detecting a symbol

4.2.2 Pooling:

Pooling is a process for reducing the dimension of any image which has large in size. As, we have discussed that in CNN while implementing, we must shrink the size of an image has, bigger the size is more is hidden layers and thus more the process becomes complex. Pooling is tool that reduces the matrix size of an image. It stacks up the matrix of an image and this reduces the dimension of the given image. All the layer of CNN re multiple times implemented in a single image, so we can understand the tediousness of the process. The mechanism of pooling technique is to generate a threshold with some mathematical form and then chopping of the pixel value which does not clears that threshold value and hence reduces the dimension of the bigger image. For pooling, we can take a threshold like the maximum value which can be selected, now those filter which does not have highest value are neglected. To, implement this we choose a 2x2 or 3x3 size of a window which will be placed all over image and the maximum value will be only consider. For example let us consider an image (which is refined after convolutional filter and activation filter), we are taking a 2x2 window for pooling.

0.77	0.34	0.55	.34
0	1	0	.33
0.77	0.34	0.55	.34
0	1	0	.33

Table III. Example of pooling layer

Now as we have discussed, we have a 2x2 window to apply pooling, the result will be a 2x2 image which will stack up for all pixel value (for red, green, blue).

1	0.55
.77	.55

Table IV. Dimension Reduction after Pooling

This shows how dimension reduction works in image. Pooling is done many times to resize the image again and again. This will done of all the pixel values, hence we reduce the image size.

4.2.3 Activation function

It is the function that takes a vector of M real numbers as its origin and normalizes it into a probability distribution composed of M probabilities proportional to the input number exponentials. SOFTMAX is generally used in deep learning which consists of a neural network. The very reason to used SOFTMAX in sleep classification based on EEG signals is, it confines the distribution in range to (0-1), which becomes easy to analyze, given the fact EEG signals are non-stationary signals and samples for 30s-epochs. SOFTMAX is generates probability distribution of any event, pixel which are passed from various layers of CNN, is highly refined and SOFTMAX makes it to work in a confine range. SOFTMAX is mathematically defined as:

The standard (unit) Softmax function : $\mathbb{R}k \rightarrow \mathbb{R}k$ is described as:

$$\sigma(z)i = \frac{e^{zi}}{\sum_{i=1}^{m} e^{zj}} \text{ for } i = 1, 2, \ldots\ldots\ldots\ldots k \qquad 4.9$$

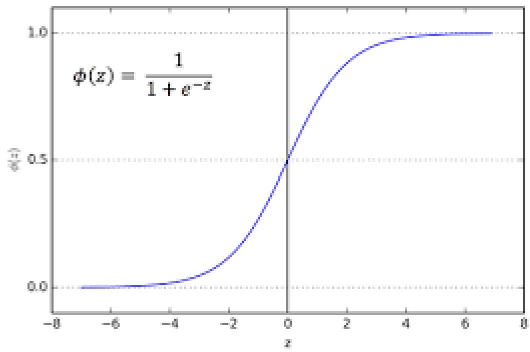


Fig 4.4 SOFTMAX activation function

We use two CNNs with small and large filter sizes in the first layers to extract time-invariant features from raw single channel 30-s EEG epochs. This arrangement is associated with the way that signal processing specialists monitor the exchange-off between the precision of the period and the frequency in their extraction algorithms[8].The tiny filter is best for capturing time information i.e. when any of the EEG signals occur, whereas the wider filter is best for capturing frequency information (i.e. frequency components). In our layout, each CNN comprises of 4 convolutionary layers and two max-layer layers. Every convolutionary layer performs three operations sequentially.

To indicate temporal and also frequency relevant information from the EEG, depending on to the guidance given for [2], the variables CNN-1 and also CNN-2 were actually decided on for the representational learning component. Filters in Fs/2 (i.e. half the testing price (Fs) of the conv1 coatings in CNN-1 were set and its stride size in Fs/16 were actually established to identify when some norms in EEG showed up [18]. However it was readied to fs cu4 to better squeeze the frequency elements coming from the EEG through filtering system the conv1 layer of the CNN-2 array.

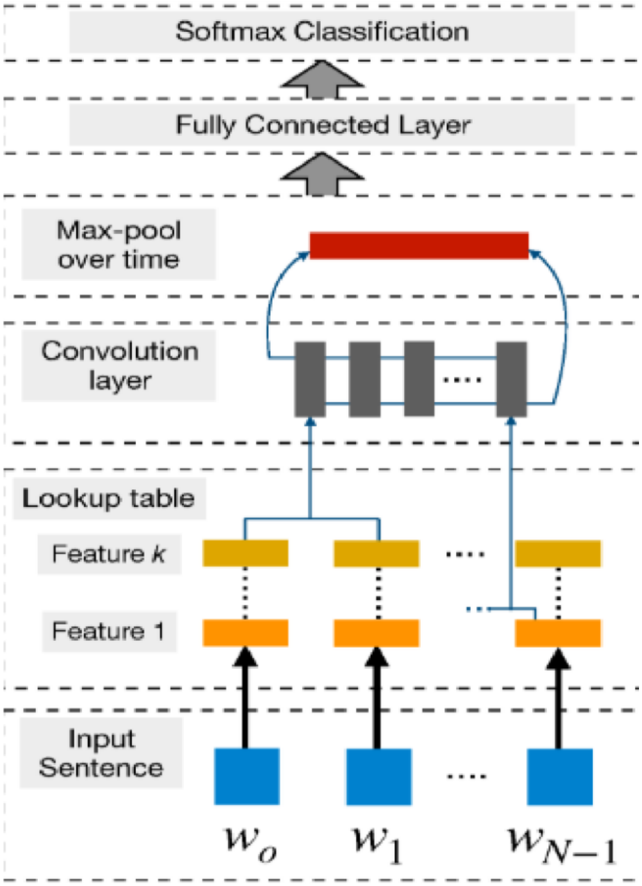


Fig4.5 Layout of Convolutional Neural Network Implementation

4.3 RECURRENT NEURAL NETWORK

Recurrent neural networks (RNNs) are generally applied to sequence of data. RNNs are similar to Artificial Neural Networks (ANNs). It works on a backward feedback network. RNNs works by adding input links within layers, as conventional Forward Neural Network-based architectures are not well adapted for managing sequential data. Many forms of RNNs have been developed over the past few years, for example, Elman RNNs, vanilla RNNs, bi-directional LSTM, Gated Recurrent Unit (GRU) networks.

There are multiple hidden layers that are assembled, receives input from previously hidden layers. Adding input connections on layers allows an RNN to let information flow across time phases, whereby the hidden layers create initiations that serve as memories in the network. The secret layers create up an internal state gradually through their vectors of activation ht. So at any given time the output will be a function of inputs $\{X_1, X_2, \ldots\ldots.,X_t\}$ and hidden layers $\{h_1 , h_2,\ldots\ldots\ldots h_t\}$.

Hence the output of feedback based RNN ŷt is given as:

$$ht = \alpha 1(Wxhxt+Whhht\text{-}_1+bh) \tag{4.10}$$

$$\hat{y}t = \alpha 2(Wh\hat{y}ht+ b\hat{y}) \tag{4.11}$$

Where:

$\{X_1 , X_2 , \ldots\ldots.X_t\}$ is sequence of input vectors

$\{h_1, h_2,\ldots\ldots\ldots h_t\}$ are hidden layers

$\{\hat{y}_1, \hat{y}_2\ldots\ldots\ \hat{y}_t\}$ are output vectors for time t € [1,…….,t].

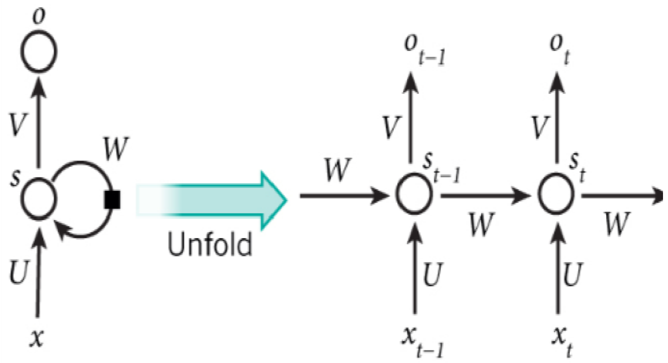


Fig 4.6 Recurrent Neural Network with a Single Hidden Layer with One Neuron and Back-Propagated Network

The typical property of RNN is that prediction of ŷt is done in such a manner that it not only considers the impact of Xt but also Xt-1, through the activation of hidden layers ht, the estimation becomes more accurate.

However, the accuracy improves by many folds in bidirectional RNN because of the factor that weights and bias are iteratively modernized with the help of adaptive algorithms. This type of RNN is called backpropagation RNN.

The RNNs attribute is that the prior activation of each neuron in the secret layer time phase to measure the current time stage activation. In the same way, RNN, the output prediction is done in the current step not just with the input X_t information, but also with the X_1 to X_{t-1} details by allowing α_{t-1} at time step previous. This is considered a unidirectional RNN since it utilizes earlier sequence data knowledge to estimate prediction at some point, but no details later in the prediction a bidirectional RNN sequence like. The values and prejudice constraints are modified recursively using an approximation algorithm for the backward propagation. In this case, the cost function's partial derivatives are determined by extending out across all time periods.

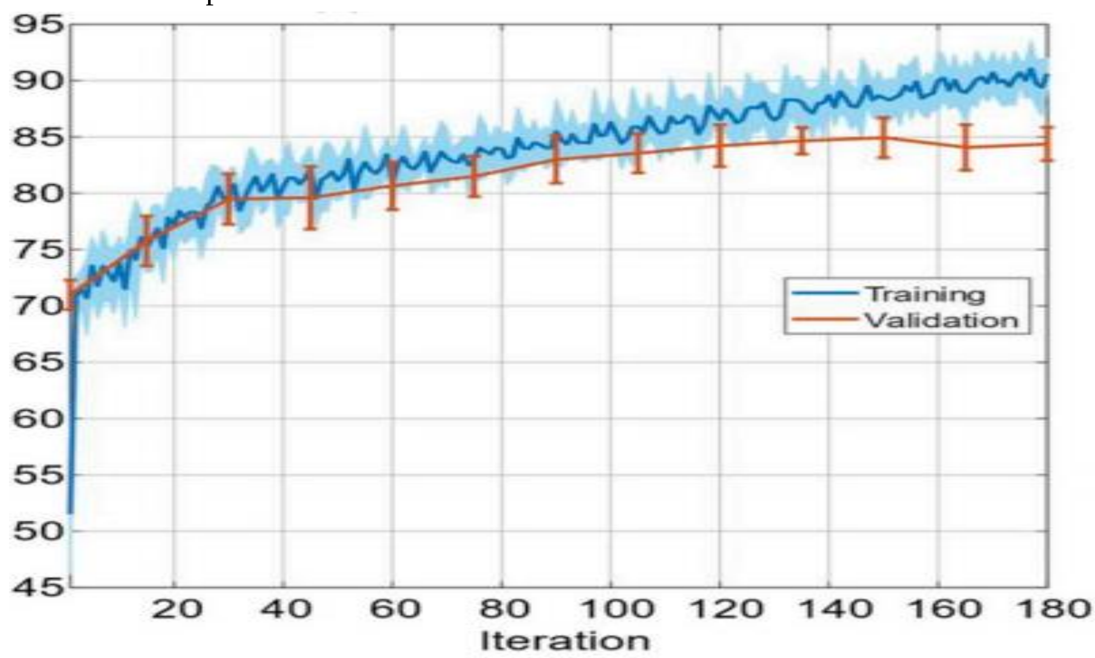


Fig 4.7 RNN implementation graph of iteration between accuracy

This process is therefore referred to as time background reproduction (BPTT). Due to the fading problem of partial derivatives in deep layers during large time stages, the main difficulty of training RNN is that the network parameters (weight and preference terms) cannot change during the successive iterations and thus prevents the network. Research. For the resolution of this issue the RNN Module is supplemented by a gated cell known as long-term storage (LSTM). That's the moment for EEG to use RNNs for EEG detection and an extremely essential nature. In this study we used a series of two RNNs. The former network took into account the functions selected by mRMR and was graded in 4 groups (W, N1-

REM, N2 and N3) with the latter network utilizing the better categorized N1-REM period feedback by the former RNN, which were split into 2 classifications (N1 and REM).

CHAPTER5

RESULT

5.1 DISCUSSION

Sleep classification on the raw single-channel EEG has been implemented successfully. We have also briefly discussed various methods and techniques used to apply a sleep classification, while different methods lead to different accuracy for each class, we understand that in-depth learning allows the new aspect to the classification of sleep. Furthermore, the iterative character of different hidden layers indicates that the fine line between sleep stages will definitely deplete by more refined datasets and the repeat of various hidden layers. The findings revealed that the method could be used on different EEG channels (F4-EOG (left), Fpz-Cz, and Pz-Oz) without modifying the software design and the training algorithms.

In comparison with state-of-the-art hand-engineered procedures for both the Sleep-EDF and MASS datasets, the total exactness and macro F1 score have been similar, with different features, such as sampling rates, entropy and non-linear attributes (AASM) and R&K standards [5][6]. The results show that the spatial data obtained from the extraction of features leads us to better performance. Our model is based on RNN and CNN which enable us to classify in N2 and N3 sleep stages of NREM because it distinguishes between sleep spindles of N2 sand N3 sleep stages. RNN classifies between wakefulness and N1 sleep stage of NREM because the transition from wakefulness to N1 sleep stages is so smooth that to differentiate them we require a back-propagating neural network. Our code uses RNNs which evaluated temporal information from dataset, the EEG epoch sequence. In particular, we examined how they managed their neural connections with RNN and CNN layers. We found a number of forward CNN neural connection which were interpretable. Many neurons, for example, kept track of the beginning of wakefulness or sleep Favorable stats qualities (i.e. active) when a topic was present at either stage W or N1. These neural connection helps us to differentiate between different sleep stages, like, N2, N3 and REM sleep stages.

While our results are encouraging, we still have a number of limitations in our model. First, our methods needs a sufficient sleep dataset to be trained. This is due to the nature of the profound learning techniques, which require a considerable number of training information to learn useful information.

Sleep classification is a tedious, costly and prolonged process when performing manually. To overcome this, we have considered automatic sleep classification on raw single-channel EEG signals using deep learning, especially neural networks. SLEEP-EDF is the public platform from which we have to consider our dataset. Our work objective was to get a comprehensive analysis of sleep-classification of various sleep stages. To pursue this, we have applied a combination of CNNs and RNNs neural networks. Our model gives better results in term of accuracy as it is implemented in a systematic way with 2 layers of CNN itself, and hidden layers. This work is performed on a single raw channel hence it reduces human motion, noise and various other factors, which makes this process very difficult. There are different types of machine learning algorithms that have been implemented to decode the classification of sleep stages, like supervised learning, unsupervised learning, and of-course reinforcement learning. Various algorithms are compared alongside our work in the table given below which shows the comparative analysis of our work, based on a single & Multichannel raw EEG dataset.

5.2 Performance of Our Model

There are many methods evolved in recent times. Most of the method involves artificial intelligence, to improve accuracy. Some uses machine learning methods and other methods are based on deep learning. We have compare our model against some of the higher accuracy model. Shunyuan et.al[7] have performed sleep classification on multi-channel EEG (MC EEG), which drafted great accuracy particularly in N3 and REM sleep stage. The model given by him has used k-means machine learning technique. Archarya et.al[1][3] have performed sleep classification on Gaussian mixture model (GMM) on MC EEG . It has more than 98 % accuracy in REM sleep stage. Sors et.al[8] has used CNN in single-channel (SC EEG). It is based on deep learning and has 91 % accuracy in wakefulness sleep stage. N.Michielli et.al[1] has performed sleep classification on long short term memory (LSTM) RNN. It performs exceptionally in wakefulness sleep stage with more than 95% accuracy. R.sharma et.al [10] have performed on iterative filtering on SC EEG which has best result for wakefulness sleep stage classification with more than 97% accuracy. Our method which is performed on the combination of CNN and RNN gives 87.49 and 86.92 % in N3 and REM sleep stage respectively.

AUTHORS	METHODS	W (%)	N1 (%)	N2 (%)	N3 (%)	REM (%)
Shunyuan.et.al[7]	k-mean	76.14	11.76	69.94	97.12	94.44
Archarya.et.al [1][3]	GMM	87.13	94.02	85.24	82.83	98.34
Sors et.al[8]	CNN	91.40	34.92	89.24	85.08	83.98
N.Michielli et.al[1]	LSTM RNN	95.29	61.09	89.48	91.66	83.76
R.sharma et.al [10]	Iterative filtering	97.80	30.40	89.00	85.50	82.50
Prposed method	CNN and RNN	90.74	46.02	89.40	87.49	86.92

TABLE V Comparison of different techniques used for classification

The shown result is reasonable because these classified stages are marked by equivalent EEG stimulation and the absence of EOG and EMG signals makes the identification much tougher. Charbonnier et al. [11] states that the inclusion of EOG and EMG will give higher accuracy up to 20%. Moreover, REM is analyzed by rapid eye moment hence to classify REM vs N1 becomes easy. Because at this stage muscle activity is lower compared with stage W and stage N1. The various attributes (parameter) help classify different stages, are summed up as below:

ATTRIBUTES	CLASSIFIED STAGES
The amplitude of beta sub-band Energy of beta sub-band Power of beta sub-band	W STAGE
The amplitude of sigma sub-band Power of sigma sub-band	N2
The amplitude of theta sub-band	N1, N2, REM
Hjorth complexity (delta wave is present) Hjorth mobility	N3
Lower variance	N3

Table VI: Stage Classification Based on Attributes

CONCLUSION AND FUTURE WORK

Deep learning helps solve complex problems such as sleep classification, which differs from one human brain to others. Deep learning makes classification easy as it works on reinforcement learning, which requires continuous forward/backward feedback. Hidden layers and their iteration help for better accuracy. The more hidden layers we include, the better result will be yield but at the same time complexities increase too. Given statistics state that our sleep stage detection system outperforms advanced methods that used EEG raw single-channel signals. It encourages digging more in deep learning so that accuracy increase by many folds. Further, there are many variations of the back-propagation technique and this domain is still new, so the possibilities are immense. We have understood that to classify any non-stationary signal, especially bio-medical requires a lot of training datasets. Typically, a 75-80% dataset should be used for training any algorithm, and remaining only should be used for testing.

The limitation of our work is implementing a deep learning based neural network, which is costly. In cascading RNN the algorithm becomes complex with each passing hidden layers. Human movement (while data-processing) makes classification difficult, especially the REM stage. However deep learning is the way to excel accuracy in EEG signals. RNNs, LSTM is only the tip of the iceberg. Implementing GRU, a combination of deep learning techniques will certainly enhance the research. Because the limited availability of EEG data poses a problem for deep learning strategies, transfer learning could be the remedy for stagnating decoding accuracies in BCI research.

Sleep is an indispensable part of human life. Often people neglect the importance of sleep which directly impacts our daily energy level and performance. With the advancement of deep learning, one must understand that the neuron becomes relatively slow in terms of their immediate response as we grow and the sole reason behind this is nothing but lack of quality sleep. Sleep analyzes enable us identify the most "profound" pacing of our sleep and quality sleep at the same time.

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