TOBB UNIVERSITY OF ECONOMICS AND TECHNOLOGY

INSTITUTE OF NATURAL AND APPLIED SCIENCES

ANALYSIS OF RELATION OF ATTENTION CONTROL AND MENTAL FATIGUE WITH APNEA HYPOPNEA INDEX IN OBSTRUCTIVE SLEEP APNEA PATIENTS

MASTER OF SCIENCE THESIS

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AUGUST 2019

Graduate School of Engineering and Science Approval

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I confirm that this thesis meets the requirements of a Master of Science degree thesis.

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Master of Science student of TOBB University of Economics and Technology **Farhad Nassehi** with student number 161711035 paid close attention to the information in this thesis to be presented in an ethical manner based on academic policies and regulations. This thesis with "**ANALYSIS OF RELATION OF ATTENTION CONTROL AND MENTAL FATIGUE WITH APNEA-HYPOPNEA INDEX IN OBSTRUCTIVE SLEEP APNEA PATIENTS**" title was approved on 8 August 2019 by following jury members.

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THESIS NOTIFICATION

I declare that all the information in the thesis has been obtained and presented within the framework of ethical behavior and academic rules, references are given exactly and that this thesis has been prepared in accordance with TOBB ETU Institute writing rules.

Farhad NASSEHI

ÖZET

Yüksek Lisans Tezi

OBSTRÜKTİF UYKU APNELİ HASTALARDA DİKKAT KONTROLÜ VE

ZİHİNSEL YORGUNLUK İLE

APNE-HİPOPNE İNDEKSİ ARASINDAKİ İLİŞKİNİN ANALİZİ

Farhad Nassehi

TOBB Ekonomi ve Teknoloji Üniversitesi
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Danışman: Prof. Dr. Osman Eroğul

Tarih: Ağustos 2019

Obstrüktif uyku apnesi (OUA) en yaygın uykuda solunum bozukluklarından birisidir. Gün içi uykululuk hali ve zihinsel yorgunluk OUA hastalarının kliniğe başvuru şikayetleri arasında yer almaktadır. OUA hastalarının bilişsel becerilerinin gerilediği bilinmektedir. OUA hastalığının teşhisi ve şiddeti gece boyunca süren zahmetli polysomnografi (PSG) oturumuyla yapılmaktadır. Bu tezin amacı, dinlenim durumu ve dikkat kontrolü görevi sırasında elde edilen Elektroansefalografi (EEG) sinyalleri kullanılarak, hastaları Apne – Hipopne İndeksi (AHI) ve Epworth değerlerine göre sınıflandırmaktır. Bu doğrultuda 25 katılımcı PSG kaydından sonra, toplam 13 dakika süren dinlenim durumu ve dikkat kontrolü oturumlarına katılmış ve kendilerinden EEG kayıtları alınmıştır. EEG sinyalleri arasından önemli öznitelikleri seçmek amacıyla istatistiksel olarak analiz edilmiştir. Anlamlı farklılıklar gösteren öznitelikler Yapay Sinir Ağları (YSA) için girdi olarak kullanılmıştır. YSA algoritmalarıyla elde edilen sonuçlar, oturumlar arasında farklılık gösteren EEG özniteliklerinin, hastalığın şiddetini ve semptomlarını ortalama %79.98 oranında sınıflandırılabileceğini göstermiştir. YSA ile hastalığın şiddetinin tanısında hekimlere yardımcı olabilecek bir karar destek sistemi geliştirilmiştir.

Anahtar Kelimeler: Obstrüktif uyku apnesi, Dikkat kontrolü, Elektroansefalografi sinyalleri, Yapay sinir ağları, Karar destek sistemi.

ABSTRACT

Master of Science

ANALYSIS OF RELATION OF ATTENTION CONTROL AND MENTAL

FATIGUE WITH

APNEA-HYPOPNEA INDEX IN OBSTRUCTIVE SLEEP APNEA PATIENTS

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Date: August 2019

Obstructive sleep apnea (OSA) is one of the most widespread breathing-based sleep disorders. Daytime sleepiness and mental fatigue are among the common symptoms that are reported for OSA patients. Previous studies reported cognitive decline in patients with OSA. The diagnosis of OSA is done with laborious overnight polysomnography (PSG) recording. The aim of this thesis is to classify OSA patients according to their Apnea – Hypopnea Index (AHI) and Epworth scores using electroencephalography (EEG) signals that recorded during resting-state and selective-attention-test sessions. For this aim, 25 patients participated to resting-state and selective-attention-test sessions, which lasted 13 minutes in total, following their PSG recordings. Statistical analyses were conducted to detect important features from the EEG signals. Statistically significant features were used as input to Artificial Neural Networks (ANNs). The results show that the EEG features that differed between sessions could classify the disease severity and symptoms with a 79.98% success rate on average. A decision support system that may help doctors to diagnose the disease severity was developed with ANNs.

Keywords: Obstructive sleep apnea, Attention control, Electroencephalography signals, Artificial neural networks, Decision support systems.

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I would like to thank my supervisor, Prof. Dr. Osman EROĞUL for his guidance. I also would like to thank my co-supervisor Assoc. Dr. Nart Bedin ATALAY for his unfailing support and insightful comment. I would like to thank Assoc. Dr. Hikmet FIRAT, head of Sleep laboratory of Diskapı Yildirim Beyazit Educational and Research Hospital, for his contributions.

Finally, I would like to huge thank my family and my friends for their support and encouragement.

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LIST OF ABBREVIATIONS

PSG	: Polysomnography
EEG	: Electroencephalography
EOG	: Electrooculography
ECG	: Electrocardiography
EMG	: Electromyography
REM	: Rapid eye movements
NREM	: Non- Rapid eye movements
EFS	: Executive functions
ESS	: Epworth sleepiness score
CSA	: Central sleep apnea
OSA	: Obstructive sleep apnea
RTP	: Relative theta power
RDP	: Relative delta power
RAP	: Relative alpha power
RBP	: Relative beta power
SNR	: Signal noise ratio
ANN	: Artificial neural network

LIST OF SYMBOLS

Symbols	Definition
α	Alpha band
β	Beta band
θ	Theta band
δ	Delta band
γ	Gamma band
P	Power

1. INTRODUCTION

Sleep is one of the most popular subjects for scientists from various disciplines. Medical doctors, biomedical engineers and psychologists are all interested in sleep because an understanding of the nature and function of sleep requires an interdisciplinary study. Sleep studies became possible with the invention of the electroencephalography (EEG) technology. In a pioneering study, Berger recorded neuronal activity of brain in sleep [1].

The most basic definition of the sleep is related with organism's response to environmental stimuli. Sleep can be defined as a reversible, less-than-awake response to the environment, which recurs on a daily (circadian) cycle [2]. Almost all animals regulate their bio-behavior functions via circadian rhythms. Most of the physiological and biochemical events in the human body, including hormone levels, body temperature, blood flow, and the sleep, are controlled by circadian rhythms (see figure 1.2) [3]. In humans, circadian rhythms start to occur in the second or third month after the birth [3]. They are sensitive to the light, and they are regulated by the suprachiasmatic nucleus (SCN) in the human central nervous system [3]. Figure 1.1 shows the location of the SCN in the nervous system. At beginning of sleep, neurons in the ventrolateral preoptic area (VLPO, seer Figure 1.1) become active and they inhibit ascending arousal system, composed of brain stem, posterior hypothalamus and basal forebrain.

1.1 Architecture of Sleep

Human sleep is a cyclic activity. Ultradian rhythms (which are defined as period shorter than a day but longer than an hour [4]) regulates the stages of sleep cyclicity [4]. Human sleep has two major stages, rapid eye movement (REM) and non-rapid eye movement (NREM). NREM stage is also divided to three substages.

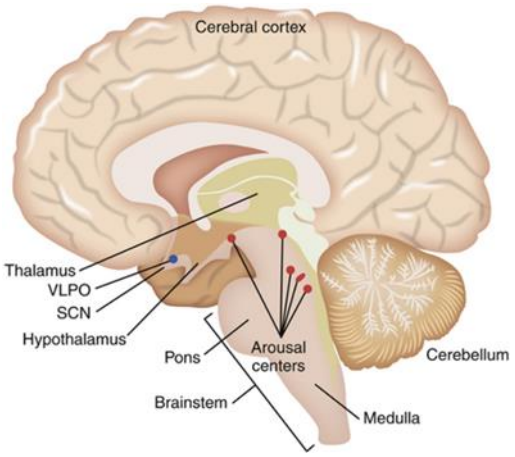

Figure 1.1: Location of SCN and VLPO in human brain [4].

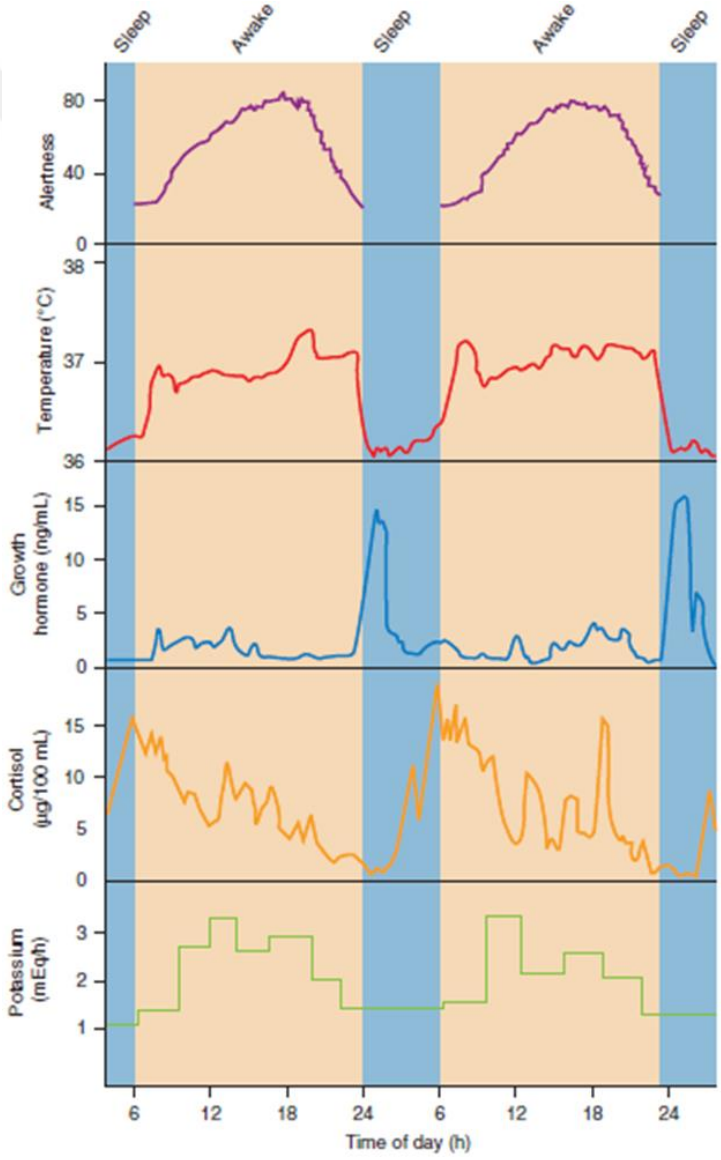

Figure 1.2: Circadian rhythms [5]

Transition from the awake state to NREM and REM states is regulated by ultradian rhythms that have a period between 90-120 minutes [4]. The diagram that shows the transition and duration of sleep stages is known as hypnogram (see Figure 1.3 for an example).

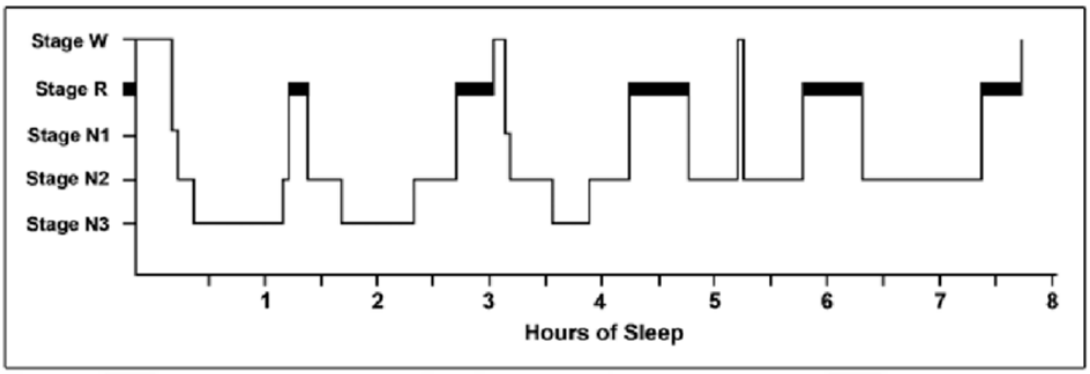

Figure 1.3: Example of Hypnogram [6]

Polysomnography is the gold standard of the measurement of sleep [7]. Polysomnography is derived by three words include "polus", which means many, "somnus", which means sleep, and "graphein", which means write. A polysomnography device records electroencephalography (EEG), electrooculography (EOG) and electromyography (EMG) activities at the same time. According to the Alan Rechtschaffen and Anthony Kales Manual Sleep Stage Scoring Technique [8], these three signals are the essential components of polysomnography that are used to classify the sleep stages. A polysomnographic measurement can be extended with recording additional bio-signals, like electrocardiography (ECG) and body position, oxygen level in the blood, and snoring. These additional signals are important for the diagnosis of sleep disorders. Defining sleep stages from PSG recordings is done manually by analyzing EEG, EMG and EOG signal's amplitudes. As a first step, PSG signals are divided to smaller parts called epochs. Epoch length is usually 30 seconds. Then, each epoch is assigned only one of the sleep stages [8].

A normal sleep starts with N1 stage, then continues with N2 and N3 stages (see Figure 1.3). Then comes the REM stage. On average, 75% of sleep spends in NREM, and 25% in REM stage. As the sleep continues, duration of REM stage increases while

duration of NREM stages decrease [4]. Sleep onset starts with transition from the awake state to the N1 stage.

The summary of differences between awake, REM and NREM stages with respect to EEG, EOG and EMG signals is presented in Table 1.1. EEG signals of the wake stage have low amplitude and high frequency rate. An epoch is classified as wake when least 50% of the epoch shows alpha (8-12 Hz) activity. EMG signals have high amplitude, because of muscle contractions. EOG signals also have high amplitude because eyes may move (see Figure 1.6 for an example of the PSG recording of the awake stage).

Table 1.1: Characteristic of physiological in sleep stages.

Behavior	**Awake**	**NREM**	**REM**
EEG	Low amplitude, fast frequency	High amplitude, slow frequency	Low amplitude, fast frequency
Movement (EMG)	Continuous, voluntary	Occasional, involuntary	Muscle paralysis
Rapid eye movement	Often	Rare	Often

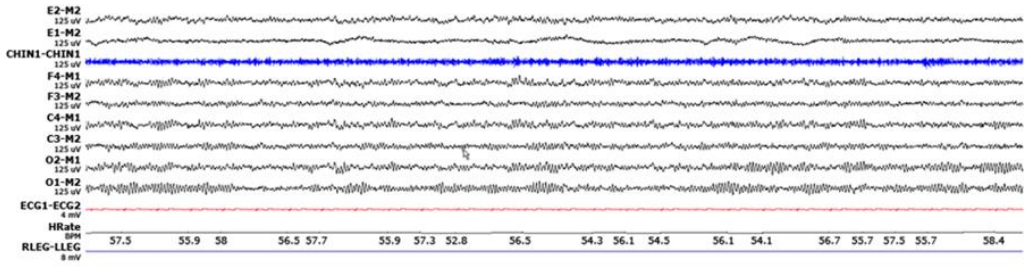

Figure 1.4 : PSG signals of wake stage [9].

First substage of NREM sleep is called N1. This stage is also known as light sleep. N1 is the transition stage from wake to sleep. In this stage EEG signals have low amplitude and mixed frequencies. Critically more than 50% of epochs should show theta (4-7 Hz) activity. This is the shortest stage of sleep (see Figure 1.6 for an example of the PSG recording of the N1).

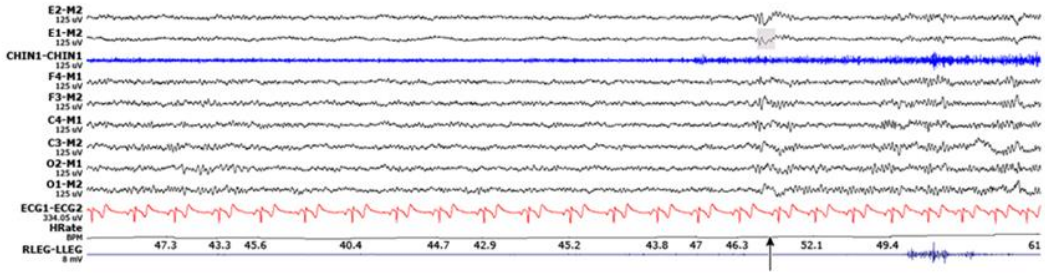

Figure 1.5 : PSG signals of N1 [9].

In the second stage of NREM sleep (N2), theta (4-7 Hz) activity in EEG signals is dominant, like the N1 stage, but spindles and k-complexes are markers of the N2. Spindles are oscillations between 10-16 Hz with duration between 0.5-2s [10]. The functional role of sleep spindles is not well-known, but some studies show role in memory, cortical development, and regulation of arousal [11-14]. K-complexes are described as short surface-positive wave that followed by a larger surface-negative wave, and then a positive wave. K-complexes are usually followed by spindles [15-16] (see Figure 1.7 for an example of the PSG recording of the N2 and Figure 1.8 for spindles and K-complexes).

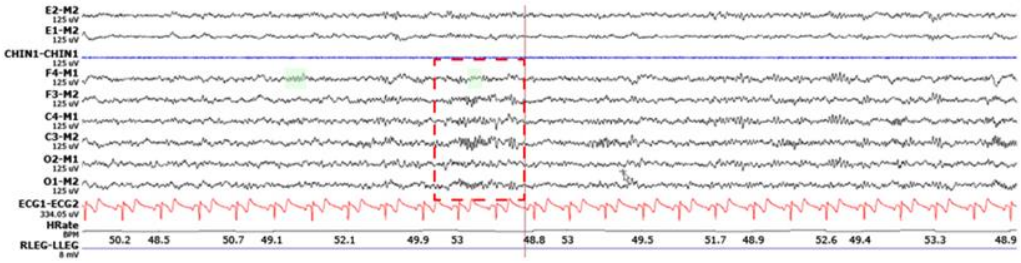

Figure 1.6 : PSG signals from N2[9]

Figure 1.7 : Sleep spindles and K-complex

The third stage of NREM sleep (N3) is also known as deep sleep. EEG signals of this stage characterized by low frequency bandwidths called delta band (0.5-4 Hz). The duration of deep sleep is longer at beginning of the sleep while it shortens as the sleep progresses [8] (see Figure 1.9 for an example of the PSG recording of the N3).

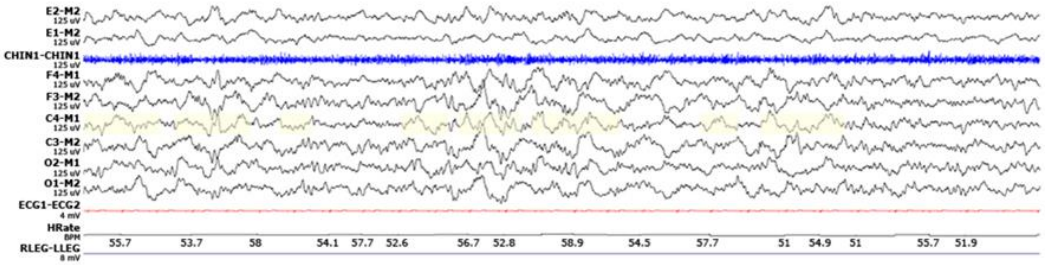

Figure 1.8 : PSG signals of NREM3 [9].

In the REM stage, EEG signals are like the wake stage. They have low amplitudes and high frequency. As its name implies, EOG signals are the marker of this stage because of continuous rapid eye movements. In this stage, brain consumes more energy than when it solves a hard math problem in the wake state [4]. Sleepers report dreams more often in the REM stage compared to NREM stages. Although REM stage is only a small part of the sleep, it is one of the most interesting stage of the sleep because of its association with dreams [8]. During REM, heart rate, temperature and respiration rate increases and but get irregular (Figure1.11). According to William Dement, the leading authority in sleep research and the founder of the Sleep Research Center at Stanford University, "NREM sleep as an idling brain in a movable body, in contrast REM sleep an active brain in a paralyzed body." [4]. (see Figure 1.10 for an example of the PSG recording of the REM sleep).

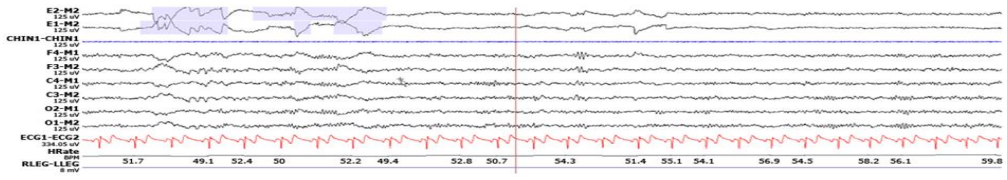

Figure 1.9 : PSG signal of REM [9].

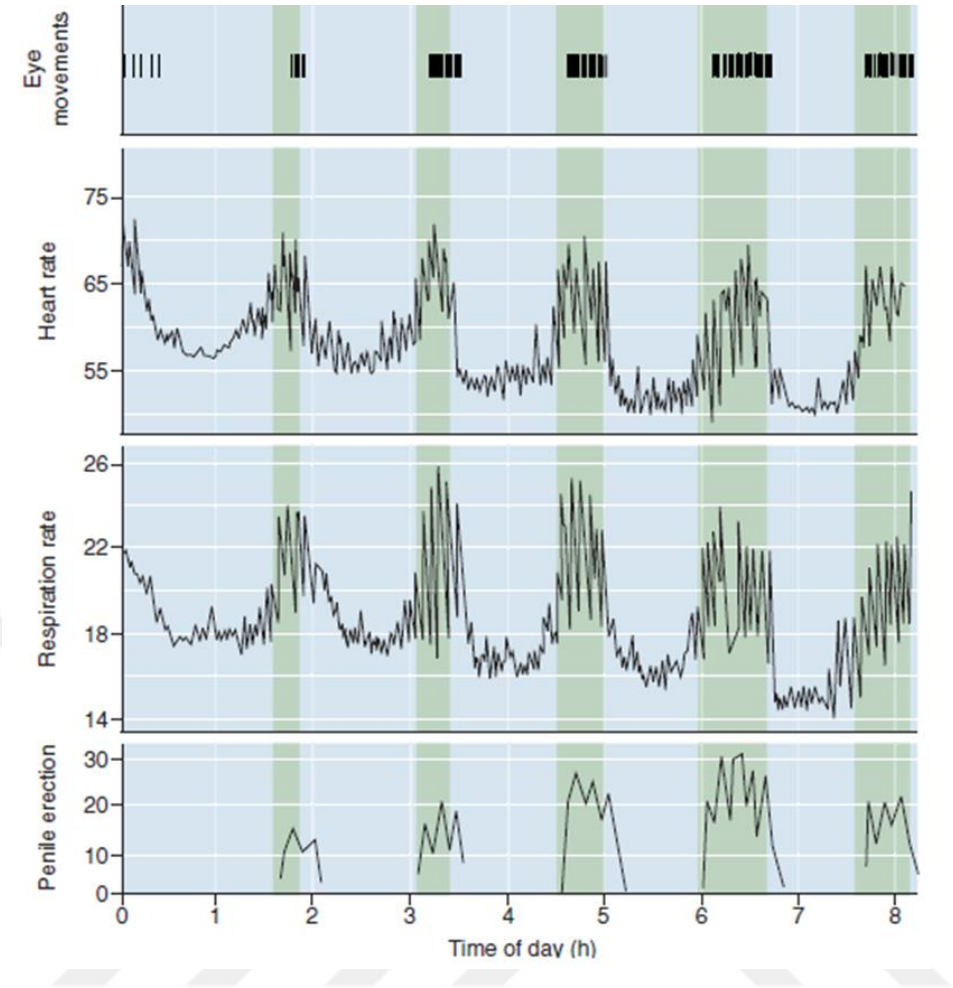

Figure 1.10 : Physiological changes in REM stage [4]

1.2 Obstructive Sleep Apnea

Sleep apnea is a widespread breathing-based sleep disorder. Apnea can define as the pause of breathing for more than 10 seconds as a result of the collapse of the upper airway functions during sleep [11]. Hypopnea occurs when maximum amplitude of the upper airway signal (airflow) during sleep is down at least for 10 s with 50% decrease in oxygen saturation. Arousal, defined as sudden transition between sleep and awake stage, is common in sleep apnea. Therefore, normal sleep architecture is disturbed in sleep apnea patients. Sleep apnea is divided to three types; which are central sleep apnea (CSA), obstructive sleep apnea (OSA) and mixed type apnea. Distinguishing these types is clinically essential because they have different cause, and each require different types of treatments. Among all signals that are recorded by PSG, signals from the chest and abdominal regions play important role to distinguish these different types

of apnea [14] (see Figure 1.11 and Figure 1.13-14 for PSG recording of sleep apnea types). CSA is defined as absent of drive to breath in sleep. OSA is defined as the repetitive collapse of the upper airway during sleep. The mixed apnea shows the characteristics of both CSA and OSA [15].

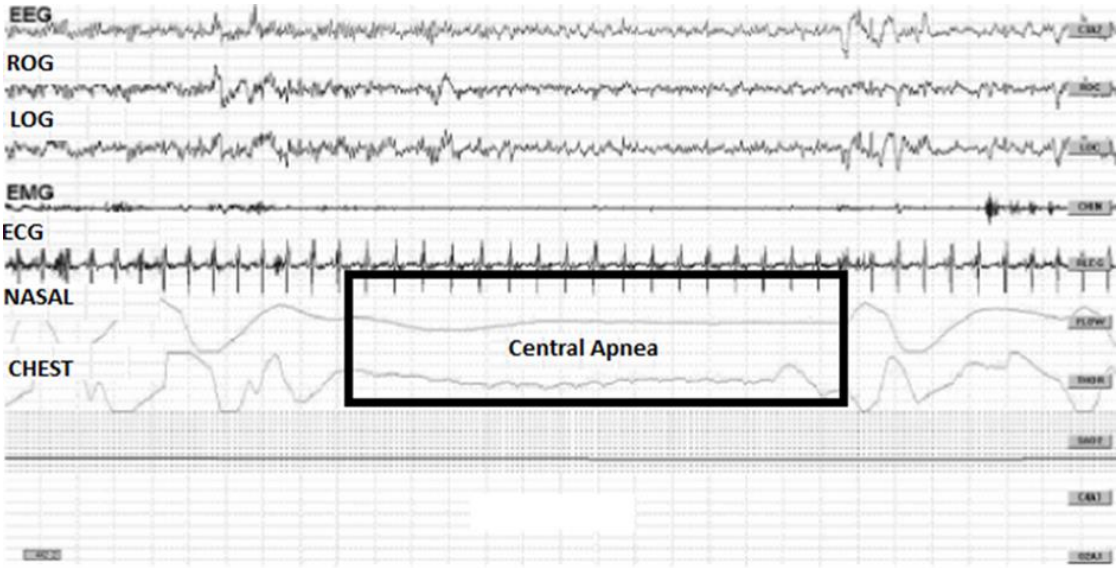

Figure 1.11: PSG signal of CSA [15]

OSA is the most common type of the apnea. The prevalence of OSA rises to 42% for individuals over the age of 65 [16]. The OSA and its severity are diagnosed with symptoms and apnea hypopnea index (AHI). The Epworth Sleepiness Scale (ESS) is the one of the standard measurements of apnea symptoms. This questionnaire consists of eight question (see Figure 1.12). Each question is assigned a point between 0 and 3 based on the severity of the symptom. The maximum score of the scale is 24 [17]. ESS measures daytime sleepiness. According to the total test score, patients are classified into five groups [18] (see Table 1.2).

AHI is the total number of hypopnea and apnea in per hour. AHI is determined by an overnight polysomnography (PSG) recording [19]. Severity of OSA is diagnosed by AHI, sleep efficiency (ratio of total sleep time to total time spent in bed), REM latency (duration between N1 and REM stages) [20]. According to AHI, patients are classified into three groups [18] (see Table 1.2).

Table 1.2 : Definition of Epworth sleepiness scale scores

Epworth sleepiness scale score range	Definition
0-5	Lower normal daytime sleepiness
6-10	Higher Normal Daytime Sleepiness
11-12	Mild Excessive Daytime Sleepiness
13-15	Moderate Excessive Daytime Sleepiness
16-24	Severe Excessive Daytime Sleepiness

Situation	Chance of dozing			
Sitting and reading	0	1	2	3
Watching TV	0	1	2	3
Sitting inactive in a public place (e.g. movie theatre or a meeting)	0	1	2	3
As a passenger in a car for an hour without a break	0	1	2	3
Lying down to rest in the afternoon when circumstances permit	0	1	2	3
Sitting and talking to someone	0	1	2	3
Sitting quietly after lunch	0	1	2	3
Sitting quietly after lunch	0	1	2	3

Figure 1.12 : Epworth Sleepiness Scale in English [18].

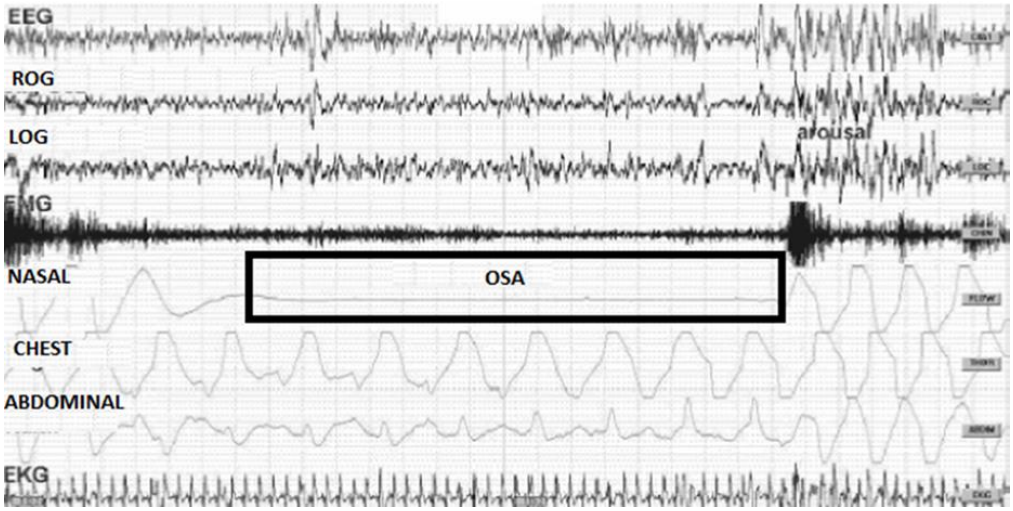

Figure 1.13 : PSG signal of OSA [15]

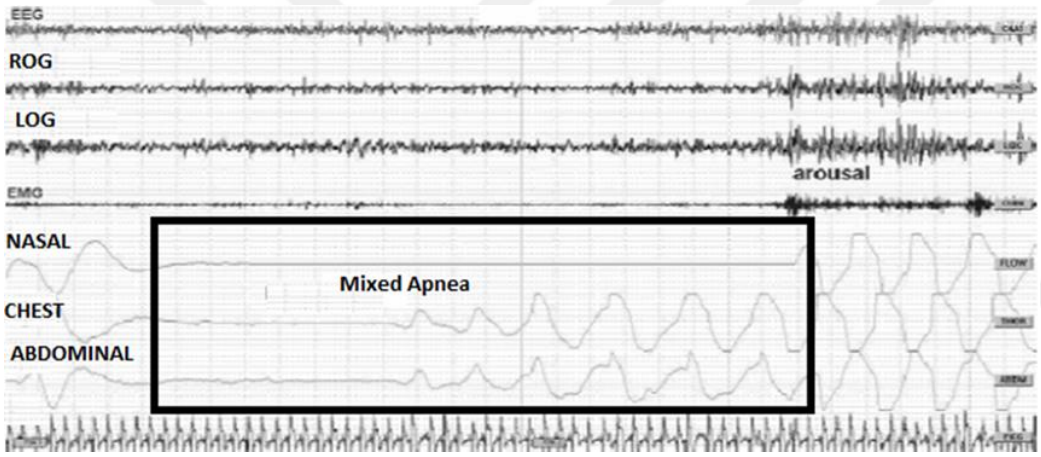

Figure 1.14 : PSG signals of Mixed-Type apnea [15]

Table 1.3 : Groups of OSA patients in according to their AHI [21]

OSA level	AHI ranges
Mild	5-15
Moderate	15-30
Severe	>30

1.2.1 Treatment for OSA

A treatment is not suggested for patients with mild OSA. For moderate to serve OSA patients the most common type treatment is the continuous positive airway pressure (CPAP). CPAP opens the upper airway by applying constant air pressure [22]. Sometimes medical operations to reduce the obstruction of the pharynx or to reduce the tongue volume are suggested for treatment [23]. Diet therapy for obesity has shown positive outcomes in the treatment of OSA [24].

1.3 OSA and Executive Cognitive Functions

Cognition is a term that refers to mental processes. Executive functions (EFS) are collection of neuropsychological processes that help to person concentrate and pay attention to an ongoing behavior or stimuli [25]. EFS are related with frontal lobe of the human brain. Attention is defined as the ability to select and concentrate on relevant stimuli [26-28].

Control of attention process is one the most important parts of EFS [29]. Attention control tested by selective attention tasks like Simon and Flanker. In selective attention tasks, participants are required to focus on one dimension and ignore another dimension. In the Flanker task, five consecutive letters are presented on the screen (e.g. HHSHH) and participants are required to respond to the central letter (S) while ignoring the flanking (Hs) letters. When the central and flanking letters are the same (SSSSS), the stimulus is called congruent, and when they are different (SSHSS), it is called incongruent stimulus. In the Simon task, a letter is presented on the left or right of the screen, and participants are required to respond with a left or right button press. In a congruent stimulus, the stimulus and response are on the same side, and in incongruent stimulus, they are on different sides. Reaction time and response accuracy in computer-based tasks are used to observe selective attention. A common observation is that, when the target and distractor dimension are congruent responses are faster and more accrue compare to incongruent. This difference called congruency effect. The congruency effect is observed because people should focus their attention to the relevant feature while ignoring the irrelevant dimension. The magnitude of congruency effect shows how well attention is controlled [29].

OSA is associated with poorer attention, executive functioning and psychomotor speed in nondemented person [30 31]. In 25% of patients with OSA have shown neurophysiological impairment [32]. Frontal lobe dysfunction has been reported in OSA patients [33]. Tulek and colleagues showed that executive dysfunctions in OSA depend on attention deficits [29]. Because, attention is the primary process essential to more sophisticate cognitive abilities, it is possible that cognitive impairments in OSA, mirroring a primary deficit in attention [34].

There are several studies which showed positive outcomes of OSA treatments for cognitive dysfunctions. For instance, a study showed that after 2 months CPAP therapy, patient's memory performance significantly improved [35].

Considering the positive effects of therapy on for cognitive impairment, it is essential to diagnose the severity of OSA as quickly as possible. In this thesis, a decision support system was developed to diagnose severity of OSA with a simple EEG-based test. EEG is commonly used tool in the measurement of executive functions, specifically attention, because of its accessibility.

1.4 EEG Sub-bands and Cognitive Functions

EEG records electrical activity of the brain. The brain electrical activities are related with cognitive abilities such as memory, attention, perception as well as mental fatigue [36,37]. EEG signals can be divided in to five sub-bands. Each band is associated with some psychological events. Delta waves do not have important reported role in cognitive abilities, but they are marker of transition to drowsiness, mental fatigue and during sleep. Theta waves are related with hypnagogic imagery, mental tasks, arithmetic tasks and low level of alertness [38]. These waves occur in frontal midline. Alpha waves occur in wakefulness, appears at eye closed mode and decrease at eye open mode, also attenuated during attention. These waves usually observe in relaxing mode. Beta activity is observed during reaction time and attention task [38].

Table 1.4 : Frequency ranges of EEG [39]

Name of band	Frequency range (Hz)
δ	0.5-4
θ	4-7
α	8-12
β	12-30
ɤ	>30

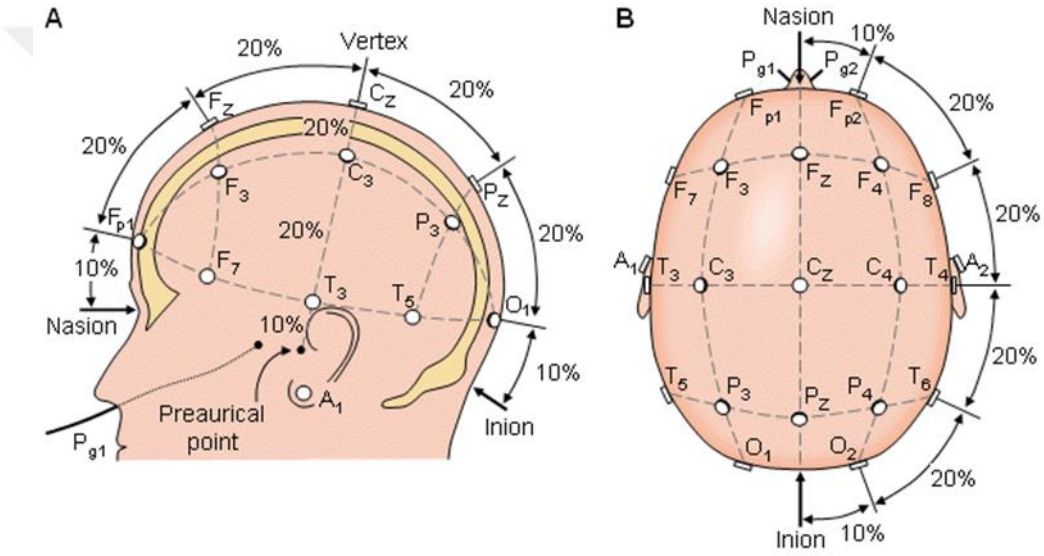

Figure 1.15 : Electrodes of EEG montage on scalp by the 10/20 systems [40]

1.5 Aim of Thesis

Aim of this thesis is to investigate the potential of EEG markers to classify OSA patients according to their AHI or ESS scores without using PSG. Decision support systems for use of medical doctors are introduced to classify patients as mild vs. moderate-severe AHI or normal vs. mild-excessive daytime sleepiness.

In this purpose, participants with suspected with OSA, attended to two different EEG recording sessions after their first overnight PSG recordings. First session was the resting state session to record patient's brain activity without an attention task. The duration of the first session was three minutes. The wakeful brain is never idle, but it

is always neuro-electrically active [41]. It is well-known that in the resting conditions the human brain engages in spontaneous and well-organized activity [42]. The rest session was used to measure the baseline of the electrical activity following the overnight sleep of patients with OSA.

To our knowledge this study is the first that investigated the electrical brain activity of patients with OSA during resting. We specifically investigated whether the electrical activity would change according to the degree of the disease in patients with OSA. It might be the case that electrical signals related with cognitive functions, originated from medial frontal gyrus, superior frontal gyrus and anterior cingulate cortex, would be correlated with the degree of the disease. In this thesis, after the patients woke up, their resting state activity were measured long 3 minutes. Immediately following the resting state, they participated in the task session.

In the second task session, they attended to Simon – Flanker task to observe their EEG during a selective attention task. The duration of this session was 10 minutes. In both Simon and Flanker tasks, participants' responses are usually faster and more accurate when the stimulus is congruent compared to incongruent. In congruent condition, both the relevant and the irrelevant dimension of the stimuli may be used to select the response. In incongruent trials, on the other hand, participants need to inhibit the position information to choose the correct answer. Because of studies are reported difficulties in selective attention ability of OSA patients, this thesis is declared that OSA patients may be classified more faster and easier than PSG recording by using EEG signals that are recorded during resting state and selective attention sessions.

First, patients were classified into two groups, according to their AHI or ESS by certified sleep technician. As the second step, EEG signals of both sessions were analyzed to extract features by the author of this thesis. Using statistical models differences in EEG features were investigated between sessions, electrodes and groups. The statistical analysis is used as a feature selection method. The statistically significant features were considered as the best features for a decision support machine. Artificial Neural Networks (ANN) method is used to design decision support systems, which takes input EEG features to classify patients according to their AHI or ESS.

2. MATERIALS AND METHODS

2.1 Participants

Subjects were among the applicants to the Sleep laboratory of Diskapı Yildirim Beyazit Educational and Research Hospital. Participants were invited after physical inspection by a chest disease specialist. Patients with AHI < 5, who used drug that may affect sleep and cognitive processes and who have a neuropsychiatric disorder were excluded from the study. Twenty-eight patients, in the morning of their first overnight PSG record, were invited to the study. The experimental protocol was approved by the Human Research Ethics Committee of TOBB ETU.

Data from 3 participants were excluded due to technical errors. All the remaining 25 participants were men and right- handed. The demographic information is presented in Table 2.1. In statistical analyses, subjects were divided in two groups based on two criteria. First, they were split according to the AHI, and AHI ≥ 15 was selected as criteria. Second, they were split in two groups based on their ESS score, and ESS score ≥ 11 was selected as criteria There are 15 of patients have AHI equal or more than 15 and 13 of patients have Epworth score more than 11.

Table 2.1: Demographic information of subjects.

Statistics / Parameters	Mean	Standard deviation	Maximum	Minimum
Age	51.24	12.85	76	18
AHI	28.29	25.7974	108.90	7.7
BMI	31.58	5.7	46.90	23.90
Education (years)	11.36	3.1475	16	8
Epworth score	10.56	5.58	21	0

2.2 Data Acquisition

PSG is the gold standard of sleep measures. In this thesis, PSG signals of patients were recorded overnight at the Sleep laboratory of Diskapı Yildirim Beyazit Educational

and Research Hospital by experienced sleep technicians. Participants were instructed to not to use drinks, such as caffeine alcohol, that may affect sleep during the night.

A 44 channels E-series Compumedics PSG system was used. The EEG component recorded brain signals, the ECG recorded heart signal, the EMG recorded legs and chin movements, EOG recorded eyes movements. There was a pulse oximetry electrode for recording the oxygen level of blood (SpO2), microphone for snore, thermistor, strength electrodes recorded signal from chest and abdominal to detect apnea types. The frequency sampling of ECG, EEG, EOG, thermistor signals was 256 Hz, and frequency sampling of other signals was 128 Hz.

EEG electrodes were positioned on "Fp1, Fp2, F3, F4, P3, P4, C3, C4, O1, O2" sites according to the 10-20 system (see Figures 1.17 and 2.2). "F3, F4, C3, C4, O1 and O2" are the standard in PSG recordings. Fp1, Fp2, P3, P4 were added additionally. Fp1 and Fp2 were added because frontal lobe is related with EFS. P3 and P4 were added because parietal lobe is related with attention. Electrodes were either silver or gold. These electrodes were placed on patients' skull over hair by caladium mix. Electrodes were placed carefully by an experienced sleep technician.

2.3 Epworth Sleepiness Scale (ESS)

ESS is a questionnaire to measure the tendency to sleep in daytime. Participants were divided into two groups based with normal daytime sleepiness (ESS <11) and excessive daytime sleepiness (ESS ≥ 11). There were 13 participants with normal and 12 with excessive daytime sleepiness. In this thesis Turkish version of the questionnaire was used (see Figure 2.5).

2.4 Experimental Procedure

The experiment consisted of the rest and task sessions. In the rest session, participants sit quietly with their eyes closed for 3 minutes to observe the base line of their electrical brain activity. In the task session, participants completed a selective attention task.

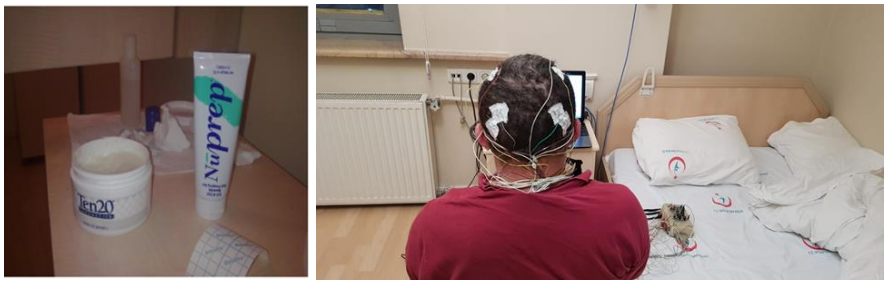

Figure 2.1 : Left, caladium mix to reduce impedance of EEG electrodes, right, position of electrodes after a placement.

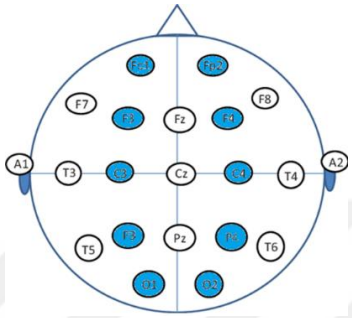

Figure 2.2 : Position of selected electrodes.

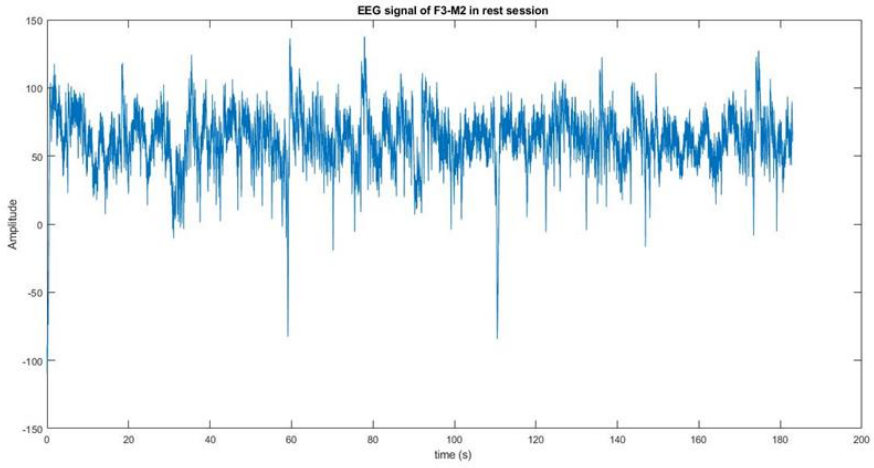

Figure 2.3 : EEG signal of F3 electrode during rest session in MATLAB®

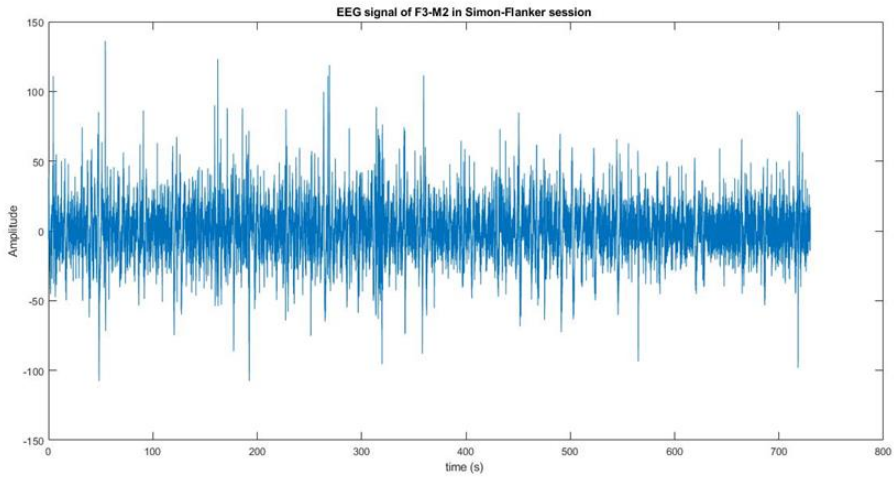

Figure 2.4 : EEG signal of F3 electrode during task session in MATLAB®

Durum	Uyuklama İhtimali			
1. Otururken ve okurken	0	1	2	3
2. TV seyrederken	0	1	2	3
3. Tiyatro veya toplantı gibi bir ortamda hareketsiz otururken	0	1	2	3
4. Ara vermeksizin 1 saatlik araba yolculuğu yaparken	0	1	2	3
5. Öğleden sonra dinlenmek üzere uzanınca	0	1	2	3
6. Otururak biriyle konuşurken	0	1	2	3
7. Öğle yemeğinden sonra sessizce otururken	0	1	2	3
8. Arabada ilerlemeyen trafikte durulduğunda	0	1	2	3
Toplam Puan				

Figure 2.5 : Turkish version of the Epworth sleepiness scale questionnaire [Url-1].

2.4.1 The rest session

During the rest session participants did not do any task. They waited for 3 minutes with their eyes closed. In some studies, participants focused on a fixation "+" in center of the screen during the resting state [43]. However, in the eyes-open conditions, photon may disturb the brain activity in the alpha band. Since we would like to investigate the alpha band activity, in addition to, we instructed patients to close their eyes.

2.4.2 The task session

In the task session, participants completed the Simon and the Flanker tasks. Both tasks are used to observe selective attention processes [61]. In the Simon task, “H” or “S” letters appear on the screen. Subjects are instructed to respond identify the letters with pressing “1” and “x” keys. These keys were assigned because in the Simon task the stimuli must be in same alignment with the keys. The letters were presented either on the left or the right side of the screen. The Simon task consisted of 108 trials plus 12 practice trials to familiarize the participants to the task. After the Simon task, participants rest for a minute, then they completed the Flanker task.

In the Flanker task, stimuli were a sequence of five letters in a row (“HHHHH”, “HHSHH”, “SSSSS”, “SSHSS”) presented at the center of the screen. Participants were instructed to respond to the letter in the middle (the target letter) while ignoring the letters on the side of it (the flankers). They pressed the same keys to identify the letters as in the Simon task. Participants responses are faster and more accurate when the letter in the middle is same as the letter on the sides (when they are congruent) compared to when they are different (when they are incongruent) [61]. The difference between congruent and incongruent conditions is called the Flanker effect. In the congruent condition, participants may use the flanking letters as well as the target letter to select the respond. In the incongruent condition, participants must inhibit the flanker letters to choose the correct answer, which requires higher levels of control. Flanker task consists from 108 trials in addition to 12 of trails of practice). Total duration of both tasks is about 13 minutes.

2.5 Data Analysis

All procedures that are explained in this section, were applied on each electrode.

2.5.1 Preprocessing

2.5.1.1 Band passing

The PSG device, used in this thesis, band passed signals between 0.5-35 Hz. Also, the device applies a notch filter in 50 Hz. A bandpass filter was used to select 0.5-30 Hz signal band because we interested in delta, theta, alpha and beta bands.

2.5.1.2 Smoothing

The EEG signals that were recorded during both the rest and the task sessions were applied a finite impulse response (FIR) filter, called Savitzky Golay (SG) filters. They are used widely in the biomedical signal processing [44]. SG filters perform both denoising and smoothing of the signal. The SG filter was used because it has advantage over the other types of filter for regaining the signal during the denoising processing. The SG filter divide signal to small epochs with specific length and fit a polynomial with specific order. In this thesis, the length of each is epoch is 61 samples and the order of polynomial is 5. These values were selected experimentally to get the best result.

2.5.1.3 Eye movement artifact removing

In many studies, eye movements are removed because they suppress or disrupt brain signals. To remove EEG signals from these artifacts, least square template matching method is used [Url-2]. This method is based on regression.

In this model, we tried to fit a model that was estimated from two EOG signals, on EEG signal.

$$\beta = (X^T X)^{-1} X^T y \tag{2.1}$$

$$r = y - X\beta \tag{2.2}$$

Where X is n x 2 matrix, and n is length of EOG signal.

$$X = \begin{pmatrix} 1 & a_1 \\ 1 & a_2 \\ . & . \\ . & . \\ 1 & a_m \end{pmatrix} \tag{2.3}$$

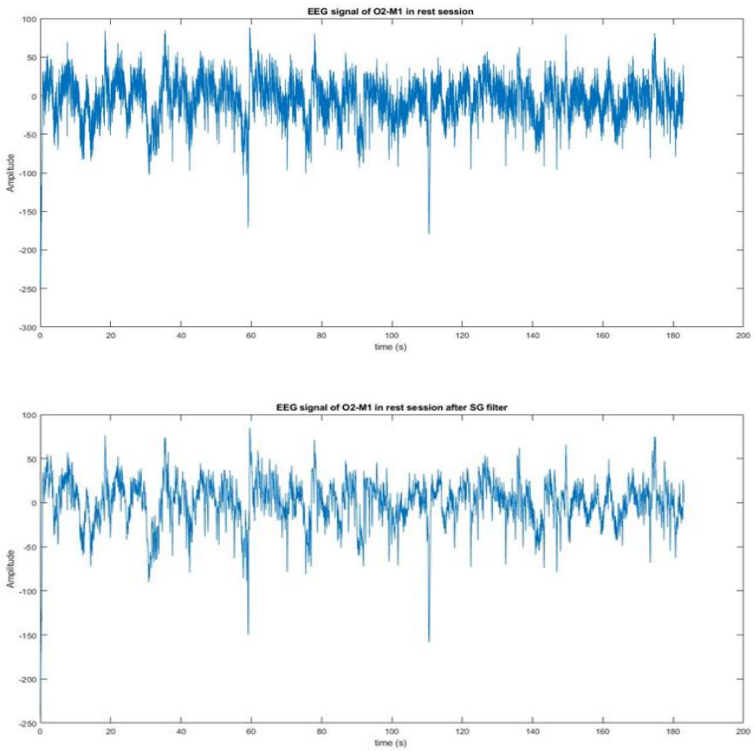

Figure 2.6 : Up: raw signal from O2 in rest session of participant. Down: the same signal after SG filter.

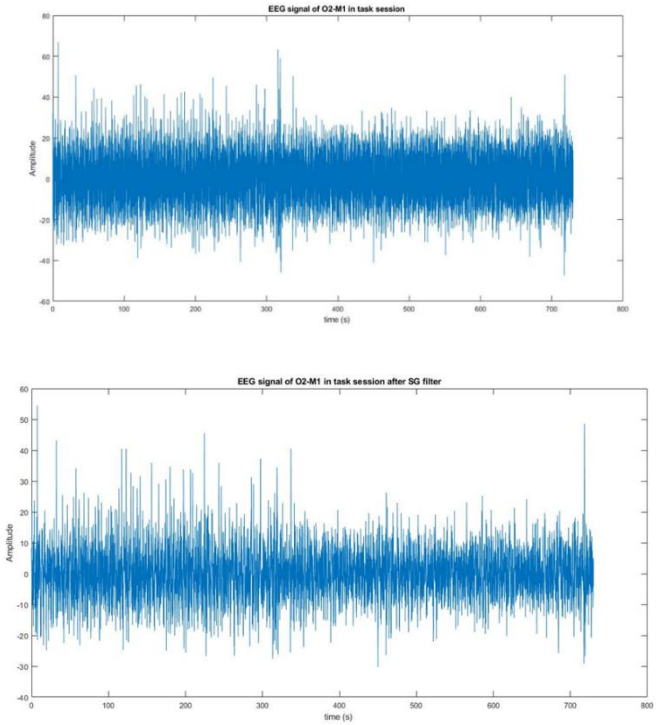

Figure 2.7 : Up: raw signal from O2 in task session of participant. Down: the same signal after SG filter.

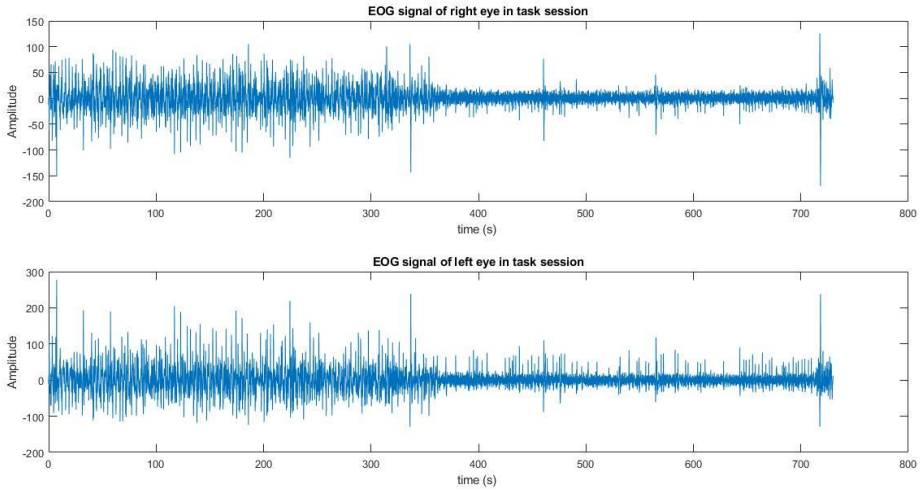

Figure 2.8 : EOG Signals of each band in task session.

2.5.2 Feature extraction

In this thesis statistical features that were extracted from signal include, mean, standard deviation, skewness, kurtosis, Hjorth parameters and zero crossing. due to observe behavior of signal during both tasks.

Mean: One of the common features that is used in signal processing is the mean of signal. It defines as summing all point of the signal. Median is defined as middle value of series, and mode is defined most repeated value of series [45]. In the normal distribution, the mean, median and mode are identical. The equation of mean is presented in eq. 2.4, N is length of signal and X(t) demonstrates signal.

$$\mu = \frac{1}{N} \sum_{i=1}^{N} X(t_i) \qquad 2.4$$

Standard deviation: This feature shows that how data is spread out relative to its mean.

$$\sigma = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (x(t_i) - \mu)^2} \qquad 2.5$$

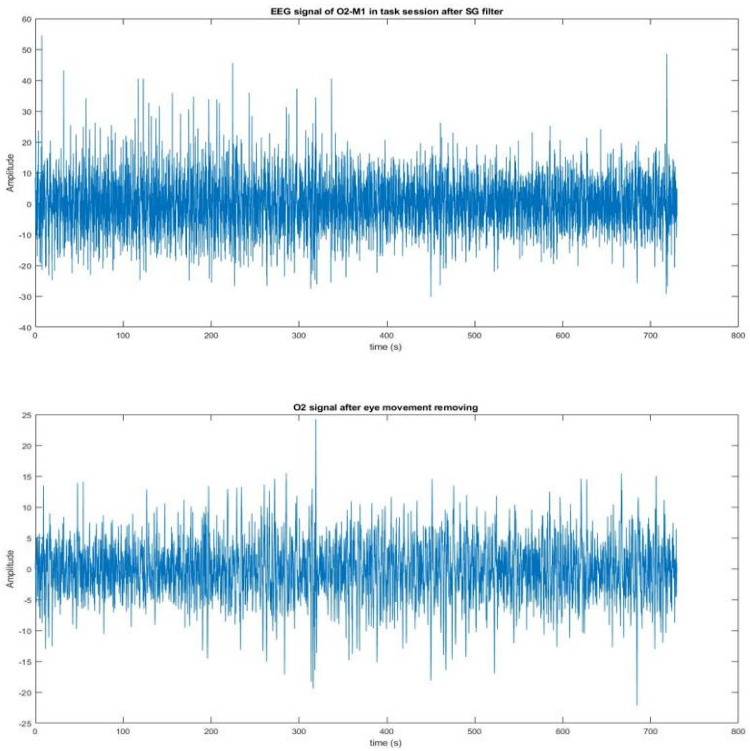

Figure 2.9 : EEG signal of O2 (occipital) electrode after eye movement removing in task session.

Skewness: It measures symmetry of amplitudes of signal over time. The distribution is symmetric if it looks the same from the center point both on the left and the right [46, Url-3]. In the positively skewed distribution, the tail at the right side of the mean is longer than the left. In the negatively skewed distribution, the left tail is longer than the right tail. In a positively skewed distribution, the mean and the median of the distribution is greater than its mode. [46, Url-3].

Formula of skewness is defined as a function mean and standard deviation of the distribution

$$s = \frac{E[x(t_i)-\mu]^3}{\sigma^3} \qquad 2.7$$

Kurtosis: It measures the tailedness in the distribution [65].

$$k = \frac{E[x(t_i)-\mu]^4}{\sigma^4} \qquad 2.8$$

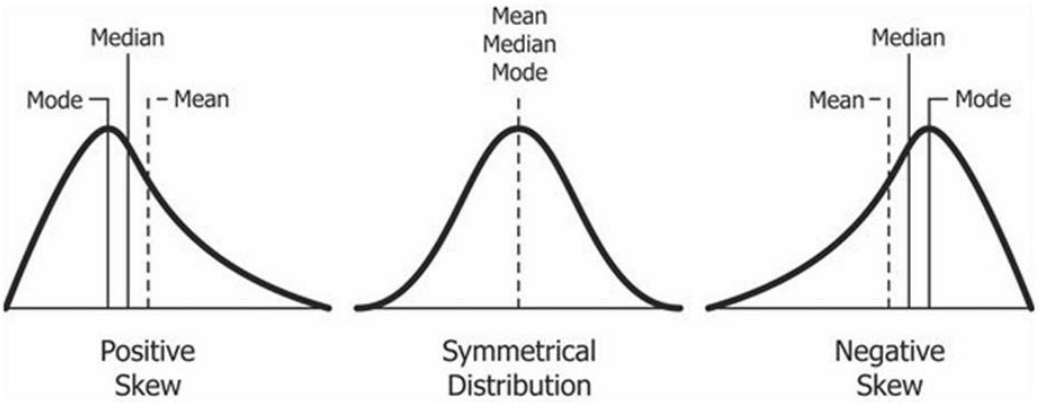

Figure 2.10 : Types of skewness [Url-3].

Signal Noise Ratio (SNR): This feature is calculated as ratio of mean on standard deviation [Url-2].

$$SNR = \frac{\mu}{\sigma} \qquad 2.9$$

Entropy: Entropy shows uncertainty and chaos of signal [47]. It is a nonlinear feature. Entropy is used to predict behavior of signal. In this thesis Shannon entropy (SE) is used.

$$SE = -\sum_{i=0}^{N-1} p_i \log_2 p_i \qquad 2.10$$

Where P_i is the probability density function of signal.

Inter Quartile Range (IQR): IQR is defined as difference between value of the 25th and 75th quartile of the signal [48].

Mean Absolute Deviation (MAD): MAD of signal is absolute distance between each point of signal from mean [49].

Hjorth Parameters [50] involve 3 different parameters. These are activity, mobility and complexity.

Activity: It is also known as variance or mean power, because it is equal to squared standard deviation of the amplitude.

$$Activity = var(x(t)) \qquad 2.11$$

Mobility: It is defined as the square root of the ratio between activity of first derivative of signal and activity of signal.

$$\text{Mobility} = \sqrt{\frac{\text{var}(\frac{dx(t)}{dt})}{\text{var}(x(t))}} \quad 2.12$$

Complexity: It is defined as the ratio between mobility of first derivative of signal and mobility of signal.

$$\text{Complexity} = \sqrt{\frac{\text{Mobility}(\frac{dx(t)}{dt})}{\text{Mobility}(x(t))}} \quad 2.13$$

These parameters characterize the EEG pattern in terms of amplitude, time scale and complexity [50].

Absolute power: It is total power of signal. It is calculated in continuous time by equation 2.13 [51].

$$P = \lim_{T\to\infty} \frac{1}{T} \int_{-T/2}^{T/2} |x(t)|^2 \, dt \quad 2.14$$

Relative power: It is ratio of absolute power of each band [52].

$$RDP = \frac{\text{Absolute power of } \delta}{\text{total signal power}} \quad 2.19$$

$$RTP = \frac{\text{Absolute power of } \theta}{\text{total signal power}} \quad 2.20$$

$$RAP = \frac{\text{Absolute power of } \alpha}{\text{total signal power}} \quad 2.21$$

$$RBP = \frac{\text{Absolute power of } \beta}{\text{total signal power}} \quad 2.22$$

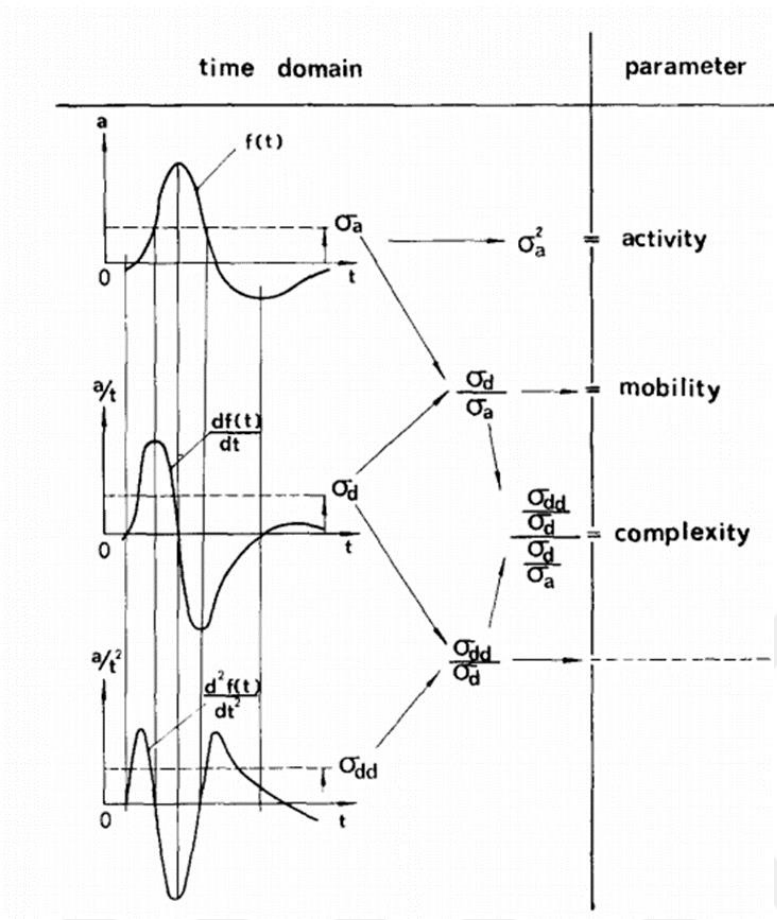

Figure 2.11 : Graphical presentation of Hjorth parameters [50].

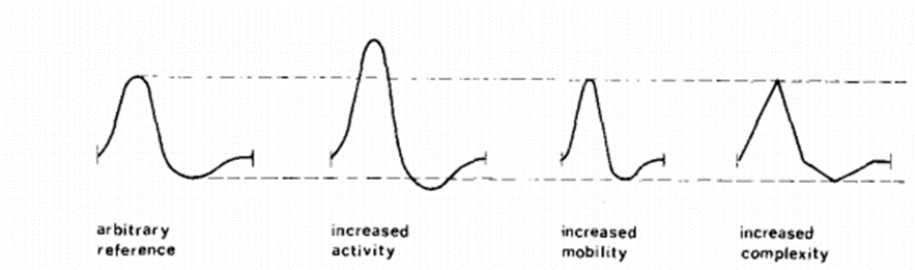

Figure 2.12 : Behavior of Hjorth parameter [50].

Another family of features that is based on frequency band is cordance.

Cordance is calculated by equation 2.22 [53].

$$\text{Cordance}=(A_{norm(f)}-0.5)+(R_{norm(f)}-0.5) \qquad 2.23$$

Absolute and relative power are normalized by using Z score. Z score is calculated by equation 2.23 [53].

$$Z=\frac{\text{measurement-mean}}{\text{standarddeviation}} \quad 2.24$$

Another two features are based on ratio of low frequency on high frequency [52].

$$\text{Ratio1}=\frac{\theta+\alpha}{\beta} \quad 2.25$$

$$\text{Ratio2}=\frac{\theta}{\alpha} \quad 2.26$$

Zero-crossing: Zero-crossing give information about dominant frequency of signal. It depends on number of crosses the x-axis [54].

2.6 Statistical Analysis for Feature Selection

Patients were divided into two groups by their AHI and ESS scores. For all the features, differences between patient groups and sessions were analyzed with mixed-ANOVA models. Mixed-ANOVA models are used to test for differences between two or more independent variables. In our mixed-ANOVA model, the repeated measures were electrodes (Fp1, Fp2, F3, F4, C3, C4, P3, P4, O1 vs.O2), and sessions (task vs. rest), and between subjects measures was either AHI ($\geq$15 vs. < 15) or ESS ($\geq$11 vs. < 11). The mixed-ANOVA model parameters were calculated with the JASP® software. The cut-off for statistical significance (the p-value) was $p < 0.05$. A statistically significant result shows that a difference between two or more variables is not observed due to chance. If a significant result was observed with a mixed-ANOVA model, t-tests were used to reveal the source of the difference between the conditions. The paired samples t-test was used to investigate the difference between repeated measures, and the independent samples t-test was used to investigate differences between groups.

2.7 Classification

The primary aim of the thesis is to classify patients' AHI and ESS scored based on their EEG signals at the resting and task sessions. Multiple-input feed forward Artificial Neural Network (ANN) models were used for classification. Units on the ANN models implement three aspects of neural function. Each unit receives weighted

input from other units, add a bias, converts the sum of inputs and biases with a transfer function (TF).

In this thesis a two-layer feed-forward with sigmoid activation function in hidden layer and softmax activation function in output layer was used. Number of neurons in hidden layer was selected as 10 (default) and number of inputs are 520 (See Figure 2.13). Scaled conjugate gradient backpropagation method was used to update weights in the training function. The backpropagation architecture uses first order gradient descent method as learning algorithm. The scaled conjugate gradient is one of the most common training algorithms. Scaled conjugate gradient method is used second order gradient as a minimization method. This method is the fastest method among the training algorithms because of it uses second order gradient. Conjugate gradient method proceeds the gradient in a direction that is conjugate to the direction of previous step [55].

Dataset was divided into train, validation and test parts with 50%, %25 and %25 ratio randomly. Training part adjusts network according to its error. Validation part is used to measure network's generalization, and to halt training when generalization stops improving. Testing part do not have effect on training, this part is used to measure performance of the network. ANNs was implemented with MATLAB ® neural pattern recognition toolbox. The performance of ANNs are calculated with the confusion matrix, which is a tool to show performance of the classification method (Equations 2.26-28).

$$\text{sensitivity} = \frac{TP}{TP + FN} \tag{2.26}$$

$$\text{specificity} = \frac{TN}{TN + FP} \tag{2.27}$$

$$\text{accuracy} = \frac{TN + TP}{TN + TP + FN + FP} \tag{2.28}$$

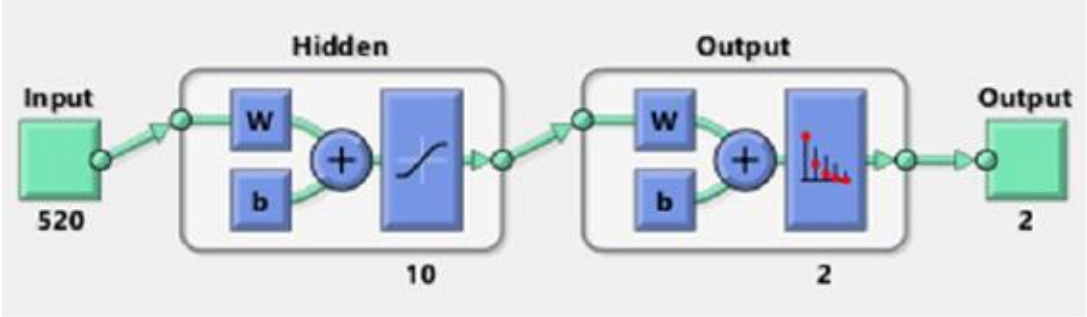

Figure 2.13: Architecture of network in this thesis.

3. RESULTS

3.1 Results from Attention Tasks

The average error rate (ER) and response times (RT) for correct responses for Simon and Flanker tasks were calculated. Separate mixed-ANOVA models with congruency (congruent vs. incongruent) x previous congruency (congruent vs. incongruent) x patient group (AHI $\geq$ 15 vs. AHI < 15 or ESS $\geq$ 11 vs. ESS < 11) were calculated with the JASP® software. The cut-off for statistical significance (the p-value) was $p < 0.05$. A statistically significant result shows that a difference between two or more variables is not observed due to chance. If a significant result was observed with a mixed-ANOVA model, t-tests were used to reveal the source of the difference between the conditions.

The significant results in RT and ER from both tasks with AHI in the mixed-ANOVA model are shown in Table 3.1. There was a significant main effect of congruency for both RT and ER. There was a two-way interaction between congruency and previous congruency in RT of the Flanker task. These results showed that behavioral measures were not different among AHI groups.

Table 3.1 : Results of Mixed ANOVA with AHI as the between subjects factor for RT and ER of the Simon and Flanker tasks.

Main effects and Interactions / Dependent variables	Cong.	Pre. Cong.	AHI	Cong. x AHI > 15	Pre. Cong x AHI > 15	Cong. x Pre. Cong.	Cong. x Pre. Cong. x AHI > 15
RT of Simon task	**	-	-	-	-	-	*
RT of Flanker task	-	*	-	-	-	**	-
ER of Simon task	**	-	-	-	-	-	-
ER of Flanker task	-	-	-	-	-	-	-

*significant value $p < 0.1$. **significant value $p < 0.05$. - : non significant. cong = congruency, pre. cong. = previous congruency

The significant results in RT and ER from both tasks with ESS in the mixed-ANOVA model are shown in Table 3.2. There was a significant main effect of congruency for both RT and ER. There was a two-way interaction between congruency and previous congruency in RT of the Flanker task. These results showed that behavioral measures were not different among ESS groups.

Table 3.2 : Results of Mixed ANOVA with ESS as the between subjects factor for RT and ER of the Simon and Flanker tasks.

Main effects and Interactions / Parameters	Congruency	Previous Cong.	ESS	Cong. x ESS > 11	Pre. Cong x ESS > 11	Cong. x Pre. Cong.	Cong. x Pre. Cong. ESS > 11
RT of Simon task	**	-	-	-	-	-	-
RT of Flanker task	-	-	-	-	-	**	-
ER of Simon task	**	-	-	-	-	-	-
ER of Flanker task	-	-	-	-	-	-	-

*significant value $p < 0.1$. **significant value $p < 0.05$. - : non significant. cong = congruency, pre. cong. = previous congruency

3.2 Mixed – ANOVA Analysis for Feature Selection

Then we analyzed variety of features that were extracted from EEG signals during both sessions (rest and Simon-Flanker tasks) between two groups. Features that showed a significant interaction including sessions were selected as an input for the classification algorithm. Significant results with AHI in the mixed-ANOVA model are shown in Table 3.3. A significant interaction including sessions with AHI was observed in mobility, Ratio1, Ratio2, relative delta power (RDP), skewness, standard deviation, absolute theta power (ATP) features.

Then we analyzed variety of features that were extracted from EEG signals during both sessions (rest and Simon-Flanker tasks) between two groups. Features that showed a significant interaction including sessions were selected as an input for the classification algorithm. The significant interactions with ESS in the mixed-ANOVA model are shown in Table 3.4. A significant interaction including sessions with ESS was observed in mobility, Ratio1, Ratio2, relative delta power (RDP), skewness, standard deviation, absolute theta power (ATP) features and complexity.

Table 3.3 : Results of Mixed-ANOVA model with AHI as the between subjects factor for EEG features.

Main effect &Interaction Features	Electrodes	Session	AHI	Electrodes x AHI	Session x AHI	Electrodes x Session	Electrodes x Session x AHI
Activity	-	-	-	-	-	-	-
Cordance-Alpha	-	-	-	-	-	-	-
Cordance-Beta	-	**	-	-	-	-	-
Cordance-Delta	-	**	-	-	-	-	-
Complexity	***	-	-	-	-	*	-
Cordance-Theta	-	-	-	-	-	-	-
Entropy	-	**	-	-	-	-	-
Inter range quartile	-	**	-	-	-	-	-
Kurtosis	-	**	-	-	*	-	-
Mean	-	-	-	-	-	-	-
Mean absolute deviation	**	-	-	-	-	-	-
Mobility	***	-	-	-	-	***	-
RAP	-	-	-	-	-	-	-
Ratio1	***	-	-	-	**	**	-
Ratio2	***	-	-	-	-	**	-
RBP	-	-	-	-	-	-	-
RDP	***	***	-	-	-	***	-
RTP	-	-	-	-	-	-	-
Skewness	***	-	-	-	-	***	*
SNR	-	-	-	-	-	-	-
Standard deviation	**	-	-	-	-	***	-
AAP	-	-	-	-	-	-	-
ABP	-	-	-	-	-	-	-
ADP	-	**	-	-	-	-	-
ATP	-	-	-	-	-	**	-
Zero crossing rate	***	***	-	-	-	***	-

*significant value ($p<0.1$). **significant value ($p<0.05$). ***significant value ($p<0.001$). - : non significant.

Table 3.4 : Results of Mixed-ANOVA test in Epworth criteria between features and Electrodes, Session, Epworth and their interactions.

Interaction / Features	Electrodes	Session	ESS	Electrodes x ESS	Session x ESS	Electrodes x Session	Electrodes x Session x ESS
Activity	-	-	-	-	-	-	-
Cordance-Alpha	*	-	-	-	-	-	-
Cordance-Beta	-	**	-	-	-	-	-
Cordance-Delta	-	**	-	-	-	-	-
Complexity	***	-	-	-	-	**	*
Cordance Theta	-	-	-	-	-	-	-
Entropy	-	**	-	-	-	-	-
Inter range quartile	-	**	-	-	-	-	-
Kurtosis	-	**	-	-	-	-	-
Mean	-	-	-	-	-	-	-
Mean absolute deviation	**	-	-	-	-	*	-
Mobility	***	-	-	-	-	***	-
RAP	-	-	-	-	-	-	-
Ratio1	***	*	*	**	-	***	**
Ratio2	***	-	-	-	-	**	-
RBP	-	-	-	-	-	-	-
RDP	***	***	-	-	-	***	-
RTP	-	-	-	-	-	-	-
Skewness	**	-	-	-	-	***	-
SNR	-	-	-	-	-	-	-
Standard deviation	**	-	-	-	-	***	**
AAP	*	-	-	-	-	-	-
ABP	-	*	-	-	-	-	-
ADP	-	**	-	-	-	*	-
ATP	**	-	-	-	-	***	-
Zero crossing rate	***	***	-	**	-	***	-

*significant value ($p<0.1$). **significant value ($p<0.05$). ***significant value ($p<0.001$), -: non-significant.

As a result of statistical analyses, almost the same features were selected for the classification algorithm regardless of whether the groups were divided according to AHI or ESS. To further select the important electrodes for classification (in other words to understand the source of significant interactions involving electrodes) t-tests were conducted.

For complexity, the significant difference was observed with P3 and Fp1 (See Table 3.5 and Figure 3.1). In both electrodes rest was lower than task session.

Table 3.5: Results of t-test in electrodes between two tasks for complexity.

Electrodes	Significant difference (p <0.05)
P4	No
P3	Yes
Fp2	No
Fp1	Yes
F3	No
F4	No
C3	No
C4	No
O1	No
O2	No

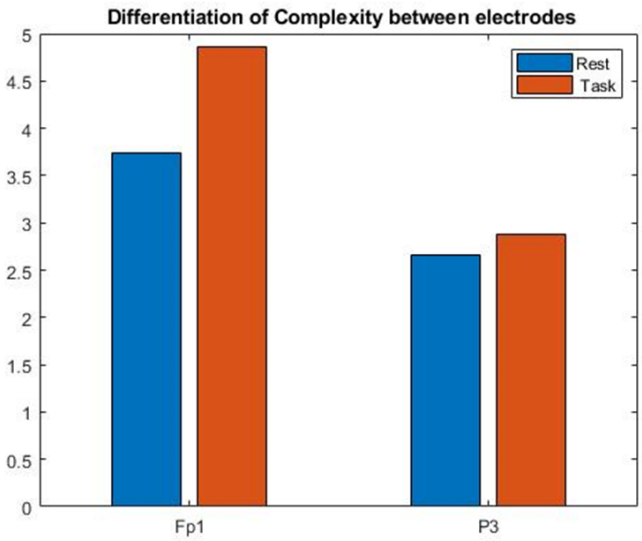

Figure 3.1 : Mean of complexity value for Fp1 and P3.

For mobility, the significant difference was observed with Fp2, O1, O2 and P4 (See Table 3.6 and Figure 3.2).

Table 3.6 : Results of t-test in electrodes between two tasks for mobility.

Electrodes	Significant difference ($p < 0.05$)
P4	Yes
P3	No
Fp2	No
Fp1	Yes
F3	No
F4	No
C3	No
C4	No
O1	Yes
O2	Yes

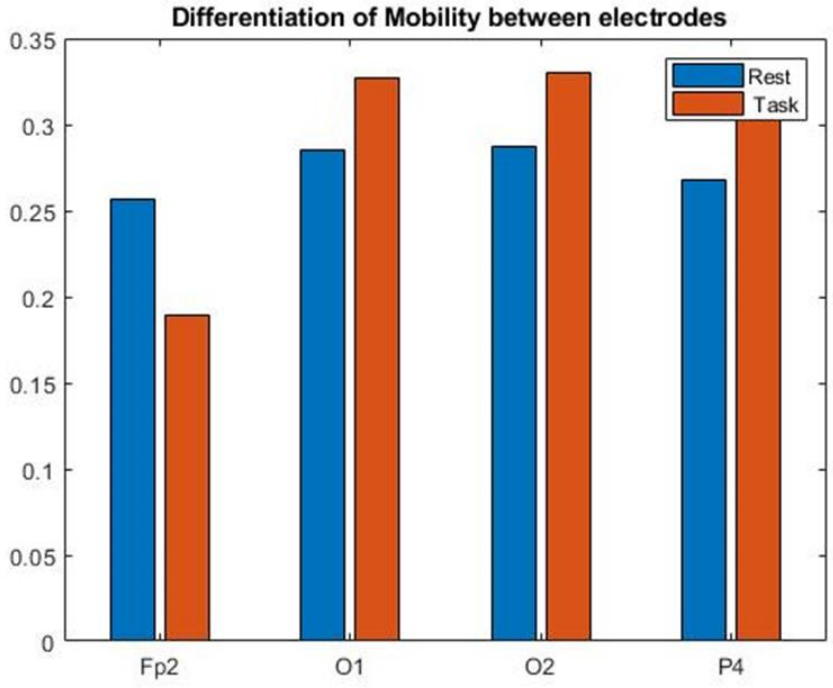

Figure 3.2 : Mean of mobility value for Fp2, O1, O2 and P4.

For skewness, the significant difference was observed with C3, F3, Fp1, Fp2, O1(See Table 3.7 and Figure 3.3).

Table 3.7 : Results of t-test in electrodes between two tasks for skewness.

Electrodes	Significant difference ($p < 0.05$)
P4	No
P3	No
Fp2	Yes
Fp1	Yes
F3	Yes
F4	No
C3	Yes
C4	No
O1	Yes
O2	No

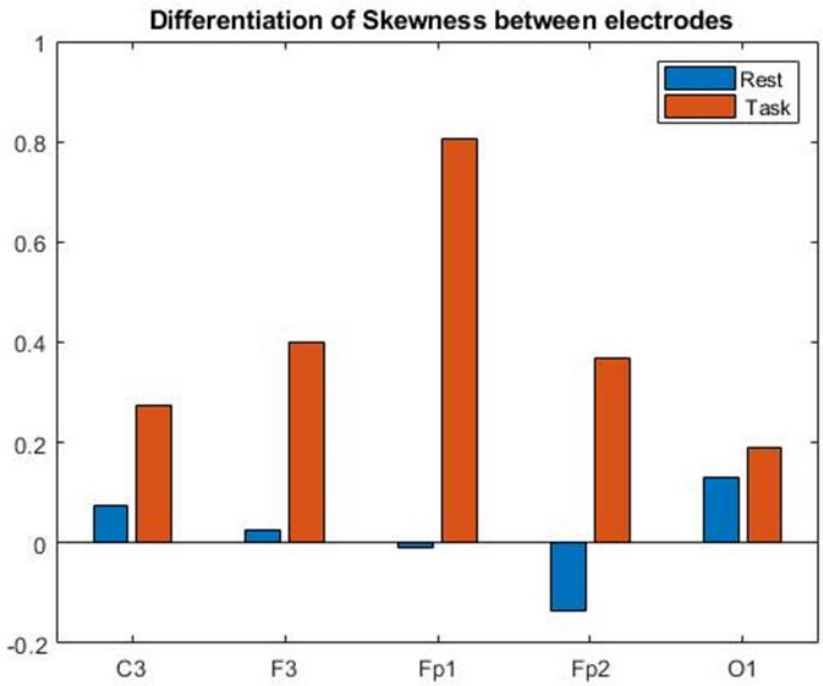

Figure 3.3 : Mean of skewness value for C3, F3, Fp1, Fp2, and O1.

For standard deviation, the significant difference was observed with C3, F3, F4, Fp1, Fp2 (See Table 3.8 and Figure 3.4).

Table 3.8 : Results of t-test in electrodes between two tasks for Standard deviation

Electrodes	Significant difference ($p < 0.05$)
P4	No
P3	No
Fp2	Yes
Fp1	Yes
F3	Yes
F4	Yes
C3	Yes
C4	No
O1	No
O2	No

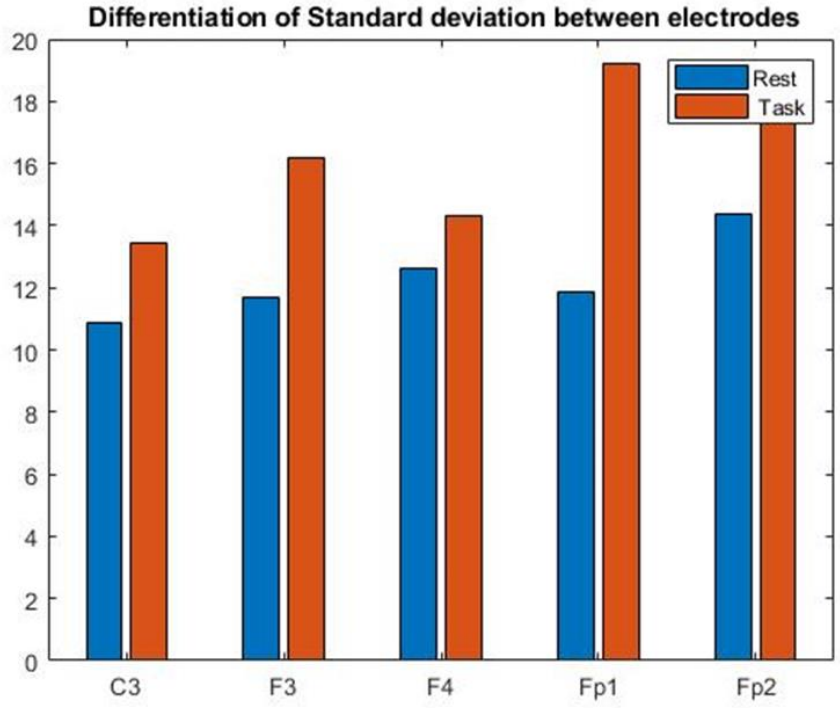

Figure 3.4 : Mean of skewness value for C3, F3, F4, Fp1, Fp2.

For Rato1, the significant difference was observed with F4, O1, O2, P4 (See Table 3.9 and Figure 3.5).

Table 3.9 : Results of t-test in electrodes between two tasks for Ratio1.

Electrodes	Significant difference ($p < 0.05$)
P4	Yes
P3	No
Fp2	No
Fp1	No
F3	No
F4	Yes
C3	No
C4	No
O1	Yes
O2	Yes

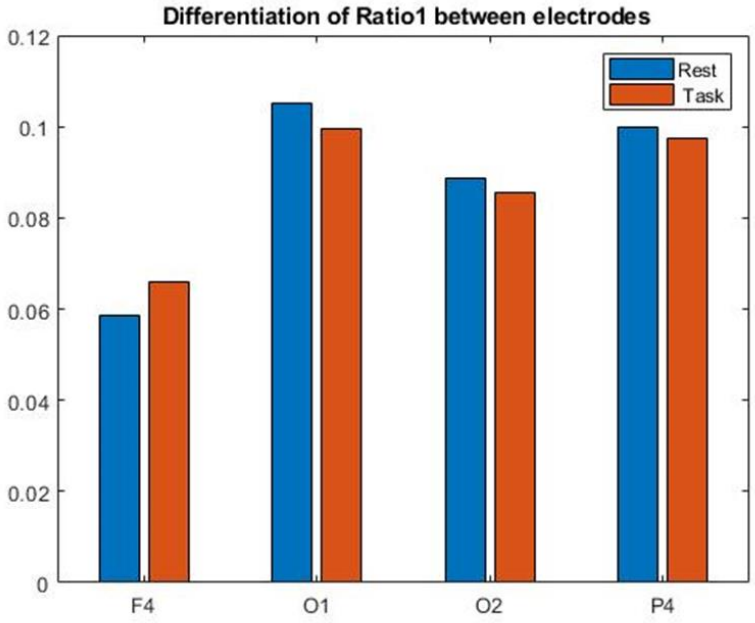

Figure 3.5 : Mean of Ratio1 value for F4, O1, O2 and P4.

For Ratio2, the significant difference was not observed (See Table. 3.10). For relative delta power (RDP), the significant difference was observed in all electrodes (See Table 3.11, Figure 3.6).

Table 3.10 : Results of t-test in electrodes between two tasks for Ratio2

Electrodes	Significant difference ($p < 0.05$)
P4	No
P3	No
Fp2	No
Fp1	No
F3	No
F4	No
C3	No
C4	No
O1	No
O2	No

Table 3.11 : Results of t-test in electrodes between two tasks for RDP.

Electrodes	Significant difference ($p < 0.05$)
P4	Yes
P3	Yes
Fp2	Yes
Fp1	Yes
F3	Yes
F4	Yes
C3	Yes
C4	Yes
O1	Yes
O2	Yes

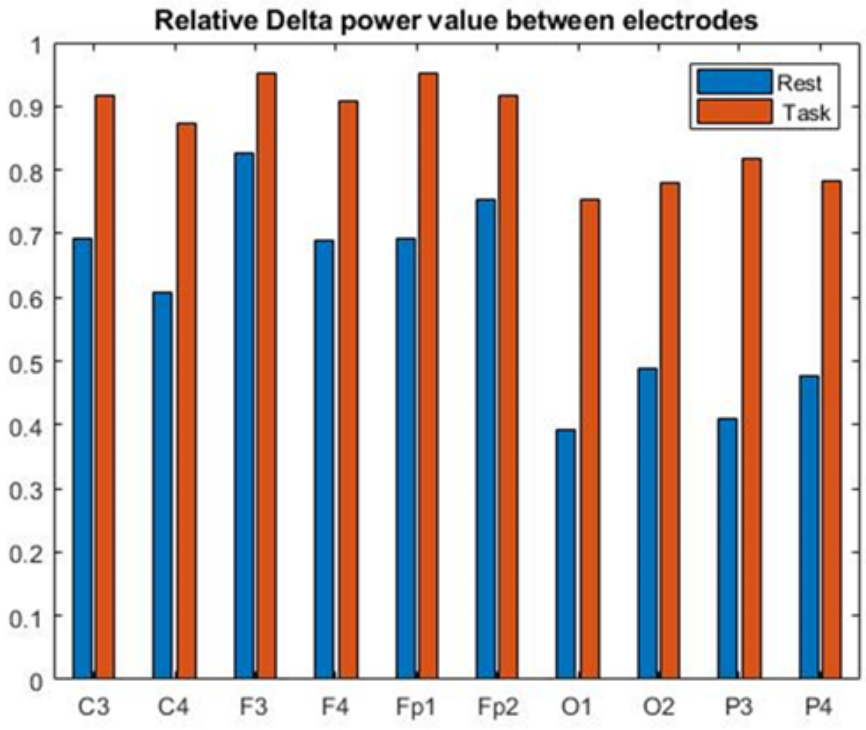

Figure 3.6 : Mean of RDP for all electrodes.

For absolute theta power (ATP), the significant difference was observed in Fp1, Fp2, F3 and C3. ATP values in rest session are lower than in task session (See Table 3.12, Figure 3.7).

Table 3.12 : Results of t-test in electrodes between two tasks for ATP.

Electrodes	Significant difference ($p < 0.05$)
P4	No
P3	No
Fp2	Yes
Fp1	Yes
F3	Yes
F4	No
C3	Yes
C4	No
O1	No
O2	No

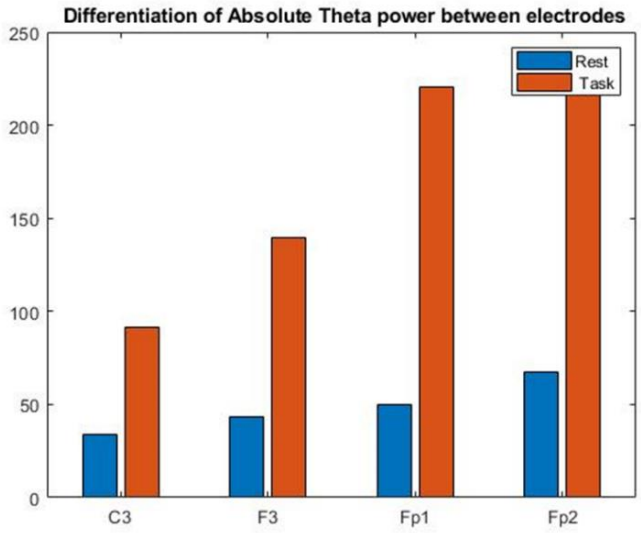

Figure 3.7 : Mean of ATP in Fp1, Fp2, F3 and C3.

For zero crossing, the significant difference was observed in all electrodes (See Table 3.13, Figure 3.8).

Table 3.13 : Results of t-test in electrodes between two tasks for Zero crossing.

Electrodes	p-value
P4	Yes
P3	Yes
Fp2	Yes
Fp1	Yes
F3	Yes
F4	Yes
C3	Yes
C4	Yes
O1	Yes
O2	Yes

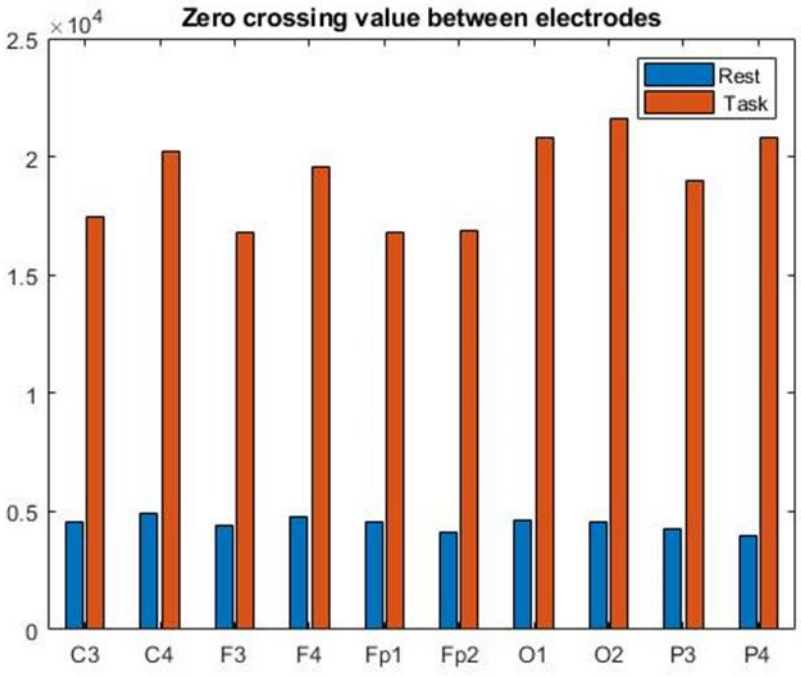

Figure 3.8 : Mean of zero crossing in all electrodes.

3.3 Classification Results

The aim of this thesis is to develop a decision support system with ANN algorithms to classify OSA patients according their AHI and Epworth scores using EEG signals that are recorded during rest and task sessions. We used mixed-ANOVA model results as a first step to select important features for classification. The selected features for classification according to the AHI criteria were mobility of Fp2, F4, O1 and O2 electrodes, skewness of Fp2, Fp1, F3, C2 and O1 electrodes, standard deviation of Fp2, Fp1, F3, C3 and C4 electrodes, Ratio1 of P4, F4, O1 and O2 electrodes, ATP of P4, Fp2, F3 and C7 electrodes and all electrodes of zero crossing and RDP. For ESS criteria, complexity of Fp1 and F3 electrodes were added to features that were used in AHI criteria. In summarize, the EEG recordings and analyses generated in total of 520 features, and with statistical analysis the number of features was reduced to 84 for AHI and 88 for ESS classifications.

We compared the performance of the different models with variety of inputs to investigate the best performing ANN model. The same ANN architecture was trained with five different input types: all EEG features, all attention test features, all EEG + attention test results, the selected EEG features and PSG recording features.

Table 3.14 shows the statistical result of five iterations using all EEG features to classify patients according to their AHI. The average performance was quite high. Figure 3.9 shows the confusion matrix of best classifier with using all EEG features for AHI. The best performing ANN classified all patients correctly.

Table 3.14 : Statistical result of five iteration using all EEG features in Apnea Hypopnea Index (AHI) criteria.

Average	Standard deviation	Maximum	Minimum
70.02%	18.25%	100%	50%

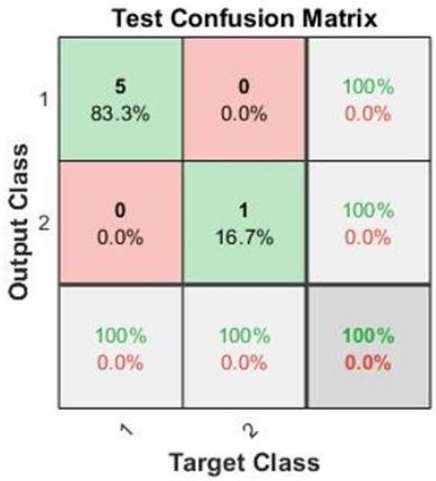

Figure 3.9 : The best result of the ANN classification with all EEG signal. 1 = AHI ≥ 15, 2 = AHI < 15.

Table 3.15 shows the statistical result of five iterations using all EEG features to classify patients according to their ESS. Figure 3.10 shows the confusion matrix of best classifier with using all EEG features for ESS. The best performing ANN classified 83.3% patients correctly.

Table 3.15 : Statistical result of five iteration using all EEG features in Epworth Sleepiness Score (ESS) criteria.

Average	Standard deviation	Maximum	Minimum
70.00%	13.92%	83.3%	50%

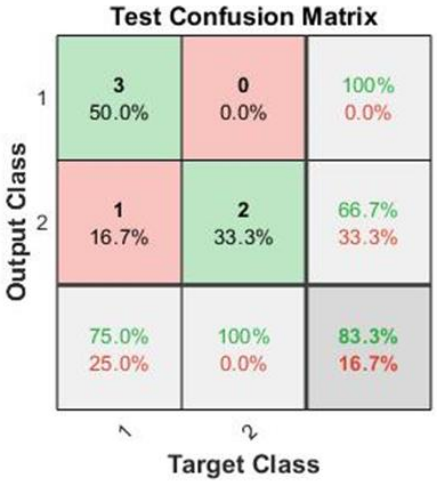

Figure 3.10 : The best result of the ANN classification with all EEG signal. 1 = ESS ≥ 11, 2 = ESS < 11.

Table 3.16 shows the statistical result of five iteration using all attention test results as features to classify patients according to their AHI. Figure 3.11 shows the confusion matrix of best classifier. The best performing ANN classified 83.3% patients correctly.

Table 3.16 : Statistical result of five iteration using all attention test results as features in AHI criteria.

Average	Standard deviation	Maximum	Minimum
70.02%	7.42%	83.3%	66.7%

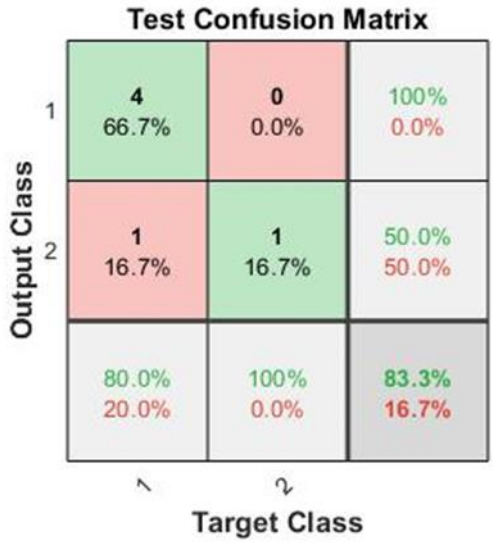

Figure 3.11 : The best result of the ANN classification with all attention test results.1 = AHI ≥ 15, 2 = AHI < 15.

Table 3.17 shows the statistical result of five iteration using all attention test results as features to classify patients according to their ESS. Figure 3.12 shows the confusion matrix of the best classifier. The best performing ANN classified 66.7% patients correctly.

Table 3.17 : Statistical result of five iteration using all attention test results as features in ESS criteria.

Average	Standard deviation	Maximum	Minimum
50.68%	14.93%	66.6%	50.0%

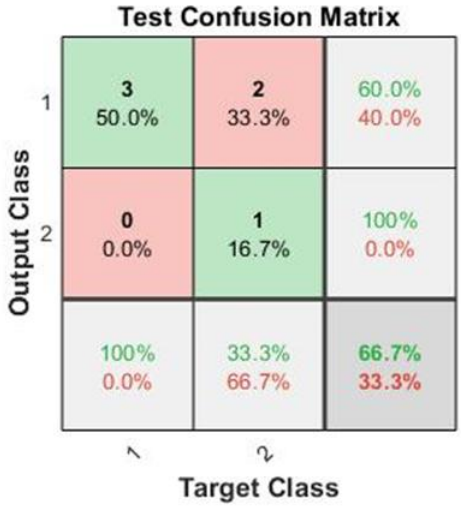

Figure 3.12 : The best result of the ANN classification with all attention test results.1 = ESS ≥ 11, 2 = ESS < 11.

Table 3.18 shows the statistical result of five iteration using all EEG features and attention test results as features to classify patients according to their AHI Figure 3.13 shows the confusion matrix of the best classifier. The best performing ANN classified 83.3% patients correctly.

Table 3.18 : Statistical result of five iteration using all EEG features and attention test results as features in AHI criteria.

Average	Standard deviation	Maximum	Minimum
66.68%	11.73%	83.3%	50.0%

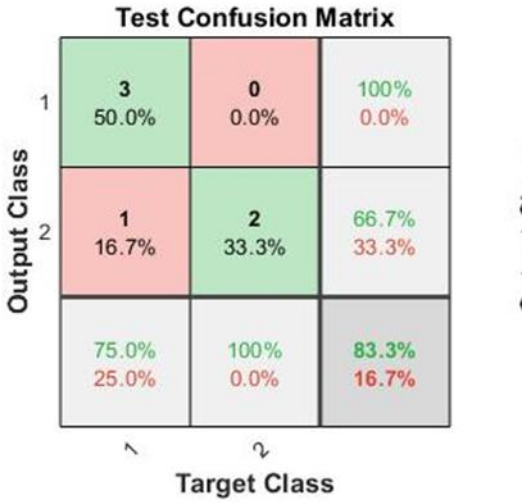

Figure 3.13 : The best result of the ANN classification with all EEG features and attention test results.1 = AHI ≥ 15, 2 = AHI < 15.

Table 3.19 shows the statistical result of five iteration using all EEG features and attention test results as features to classify patients according to their ESS Figure 3.14 shows the confusion matrix of the best classifier. The best performing ANN classified 83.3% patients correctly.

Table 3.19 : Statistical result of five iteration using all EEG features and attention test results as features in ESS criteria.

Average	Standard deviation	Maximum	Minimum
73.34%	9.09%	83.3%	66.7%

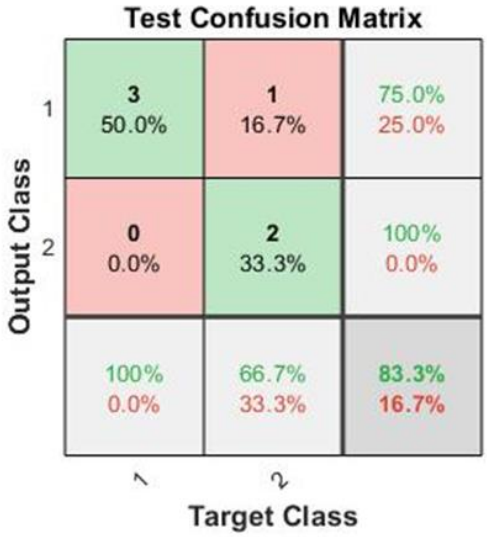

Figure 3.14 : The best result of the ANN classification with all EEG features and attention test results.1 = ESS ≥ 11, 2 = ESS < 11.

Table 3.20 shows the statistical result of five iteration using PSG recording results as features to classify patients according to their AHI. Figure 3.15 shows the confusion matrix of the best classifier. The best performing ANN classified 88.3% patients correctly.

Table 3.20 : Statistical result of five iteration using all PSG results as features in AHI criteria.

Average	Standard deviation	Maximum	Minimum
66.68%	11.77%	83.3%	50.0%

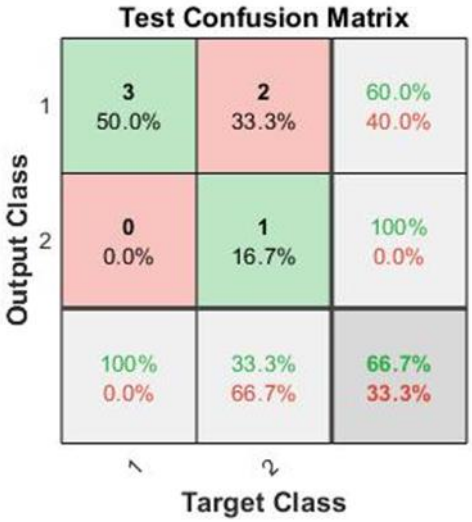

Figure 3.15 : The best result of the ANN classification with all PSG recording results.1 = AHI ≥ 15, 2 = AHI < 15.

Table 3.21 shows the statistical result of five iteration using PSG recording results as features to classify patients according to their ESS. Figure 3.16 shows the confusion matrix of the best classifier. The best performing ANN classified 66.7% patients correctly.

Table 3.21 : Statistical result of five iteration using all PSG results as features in ESS criteria.

Average	Standard deviation	Maximum	Minimum
66.7%	0.0%	66.7%	66.7%

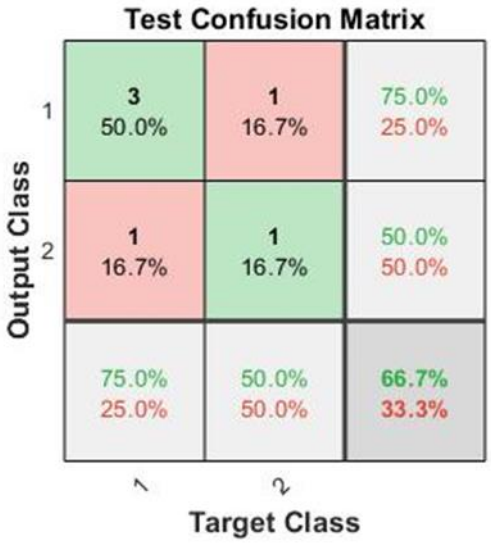

Figure 3.16 : The best result of the ANN classification with all PSG recording results.1 = ESS ≥ 11, 2 = ESS < 11.

Table 3.22 shows the statistical result of five iteration using selected EEG features to classify patients according to their AHI. Figure 3.17 shows the confusion matrix of the best classifier. The best performing ANN classified 83.3% patients correctly.

Table 3.22 : Statistical result of five iteration using selected EEG features in AHI criteria.

Average	Standard deviation	Maximum	Minimum
79.98%	7.42%	83.3%	66.7%

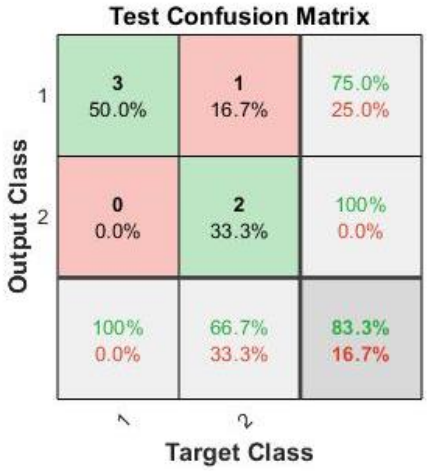

Figure 3.17 : The best result of the ANN classification with selected EEG features. 1 = AHI ≥ 15, 2 = AHI < 15.

Table 3.23 shows the statistical result of five iteration using selected EEG features to classify patients according to their ESS. Figure 3.18 shows the confusion matrix of the best classifier. The best performing ANN classified 83.3% patients correctly.

Table 3.23 : Statistical result of five iteration using selected EEG features in ESS criteria.

Average	Standard deviation	Maximum	Minimum
70.00%	13.92%	83.3%	50%

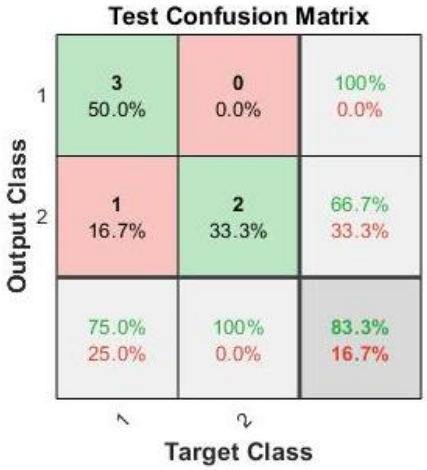

Figure 3.18 : The best result of the ANN classification with selected EEG features. 1 = ESS ≥ 11, 2 = ESS < 11.

4. DISCUSSION

In this thesis EEG signals that were collected from patients with OSA following an overnight PSG recording was investigated. During the collection of EEG signals, participants rested for 3 minutes to observe base of neural activity, and then they completed selective attention (Simon-Flanker) tasks to observe brain dynamics while executing cognitive functions. To the knowledge of the author of the thesis, there is no study in literature that analyzed EEG signals during resting and attention tasks among OSA patients.

The aim of the thesis was to develop a decision support system to classify patients according to their AHI and ESS scores. Overnight PSG recording, the gold standard of the measurement of disease severity, was laborious and expensive. ESS scores are subjective, and they are not reliable. Therefore, a decision support system to classify patients according to their AHI and ESS scores may help to medical professional by reducing their burden.

Important features for the classification algorithm were selected after mixed-ANOVA models. The performance of the decision support system using the selected features was quite good compared to other inputs types performances in AHI criteria. This result shows that mixed-ANOVA models could be used as a feature selection method.

In conclusion, features that were suggested in this thesis and were selected by mixed-ANOVA models, have quite good classifier ability for classification of OSA patients according to their AHI. A decision support system to predict OSA severity might help medical doctors during initial screening of patients.

As futures works, connectivity analysis of EEG signals that were recorded during both sessions may be used to increase the classification performance. In addition, ECG and respiratory signals that were recorded during both sessions will be investigated to predict the severity of OSA.

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PUBLICATIONS, PRESENTATIONS AND PATENTS FROM THE THESIS:

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