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Early Detection of Sleep Deprivation: Impact on Cognitive Performance using Deep Learning Techniques

by

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Problem statement

Examine the changes during sleep deprivation that can provide critical information on the brain's ability to perform decision-making tasks to reveal significant cognitive consequences.

- Understand the variation of ECG, EOG, and EEG signals in non-healthy subjects with respect to healthy subjects.
- Identify the distribution statistics of NREM and REM sleep stages of subjects who suffer from diagnosis and other problems using ECG, EOG, and EEG signals.
- Analyze the abnormalities in heart rate, and the amount of hemoglobin saturated with oxygen during the episodes and examine how it is associated with cognitive changes.

Background Study

- Analyzing the signals emitted through the subject's body movements can be monitored, and the measures can be translated into types of sleep stages, i.e., light, deep, and rapid eye movement (REM).
- The data can be collected through Polysomnography (PSG) test.
- The existing models used to predict sleep disorders or stages of sleep have shown 70% accuracy or less; in some cases, the models couldn't perform well and didn't give accurate results due to incorrect data recording.

Background Study

Polysomnography (sleep study)

- Identify the type and root causes of various sleep problems.
- Record eyes, legs, blood oxygen levels, heart rate, respiration and brain waves.
- Monitor when and why your sleep patterns are disrupted, and also track your sleep cycles and phase.

Sleep Stages

Based on the R&K (Rechtschaffen & Kales) standards, the American Academy of Sleep Medicine (AASM) defined new criteria for sleep scoring.

Background Study

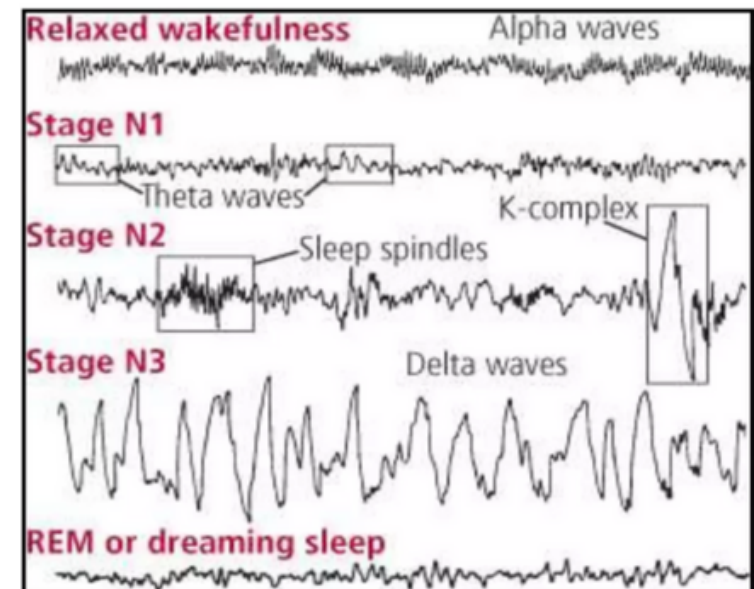
Adult sleep-wake cycles are divided into three stages:

- Awake
- Non-Rapid Eye Movement (NREM) / Quiet Sleep
- Rapid-Eye Movement (REM) / Dreaming sleep

NREM is further split into

- N1 (drowsiness/transitional sleep)
- N2 (light sleep)
- N3 (deep sleep)

Approx 75% of sleep is spent in the NREM with the majority spent in the N2 stage.



Background Study

- Alpha waves are seen during a normal wakeful state where the subject is quietly resting.
- Beta EEG is present when a person is alert/attentive and thinking actively.
- Theta rhythm (Stage 1) of sleep is present during the transition from wakefulness to sleep.
- Light non-REM sleep includes stage 1, characterized by a transition from alpha waves to theta waves, as well as stage 2, which is characterized by the occurrence of sleep spindles and K complexes.

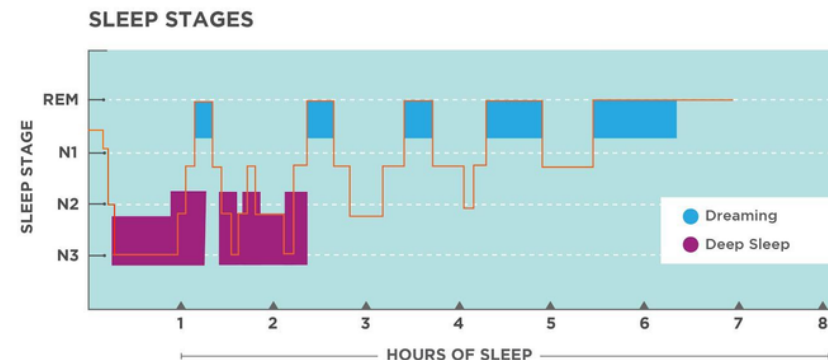
Background Study

- The sequence of sleep stages

It's important to realize that sleep does not progress through the four stages in perfect sequence.

When you have a whole night of uninterrupted sleep, the stages progress as follows:

1. Sleep begins with NREM stage 1 sleep.
2. NREM stage 1 progresses into NREM stage 2.
3. NREM stage 2 is followed by NREM s
4. NREM stage 2 is then repeated.
5. Finally, you are in REM sleep.



Background Study

Effect of sleep-related disorders on sleep stage pattern

- The most typical sleep condition seen in sleep medicine clinics is sleep apnea.
- Encourage fragmented sleep, often affecting sleep architecture by reducing or even eliminating REM and N3 sleep.
- Primary insomnia postulates that a lack of reduced arousal during sleep may cause non-restorative sleep.
- A rise in cortical arousal and a measure of sleep-protective mechanisms (spindles) may support the idea that primary insomnia patients experience non-restorative sleep due to the simultaneous activation of wake-promoting and sleep-protective brain activity patterns.

Proposed Solution & Novelty

- The short-term implications of poor sleep on the brain and cognition can result in forming false memories, frequent affects on mood, migraine etc. On the other hand, long-term effects of poor sleepers are cognitive impairment and Alzheimer's, dementia, increased beta amyloid in brain which can result in disruption of nerve cells.
- Therefore our proposed solution will help in identifying the subjects with a probability of developing impairment by analyzing their EEG or ECG by itself or in whole, and therefore prevent the risk of permanent impairment by exposing them to required medications
- Even though many researchers have worked on sleep stage classification using the PSG signals, few number of studies have been done to identify the variation of signals observed in subjects with sleep deprivation and cognitive impairment. This work will be a triangulation of subject's *medicinal drug intake* for a condition, his reaction to it observed on *PSG signals*, and the *diagnosis of disorders*.

Methodology & Implementation

ABOUT THE DATASET

- The data used is from the ISRUC-Sleep dataset collected using the Polysomnographic (PSG) test on the subjects.
- The data is concerned with two subgroups; Subgroup I, with subjects diagnosed with sleep disorders and having other problems such as Insomnia, depression, dementia, Parkinson, etc., which are our focus of interest, and Subgroup II, with subjects who are healthy with no medical history of sleep disorders or other problems as such.
- The AASM manual's guidelines were followed when recording the PSG signals. There are 19 channels of signals in each recording.

- The sleep data of the subjects are recorded in two formats, i.e., PSG (Hypnogram) data, including the parameters W (wake stage), N1, N2, N3 (stages of eye movements), and REM (Rapid Eye Movement).
- The other format is the signal data recorded during the 8-hour night duration using standard EDF+, which includes parameters such as EOG (Electrooculography), EEG (Electroencephalogram), ECG (Electrocardiogram), Snore (derived), SaO2 (Pulse Oximetry), BPOS (Body Positioning) with .rec extension and sampled at 200 Hz.
- According to the recommendations of the AASM, all recordings in the dataset were segmented into epochs of 30 s and visually assessed by two distinct sleep specialists at CHUC (Centre of Hospitalar and University Centre of Coimbra).
- The signal data is converted to .edf files, which would be further combined with the hypnogram data for further analysis.

IMPLEMENTATION

- In recent years, machine learning and deep learning approaches have attracted attention for classifying sleep stages with the availability of deep learning techniques.
- Computational advances now enable computers to recognize patterns within data and perform complex calculations to provide insights to inform the diagnosis and clinical care of sleep disorders in the form of classification.
- Our study proposes to examine the neural and cognitive changes associated with sleep deprivation using Deep Learning algorithms. A study examining the neural changes during sleep deprivation can provide critical information on the brain's ability to perform decision-making tasks to reveal significant cognitive consequences.

IMPLEMENTATION

- The details from the two subgroups are used to:
 1. Analyze each sleep stage's percentage and how it affects diagnosis and other medical conditions.
 2. Identify the percentage of each sleep stage for people with insomnia and other conditions related to our study.
 3. Perform correlation to understand how the parameter varies in each subject if they are diagnosed with insomnia or other condition.
- A classification model can be built to compare the variations in the signals concerning the two subgroups, including the subjects with insomnia and other problems and healthy subjects. The result can be further analyzed to evaluate the effect on the cognitive performances between the two subgroups.

Subject	Age	Age Range	Sex	Diagnosis	Other problems	Epoches	W%	N1%	N2%	N3%	REM%
94	45	40 - 50	F	SAOS	Depression	846	25.41	8.87	36.41	15.25	14.07
30	51	50 - 60	M	SAOS	Shift work	882	30.73	14.06	39	8.16	8.05
10	53	50 - 60	F	SAOS	depression	842	38	10.69	36.58	11.4	3.33
71	53	50 - 60	F	SAOS	Depression	829	13.15	19.9	46.08	9.77	11.1
64	55	50 - 60	F	SAOS	Depression	892	23.77	27.47	19.17	20.07	9.53
5	58	50 - 60	F	SAOS	Insomnia	875	33.83	12.34	30.29	18.74	4.8
35	59	50 - 60	M	SAOS	Depression	788	43.65	11.17	21.95	17.51	5.71
63	62	60 - 70	F	SAOS	Depression	954	31.55	16.14	33.23	10.59	8.49
1	64	60 - 70	M	SAOS	Depression	880	30	8.3	22.05	26.25	13.41
8	76	70 - 80	M	SAOS	Parkinson; Cen	904	24.45	13.94	31.08	23.67	6.86
83	77	70 - 80	F	SAOS	Depression	925	24.54	10.05	37.84	12.43	15.14
22	85	70 - 80	M	SAOS	Dementia; PLM	849	36.04	7.89	35.45	12.6	8.01

Fig. Subjects With Sleep Disorder Dataset (Subgroup-I).

Subject	Age	Age Range	Sex	Diagnosis	problems	Epoches	W%	N1%	N2%	N3%	REM%
1	30	30 - 40	M		no problem	954	17.3	12.47	39.1	18.66	12.4
2	31	30 - 40	M		no problem	941	12.22	15.3	34.33	20.94	17.2
3	31	30 - 40	M		no problem	824	10.8	7.89	30.34	38.47	12.
4	33	30 - 40	M		no problem	794	21.91	17.25	29.47	20.03	11.3
5	33	30 - 40	F		no problem	944	31.99	7.63	31.14	20.66	8.5
6	38	30 - 40	M		no problem	853	9.14	15.94	34.7	28.96	11.2
7	41	40 - 50	M		no problem	814	27.27	8.35	19.78	32.19	12.4
8	49	40 - 50	M		no problem	1000	37.6	11.9	20.1	14.3	16.
9	52	50 - 60	M		no problem	963	15.38	17.23	37.67	23.22	6.
10	58	50 - 60	M		no problem	796	18.47	27.76	22.74	14.07	16.9

Fig. Subjects Without Sleep Disorder Dataset (Subgroup-II).

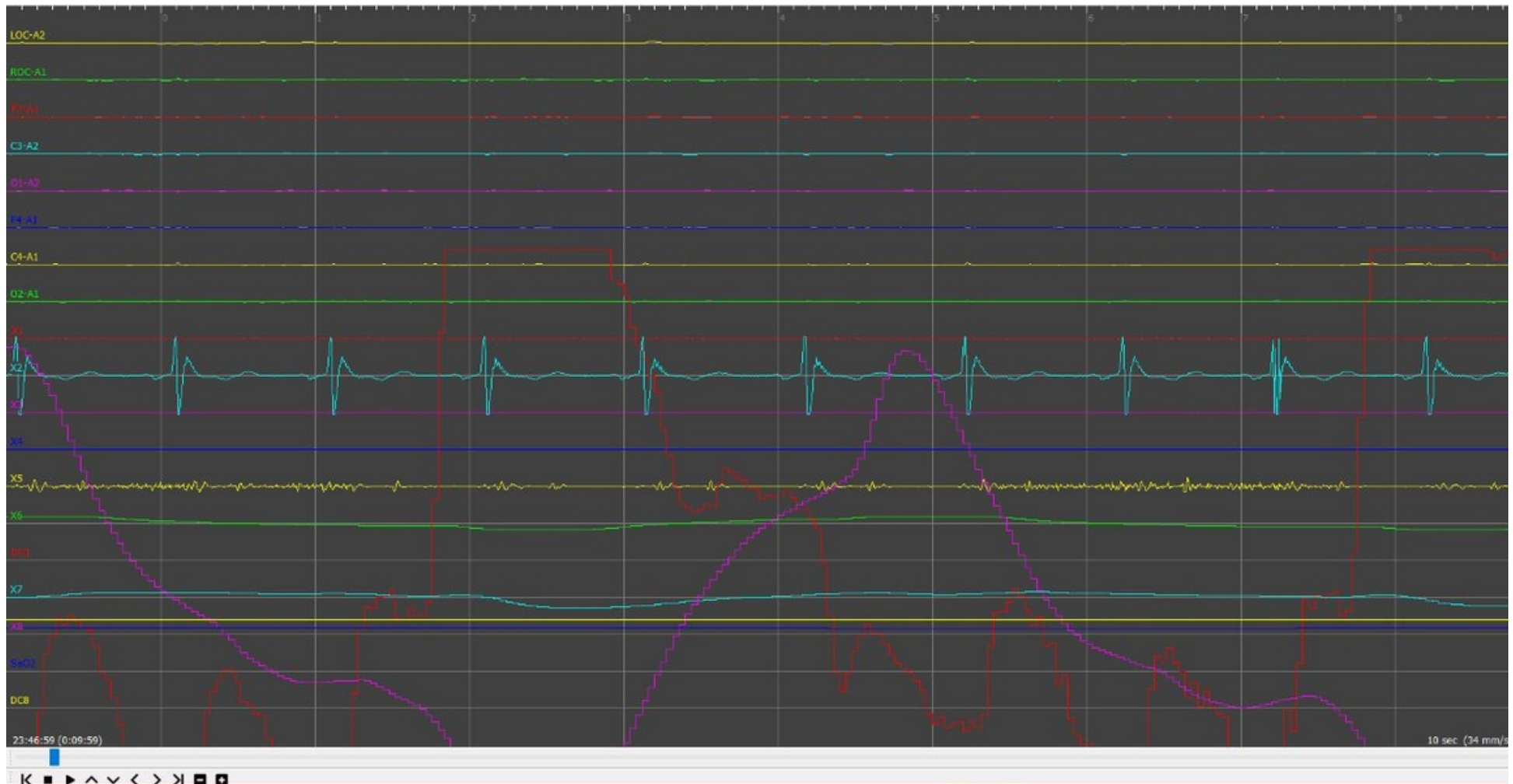


Fig. Recorded Signal Data .edf file

C4-A1	O2-A1	X1	X2	X3	X4	X5)
1.18E-08	1.34E-08	-6.32E-08	-1.87E-07	1.93E-07	2.24E-07	7.77E-06	
1.24E-07	2.73E-07	2.67E-06	-3.03E-06	1.73E-06	2.29E-06	1.13E-06	
7.06E-07	1.30E-06	3.91E-06	1.41E-06	-2.40E-06	-1.80E-06	-1.99E-05	
1.85E-06	2.76E-06	-1.02E-05	8.30E-06	-9.98E-06	-9.38E-06	8.60E-06	
2.34E-06	2.92E-06	-1.35E-05	1.34E-05	3.40E-06	5.10E-06	2.16E-05	
1.29E-06	1.31E-06	9.75E-06	2.42E-05	1.78E-05	1.56E-05	-2.51E-05	
-4.23E-08	-2.07E-07	1.10E-05	2.65E-05	2.08E-07	-6.55E-06	-1.86E-05	
-4.26E-07	-5.31E-07	3.10E-06	1.62E-05	-1.29E-05	-1.38E-05	2.10E-05	
-2.19E-07	-2.42E-07	7.30E-06	6.77E-08	8.03E-07	5.31E-06	1.65E-05	
6.29E-08	7.36E-08	-6.83E-06	-1.93E-05	8.95E-06	9.60E-06	-1.18E-05	
1.72E-07	1.35E-07	-8.53E-06	-2.48E-05	-2.51E-06	-4.49E-06	-1.51E-05	
-2.02E-08	-1.07E-07	5.29E-06	-2.65E-05	-1.02E-05	-8.65E-06	8.47E-06	
-2.15E-07	-2.64E-07	-5.19E-06	-2.19E-05	-3.73E-07	3.68E-06	7.57E-06	
-1.42E-07	-1.38E-07	-9.81E-06	-1.44E-05	6.41E-06	7.27E-06	-1.04E-05	
6.60E-08	3.62E-08	5.32E-06	-1.04E-05	-1.24E-06	-2.98E-06	-5.69E-06	

Fig. Values of different signals from .edf file

The labels in the figure represent the EEG and ECG signals

Diagnosis and Other Problems Concerning Age Group

For the age group 50 - 60, the highest number of subjects were diagnosed with SAOS, and the second highest age group diagnosed with the same is 60 - 70. For all the age groups, most of the subjects were diagnosed with only SAOS and had no other problems.

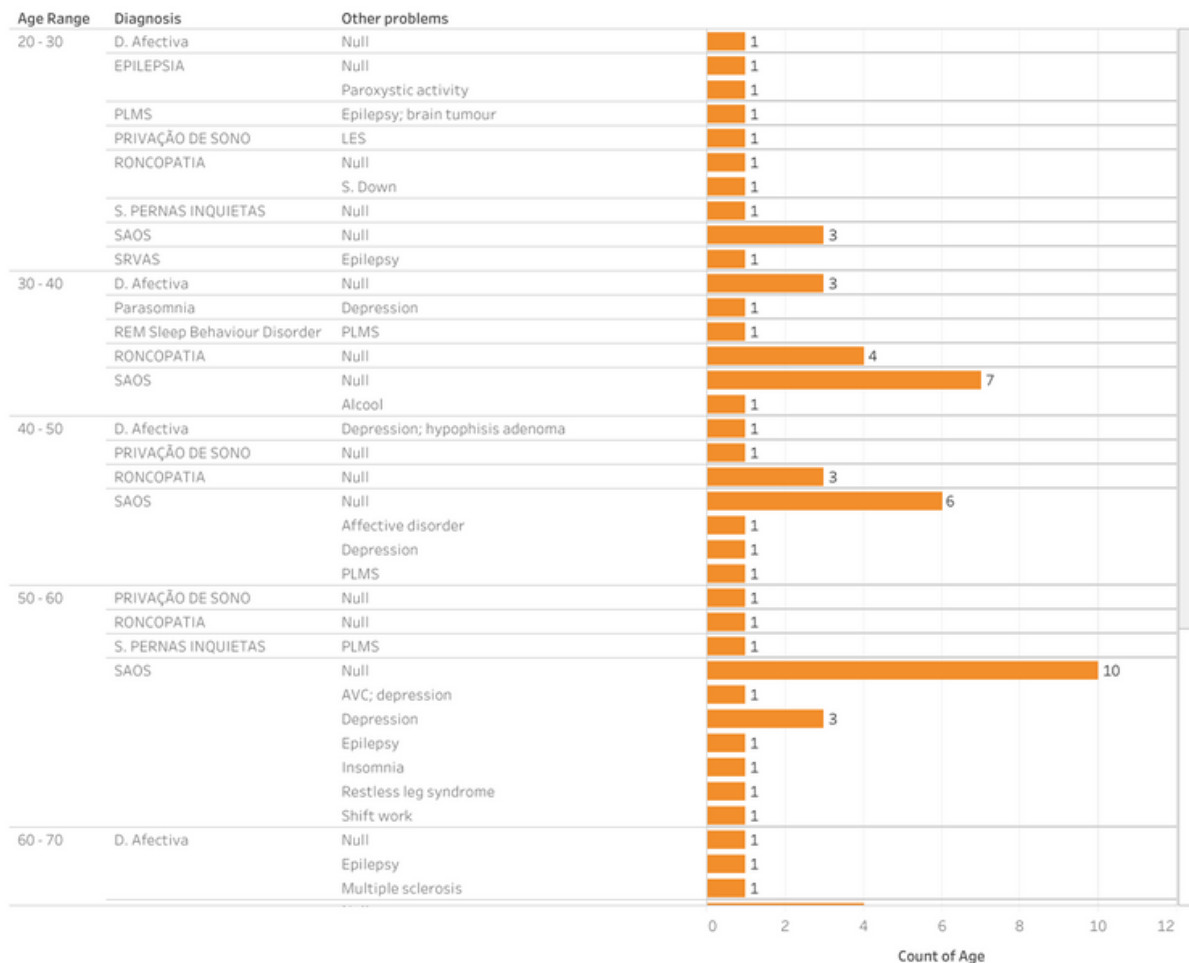


Fig. Diagnosis and Other Problems Concerning Age Groups

Percentage of Stages With respect to the Subjects

The highest average wake stage is 80.49% among all the 100 subjects considered. And there is only a slight difference in the other average percentage of stages.

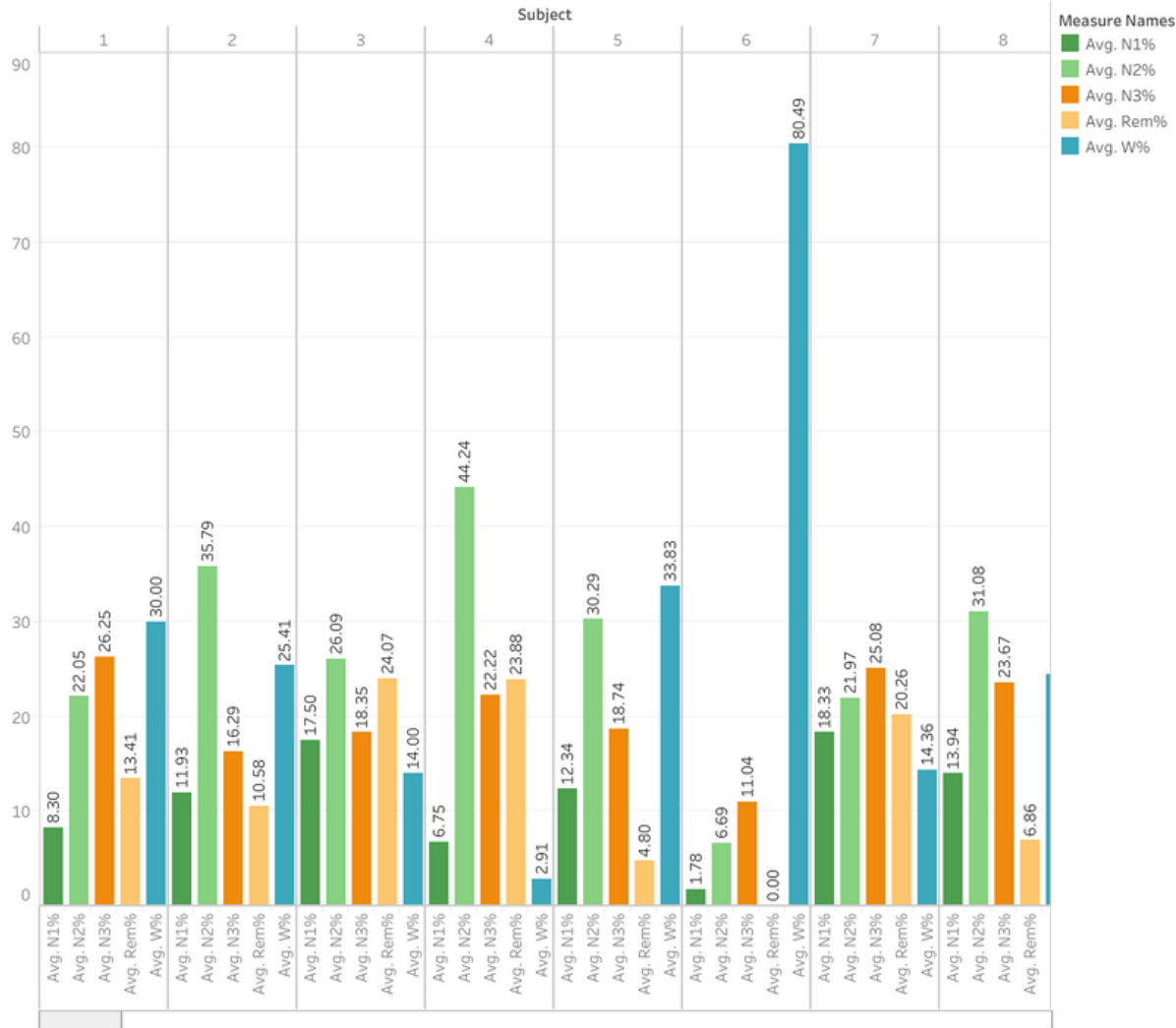


Fig. Percentage values of the Stages concerning the subjects

Distribution of Age group and Sex

The count of females in the age group 50 - 60 is more, and for the males in the range 60 - 70, the count is more.

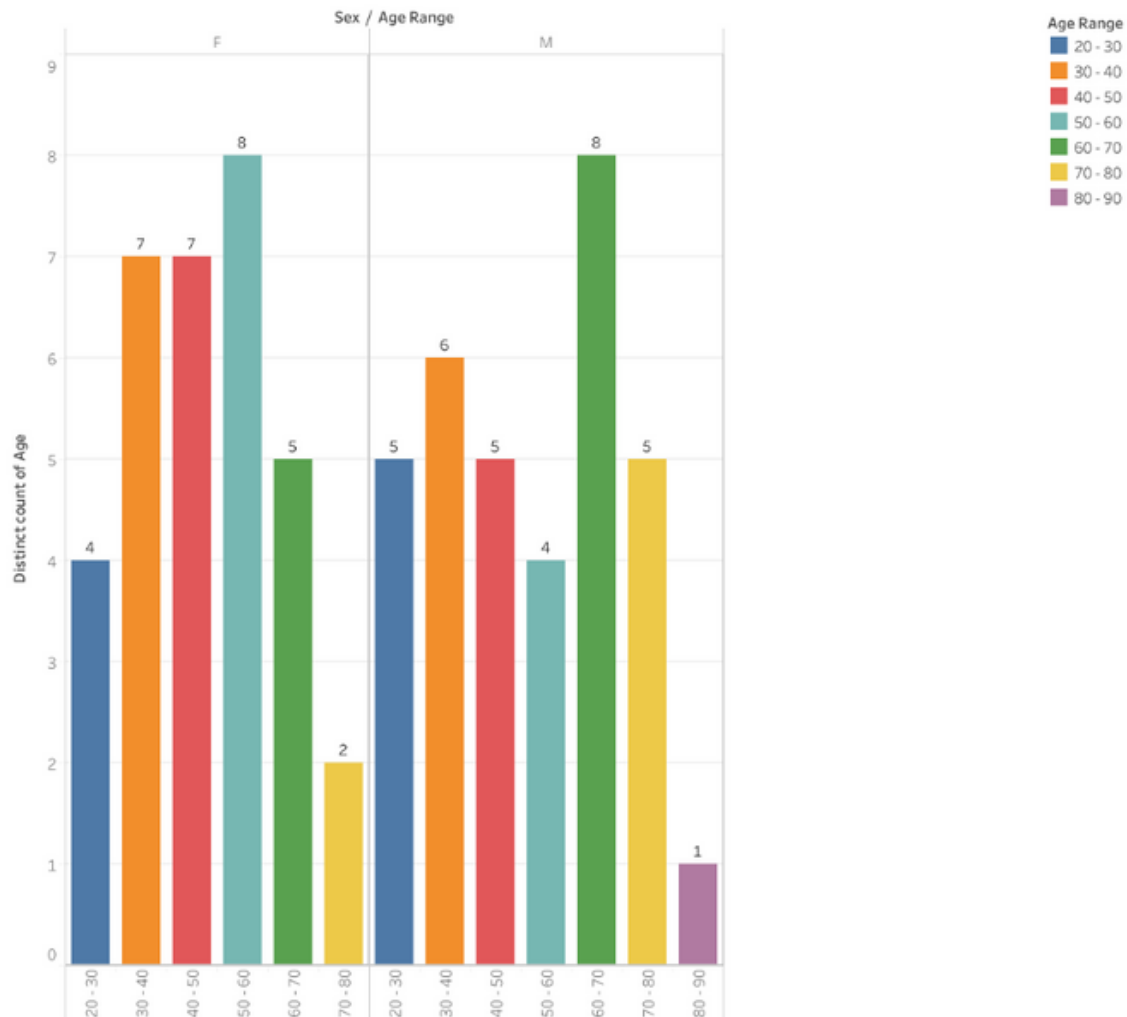


Fig. Distribution of age group and sex of the subjects

Results & Future Plans

- Enable clinicians to provide personalized recommendations frequently based on the interpretation of the data collected through changes in sleep patterns.
- We are expected to provide new insights to inform the clinical care of sleep disorders and advance our understanding of sleep's integral role in human health.
- We streamline day-to-day operations and optimize direct patient care, focusing on treatment outcomes.
- Simplify sleep disorder diagnosis by increasing patient services, making it cost-effective.

Results & Future Plans

- The future scope of the study will include modeling for better accuracy on real-time data that is not confined to a single race.
- The limitation of the study is the need for more availability of specific parameters to merge data from different formats, i.e., the recorded signal is in the interval of 2 seconds, and the hypnogram data contains epochs as an index. The exported signal data from the EDF browser has to be timescale based on what each epoch value could mean. The unavailability of the time recorded index in the data under sleep labels must be worked upon because merging data is possible with a standard index.

Learning & Feedback

- Converted signal data into EDF format
- With the help of MATLAB, the epochs were achieved, which we couldn't get in EDF format.
- Analyse the changes in the signals during the sleep deprivation stage that can provide insights into the brain's ability of decision-making (cognitive performance)

Thank you