Optimizing Sleep Time Slot for Bruxism and Insomnia Identification based on Frequency based EEG Patterns using Machine Learning Techniques

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ABSTRACT

Many science researchers believe that a healthy thinking depends on the quality of human sleep. Giving importance to the quality sleeps, several systems for the measurement of sleep quality were developed. All the systems can be divided into two sections - Wearable Devices & Automated devices. Exact estimation of the sleep quality by both the systems is quite difficult. Accurate assessment the quality of sleep depends on many physical and environmental factors such as dimension of bed, light effects, room temperature, any type of disease, oxygen level, etc. Accurately measurement these factors and establishing their relationship with sleep quality is a complex process. Measuring sleep quality through the systems currently available is not only complicated but also to a large extent expensive. This research attempts to summarize the systems available at present in measuring sleep quality. It divides the entire sleep-period into 4 parts and compares the accuracy of the predictions of the sleep related diseases at the end of each interval by applying machine-learning algorithms to the data of different time periods. In this research, diseases such as Insomnia and Bruxism have been included as a data set. With the results it is found that the slot 1 (12:00 - 1:20) is the most important one in the processes of measuring sleep quality.

Key words: Quality of human sleep, Wearable device, Automated device, Insomnia, Bruxism, Machine learning, Sleep-period.

1. INTRODUCTION

Human life is influenced by 2 types of health (1) mental health (2) physical health. Treatment and check-up of physical health are possible in many general ways, while both mental health treatment and testing are parts of a complex process. The mental health depends on many factors such as the quantity of food, family problems, unemployment, environment, workload etc. Along with scientific development the mental diseases also got importance in medical science. Sleep problems have become important constituents of these mental diseases. To a large extent, the origin of mental diseases depends on the quality of sleep. Sleep disorder occurs when someone cannot sleep properly it results in loss function of the body organs and muscles [19].According to scientific researches, sleep is divided into two parts. First one is REM (Rapid Eye Movement), in this kind of sleep, human eyes keep on moving. Most of the dreams are part of this type of sleep. The second one is NRAM (Non-Rapid Eye Movement), in such sleeps a man doesn't see dreams. In such sleeps the brains are in a state of complete rest. The NRAM is also divided into several stages - S0, S1, S2, S3. These stages of sleep are further, gradually, divided into light and deep sleep states. All the experiments of estimating sleep quality are quite costly and time-consuming. In this research, attempts have been made to summarize the experiments that assess the quality of sleep, so that, to a great extent, experiments that assess the quality of sleep can be made easier. In this research, sleep is divided into 4 time periods - 12:00 - 1: 20, 1: 00 - 2: 20, 2: 00 - 3: 20 and 3: 00 - 4: 20 are, respectively, Slot-1, Slot-2, Slot-3 and Slot-4. The research found that using multiple learning algorithms such as J-4, SVM, Naive Bayes, Random Forest, K-nearest neighbour, Logistic Regression, the slot number one is of paramount importance in assessing the sleep quality. By this result it is proved that all the experiments which assess the quality of sleep can be more focused in slot 1 and can keep the time of the experiment and the subject away from the radiation emanating from the devices with electric impulses through which many other diseases caused by radiation can be avoided.

2. LITERATURE REVIEW

All previous researches can be divided into two parts: (1) Assessment of sleep quality with the help of wearable devices, (2) Assessment of sleep quality by automated equipment. Understanding the usefulness of sleep in human life, assessing the quality of sleep accurately has been a special subject matter for the researchers of all times. Several methods of assessing sleep quality have been developed from time to time, such as initially testing the movement above the subject's bed by load cell sensor grid, and understanding the quality of sleep by testing the leg movement using a linear classifier [1,3]. In this experiment, sleep stages were classified with 79.3% accuracy. In the year 2016, wearable devices made subjects feel uncomfortable due to which their sleep quality could not be estimated properly. So in this research, 48 FSR (Force Sensing Resistors) were installed under the bed and Sleep quality was tested under different error rates using class logistic regression. In this experiment 95.8%, 90.2% and 88.5% accuracies were found under the 4.2%, 9.7% and 11.5% error rate respectively [2]. According to Tseng et al. [4], an accurate

assessment of sleep quality cannot be done by excluding electrical impulses originating in the human brain. In this experiment, electrical impulses originating in the human brain were recorded and the frequency of these electrical impulses were measured and the quality of sleep was understood based on the power of these frequencies. Here EEG signals were recorded through Bluetooth based device with the help of which the recorded data was sent to cloud storage for further processing. Since the brain signals are of very low voltage, the voltage signals were converted into frequency with the help of DAQ100 module for a good processing. In the year 2012, it was believed that a person spends one-third part of his entire life in sleeping. Understanding the importance of sleep in this research, many mathematical calculations were done and the formula of sleep index was calculated. And it was assumed that for different genders, estimation of sleep quality in different age groups is possible only under different sleep index [5]. Technology like IOT (Internet of Things) has made the research related to quality of sleep to a great extent easier. Through the research work conducted in the year 2016, IOT technology created a different image for itself. In these experiments, the possibility of adding noise signals to the sleep quality data was found to be very low which made the sleep quality measurement calculation easier [6]. Realizing the importance of sleep in human life, a momentum in sleep related research came when ultrasonic technology assessed the quality of sleep by examining the sonar generated movement on the subject's bed by an automated appliance. In this experiment, 62 subjects were tested. In this experiment, sleep was tested at different sleep stages and results with 87%, 89%, 84% accuracy were found in wake time, REM, and deep sleep stages, respectively [7]. Both methods of assessing sleep quality (by wearable devices & by automated devices) have their own importance. Scientific research believes that wearable devices make the subject feel uncomfortable and it is a complex process to assess the quality of sleep properly. Whereas many noise factors are added to record sleep data by non-wearable device. Accurate assessment of sleep quality can be done by processing electrical impulses originating in the brain. The deep sleep index formula was calculated with the help of EEG recordings and force sensors, which is given below.

*Deep Sleep Index (DSI) = 0.55 * No. of Small Movements + 1.05 * No. of Medium Movements + 1.02 * No. of Large Movements.*

In this research work, 95.7% accuracy was recorded for deep sleep [3, 8, 14, 16, 17]. In the research conducted in the year 2018, it was believed that the breathing pattern is an important parameter in the quality of sleep. In this experiment, Sleep Disorder Breathing Algorithm was written and after implementation, 93% accuracy was obtained [9, 16]. Sleep data was collected using I-Sleep sensors in an experiment conducted in the year 2019 and machine learning algorithms k-nearest neighbour, logistic regression and SVM were used to test the sleep quality. Results found 95.2%, 94.9%, 94.7% and 95.8% accuracy by k-nearest neighbour, logistic regression and SVM, respectively [2, 10]. In another research conducted in the year 2019, it was assumed that different sleep patterns are

seen at different locations, for different age groups & different genders. In this research, electrical implants were divided into different frequency ranges - 0.5 - 4, 4- 8, 8-12 and 12-32 Hz, termed as delta, theta, alpha and beta respectively. The research found that the fluctuation in delta frequency is higher in females than in males. In this experiment, 10-20 instruments were used for EEG recordings [11, 17]. According to Ravan et al. [12], frequent use of the 10-20 system can cause brain related disorders and therefore such experiments should be avoided. Ravan introduces a Vagus Therapy. This research found that daily use of Vagus Therapy can enhance sleep quality. In this experiment 90% accuracy was achieved by using SVM algorithm [12]. All the researches in assessing the quality of sleep are in order to make experiments cheaper and simpler. In this order only, in the year 2017, a mobile application was developed, which was capable to measure major factors even like heart rate also. In this experiment the architecture of the application system is divided into 4 parts (1) data collection, (2) pre analysis (3) application role & (4) result [13]. Most of the scientific researchers believe in the processing of EEG signals. Researchers suggest that EEG readings repeat itself at a particular intervals. Scientists call it Periodic K- alpha. Many scientific researches on these Periodic K-alpha confirm that these Periodic K-alpha are found in different patients in different diseases. Thus sleep quality index can be calculated with the help of Periodic K-alpha [14, 16, 17]. In 2011, research on narcolepsy patients considered that the Cyclic Alternative Pattern (CAP) is an important parameter in sleep quality assessment. Different CAP patterns were tested in all aspects of narcolepsy patients in this experiment.

Table 1: Summary of Literature Review

Types	Sensor/Technology Used	Assessment	Reference
Through Wearable Device	Bluetooth based EEG device, DAQ100	RAM takes 25% of total sleep, NRAM (5%, 45%, 45%, 13% of NRAM takes N1, N2, N3, N4 respectively)	[4]
	Theoretical framework of internet of things	A model is proposed to measure sleep quality	[6]
	EEG device, Force sensor	Deep sleep index formula is calculated	[8,14,16,17]
	10-20 system	Different gender, age shows different EEG pattern	[11,17]
	EEG device	CAP pattern is important parameter for sleep study	[14,16,17]

	EEG device	cyclic alternative pattern is found lesser in narcolepsy patient.	[14,15,17]
Through Self Operating Device	Grid of 24-GHz microwave radar, Linear discriminant function	79.3% accuracy to classify Sleep stages	[1]
	Force sensing resister, Logistic regression	>90% accuracy in classification	[2]
	Linear classifier, Load cell sensor grid	97% accuracy to classify leg and body movement	[1,3]
	Mathematical calculation of sleep index	modified sleep index formula	[5]
	Sonar measurement	>84% accuracy to classify sleep stages	[7]
	Sleep disorder breathing algorithm is written and implemented	93% accuracy to classify breath disorder	[9]
	A grid of 48 pressure sensor, KNN, logistic regression, SVM, random forest	86.7% accuracy to detect sleep posture, 95.2%, 94.9%, 94.7%, 95.8% accuracy obtained by KNN, logistic regression, SVM, and random forest.	[2,10]
	Vagus nerve therapy, SVM	90% accuracy to classify epilepsy patient	[12]
	Oximeter	System design concept	[13]

3.DATA SET AND EXPERIMENTAL SETUP

Any type of research is incomplete without data. The accuracy of the result of the research depends on the accuracy of the data used in that research. The accuracy of the data depends on the way it is collected. Many times, due to some technical fault during data collection, there are unknown changes in the dataset. To perform the research, the dataset can be collected or generated in two ways: first one, data collection by equipment, and the second one, previous collected data. Both processes have their own advantages. If someone wants to generate data, then many types of equipment will be needed such as 10-20 systems, EEG device, force sensors, computing system and video recorder, etc. Data generation method totally depends on which method is used in research. Some researches suggested collecting data in a very efficient and on a very low cost manner such as Sonar application method. To generate sleep dataset it is very expensive. Let's talk about previous collected dataset. The accuracy of the result of the research depends on the accuracy of the data used in that research. So it is important to use dataset of only a very authentic organization. Some authentic organizations that should be recommended here are:(1) National Sleep Research Resource (https://sleepdata.org) & (2) https://physionet.org/content/capslpdb/1.0.0/. Both organizations have better collection of sleep datasets. Now the question is how to access sleep data from any authentic organization? Considering National Sleep Research Resource, one should register first with some basic details, signature, verify email and then submit it. After 2 or 3 days one will get a mail with download link. Now talk about Physionet, this is open source and no need to register, there is a download button to access the data which is more than 40 GB. You can only download these files that you need in your research. The sleep pattern of Insomnia and Bruxism patients has been tested in this experiment. In this experiment the sleep patterns of 7 patients of Insomnia, 2 of Bruxism and 3 of No Pathology have been included. The aim of the research is to make sleep related experiments concise and easy. With this approach all 12 sleep pattern data sets in this research are divided into 4 time periods as follows - 12:00 - 1:20, 1:00 - 2:20, 2:00 - 3:20 and 3:00 - 4:20, namely slot1, slot2, slot3 and slot4 respectively. Each slot is referred to an input data. Their sleep patterns were tested by applying machine learning algorithms to data sets of different time intervals. The experiment uses machine learning algorithms - J-48, SVM, Naive Bayes, RF, K-Nearest Neighbour, logistic regression. Results accuracy was found to be different at different time periods. The WEKA tool has been used in this research work. This research follows following flowchart, given in figure 1.
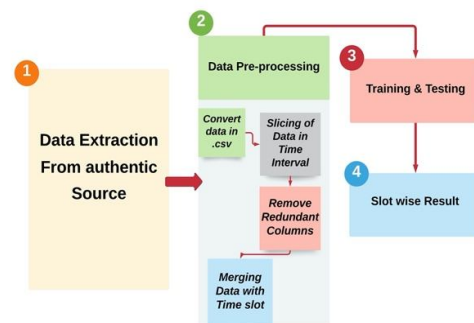

Figure 1: Experiment Flow chart

4.RESULT AND DISCUSSION

In this research work, facts have been tested using 6 machine learning algorithms. In this experiment, the daily time period of sleep is considered around 7:00 pm - 7:00 am. The sleep related data is divided into 4 slots. In this research, the importance of sleep quality testing for every time period has been analyzed. The result found that slot-1 (12:00 pm - 1:20 pm) plays an important role in improving sleep quality. Through this research it can be announced that the quality of sleep is dependent on slot-1. Therefore, sleep-related experiments need to focus more on slot-1 and not elsewhere. On the basis of this research, it can be proved that the radioactive effects caused by electrical impulses can be reduced to a great extent. Many researches analyse the dangers of radioactive effects arising due to electrical impulses [16, 17, 18]. This research will prove effective to reduce the effects of radiation and to make the experiments related to sleep quality brief and simple. The following results were examined through accuracy distribution graph related to sleep quality given in figure 2.
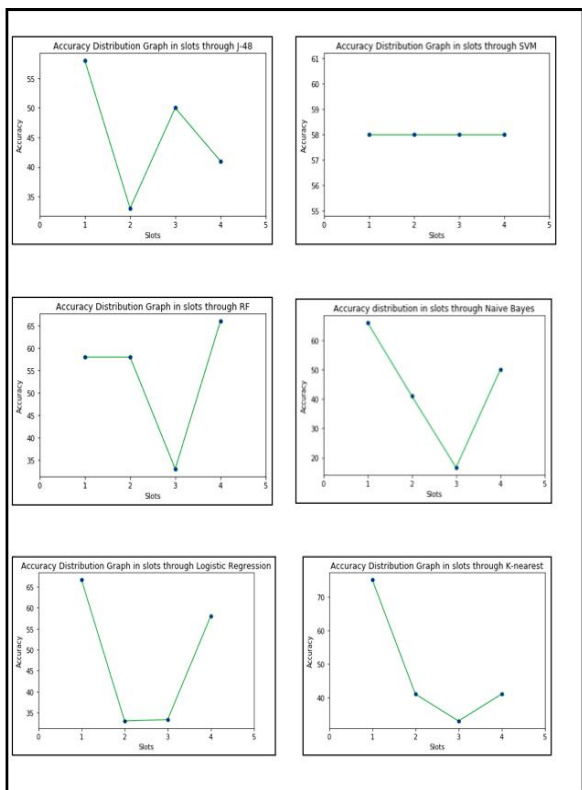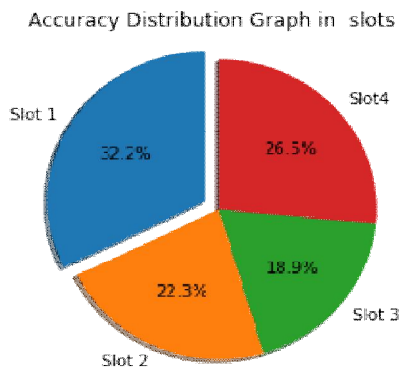
Figure 2: Accuracy Distribution in Sleep slots by Using J-48,SVM,LR,K-nearest,RF,Naive Bayes

Above figure 2 shows different machine learning algorithms show on an average same result of slot 1 have a crucial reason to measure quality of sleep. For better visualization of result, the accuracy distribution can be understood by taking average of all 6 machine learning algorithms in slots and draw a bar - chart as shown in figure 3 and Now considering 100 is the maximum buffer size then distribution of slot wise accuracy in buffer size can be drawn in pie chart in figure 4.
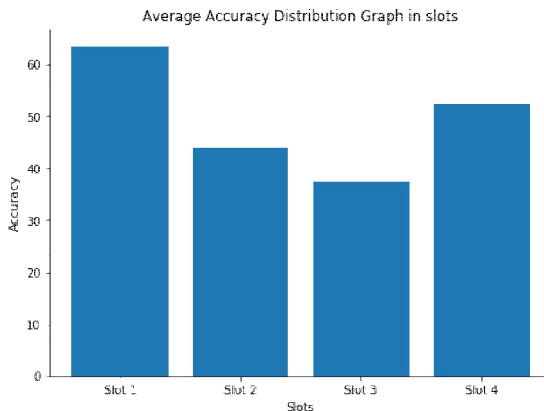
Figure 3: Average accuracy distribution graph in slots

Figure 4: Accuracy distribution graph in slots (Buffer size =100)

Obtained results (Table 2) through J-48, SVM, Naive Bayes, Random Forest, K-Nearest, Logistic Regression are shown in Table 2. The average results are 63.6%, 44%, 37.33% and 52.33% in slot 1, slot 2, slot 3 and slot 4 respectively.

Table 2: Combined Accuracy Results

Algorithm Name	Slot 1 Accuracy	Slot 2 Accuracy	Slot 3 Accuracy	Slot 4 Accuracy
J-48	58	33	50	41
SVM	58	58	58	58
Naive Bayes	66	41	16.66	50
RF	58	58	33	66
K-nearest	75	41	33	41
Logistic Regression	66.6	33	33.33	58

Some important statistics are also calculated to justify the result these are - Kappa coefficient (K), mean absolute error (MAE) and root mean square error (RMSE). To calculate Kappa statistics, the formula is used,

$$K = 1 - ((1 - P)/(1 - P'))$$

Where P is the absolute probability and P' is the expected probability of success rate of classifier. Through the Results, shown in table 3, it can be examined that except slot-1, rest have negative Kappa coefficient that means slot 1 have maximum accuracy to measure sleep disorder.

Table 3: Kappa coefficient (K) results

Algorithm Name	Slot 1 (K-coefficient)	Slot 2 (K-coefficient)	Slot 3 (K-coefficient)	Slot 4 (K-coefficient)
J-48	0.0769	-0.2468	-0.1250	-0.2174
SVM	0.0000	0.0000	0.0000	0.0000
Naive Bayes	0.4839	0.0345	-0.2000	0.1628
RF	0.1176	0.1304	-0.3333	0.3333
K-nearest	0.5385	-0.0909	-0.0787	0.0233
Logistic Regression	0.4353	-0.1294	-0.0667	0.2857

Now calculate MAE by using mathematical equation,

$$MAE = \frac{\sum_{k=1}^{n} |ExpectedValue_k - ObtainedValue_k|}{n}$$

Where n is total number of samples. Greater value of MAE means the slot have less accuracy and vice versa. That means,

$$MAE \alpha (1/Accuracy)$$

Results, shown in table 4, justify the importance of slot 1.

Table 4: Mean absolute error (MAE) results

Algorithm Name	Slot 1 (MAE)	Slot 2 (MAE)	Slot 3 (MAE)	Slot 4(MAE)
J-48	0.3823	0.5182	0.4192	0.4919
SVM	0.2778	0.2778	0.2778	0.2778
Naive Bayes	0.2378	0.3778	0.5473	0.3319
RF	0.3629	0.3953	0.4357	0.3320
K-nearest	0.2277	0.4033	0.4432	0.4041
Logistic Regression	0.2222	0.4166	0.4549	0.2763

Here the average MAE results are 0.2851, 0.3981, 0.4296 and 0.3523 MAE for slot 1, slot 2, slot 3 and slot 4 respectively as shown in figure 5. Slot 1 have minimum value of mean absolute error.
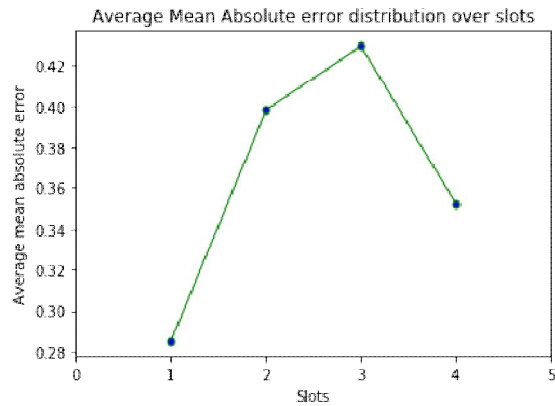
Figure 5: Average mean absolute error (MAE) distribution over slots

Now calculating RMSE by using formula,

$$RMSE = \sqrt{\frac{\sum_{n=1}^{N}(ExpectedResult_n - ObtainedResult_n)^2}{N}}$$

Where N is the sample size, results are shown in table 5.

Table 5: Root Mean square error (RMSE) results

Algorithm Name	Slot 1 (RMSE)	Slot 2 (RMSE)	Slot 3 (RMSE)	Slot 4 (RMSE)
J-48	0.4892	0.6406	0.5282	0.6060
SVM	0.5227	0.5270	0.5270	0.5270
Naive Bayes	0.4732	0.6044	0.7349	0.5659
RF	0.4287	0.4937	0.5165	0.4220
K-nearest	0.3752	0.5651	0.5969	0.5561
Logistic Regression	0.4714	0.6264	0.6576	0.5227

Here the average RMSE results (Figure 6) are 0.4607, 0.5762, 0.5935 and 0.5332 RMSE for slot 1, slot 2, slot 3 and slot 4 respectively. In figure 6 average RMSE graph tilts towards Slot 1 that means slot 1 have minimum RMSE and maximum accuracy.
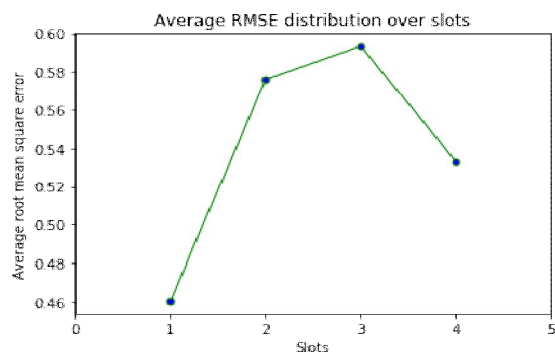
Figure 6: Average RMSE distribution over slots

With the help of statistical analysis it is proved that slot 1 have crucial importance to measure the quality of sleep.

5. CONCLUSION AND FUTURE SCOPE

Most of the people often ignore sleep-related diseases due to the time consumption, difficult and costly use of sleep related experiments. After scientific researches, it is believed that in this way, ignoring the importance of sleep is inviting many greater diseases [14, 16, 17]. Realizing the importance of sleep, in this research work, the attempt to summarize and simplify the experiments related to sleep has been made on the basis of testing of data over several time periods. This research has found that sleep quality can also be interpreted based on the data in slot-1. Thus, this research will prove effective to reduce the effects of radiation and to make the experiments, related to quality of sleep, brief and simple. In this research, works have been done to reduce the effects of radiation and to make experiments related to sleep quality compact and simple. In the future, the effort to make sleep related experiments more simple and concise will be based on Feature Extraction. This experiment has been successful in extracting important columns through the WEKA tool, but the results will be tested in future research.

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