Using Machine Learning to Determine Optimal Sleeping Schedules of Individual College Students

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Abstract. Sleep is one of the most important bodily functions for maintaining a healthy lifestyle, especially for teenagers and young adults. Though general guidelines for healthy sleeping habits for this age group are well documented, it is often difficult to know exactly what bed time, wake time, and total amount of sleep is best for a given individual based on their personal biological needs. Given this shortcoming in current sleep research, our goal is to create an algorithm that reliably classifies EEG sleep data in order to predict the optimal sleep schedule for an individual, specifically for a college student. In addition to this, we address the shortcomings of current sleep data by developing our own dataset of over 300 h of full night recordings for a single individual. Using this dataset, we implement and compare various ML models, and discuss limitations and areas of future work for prediction of optimal sleep.

Keywords: Machine learning · Supervised learning · Electroencephalogram (EEG) · Sleep research · Sleep data · Individualized healthcare · Optimal sleep duration

1 Introduction

1.1 Problem Statement

Sleep is a highly-important bodily function that helps maintain the health and general well-being of the human body. Additionally, sleep plays a major role in the development and well being of teens and young adults, a concept that has become significantly more recognized with the advancements in sleep research and analysis. For example, it has been observed that proper sleep provides various benefits, such as promoting growth, learning, and cognitive development, strengthening the immune system, and decreasing the chances of illnesses such as heart disease [6]. These benefits corroborate research which shows a strong correlation between high sleep quality and better academic performance, a factor which is without a doubt of great importance to many college students [23].

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The lack of sleep, on the other hand, is tied to various health concerns such as increased risk of obesity, increased probability of taking risk-taking behaviors, and overall detrimental effects to mental health [37]. Because of the importance of proper sleeping habits for teenagers and young adults, and especially for college students, it is necessary to determine what types of sleeping patterns are best for this specific demographic.

Plenty of research has already been done on this topic[1,2,8,16,21,24,32,33,35,36]. For instance, Chaput et al. [7] reports that young adults need more sleep than older adults. However, while these findings generally outline the optimal sleeping habits for teens and young adults, the specific needs for individuals vary depending on a large variety of biological factors as well as lifestyles. Additionally, since people naturally lead varying lifestyles, it is impossible for many individuals to follow the sleeping recommendations proposed for their demographic. College students notably fall under this category, since college life often encourages staying up to extreme hours to finish assignments and spend time with friends [12]. For the above reasons, it is necessary to devise a system that can diagnose the specific optimal sleeping patterns of an individual. Because of the usefulness such a system would provide to college students in particular, this study attempts to develop an algorithm to help college students determine their personalized optimal sleeping schedule.

1.2 Literature Review

When reviewing currently available sleep-related literature, it is apparent that such an algorithm to obtain individualized data for optimal sleep would be novel. This is seemingly the case because there is limited data available for the long-term study of an individual's sleeping patterns compared to other types of sleeping data. For instance, epidemiological data has shown chronically inadequate sleep in the general population, with various experts claiming the core sleep duration needed to be of 6 h [9]. This number has varied over the years, with a general consensus of 6 to 9 h of sleep needed by an individual [13]. However, there exists a lack of studies done on the specific sleep needs of individuals.

A sample of papers cited in Roy [32] and Craik [8] find that most sleeping studies use datasets consisting of various people whose sleep patterns are monitored for a shorter period of time. Studies such as Arnal et al. [5], Giri et al. [11], and Hou et al. [14] (and many others) have been done on sleep stage classification, the process of determining whether a person is either awake, in non-rapid eye movement sleep (NREM), or in rapid eye movement sleep (REM) at any given point during their sleep. These studies generally use Electroencephalography (EEG) technology coupled with deep learning (DL) algorithms to determine the sleep phase. Ansari et al. [4]. dives further into sleep stage classification, using EEG technology specifically with infants to help optimize their brain development during sleep. Additionally, Kemp et al. [17]. uses EEG technology to quantify how deep one's sleep is. However, because each of these studies utilize various participants with each participant studied for a shorter period of time, it is difficult to repurpose these datasets to draw conclusions pertaining to a single individual. In other words, there simply is not enough data available on any given individual to analyze their personal sleep patterns sufficiently.

Moreover, while there are a limited number of datasets available that include sufficient data for the individual to train an ML algorithm, these data sets are largely unusable for the purposes of this study. For one, because wearing EEG headsets for extended periods of time can be uncomfortable, these existing datasets are usually composed of individuals who are in critical condition and are being monitored for extended periods of time by hospital staff. Since these individuals have underlying health conditions and are generally not in the teenage and young adult demographic, their data cannot be used to train algorithms intended for the average healthy college student. Secondly, extensive data revealing a single-individual's sleeping patterns can be subject to privacy and ethical concerns. Ultimately, to the best of our knowledge, there currently exists no study which focuses on a long-term analysis of an individual, with the longest individual sleep recording from the aforementioned studies being of 3 weeks. We also reviewed the machine learning and deep learning algorithms for EEG classification to analyze our experimental data better [8,18,19,27,29,32].

1.3 Purpose of Study

For this reason, the purpose of the study is to generate long-term sleep data of a college student using a comfortable and non-intrusive EEG headset, and ultimately use the data to train a ML algorithm that can diagnose the college student's optimal sleeping patterns. If successful, the study would attempt to refine the algorithm such that it could be applied to other healthy college students to find their optimal sleeping patterns. As alluded to above, this study could be extremely beneficial to college students, since the knowledge of one's sleeping schedule can pay dividends on an individual's physical and mental health.

1.4 Research Question

Thus, the research question we intend to answer is: How can we use ML models and EEG technology to accurately detect an individual college student's optimal sleeping schedule?

2 Method

2.1 Dataset

The dataset used for this study contains 41 full nights of sleep data and was provided by an undergraduate college student (who will remain anonymous for privacy concerns). The college student is a 19 year-old Caucasian male from the United States, and is a generally healthy individual who maintains a healthy diet, drinks a sufficient amount of water, and frequently exercises. In additional to the clinical experimental devices [8,20,28], there are several consumer-grade non-invasive EEG headsets available at the time of the experiment [15,25,34]. The subject used a Muse S (Generation 2) headband for recording sleep sessions (see Fig. 1). The dataset includes a number of metrics for each of the 41 nights of sleep data. Specifically, bed time, wake time, time in bed, time asleep, sleep stages, sleep position, sleep intensity, heart rate, stillness, and a value of 1–100 representing the overall quality of a given night's sleep were recorded. Bedtime and wake time refer to the times at which the subject fell asleep and woke up for any given session, with time in bed being the difference between these two metrics and sleep duration being the amount of total time the subject was asleep. The sleep stage metric recorded the total amount of time the subject spent in each of the four sleep stages: awake, rapid eye movement (REM), light sleep, and deep. Sleep position refers to the amount of time the subject spent sleeping on each their left side, right side, back, and front. Sleep intensity measured the relative intensity of a given night's sleep. Stillness was determined by the total amount of time the subject was "active" and "relaxed" throughout the night. Lastly, the dataset includes a single statistic summarizing the quality of the subject's sleep for any given night, with a score of 75 translating roughly to an average night's sleep for the average person. This value is determined by the Muse headset's software, and is trusted to be a reasonably accurate numerical representation of the quality of a given session.

Fig. 1. Diagram of Muse S and sensors.

2.2 Note on Exportation of Dataset

When collecting data using the Muse S headset, the subject synced the headset with the official Muse mobile application, which provides an interface for viewing logged sleep sessions. In recent years, Muse removed the capability to export raw EEG files from the application, and provides no alternate method for recovering the raw EEG files. For this reason, the data that was presented in the Muse application was manually entered into a spreadsheet in .xlsx format. Thus, it should be noted that the data is preprocessed by the official Muse application.

2.3 Accessing the Dataset

For ease of reproducibility, the study's official GitHub page details the process of downloading the dataset. The page is available at https://github.com/ztgillette/optimal-sleep-algorithm.

2.4 Overview of Experimental Design

Using the set of an individual's sleep data, the intention of the experiment is to create a model that predicts the aspects of an optional night's sleep for that person. As described in the dataset section, bed time, wake time, time in bed, time asleep, sleep stages, sleep position, sleep intensity, heart rate, stillness, and a value of 1–100 representing the overall quality of a given night's sleep were recorded for a set of nights. Since a metric that represents the overall quality of sleep is provided, it is possible to apply machine learning algorithms to learn to classify certain ranges of sleep metrics with their corresponding sleep scores. In other words, machine learning can be utilized to learn what values for each of the sleep metrics correspond with better nights of sleep. Since these sets of values are determined to result in a better night's sleep, they are considered the desirable metrics that subjects would intend to emulate each night in practical use. However, given that certain metrics such as average heart rate, sleep intensity, and stillness are usually out of one's control during sleep, we are most interested in the relationship between bed time, wake time, and sleep duration and their corresponding sleep scores, since these metrics can be easily controlled by the subject. We are interested in aspects of the data that subject can control because the model can then be used as a tool to aid subjects in determining their best sleep practices. Thus, by analyzing the set of bed times, wake times, and sleep duration times that correspond to higher sleep scores, we can determine the bed times, wake times, and sleep duration that are most beneficial for the subject based on their given data.

2.5 Comparison of Algorithms

EEG data is a type of personalized time-series data [8,19,26]. In order to perform the experiment, the appropriate algorithm has to be selected to accurately determine which types of sleep data correspond with high sleep scores. Because the experiment requires selecting a known class for a collection of data, a supervised classification algorithm is ideal. A number of algorithms meet this criteria, including K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), and Decision Tree Classifiers, among others [18,29,30]. Two of the most common and widely discussed algorithms used when processing EEG signals are KNN and SVM. More specifically, both KNN and SVM have been extensively used and analyzed in previous work in relation to EEG signals, with a range of results from different studies. For example, Mousa et al. [22] demonstrates a relative higher accuracy and fidelity in the KNN model when used for EEG signals compared to the SVM model. However, Amancio et al. [3] shows a greater accuracy of SVM models in comparison to KNN models.

Generally speaking, the KNN Machine learning model takes a predefined number of K samples closest to a point and predicts the label from these. The number of K samples can be user defined and a constant, or can vary based on density of points. The distance between points is usually measured in Euclidean distance. As a supervised model, KNN first computes the K nearest neighbors through training, and then uses that training to predict the nearest neighbors for a given dataset, hence categorizing data points into the predetermined labels (see Fig. 1). While SVMs are also supervised machine learning models, their implementation varies from that of KNNs. SVMs work by projecting non-linear data onto higher dimension space (also known as the kernel trick). In doing so, SVMs make it easier to classify data. Through this process, an optimal boundary between possible output can be found. This allows the algorithm to figure out how to separate or classify the data based on defined labels or outputs (see Fig. 2). Additionally, LDA is a statistical model for topic modeling. Although this topic modeling algorithm is usually used as an unsupervised form of classification, often used for preprocessing of data, it can also be used as a supervised form of classification. More specifically, LDA uses matrix factorization to solve classification problems. LDA is especially useful when needing to reduce features of a higher dimensional space onto a lower dimensional space. Hence, it is able to reduce both resources and dimensional costs (see Fig. 3). Finally, a Decision Tree Classifier (DTC) is a tree-structured classifier, where internal nodes represent the features of a dataset, branches represent the decision rules and each leaf node represents the outcome. There exists two main types of DTCs, those which have a continuous target variable - Continuous variable decision trees - and those which have a categorical target variable - Categorical variable decision trees (see Fig. 4). Hence, this study focuses on how EEG data can be precisely categorized by comparing all four of the aforementioned ML algorithms in order to assess the best approach for further research in determining optimal sleep schedules.

2.6 Implementation of the Machine Learning Algorithms

We implement SVM, KNN, LDA, and DTC models for this study. All four of the ML models are implemented using the scikit-learn machine learning library, as noted in the provided repository. Additionally, some of the ML models are implemented using specific parameters. For instance, for the SVM algorithm, we implement a SVM model using a linear kernel, creating a single hyperplane to categorize sleep data into two categories: accurate and not accurate. Due to only needing one kernel for the two categories, we can maximize scalability and practicality in using a linear SVM as opposed to a non-linear SVM algorithm. Another specific parameter that we use is for the KNN algorithm, for which we implement a KNN model using $K = 5$ as the K value.

We implement all four of the ML algorithms using a train-test split of 80/20 (see Fig. 2). We run each model 100,000 times, each iteration with a new train-test set of data, and use the mean accuracy rate to determine the algorithm performance. The accuracy rate of a given algorithm is determined by comparing the predicted overall quality score with the actual overall quality score. If the predicted overall quality value is within a certain window, we deem the given prediction accurate. We coin this term the correctness window. For instance, a predicted sleep quality score of 83 with an actual sleep quality score of 85 would fit within a correctness window of 5, as 83 is less than 5 over or under the actual score of 85 (see Fig. 3). In order to analyze and test the four ML models, we utilize a correctness window of 7.5, deeming a predicted score within that window accurate.

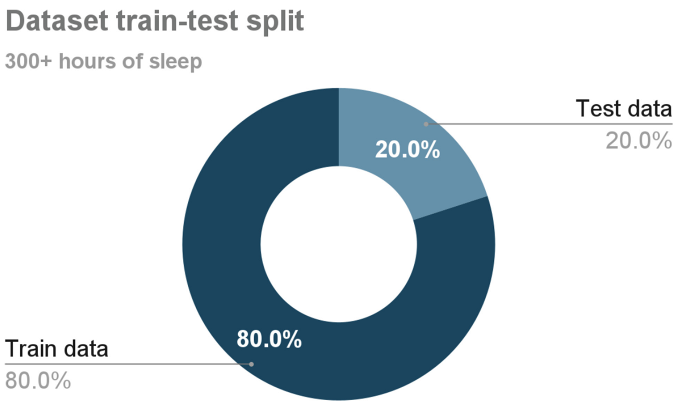

Fig. 2. The pie chart represents an 80/20 train-test split with over 300 h of sleep collected.

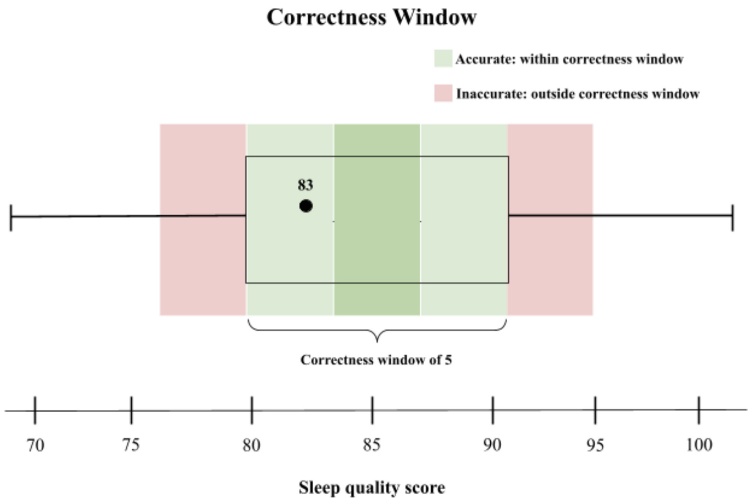

Fig. 3. Diagram of correctness window. A predicted sleep quality score of 83 with an actual score of 85 fits within a correctness window of 5. Hence, the predicted score is deemed accurate.

2.7 Effectiveness of the Machine Learning Algorithms

As indicated by Fig. 4, SVM is shown to be the most effective classification algorithm for our task with an accuracy rate of over 65%. The other algorithms follow in accuracy in descending order: KNN, DTC, and LDA, respectively. It is worth noting that neither ML model demonstrates a relatively high accuracy, being evident of a need for future research and the possible limitations of this study. This is further discussed in the Discussion and Conclusion. However, due to being the algorithm with the highest accuracy, SVM is used in the second part of this study.

2.8 Applying SVM

Given that SVM is shown to be the most effective classification algorithm for our task with an accuracy rate of over 65%, we select it for the task of determining the relationship between sleep metrics and their overall sleep scores. With the algorithm already trained from the previous phase of comparing the effectiveness of the algorithms on the dataset, the SVM algorithm is then used to generate the bed times, wake times, and sleep duration times that correspond to desirable sleep scores. Here, we consider "desirable" to be any sleep score that meets or exceeds a certain threshold determined by the user. In our results, we set this mark as a sleep score of 90, meaning that only bed times, wake times, and sleep duration times that resulted in a score of 90 or more would be considered in the final output.

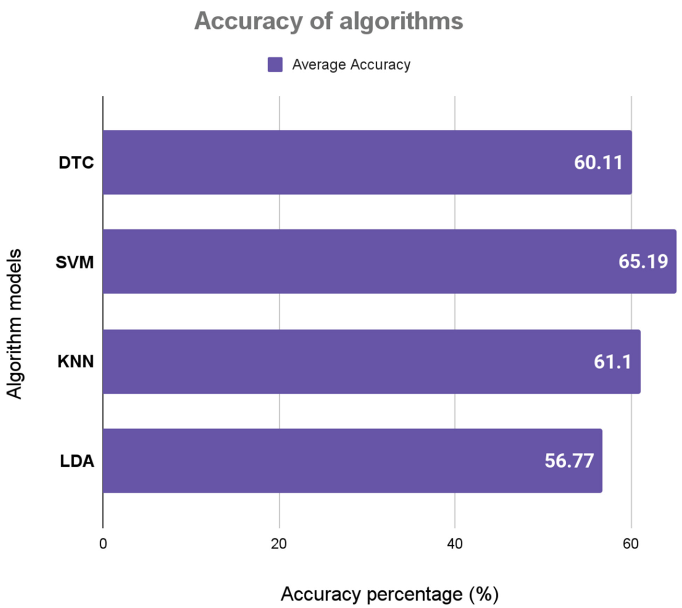

Fig. 4. Average accuracy of ML models based on a correctness window of 7.5; 100,000 total iterations.

To determine these sleep times, we first generated a set of 100,000 sample nights of sleep. Each sample night was set with data that was generated randomly using realistic values from the dataset. Specifically, for each category of data for any given sample night, a random value between the minimum and maximum for that value in the dataset was selected. By creating these 100,000 sample nights, we then could apply the trained SVM algorithm to determine which of the nights would be expected to yield a score of 90 or more. We filtered out sample nights of data that were not expected to reach an overall sleep score of 90, leaving only data that was expected to yield "desirable" scores. From this subset, we then considered only the bed times, wake times, and sleep duration values, and calculated their mean and median values. Presented in the figure below are the Sleep Prediction Results that were determined from the median values for each bed time, wake time, and sleep duration. Note, the results include a window of 15 min to provide a more logistically-attainable bed, wake, and sleep duration time.

3 Result

The predicted sleep schedule for the subject is as follows: 9 h and 30 min of sleep, with a bedtime of 1:00am with a precision of up to 15 min, and a wake time of 10:04 am with a precision of up to 15 min (see Table 1).

Table 1. Optimal sleep prediction results using a SVM classification model; 1000 iterations.

Sleep prediction results	
Optimal bedtime	1:00 AM + / – 15 min
Optimal wake time	10:04 AM + / – 15 min
Optimal sleep duration	9 h 30 min + / – 15 min

4 Discussion and Future Work

Based on the reasonable nature of our results given our dataset, as well as their correspondence with general sleep recommendations for teenagers and young adults, we believe that our algorithm is generally effective in predicting the optimal sleep schedules for teenagers and young adults. This can be compared to studies by Richards et al. [31] as well as Gillen-O'Neel et al. [10], which show that teenagers and young adults need approximately a little over 9 h of sleep.

However, we also believe that three specific improvements to our dataset would greatly improve the accuracy. Firstly, it would be greatly beneficial to collect additional nights of sleep data, since this would improve the ability of the SVM algorithm to accurately classify the sleep data with its overall sleep score. Specifically, we would like to curate upwards of 100 nights of sleep data.

On that front, a significant increase in the number of nights of data would make it possible to apply a deep learning algorithm such as CNN or RNN to the dataset. We refrained from implementing deep learning algorithms during this initial stage of research, since deep learning algorithms tend to require large amounts of data to be effective. In addition to opening the door to deep learning algorithms, adding additional nights of sleep data would also create the possibility that another machine learning algorithm (KNN, LDA, etc.) exceed SVM in accuracy. This is due to the general trait of machine learning algorithms of having varying accuracy rates depending on the size of the datasets. Secondly, it would be optimal to recruit additional subjects to partake in the study. An inherent limitation to the study as it has currently been performed is that only one subject was utilized. While our algorithm proved effective for our single subject, there is no evidence to say that such an algorithm would be effective if applied to an alternate set of sleep data from a different subject. For this reason, we intend in our future work to recruit 10–15 additional college-aged individuals so that the algorithm can be trained to be effective for generally for college students rather than for the single subject that was used in this initial stage of the experiment. Thirdly, we recognize that manually creating a dataset using preprocessed data from the Muse mobile application is neither a desired nor logistically sustainable approach for the future work of this study. For this reason, we have recently begun advising that our subject use a third-party application called Mind Monitor to record their nights of sleep, since the application allows for the raw EEG data from the Muse headset to be collected in DropBox and exported in a variety of file types.

In addition to the limitations posed by our dataset, we also want to address some potential limitations in our future work so that they can be avoided. We expect our primary limitation to be our ability to recruit additional subjects to partake in the study. One reason for this is due to the inconvenience of wearing the Muse headset while sleeping. While the Muse S headset is significantly more comfortable than other EEG-collecting head trackers, it is still an instrument that can be uncomfortable while sleeping. Additionally, since the Muse S is powered by rechargeable batteries, charging and/or battery issues often result in the headset not being fully charged when the subject desires to go to bed. Moreover, in order to get the most accurate EEG readings, it is necessary for the headset to maintain direct contact with the skin on one's head. This means that individuals with hair on the sides of their head may have significant trouble creating a sufficient connection between the headset and their skin, meaning that a close-cut haircut or a significant amount of nightly hair manipulation is necessary. In addition to inconveniences regarding the Muse headset, we also expect the length of the study to deter potential subjects. As noted in our discussion of the dataset, we plan to collect over 100 nights of sleep for each subject to ensure that the machine learning algorithms have sufficient data to train. Given that 100 nights is well over 3 months of commitment, we find it unlikely that college students would be willing to participate. An alternative that we have considered is using smart watches to track sleep data. This solution would provide a more comfortable and less invasive alternative to wearing Muse headsets. Additionally, smart watches tend to have longer and more consistent battery lives than the Muse headsets, meaning that charging-related issues would not pose as much of a barrier. Finally, due to their comfortable and easy-to-use design, it is more likely that college students would be willing to commit to months or potentially years of nightly data collection.

5 Conclusion

Given the importance of sleep in maintaining a healthy lifestyle, especially for teenagers and young adults, our research was focused on devising an algorithm to optimize sleep schedules on an individualized level. We created a dataset of over 300 h of sleep data for a single subject, and used that dataset to train four machine learning algorithms. We found that SVM proved most accurate in classifying our sleep data, and selected it as our algorithm of choice for determining the optimal bed times, wake times, and sleep duration times for the subject. Using SVM, we determined that based on the collected dataset, the subject's ideal bedtime was about 1:00am and ideal wake time was about 10:00am, with their ideal total sleep duration being around 9.5 h. While these results appear reasonable based on the dataset, we expect that a number of adjustments in our dataset would lead to increased precision. In our future work, we would like to record additional nights of data in our dataset, recruit 10–15 subjects to record nightly data, and use raw EEG data rather than preprocessed data. Ultimately, we hope that with this study we are able to provide a foundation for future work towards more accurate results, and towards more individualized sleep data collection and healthcare.

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