Visibility of Machine Learning Based Sleep Efficiency Prediction from Physiological Perceptions, Activities and Hormones

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***Abstract*—Sleep quality can be influenced by many things including psychological (e.g. anxiety status and stressful events) and biological (i.e. hormones) factors. Therefore we use machine learning to predict sleep efficiency by regression. Algorithm tested and trained with open source data Multilevel Monitoring of Activity and Sleep in Healthy people (MMASH) which contains 22 samples. The regression method used is multiple variable linear regression, decision tree, support vector regression, and k-nearest neighbor. The results obtained from the four methods are mostly negative R2 and large RMSE values. The conclusion still needs to be developed again to predict sleep efficiency with machine learning when viewed from physiological perceptions, activities, and hormones.**

Keywords*—*sleep efficiency, machine learning, regression.

I. Introduction

Sleep is important for human health, both physical and psychological. Sleep affects productivity, cardiac system, memory, emotional stability, and so on. Sleep disorders can indicate a serious health problem. The importance of sleep quality [1] can be seen from many factors, such as lifestyle changes [2], activities, even from a psychological perspective. Psychological disorders, such as anxiety, stress, and depression can be an indication that a person has a bad sleep quality. But, it can be two perspectives, having a bad sleep quality or having a sleep disorder can also contribute to a person's psychological disorders. About 3.6% or 260 million people in the world have anxiety disorders, and 4.4% or 322 million people have depression [3], especially women. And also, during the COVID-19 pandemic, the level of depression and anxiety is increasing[4].

Sleep disorders can also trigger the development of depression levels through changes in systems in the body, one of them is hormone. Changes that occur in the function of serotonin [5] and melatonin hormone related to the sleep activity can cause increased of stress, bother heart performance [5], and and make depression worse [6]. On the other side, activity also affects sleep quality too. High levels of physical activity such as exercise can improve sleep quality[6]. Therefore, an assessment of sleep quality will play a role in minimizing more serious sleep disorders..

To determine the pattern of activity that occurs during sleep, Polysomnography (PSG)[7] was used to collect several physiological parameters. In addition, PSG can be the gold standard[8] for diagnosing many sleep disorders such as apnea, hypoxia, and narcolepsy[7]. However, the many procedures carried out, the length of time, and the expensive services make PSG unable to be used every day, especially at home[9]. Recently, many technological developments, especially wearable devices for monitoring, have been

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developed. This can make the monitoring system easier and can be used every day.

Many methods have been used to detect the level of sleep quality from various factors. Many studies use the heart rate indicator as an influential indicator in the sleep stage [10-12]. From the previous explanation, we suggest that sleep quality or efficiency have correlation with a person's level of anxiety, activity, and the performance of hormones in the body. Machine learning is widely used to classify the level of sleep and the quality of a person's sleep. However, there are still several factors that can affect a person's sleep quality. In previous studies, Supervised machine learning, such as random forest[13], support vector machine (SVM)[14], neural network [12] and decision tree[15] was used to detect sleep stages. but for some data, the classifier method is not suitable to be used, so it is necessary to use other methods, such as regression.

In this study, we will use supervised machine learning using regression to predict sleep efficiency from psychological, activity, and hormonal factors during sleep.

II. Methods & Materials

A. Dataset

The dataset we use is titled Multilevel Monitoring of Activity and Sleep in Healthy People (MMASH) by Alessio Rossi, et al. published on June 19, 2020 on the website physionet.org [16]. MMASH provided 24 hours of continuous heart rate data, triaxial accelerometer data, sleep quality, physical activity, psychological characteristics (anxiety status, stressful events, and emotions), saliva biomarkers (cortisol and melatonin) and activity logs for 22 adult male participants. Utilization of the MMASH dataset in this study was to examine the correlation between anthropomorphic characteristics (ie age, height and weight), physical activity, psychological characteristics, and cortisol and melatonin levels in saliva with sleep efficiency.

In this dataset there are seven files from each healthy adult male subject, but in this study only five files and some features were taken. The five files and features used are:

- user_info.csv which contains the participant's anthropomorphic characteristics:
    - age (years).
    - height (cm).
    - weight (kg).
- sleep.csv which contains information on the duration and quality of participants' sleep:
    - Efficiency in terms of percentage of sleep time (minutes) to total sleep in bed (minutes).
- questionnaire.csv scores for all questionnaires:
    - MEQ: Morningness-Eveningness Questionnaire value. The chronotype score is ranging from 16 to 86:
        - Scores of 41 and below indicate Evening types.
        - Scores of 59 and above indicate Morning types.
        - Scores between 42-58 indicate intermediate types.
    - STAI1 and STAI2: State Anxiety value obtained from State-Trait Anxiety Inventory. The results are range from 20 to 80:
        - Scores less than 31 may indicate low or no anxiety.
        - Scores between 31 and 49 an average level of anxiety or borderline levels.
        - Scores higher than 50 a high level of anxiety or positive test results.
    - PSQI: Pittsburgh Sleep Quality Questionnaire Index. It gives a score rating from 0 to 21, with values lower than 6 indicating good sleep quality.
    - BIS/BAS: Behavioural avoidance/inhibition index. BIS/BAS scales are a typical measure of reinforcement sensitivity theory that establish biological roots in personality characteristics, derived from neuropsychological differences. The BIS/BAS scales comprise a self‑report measure of avoidance and approach tendencies that contains four sub-factors (A high score in one of the subscale describes the degree of that temperamental characteristic for the individual, according to the original sample):
        - Bis facet reflects subject sensitivity toward aversive events that promote avoidance behaviours.
        - Drive describes individual persistence and motivational intensity.
        - Reward corresponds to Reward Responsiveness that indicates a propensity to show a higher degree of positive emotion for goal attainment.
        - Fun corresponds to Fun-Seeking that is related to impulsivity and immediate reward due to sensory stimuli or risky situations.
    - Daily_stress: Daily Stress Inventory value (DSI) is a 58 items self-reported measures which allows a person to indicate the events they experienced in the last 24 hours. After indicating which event occurred, they indicate the stressfulness of the invent on a Likert scale from 1 (occurred but was not

stressful) to 7 (cause panic). It gives a score between 0 and 406. The higher is this values, the higher is the frequency and degree of the events and the perceived daily stress.
  - PANAS: Positive and Negative Affect Schedule. It gives a score rating between 5 and 50 for both positive and negative emotions. The higher is the PANAS value, the higher is the perceived emotion. Columns name with 10, 14, 22 and 9+1 refer to the time of the day when the questionnaire is filled in. 9+1 indicates the 9 AM of the second recording day.
- Activity.csv which contains lists the activity categories throughout the day. The categories are the activities listed below according to the numeric ID of each activity in the csv file :
  1. Sleeping.
  2. Laying down.
  3. Sitting, e.g. studying, eating and driving.
  4. Light movement, e.g. slow/medium walk, chores and work.
  5. Medium movement, e.g. fast walking and cycling.
  6. Heavy movement, e.g. gym, running.
  7. Eating.
  8. Small screen usage, e.g. smartphones and computers.
  9. Large screen usage, e.g. television and cinema.
  10. Caffeinated drink consumption, e.g. coffee or coke.
  11. Smoking.
  12. Drink alcohol.
- saliva.csv containing salivary concentrations of cortisol and melatonin are recorded before going to bed and immediately after waking. The concentration of melatonin is in µg per µg of protein, while cortisol levels are in µg per 100µg of protein. There are no concentration data for User_21 due to problems in the salivary samples that do not permit to analyze it.

In this study user_info.csv, questionnaire.csv, activity.csv, and saliva.csv as features or inputs, while the efficiency column from the sleep.csv file as the output.

B. Pre-processing

There are several empty cells in the data. We first handle the empty cells by calculating the mean of the feature. Then, inserting the means into the empty cells.

The second preprocessing step is to categorize some features. Morningness-Eveningness Questionnaire (MEQ) value indicates whether a person is a morning (0), an evening (2), or an intermediate type(1). State-Trait Anxiety Inventory (STAI) 1 and 2 is the value of state anxiety and range between 20 until 80. The STAI value indicates low to no anxiety (0), high anxiety (2), and average anxiety (1). There are two state anxiety recorded, the first (STAI1) is measuring the user anxiety at the time of the test and the second (STAI2) is measuring the general tendency for anxiety. Pittsburgh Sleep Quality Questionnaire Index (PSQI) is a measurement of the quality and patterns of sleep in the past month. It categorizes sleeping quality into good (0) and bad (1).

The last step of preprocessing is to normalize all the values except the categorized feature. It is done because the value range of each feature is different. The data is then preprocessed split into training data (80%) and testing data (20%).

C. Regression

Regression is a supervised machine learning technique to find correlations between existing variables, especially to predict continuous output based on one or more predictive variables. Regression analysis can help to understand the value of the target variable which changes with the predictor variable. This analysis is suitable for predicting continuous data, knowing the relationship between predictive and target variables, and knowing the important variables in predicting. There are several types of regression analysis, with different types of predictions. The regression methods used to predict sleep efficiency are:

1) Multiple Variable Linear Regression

   Multiple variable linear regression or multiple regression is statistical techniques that attempt to model the relationship between more than one variable and a dependent variable.

2) Decision Tree

   In regression using a decision tree, it learns local linear regressions approximating the sine curve. There is a max_depth parameter that represents the maximum depth of the tree. If it is set too high, the decision tree will study the training data in too much detail so that the noise is also read and an overfit occurs.

3) Support Vector Regression (SVR)

   In this method, from one or more predictive variables with target variables, SVR tries to find a hyperplane in multidimensional space or a line that separates these variables and predicts it. Kernel, hyperplane and decision boundary are important parameters in this SVR method.

4) K-Nearest Neighbor (kNN)

   The kNN regression algorithm will calculate the average of one value with k-nearest neighbor values to create a regression line. The value of k is the number of nearest neighbor values with a value or object that greatly affects the accuracy of the kNN method.

D. Performance Metrics

To evaluate the performance of each method, performance metrics are used. Commonly used metrics are the mean square error (MSE) and its rooted variant (RMSE), or the mean absolute error (MAE) and its percentage variant (MAPE). This paper uses RMSE that shows the best value when 0 and gets worse as its value increases. Because if only looking at one metric value does not describe performance [17], then the R-squared (R2) is used as well. R-squared indicates poor algorithm performance if it shows a negative value and a value between 0-1 if it is good.

These metrics are applied not only to test data but also to train data. The reason is that this regression is carried out on small data so that the possibility of overfitting is large.

E. Feature Importance

The search for feature importance aims to see the contribution of various trained feature data to the performance of the prediction model. Through feature importance, it can be obtained which features are most relevant and have a high impact on the model that has been made from the training data. In this study, feature importance linear regression, decision tree regression, and support vector regression algorithms were used to obtain features that have a high correlation and effect on sleep efficiency.

III. Result & Discussion

The correlation between sleep quality perception in chronic fatigue syndrome and sleep efficiency has been analyzed [18]. The effect of physical activity on sleep is examined [19]. Exercise has been shown to positively affect sleep and regular exercise moderately affects sleep quality.

Sleep efficiency is a continuous value from 0 to 100. For predicting continuous value we use regression analysis. The methods used in this paper are linear regression, decision tree, support vector regression (SVR), and k-nearest neighbor (KNN).

A. Linear Regression

TABLE I. Linear Regression Result

Type	RMSE	R2
Train Data	1.0899228028156506	1
Test Data	13.074611346310045	-3.1096120658110085

The model fits the training data perfectly and it is shown by the R-squared value of 1 and is backed up by the RMSE value of 1,08. But on the testing data the R-squared value calculated is negative, which means that the models doesn't follow the data trends. And the RMSE value is also very big compared to the training data.

B. Decision Tree

TABLE II Decision Tree Regression Result

Max depth	RMSE Training Data	RMSE Testing Data	R2 Score Training Data	R2 Score Testing Data
1	5.3145270883593705	9.010363695014595	0.2828461518329045	-0.9929007353543154
2	3.659765140327032	9.393006825411247	0.6628164392644742	-1.1688945619616744
3	1.9576318977424794	11.20652665191138	0.9023915576943409	-2.1215388481065762
4	1.1285482171495254	10.567443872573916	0.9681340750259606	-1.745783111920871
5	0.20962501534603017	10.13926032805155	0.9988674529324675	-1.518378079891828
6	0.0	10.923711823368466	1.0	-1.9479701335298731

At max_depth value of 6 or more, the algorithm shows "perfect" performance when used for training data. However, the performance on testing data did not improve and tends to deteriorate. It can be concluded that the algorithm is very overfitting.

All r2 scores on the testing data are negative, indicating a bad prediction algorithm. The r2 score that is closest to 0 when max_depth = 1 is at the same time the most balanced RMSE training & testing compared to the others. For this reason, this value will be compared with the performance of other methods.

C. Prediction using Support Vector Regression (SVR)

TABLE III. Support Vector Regression Result

SVR Kernel	RMSE Training Data	RMSE Testing Data	R2 Score Training Data	R2 Score Testing Data
Linear	3.94957360722426	9.737919431458803	0.5906101854055879	-1.2796890116317234
RBF	5.4673185183730615	8.337110115128597	0.21551370413349213	-0.6709918323836599

Polynomial	1.6567176965466415	11.150559227148387	0.9279666468188172	-1.9890731920819489
Sigmoid	6.1667510360651665	7.97853328964542	0.001956569745138914	-0.5303450909417986

By using different kernel parameters, linear, rbf, polynomial, and sigmoid show the RMSE and R-Squared values from the training data and testing data. The kernel polynomial parameter has the lowest RMSE value among other parameters taken at max_iter=19, but in the testing data, kernel polynomial parameter has the highest score than the others. In the R-Squared assessment, the values generated from several kernel parameters give negative values.

D. kNN

TABLE IV K-Nearest Neighbor Regression Result

K Value	RMSE Training Data	RMSE Testing Data	R2 Score Training Data	R2 Score Testing Data
1	0.0	10.519165366130528	1.0	-1.6610678201312394
2	3.6663068450898857	9.582062278027628	0.6474659656496718	-1.2073912954971449
3	3.774362388259572	7.597217253705464	0.626509082723709	-0.38784796098714613
4	4.064632245864027	6.738479335131925	0.5670673956799795	-0.0924136150516277
5	4.290135058891435	5.834322137146697	0.5178295523779725	0.18014790617938525
6	4.680131555047253	6.084403878405472	0.42637146127120024	0.10762041913947545
7	4.571134424622751	6.563723153260886	0.4535207408835648	-0.04014172432545593
8	4.628044794653951	6.123269206988207	0.4406479099025735	0.09353433636228997
9	4.673537942400374	6.08228667809796	0.43082792889069144	0.10381256211295098
10	4.792247345207366	5.995041042394954	0.4028473152115829	0.12672014791036512
11	4.930107618776445	6.363160365314605	0.36950786334677016	0.01497429507174225
12	5.117712749137034	6.504575916016526	0.32249035769278994	-0.03195878784966727
13	5.3097840015771	6.438461350059735	0.27277938412745784	-0.014844816597557542
14	5.5837271430938875	6.462221118602667	0.19765576878818403	-0.026249514346174063
15	5.784103197896936	6.860513433976921	0.14148702683926573	-0.15821029659003466
16	5.980050697269361	7.234799785045023	0.08494524880694243	-0.2899466497675438
17	6.259646396593072	7.353390049828278	1.6653345369377348e-16	-0.3373270300550051

The kNN method uses k values in the range 1-17 because the k value cannot be bigger than the number of existing samples. At the value of k=1 for the training data, the best RMSE and R2 values are obtained, but for the test data, the highest RMSE value is obtained and the R2 value is negative. Based on the repetition of the kNN method for different k values and using a grid search, it is obtained that the value of k=10 is the most optimal k value. This can be seen from the RMSE at the smallest value and the highest and positive R2.

E. Comparing Regression Method

To see the predictive ability of each method, we compare the best rmse and r2 scores for data testing.

TABLE V. Performance Comparison

Method	Best RMSE	Best R2 Score
Linear Regression	1.0899228028156506	-3.1096120658110085
Decision Tree	9.010363695014595	-0.9929007353543154
SVR	1.6567176965466415	-0.5303450909417986
kNN	5.995041042394954	0.12672014791036512

The interpretation of RMSE has to consider the range value of the output. The range of sleep efficiency in the dataset is from 73.49 to 94.23. The real range of sleep efficiency is from 0 until 100. The best RMSE from each method is variative. The RMSE value 9 means that the distribution of error is still big compared to the range of the output. RMSE value decreases as more data is introduced to the model this is because the model has more information for the prediction and resulted in more precise estimation.

The best value of R2 for each method, except kNN, is negative. That is, the trend of the predicted results does not follow the original value. This can be an indication of an overfit due to the small amount of data. There is research which states that the smaller the value of the data sample, the smaller the r2 value[20].

F. Feature Importance and Correlation between Features

Feature importance plays a role in showing the predictive value of how features play a role in predicting the target variable. To understand the data more deeply, correlations between variables and features are used in the form of a heatmap (Figure 1). Using Pearson's correlation, giving r value between -1 and 1 to know the correlation between two features. When r-value = 1 or have positive correlation that means, when one variable increases, the other variable also increases. Opponent with positive correlation, negative correlation or r-value = -1, when one variable increases, the other variable decreases. When the r-value = 0 means no correlation between them. . It was found that there are several features that have a positive correlation such as the Melatonin NORM after and Cortisol NORM after features, panas_pos_14 and panas_pos_18, and panas_pos_9+1 and panas_pos_10. The features of melatonin NORM after and Cortisol NORM after are related to hormones that occur during sleep, while heat_pos is related to emotion[16] and anxiety [21].

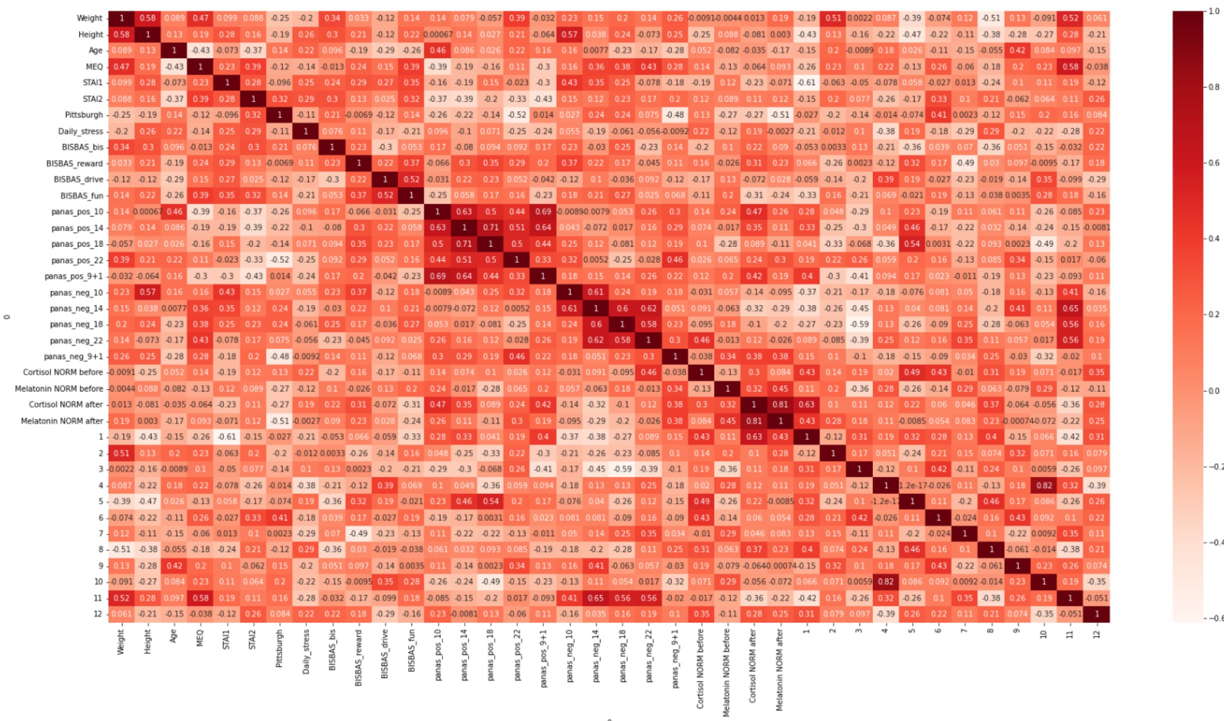

Fig. 1. Correlation

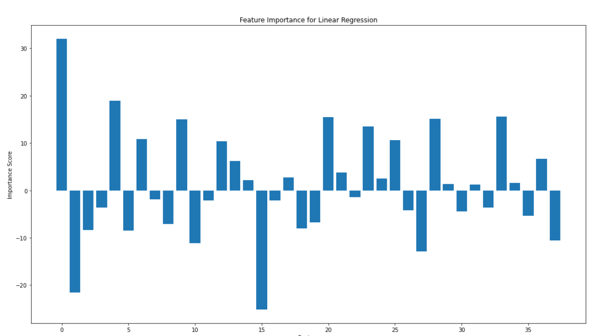

Fig. 2. Feature Importance for Linear Regression

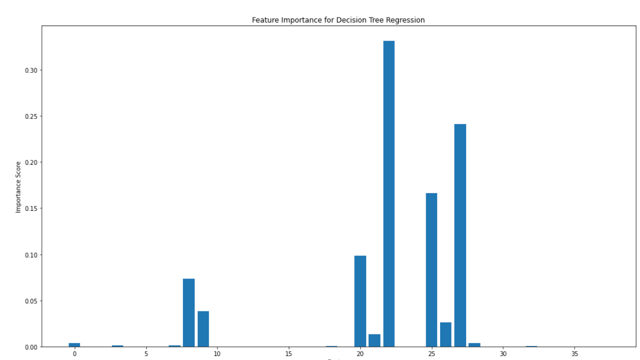

Fig. 3. Feature Importance for Decision Tree Regressor

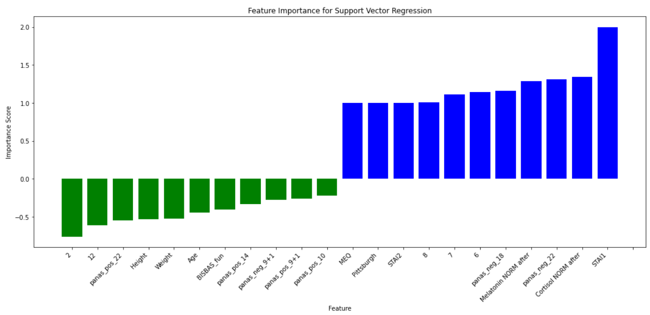

Fig. 4. Feature Importance for Support Vector Regression

For a regression model using linear regression, the results of the predicted values can be seen in the figure Fig. 2. There are three top features that have the highest values, feature ‘weight’, ‘STAI1’, and ‘activity number 8’. Feature importance of the decision tree regression method is shown in Fig. 3. The three features with the highest importance value are 'Cortisol NORM before' with a value of 0.33128, 'Melatonin NORM after’ with a value of 0.16599, and activity 'activity number 2’ with a value of 0.24139. The feature importance of the support vector regression method is shown in Fig. 4. The three features with the highest importance value are 'STAI1', ‘CORTISOL NORM AFTER' and 'panas_neg_22'.

According to several studies, sleep duration has an effect on weight [22]. According to the value of The Pittsburgh Sleep Quality Index (PSQI) Questionnaire, people who have sleep duration > 7 hours can experience significant weight loss than people who have sleep duration of 7 hours or less[22]. Bidulescu et al [23], analyzed the association between PSQI scores and an increase in Body Mass Index (BMI). In addition, sleep duration and sleep disturbance lead to increased obesity.

The State-Trait Anxiety Inventory (STAI) shows a relationship in linear regression method which indicates the level of anxiety. STAI1 has the second highest predictive score on the MMASH data with 18,95830 score. Several studies state that the level of anxiety affects the quality of sleep [24, 25]. Recent study shows that anxiety affects sleep quality with evening chronotype students having poorer sleep quality than morning chronotype students[26].

Then, in third place, activity 8 has an importance score = 15,54831. In MMASH data, activity 8 describes small screen usage activities, such as smartphones or computers. Previous studies have also shown that the use of smartphones before bed and exposure to light [27, 28] for more than 1 hour causes poor sleep quality[29]. The placement of a mobile phone near the pillow while sleeping also has a considerable influence on the quality of sleep[28].

Containing salivary concentrations of cortisol and melatonin are recorded before going to bed and immediately after waking. Larger changes in cortisol levels between sleep onset and awakening, reflecting a healthier circadian rhythm of the Hypothalamic-Pituitary-Adrenal (HPA) axis, were associated with better subjective sleep quality, but not with objective sleep quality [30]. HPA axis activity is usually assessed by the circadian rhythm of the eventual hormone, cortisol, and several studies exist linking variations in diurnal cortisol secretion patterns with sleep behavior [31]. HPA axis dysfunction, has consistently been shown to impact physiological and mental health, thus presenting a pathway that contributes to the effects of poor sleep on health [31]. Smaller changes in nocturnal cortisol were associated with lower subjective sleep quality than objective. sleep quality [30].

In humans, the primary physiological function of melatonin is to reinforce darkness-related behaviour, such as sleep propensity [32]. Endogenous melatonin synthesis is finely regulated by visual light cues received by the hypothalamic suprachiasmatic nucleus in the brain, the site of the major circadian oscillator. During daylight hours, perceived light signals inhibit melatonin production. Conversely, at night when no light signals are received, melatonin synthesis and release occur with levels peaking in the early hours of the morning [32]. Thus, the high levels of melatonin at night before sleep is a signal that the body should sleep or rest.

The intensity of physical activity is related to how hard our body works while doing that activity. Physical activity is considered an effective, non-pharmacological approach to improve sleep [33]. In addition, physical exercise is recommended as an alternative or complementary approach to existing therapies for sleep problems [33]. The intensities of activity need to be taken into consideration when elaborating the relationship between PA and sleep quality [33]. 'Activity 2' in the database is laying down with a low intensity of activity other than sleeping, when a participant is laying down then that person is in a resting state. So this activity has a high enough influence on sleep efficiency.

Positive and Negative Affect Schedule (PANAS) is questionnaires to record levels of positive and negative affect. The ‘panas_neg_22’ feature is the value of emotional and negative feelings of the participants at 22.00. Positive affect, negative affect, and emotion regulation strategies are related to sleep quality [34]. Emotion regulation can also act as either a protective factor against the development of psychopathologies, or as a risk factor for their development, and therefore may be one mechanism linking mental health and sleep [34]. Negative affect and expressive suppression were positively correlated with PSQI score suggesting that as negative affect and expressive suppression use increased, sleep quality decreased [34].

IV. Conclusion

The prediction from four different machine learning methods resulted in poor prediction of sleep efficiency. This can be seen from the value of R-squared and RMSE of each method. One of the reasons for this is the data used in predicting sleep efficiency is a small dataset with only 22 samples and makes it easier for the model to overfit the testing data. The top three feature importance from linear regression, support vector regression, and decision tree has different results. This means that sleep quality has a lot of variables to it. By using a large feature to predict sleep quality, they will have varying impact on the prediction based on the methods used.

For future work, in order to use machine learning methods for predicting sleep efficiency, the dataset needs to be added, especially the variation of the output data. Making synthetic data can be one of the solutions for this.

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