Sleep and At-Risk Health Behaviors among Adolescents

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Abstract

Sleep deprivation has been reported to have detrimental consequences on health and is overall linked to poor human functioning. Based on the evidence of previous research, insufficient sleep is highly prevalent among adolescence. This data mining project aims to investigate sleep deprivation and its' linked to several aspects of health among a nationally representative high school student. YRBS datasets published in 2015, 2017, and 2019 were used to examine the relationship between sleep and health risk behaviors and conditions related to depression, being bullied, unhealthy dietary behavior, academic performance, and physical activity. Several data mining techniques including logistic regression, decision tree, random forest, and ripper were utilized to predict sleep deprivation using Python, Weka, and Matlab. Based on the results, nearly three out of four US high school students (%76) did not get sufficient night sleep and sleep-deprivation was associated with several health-risk behaviors and conditions. Moreover, given the findings of several machine learning algorithms, the performance of logistic regression was the best and it achieved 80% of predictive accuracy. Findings could offer implications for public health and policy as adequate sleep is a critical factor for promoting health and reducing dysfunctional behaviors among adolescents.

Keywords: *sleep, adolescence, at-risk behaviors, data mining, YRBS*

1. Introduction

As an essential part of life routine, sleep is necessary for major restorative bodily processes and optimal functioning in life (Wang et al., 2020). While adequate sleep is critical for healthy development and functioning, insufficient sleep has detrimental effects on various aspects of health and is associated with a wide range of undesirable outcomes. A growing body of literature documenting the negative consequences of sleep deprivation on health and life outcomes including poor physical health (Knutson, 2013; McKnight-Eily, 2011), mental health problems (Beebe, 2011), low academic performance (Moore & Meltzer, 2008) and social and behavioral dysfunctions (Ireland & Culpin, 2006; Robert et al., 2008).

Sleep is crucial at all life stages starting from the earliest year in life to late adulthood. The amount of sleep, however, needed for healthy functioning varies in each life stage and declines with age. In other words, the required amount of sleep changes and decreases from childhood to adulthood (Ohayan et al., 2004). As one of the critical life stages, adolescence is the transitioning period from childhood to adulthood and is the stage for major growth-related changes such as physical growth, cognitive and sexual maturation, and socio-emotional functioning. As a result, getting the adequate sleep needed during adolescence is vital for healthy development.

The National Sleep Foundation and the American Academy of Sleep Medicine (AASM) recommends 8 hours as the minimum amount of sleep for adolescence (National Sleep Foundation, 2006). Although maintaining an average of 8 hours night sleep is recommended, the shift from childhood to adolescence has been reported to result in an increased lack of sleep (Roberts et. al., 2009). More specifically, existing research investigating sleep among adolescence reveals that only one out of three high school students have more than 8 hours of night sleep (Kann et. al., 2013).

Statement of the Problem

Given the importance of adequate sleep for healthy physical, cognitive and socio-emotional development, the high prevalence of sleep deprivation among adolescence leaves them vulnerable and puts them at risk for engaging in unhealthy behaviors. For example, lack of sufficient sleep among adolescence has been reported to associate with increased violence-related behaviors (Hildenbrand et al., 2013), higher chances of substance abuse (O'Brien & Mindell, 2005), depressive mood, and suicidality (Do et al., 2013; McKnight-Eily. 2011), being physically less active (Foti et al., 2011), difficulty with managing attention and regulating emotions (Wolfson et al., 1995), unhealthy dietary behavior (Cauter & Knutson, 2008; Lowry et al., 2012; Nielsen, 2011), and low academic performance (Dewald et al., 2010).

The majority of these studies revealing the consequences of sleep deprivation are not without limitations such as a small sample size that lack socio-demographic diversity. To raise awareness on the adverse consequences of sleep deprivation and call for public-wide support, documenting the negative outcomes of adolescent sleep deprivation using a recently published large and nationally representative large dataset is necessary. Thus, this data mining project will contribute to the existing literature on adolescent sleep utilizing data mining algorithms and techniques to explore and search for interesting relationships between sleep and in a nationally representative large dataset. The findings of the study could better inform scientific and public effort in order to promote healthy sleep routines among adolescence.

Purpose of the Study and Research Questions

The purpose of this study is to examine how sleep deprivation is linked to at-risk health behaviors and conditions including violence, tobacco and substance use, sexual activity, dietary behavior and physical activity among a large nationally representative US high school student sample. More specifically, we aim to employ data mining methods for the identification of students' at-risk behaviors as a result of sleep deprivation using Youth Risk Behavior Survey (YRBS) published in 2015, 2017 & 2019. The following two research questions are explored in this data mining project

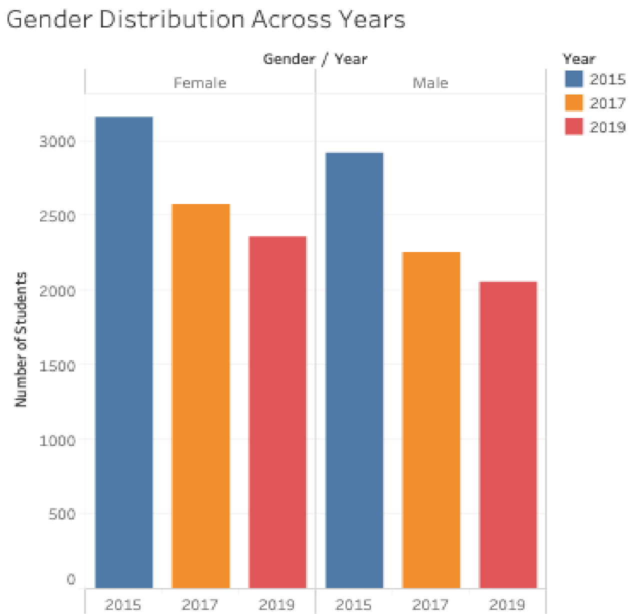
1. Which at-risk health behaviors and conditions that are linked to insufficient sleep?
2. What are the best data mining methods for detecting and predicting at-risk health behaviors significantly linked to insufficient sleep?

2. Methodology

Sample

The YRBS is a biennial, national survey of US high school students and the sample of the study consisted of a total of 15,307 US high school students who took part in the most recent three YRBS published in 2015, 2017, and 2019. More specifically, the sample is formed by 6,074 high school students who completed the YRBS in 2015, 4,824 high school students in 2017 YRBS, and 4,409 students who participated in the 2019 YRBS (see Figure 1).

Figure 1. Gender distribution across three YRBS datasets

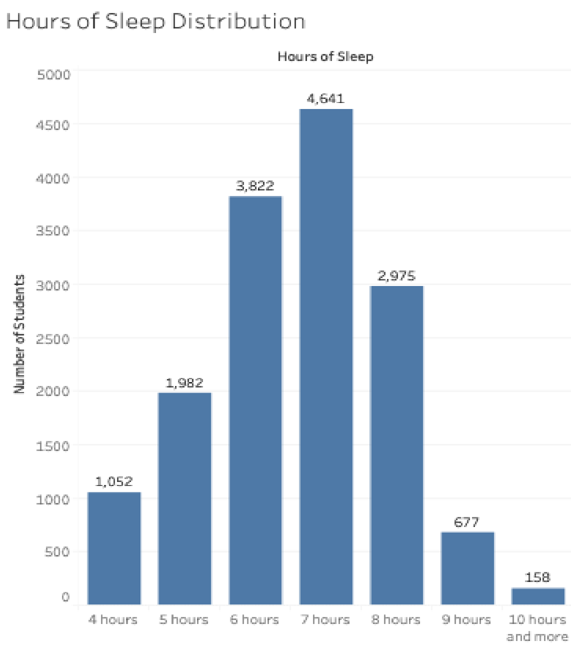


Instrument

The instrument of the project, the YRBS, was developed by the Centers for Disease Control and Prevention in 1991. YRBS contains questions assessing six major at-risk health behaviors linked to (1) injuries and violence, (2) sexual behaviors that cause teenage pregnancy and sexually transmitted diseases, (3) alcohol and drug use, (4) tobacco use, (5) unhealthy dietary behaviors, and (6) Inadequate physical activity.

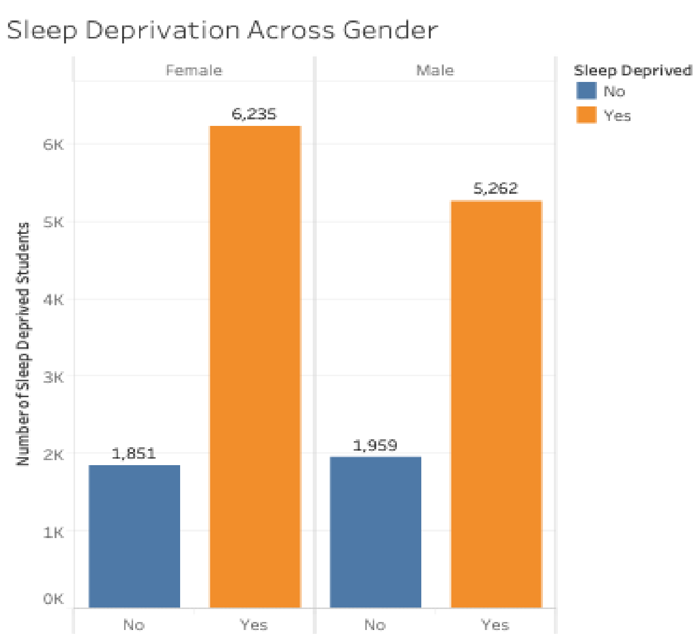
As the independent variable of this study, sleep duration was first included in the 2007 National YRBS, and later the sleep question was added to the standard high school questionnaire in 2015. Sleep was assessed by the following question: *"On average school night, how many hours of sleep do you get?"* with seven possible hours responses ranging from *4 or fewer hours* of sleep to *10 or more hours* (see Figure 2 for the response to the sleep question).

Figure 2. Students' responses to the sleep question



The responses to the question were dichotomized into two categories as less than 8 hours of sleep (sleep-deprived) and 8 hours and more sleep (not sleep-deprived) (see Figure 3).

Figure 3. Sleep deprivation across gender



Note: 8 hours of sleep is the cut-off value as recommended by AASM.

Data Preprocessing

Data preprocessing was performed in MATLAB according to the following procedure:

1. The following attribute modifications were made:
    a. A ‘year’ attribute was appended as the last attribute of each dataset, storing the original survey year for all records.
    b. The ‘site’ and ‘orig_rec’ attributes were deleted from all three data sets, as both contained no useful information.
    c. The ‘raceeth’, ‘q6orig’, and ‘q7orig’ attributes were deleted from all three data sets, as their data is redundant to that in q4 through q7.
    d. Additionally, question attributes which were not present in all three datasets, with identical wording and response possibilities, were deleted, as displayed in Table 1 below:

Table 1. Comparison of deleted data attributes

2015	2017	2019
19: Injurious physical fight	**20**: Sexual violence	**20**: Sexual violence
32: Initiation cigarette use	**31**: Initiation cig. smoking	**31**: Initiation cig. smoking
35: Cigarette source	**34**: E-vapor product use	**34**: E-vapor product use
41: Ever alcohol use	**40**: Ever alcohol use	*no similar replacement*
8: Bicycle helmet use	**84**: Concussion	**83**: Concussion
no similar replacement	*no similar replacement*	**85**: STD testing
90: Usual use of marijuana	**90**: Driving on marijuana	**90**: Current pain med. use
97: Sunburn	**97**: Sunburn	**97**: Sunscreen use

2. The remaining columns of the 2015 and 2017 datasets were permuted into the same order as the 2019 dataset, as shown in Table 2 below:

Table 2. Permutation of datasets into 2019 question order

2015	**2017**	**2019**	**2015**	**2017**	**2019**	**2015**	**2017**	**2019**
1-7	1-7	1-7	24-31	23-30	23-30	57	56	49
9-13	8-12	8-12	33-34	32-33	32-33	50-54	49-53	50-54
15	13	13	40	35	35	56	55	55
14	14	14	39	36	36	58-84	57-83	56-82
16-18	15-17	15-17	37-38	37-38	37-38	85	85	84
20-21	18-19	18-19	36	39	39	86-89	86-89	86-89
23	21	21	42-49	41-48	40-47	91-96	91-96	91-96
22	22	22	55	54	48	98-99	98-99	98-99

3. All records which did not have a value for every attribute were deleted. This process retained 5106 of 15624 records from 2015, 4364 of 14765 records from 2017, and 4080 of 13677 records from 2019, for a total retention of 38.66%.
4. Seven questions had their response values of permuted into the order "Yes; No; Not Applicable," so that they could be classified as ordinal, rather than categorical:
    a. q29: Injurious suicide attempt (N/A; Yes; No → Yes; No; N/A)
    b. q39: Quit tobacco (N/A; Yes; No → Yes; No; N/A)
    c. q62: Alcohol or drugs and sex (N/A; Yes; No → Yes; No; N/A)
    d. q63: Condom use (N/A; Yes; No → Yes; No; N/A)

e. q84: HIV testing (Yes; No; Not Sure → Yes; Not Sure; No)

f. q87: Asthma (Yes; No; Not Sure → Yes; Not Sure; No)

g. q94: Food allergies (Yes; No; Not Sure → Yes; Not Sure; No)

5. Seven questions with non-serializable categorical data were hot-encoded:

   a. q5: Race (five non-exclusive responses)

   b. q36: Electronic vapor product source (eight mutually exclusive responses)

   c. q44: Alcohol source (eight mutually exclusive responses)

   d. q64: Birth control method used (eight mutually exclusive responses)

   e. q65: Sex of sexual contacts (two intersecting categories)

   f. q66: Sexual identity (two intersecting categories)

   g. q68: Weight change goal (four mutually exclusive responses)

This procedure resulted in a tidy analytical data set which has 15308 records and 124 attributes (72 numeric data attributes, 45 Boolean data attributes, 4 statistical attributes, 2 unique identifier attributes and 1 numeric-ordinal class attribute).

3. Results

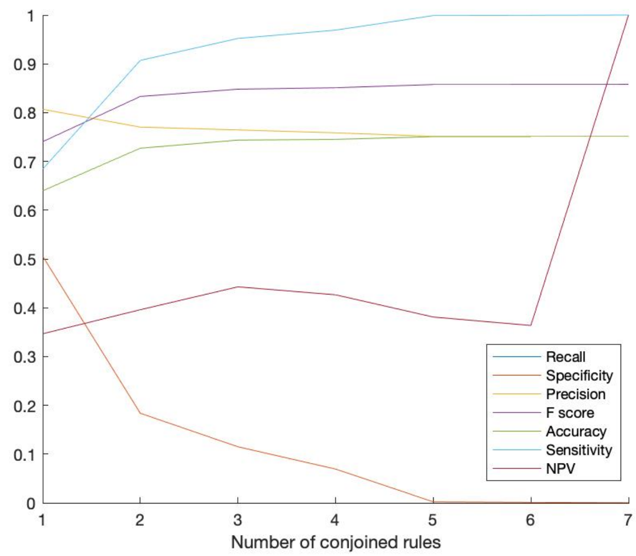
The four machine learning algorithms used to explore sleep and its linked to several at-risk health behaviors and conditions were reported below.

RIPPER

A RIPPER algorithm was written in matlab to create a ruleset that prioritises the detection of the minority class. The data set was reduced to feature the key questions identified as features, and the responses to the question on sleep was modified to a binary label for those who received less than 8 hours of sleep a night (the majority) as class 0 and those who received 8 hours or more a night (the minority) as class 1. The ruleset added new rules based on Information Gain, and covered all minority classes within 9 concatenated rules. A 10-fold validation was performed, and the length of the ruleset was pruned to maximise the Negative Predictive Value (NPV). NPV is calculated by examining the ratio of True Negatives (TN) to the sum of False Negatives (FN) and TN.

$$NPV = TN/(FN + TN) \tag{1}$$

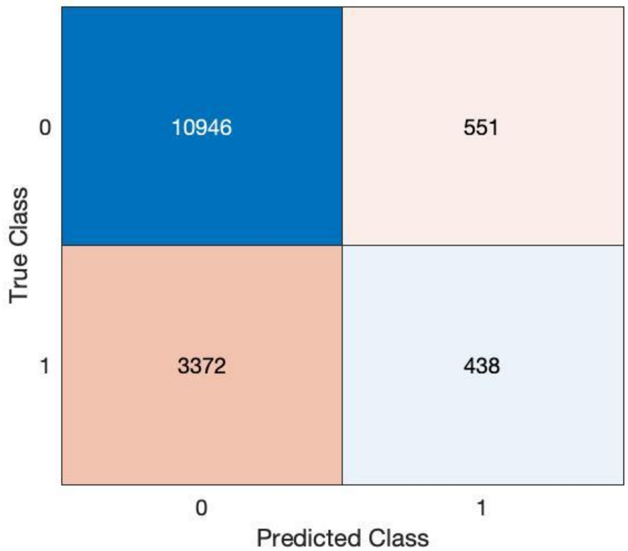
Figure 4. Ripper performance metrics calculated with 10 fold validation.



Note: Values are calculated each time a new rule is added to the ruleset.

The metrics for the RIPPER algorithm show a divergence as the length of the ruleset gets longer. This is consistent with results performed by RIPPER on noisy datasets. The NPV value is maximized at 3 conjoined rules before decreasing. It jumps to a maximum of one at seven conjoined rules because the algorithm only identifies one true negative, and zero false negatives (the minority class has been covered).

Figure 5. Confusion matrix of final RIPPER algorithm results from MatLab.



Note: Individuals getting less than 8 hours of sleep are classified as label=0, and individuals receiving 8 or more hours of sleep as label=1.

These metrics were compared to results obtained from Weka on the same data set, and our algorithm performed with similar results. In each case only two rules were built, one to label the minority class, and the other defaulting the majority. Each used a 10-fold cross validation, and achieved very similar results as seen in Table 3. Our algorithm maximized the NPV, and with it we were actually able to accurately identify a larger percentage of the minority class: 11.49% vs 4.25%.

Table 3. Ripper results and related metrics

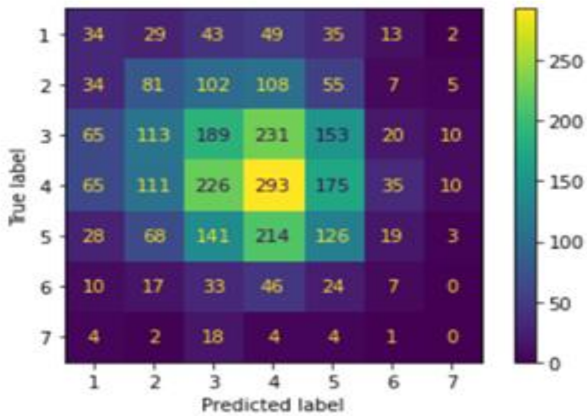
Ripper Results:		
Label	***Value (Matlab Results)***	***Value (Weka Results)***
True Positive (TP)	10946	11287
True Negative (NP)	438	162
False Positive (FP)	3372	3648
False Negative (FN)	551	210
Kappa	0.1109	0.0459
Accuracy	0.7437	0.7478
Precision	0.7645	0.7547
Recall	0.9521	0.9817
F Score	0.8480	0.8540
NPV	0.4429	0.4355

Decision Tree

Decision tree is one of the most common models and powerful algorithms in machine learning. Therefore, it was trained on the YRBS data using sklearn.tree. DecisionTreeClassifier function in a Jupyter Notebook. The data set was reduced to only 26 attributes (q2, q23, q24, q25, q26, q27, 28, q35, q39, q41, q45, q58, q60, q61, q66_1, q66_2, q68_1, q68_2, q68_3, q77, q78, q79, q80, q88, q89, q98) based on the theoretical relation and correlation values with q88 (sleep question). And all the instances 15307 were used in this model. The data set was splitted into training data set 80% and test data set 20% using “sklearn.model_selection.train_test_split” from Scikit_learn.

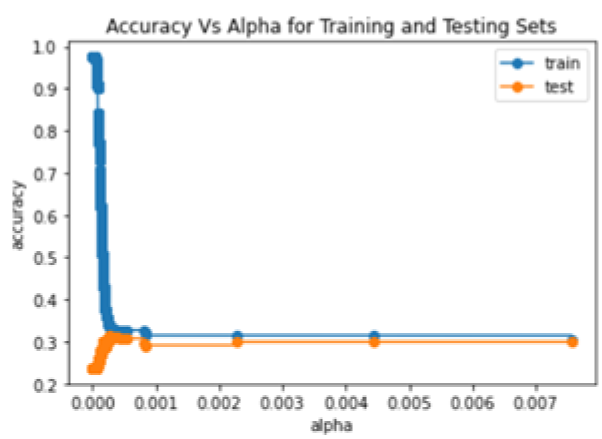
The confusion matrix of the decision tree as shown in Figure 6 shows how bad the model performed, and the decision tree needs to be pruned.

Figure 6: Decision tree confusion matrix



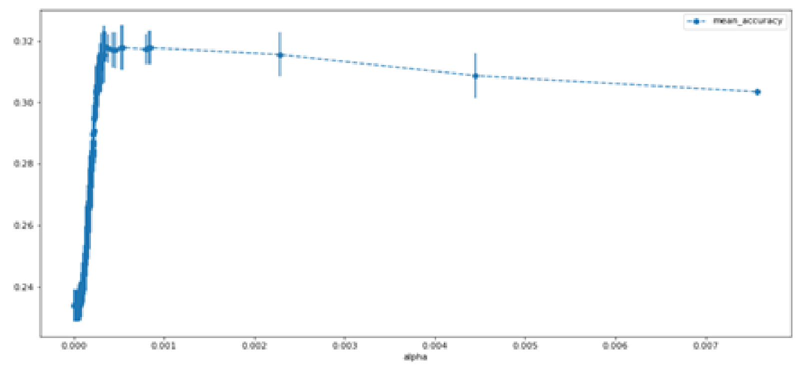
The cost complexity pruning was the first method used to find the ccp_alpha value. A ccp_alpha is a complexity parameter used for minimal Cost-Complexity Pruning. As ccp_alpha increases, more of the tree is pruned, which increases the total impurity of its leaves (Pedregosa et al., 2011). Figure 7 shows the cost complexity pruning result, and the ccp_alpha (alpha) is almost equal to zero. In this case, the decision tree could not be pruned.

Figure 7: Cost complexity pruning result.



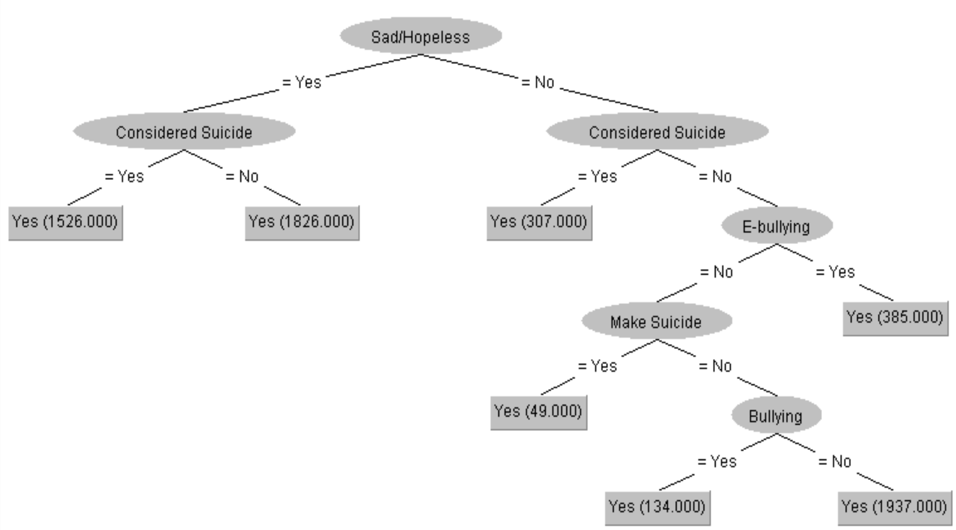
A 5-fold cross validation (sklearn.model_selection.cross_val_score) was another method to find the ccp_alpha value. Figure 8 shows the cross-validation result which is similar to cost complexity pruning result ccp_alpha (alpha) . Therefore, the decision tree could not be pruned.

Figure 8: Cross validation.



Moreover, decision trees (J48) were run by splitting the reduced dataset into smaller datasets and combining only the theoretically relevant questions into the model to illustrate how theoretically relevant questions are related to each other and predict the target variable, sleep deprivation (see Figure 9).

Figure 9. Decision tree predicting sleep deprivation based on depression and bullying



Random Forest

Random Forest model was one of the algorithms that was trained and tested on the YRBS data. The model was trained using sklearn.esemble.RandomForestClassifier function in a Jupyter Notebook. The data set was the same data that the decision tree model was trained on. The data set was splitted into Training data set 80% and Test data set 20% using “sklearn.model_selection.train_test_split” function. The confusion matrix and the accuracy score were applied to evaluate the model performance using the sklearn.matrix.plot_confusion_matrix and the sklearn.metrics.accuracy_score functions.

The accuracy_score function returns the subset accuracy in multilabel classification. If the entire set of predicted labels for a sample strictly matches with the true set of labels, then the subset accuracy is 1.0; otherwise, it is 0.0” (Pedregosa et al., 2011). If (y_i)ˆis the predicted value of the i-th sample and y_i is the corresponding true value, then the fraction of correct predictions over nsamples is defined as

$$\texttt{accuracy}(y, \hat{y}) = \frac{1}{n_\text{samples}} \sum_{i=0}^{n_\text{samples}-1} 1(\hat{y}_i = y_i)$$

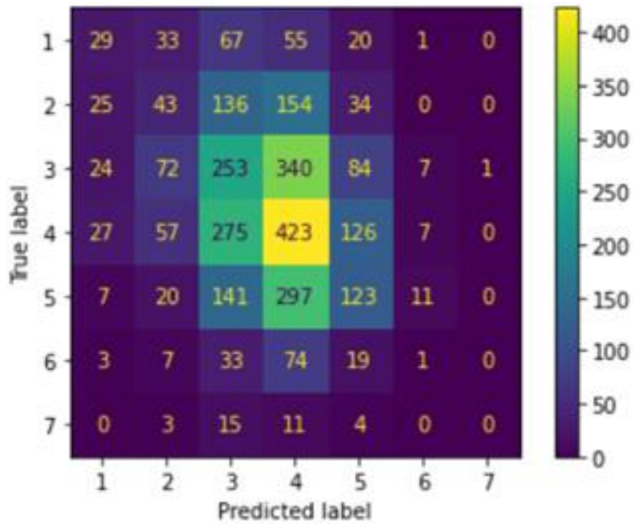
Equation 1: Accuracy score equation (Pedregosa et al., 2011).

Model Evaluation:

The model was performed in three different ways trying to get a better result.

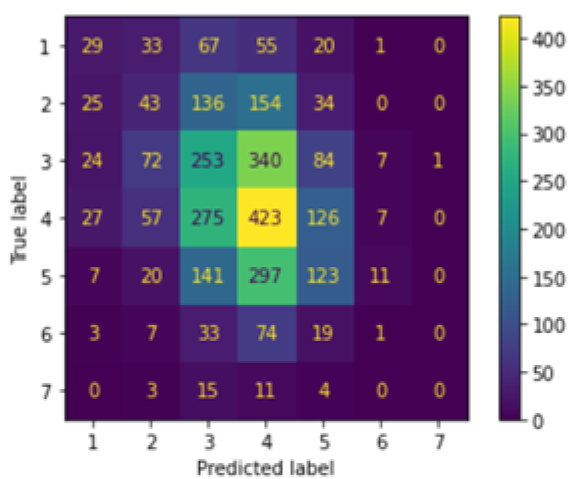
1- In the first one, the class attribute (the sleep question q88) had 7 classes 1 to 7 and there were no restrictions. The confusion matrix below (see Figure 10) shows how the model performed. As seen in the Figure, the model miss classified most of the classes and the accuracy score was 0.284.

Figure 10: Confusion matrix (7 classes and no restrictions)



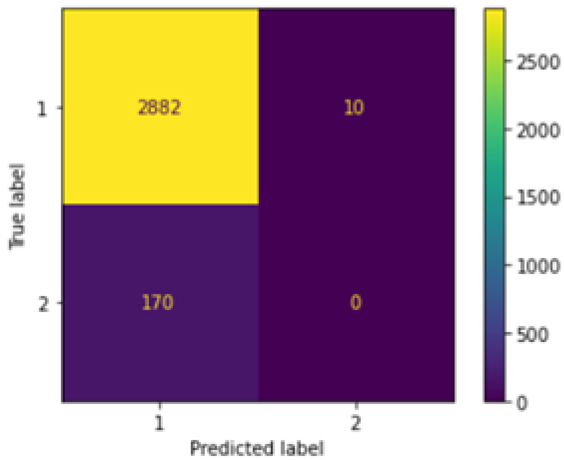
2- The "max_depth" (the maximum depth of the tree) value was adjusted between 7 and 30. It found that the "max_depth= 9" had the best accuracy score (0.319) and the confusion matrix as seen in Figure 11.

Figure 11: Confusion matrix (7 classes and "max_depth=9).



3- Lastly, the class attribute q88 "Sleep question" was divided into two classes 1 and 2. Class 1 indicated less than 8 hours of sleep and class 2 indicated more than or equal 8 hours of sleep. As seen in Figure 12, the confusion matrix shows that 2882 were correctly classified TP (true positive), 180 were incorrectly classified FP (false positive) =170 and FN(false negative)=10

Figure 12: Confusion Matrix (2 classes 1 and 2)



Logistic Regression

MATLAB's mnrfit() function was used to construct a logistic regressor, which was then trained and tested on a conventional 70-30 train-test split. This analysis was conducted with a union of the 20 most correlated data fields as well as a set of theoretically related questions, for a total of 38 attributes. The logistic regression was used to predict severe sleep-deprivation, producing the following odds ratio table for severe sleep deprivation.

Table 3. The odd rations for the 20 highly correlated questions

Q#	Label	OR	Q#	Label	OR
	Base Odds Ratio	0.6133			
1	Age	1.0447	45	Ever used marijuana	0.9981
2	Sex	1.0119	46	Initiation marijuana use	0.9934
3	Grade	1.1079	49	Ever presc. med. abuse	1.0461
4	Hispanic	1.0581	58	Ever sexual intercourse	1.1263
5	American Indian	1.2377	60	Number of sex partners	0.9935
	Asian	1.2825	61	Current sexual activity	1.0455
	African American	1.4475	65C	Sex with males	0.9543
	Pacific Islander	1.1963	66	Sex. ident. incl. hetero	0.8810
	White	0.9928		Sex. ident. incl. homo	1.2755
8	Seat belt use	0.8623	68	Goal to lose weight	1.1264
23	Bullying at school	1.0100		Goal to gain weight	0.9531
24	Electronic bullying	0.9434		Goal to keep weight	0.9215
25	Feel sad or hopeless	0.5896	77	Breakfast eating	0.8742
26	Considered suicide	0.7980	78	Physical activity	1.0024
27	Made a suicide plan	0.7501	79	Television watching	0.9436
28	Attempted suicide	1.0287	80	Computer use	1.0619
35	Current E-vape use	1.0428	82	Sport team participation	0.8861
39	Quit all tobacco use	0.9800	91	Ever used LSD	1.1450
41	Current alcohol use	1.0416	99	Speak English well	1.1498

The logistic regression produced the following results (see Table 4)

Table 4. Logistic regression accuracy

Logistic Regression Results:	
Label	***Value (Matlab Results)***
True Positive (TP)	3574
True Negative (TN)	91
False Positive (FP)	62
False Negative (FN)	865
Kappa	0.3877
Accuracy	0.7981
Precision	0.9829
Recall	0.8051
F Score	0.8852
NPV	0.0952

4. Discussion

Evaluation of the Results

Overall, the four algorithms used failed to produce significant results for the YRBS dataset in detecting at-risk behaviors that would lead to sleep deprivation.

For the Ripper algorithm, there was a significant number of false positive results. As a result, the model tended to predict that individuals were getting less than 8 hours of sleep. Also, the kappa statistic, the Negative Predictive values, and the accuracy were quite low, meaning that the algorithm was not able to distinguish a large percentage of the minority class.

When evaluating the decision tree, the dataset had a significant overfitting problem. After conducting a cross validation and a cost complexity test it was found that the tree could not be pruned more to increase the impurity of the leaves. The decision trees that were able to predict a result were only able to do so by a manual combination of theoretically relevant questions.

Much like the decision tree, the original confusion matrix for Random Forest misclassified most of the data and had an extremely low accuracy score. When the maximum depth of the tree was adjusted it had a higher accuracy score than the original tree however it was still very low, with only an accuracy of 0.319.

Logistic Regression proved to have the most successful results out of all the algorithms evaluated. From the odds ratio table, it is clear that factors like age, sex, grade, race, drug use, and sexual activity have a correlation with sleep deprivation. For example, individuals who were non-white were more likely sleep deprived (OR > 1). This can also be seen with individuals who engaged in sexual activity (OR =1.1), used drugs like LSD (OR = 1.2), and identified as a homosexual (OR = 1.3).

The failure to reach a conclusive answer to the question could be due to the nature of the dataset, which made it more difficult to determine a cause-and-effect relationship between at risk behaviors and sleep deprivation.

Conclusion

The aim of this study was to investigate the relationship between sleep deprivation and at-risk health behaviors and conditions in a large sample of adolescence using four machine learning algorithms: decision tree, random forest, ripper and logistic regression. Based on the results, nearly three out of four US high school students (%76) did not get sufficient night sleep and sleep-deprivation was associated with several health-risk behaviors and conditions as indicated in Table 2. Moreover, given the findings of several machine learning algorithms, the performance of logistic regression was the best and it achieved 80% of predictive accuracy.

Limitations of the project need to be acknowledged. The first limitation is related to the cross-sectional design of the study. Although the most recent three YRBS datasets were used in our analysis, a cause-and-effect relationship among variables cannot be drawn. Future research longitudinal in nature, therefore, is needed to explore the cause-and-effect relationships between sleep and undesirable health behaviors. Second, using a single self-reported question to measure the target variable, sleep, was not ideal. Thus, future research should rely on comprehensive and objective measurements to assess sleep as well as other health-related variables.

This project also presents implications to practice and research. This project is one of the few studies that utilized machine learning algorithms to analyze the YRBS dataset, a large and nationally representative student data. This project provides insight for future research to implement the applications of machine learning in preprocessing the YRBS dataset and discovering the relationships of the variables. The alarmingly high prevalence of sleep deprivation and its linked to undesirable health related behaviors and conditions could also inform practice, more specifically parents, school administrators and personnel, and health professionals dealing with the adolescent population. Thus, 8 hours of night sleep among adolescents could be promoted through interventions and proactive policies, which in turn would promote healthy adolescent development and reduce engagement in unhealthy behaviors.

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