Prediction of Student's Wellbeing from Stress and Sleep Questionnaire data using Machine Learning Approach

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Abstract— **A sound mental health has its benefits for the overall well-being of an individual. The decline in mental health conditions has a critical impression on other vital functionalities of the human system both psychologically and physiologically. And a student's well-being is largely contributed by the level of perceived stress and overall quality of nighttime sleep which might have evolved by various external factors over a while. The main objective of this study is to understand the correlation between Perceived Stress Scale (PSS) scores and Pittsburgh Sleep Quality Index (PSQI) global scores from StudentLife, a publicly available dataset over the period, and classify the well-being factor as 'Good', 'Average' and 'Bad'. The linear regression model significantly demonstrated the association between PSS scores and Pittsburgh Sleep Quality Index (PSQI) scores. Machine Learning techniques like Decision Trees (DT), Support Vector Machine (SVM), and K-nearest neighbors(K-NN) were implemented on both Pre-Test and Post-test questionnaire data. While SVM resulted in better accuracy for Pre-test data, the K-NN classifier resulted in best accuracy for Post-test data, and the performance was evaluated using performance metrics like accuracy Precision, recall, and F1 score.**

Keywords*— *Perceived Stress Scale (PSS), Pittsburgh Sleep Quality Index (PSQI), Mental well-being, Decision Tree, Support Vector Machine, K-Nearest Neighbor

I. Introduction

Students are exposed to too many challenges both in academics and non-academics which is said to contribute to their overall well-being [1]. As students thrive to excel in their academics, external factors have been said to contribute majorly to their day-to-day activities which in a long run have an adverse effect on their both physical and mental state [2]–[4]. But it is observed that students who fail to manage the complexities of life and adapt to challenging life scenarios are subjected to various levels of stress, anxiety, and depression [5]. Mental stress is said to negatively impact the quality of sleep and would in turn lead to deprivation of sleep in later stages [6]. Though there is a bi-directional relationship [7]between stress impacting sleep quality or the other way around, past studies have found a strong correlation between Mental health and Sleep health in understanding the overall well-being of an individual. And in recent times COVID-19 pandemic has resulted in an increased number of students with more stress, anxiety, and depression [8]. And this has added much stress and deterioration in one's life, especially the students. There exist various studies that have been conducted in recent times to understand the impact of COVID-19 on students' psychological health and academic performance [9]-[10]. Perceived stress is the major reason for the poor quality of sleep among college students. Studies about the assessment of perceived stress, understanding the sources of stress and their severity which has its impact on other determinants like sleep health becomes the topic of the hour for further investigation. A study conducted to determine the level and source of stress and its severity resulted in employing a Perceived Stress Scale-based model to gauge different types of stress levels among engineering students[4]. Mental stress and tension are found to be the most important factors in predicting sleep quality which accounts for 24% of the variance in Pittsburgh Sleep Quality Index(PSQI) scores [11]. Long-term exposure to multiple stressors simultaneously harms a person's mental and physical health which in turn, can lead to chronic health issues. Sleep quality and quantity are closely related to student learning capacity and academic performance[12]. There exist numerous studies investigating the relationship between sleep and students' academic performance which rely mostly on self-report surveys to measure stress levels and so with detection of sleep duration and quality in students using standard questionnaires as a measuring tool [13]. Also, various Machine Learning Techniques have been implemented in the interest of classification of various health conditions and have resulted in better predictions. Nearest Neighbours(K-NN)[14]-[15], Support Vector Machine (SVM)[16], Decision trees[17], and Naïve Bayes are different well-known classification methods that are applied for the data classification using various techniques.

This study was conducted with the objective to identify the correlation between Mental Stress and Sleep quality both during Pre-test and Post-test assessments. A significant correlation between PSS scores and PSQI scores was further extended to compute the well-being score and three different classification algorithms namely, Decision Tress (DT), Support Vector Machine (SVM), and K-Nearest Neighbour(K-NN)was implemented in classifying the well-being as Good, Average and Bad and the performance was evaluated using various metrics and a detailed procedure and findings are detailed in following sections.

This paper describes the literature review in section II followed by methodology in section III. Results and Discussion is elaborated in section IV and the Conclusion forms the final section of this paper.

II. Literature Review

Mental stress has an impact on various health issues and a study involving its influence over other psychological and physiological changes in the body has been a research topic for decades together. But understanding the pattern and the complexity of stress over other serious health conditions is still the objective of many research studies. PSS is a standard questionnaire used across most studies in understanding the level of stress perceived by the subject of interest. Self-

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administered questionnaires though considered not reliable [19] still are used in most research works to evaluate stress levels as many would still not want to reveal their emotional state of mind for an open discussion with professional help. Xu et al, conducted a stratified analysis to understand the association between perceived stress and poor sleep quality and its impact on people with cancer [20]. This study used Perceived Stress Scale (PSS) [21]to analyze the perceived stress levels of the subjects and Pittsburgh Sleep Quality Index (PSQI) [22]to compute the global score of the overall sleep quality. PSQI is one of the standard questionnaires used to monitor sleep quality by professionals [23]–[26]. Herawati et al , conducted a correlation analysis between Stress levels and sleep quality in students from Indonesia[23]. Correlation analysis conducted in this study resulted in a strong relationship between Stress and Sleep variables($p=0.001,\alpha=0.05$), and also it was observed that on average an individual with poor sleep quality is 4.7 times more stressed than a normal individual. Alotaibi et al. conducted a study to assess the relationship between students' Stress levels, Sleep quality over academic performance [27]. Though the study did not demonstrate a statistical difference in the academic performance of the students, the study resulted in a significant association between quality of sleep and stress levels. StudentLife is a study designed to assess the mental health, behavioral traits, and academic performance of students using smartphones [18].In an already existing stressful environment there evolved various research studies during the COVID-19 pandemic which demonstrated the significant relationship between Mental Stress and sleep quality among students and their overall well-being using various techniques [15], [28]–[30]. Prediction of Perceived stress and sleep quality using various machine learning techniques has been the topic of research in current times. Supervised Machine Learning algorithms are used mostly in such predictions [31]–[36]. But most of the prediction techniques using machine learning have used DASS-21[37] [34], CLAS[38], and WESAD[14] datasets for analysis. This study is the first of its kind which uses the StudentLife dataset for the prediction of the well-being of the students using various multilevel classification algorithms.

III. Methodology

This section of methodology explains in detail the sequence of different steps involved to conduct this study. The overall workflow of this experiment is shown in Fig.1.

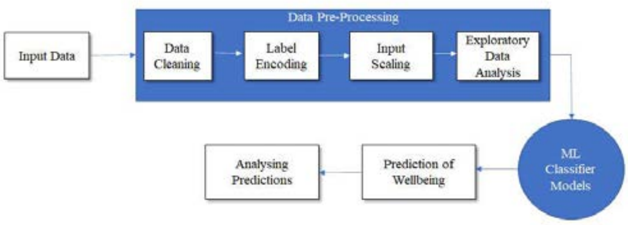

Fig. 1. Overall workflow diagram

A. Input Data

Survey responses from the Perceived Stress Scale (PSS)[21] and Pittsburgh Sleep Quality Index(PSQI)[22] was used as input data from both Pre-test and Post-test separately.

1)Perceived Stress Scale(PSS): PSS is a well-known standard measuring tool that is used mostly to assess the perceived stress levels of the subjects of interest. Fig.2. depicts the structure of the PSS scale and how the final score is computed. The items within the PSS scale mostly try to assess the impact of life events that the respondents perceive to have caused stress over a while. This scale has proved to result in the best predictions of health-related outcomes. PSS is also said to have a strong correlation with symptoms of depression which it tries to measure in the context of various day-to-day activities.

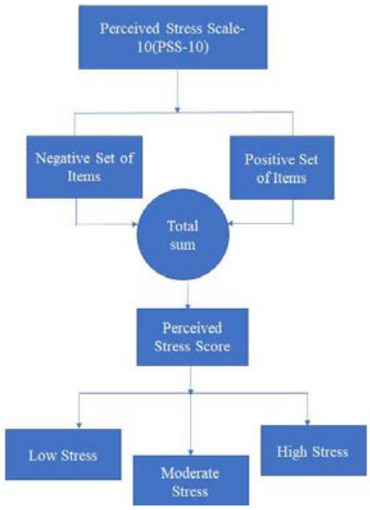

Fig. 2. Perceived Stress Scale(PSS)

This study followed a standard percentile method to classify the subjects into three different categories Low stressed, Mild stressed, and high-stressed based on the total of all 10 items within the PSS tool. And the norms followed to classify them are as follows. PSS score from 0-13 was considered Low stress, scores in the range 14-26 were considered Mild stress, and 27 and beyond is High Stress [29].

2) *Pittsburgh Sleep Quality Index (PSQI):* PSQI[22] is one of the most commonly used self-assessment questionnaire of sleep quality and difficulties over one month time interval. This tool is mainly used to administer and measure the sleep quality of the respondents and thereby categorize them as Good and Bad sleepers. However, the responses to a few questions, in particular, may help the clinician to further analyze other sequences of investigations.Fig.3.briefly describes the different components within the PSQI tool. The final global PSQI score which is the summation of 7 components is thereby said to be "transparent" as it communicates the overall complexity of subjects' problems and looks into various issues related to sleep disturbances through a simple measure. Nineteen items were further grouped into seven components namely subjective sleep quality, sleep latency, sleep duration, habitual sleep efficiency, sleep disturbances, use of sleeping medication, and daytime dysfunction. The total PSQI score is the sum of all these seven components.

B. Data Pre-Processing

Data Pre-processing was the second step that was incorporated to enhance the quality of questionnaire responses and to extract meaningful insights from both the Pre-test and Post-test datasets. Some of the pre-processing techniques adopted in this study are Data Cleaning, Label encoding, Input scaling, and Exploratory data analysis.

1)Data Cleaning: Data Cleaning step was implemented to identify the incomplete or inadequate responses, finding missing or null responses from both PSQI and PSS pre-test and post-test datasets. Responses from PSQI open-ended questions had to be standardized to a common format and hence were manually assessed. E.g.,' During the past month, when have you usually gone to bed at night?". The responses to this question from the PSQI scale were found to have appeared in multi forms. Responses were either 11.30,11.30pm,11.30p,23.30, 'Midnight', 'Immediately after food' etc., and needed manual correction of data.

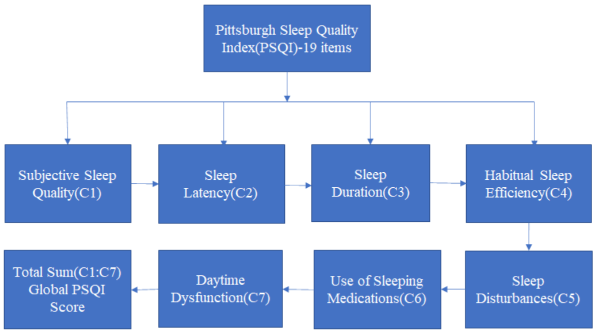

Fig. 3. Pittsburgh Sleep Quality Index(PSQI)

2) Label Encoding: Label Encoding which is a process of converting categorical variables to numerical value had to be incorporated as the mental state score which was computed using PSS and PSQI scores were summed together to compute the Mental Health Score Value.25th,50th, and 75th quartile range technique was implemented over the non-normal distribution of scores to set the norms of scoring based on the distribution. Subjects with Low mental health score was labeled as 'Good' Well-being indicated as :0, a Moderate score was labeled as 'Average':1 and a High Score was labeled as 2.

3)Input Scaling: Input data was further normalized as the PSS scores and PSQI scores were continuous data and the prediction was made for categorical value.

4) Exploratory Data Analysis (EDA): Exploratory Data Analysis was conducted on the Pre and Post dataset of both survey questionnaires of PSS and PSQI responses to analyze the association of different variables within the dataset. Linear regression resulted in a significant association between PSS scores and poor sleep status in the Pre-test dataset while the association between PSS score and PSQI score gave unsatisfactory results. The correlation matrix is also calculated to find the correlation coefficient which helps in analyzing the interrelationship or interdependency between PSS and PSQI scores and the computed Mental Health Score.

C. *Machine learning Classifier*

The final pre-processed data had 30 samples and the data was split randomly in the ratios of 75% train set and 25% test set. Based on the observed correlation between different variables within the dataset, various multiclass classification models using DT, SVM, and K-NN were trained and tested on both Pre-test and post-test data to classify the well-being of the individuals.

D. *Predictions of wellbeing*

All three classifiers have predicted the well-being category with appreciable accuracies. Prediction of wellbeing was categorized as 'Good', 'Average', and 'Bad'.

E. *Analyzing Predictions*

Classification models were analyzed based on various classification metrics namely accuracy, precision, recall, and F1-score the details of which are tabulated in Table 1.

IV. Results and Discussion

"StudentLife"[18], a publicly available dataset is the result of an experiment conducted on students from Dartmouth College, London. This project involved assessing mental health to understand its overall impact on academic performance and the behavioral attitudes of the students from the beginning of the course towards the end of the course. It developed a continuous sensing app that collected data for 10 weeks from 48 students using sensors. And a survey was also conducted using standard questionnaires to understand the ground truth of subjects of interest. This study operated in two phases both during the entry and exit point of the course of which 48 students participated in pre-test assessments whereas only 41 students continued to participate in post-test assessments.

The original PSS had 14 items which later has its other two variants namely PSS-10 and PSS-4 which are used for various other case scenarios based on the context of the study. This study has made use of PSS-10, and the same questionnaire is floated among students both during the beginning of the course/semester and the during the end of the course/semester.PSS-10 has items that are 5-point Likert type, where the convention followed in the items follows different patterns for both negative and positive sets of questions. Negative Questions numbered 1,2,3,6,9,10 have items where responses are scored as 0 represents Never,1 means Almost Never,2 is Sometimes,3 means fairly often and 4 represents very Often. Positively stated questions 4,5,7 and 8 responses are reverse scored like (0:4,1:3,2:2,3:1,4:0). The sum of all the items results in PSS total score which will range from 0-40. An individual who scores less PSS score is considered to be less stressed and the other way around. This study is designed to classify the participants into three categories Low stressed, Mild stressed, and highly stressed and the norms followed to classify them are as follows. A PSS score between 0-13 is considered Low stress, Mild stress is between 14-26, and 27-40 is considered High Stress [39].

The PSQI questionnaire has in total of 19 questions and these questions have been categorized into 7 different components which are intended to compute subjective sleep quality, sleep latency, sleep duration, habitual sleep efficiency, sleep disturbances, use of sleeping medication, and daytime dysfunction respectively. The Global PSQI score is the result of the total sum of these individual 7 components. An individual whose Global PSQI score >5 is considered to sleep with much difficulty or sleep of bad quality else it is considered of good quality.

One of the challenges encountered while using this StudentLife dataset was to map the two variables considered for predictions. Linear regression resulted in a significant association between PSS scores and poor sleep status($r=0.4,p=0.03$)in the Pre-test dataset while the association between stress score and sleep score gave unsatisfactory results(r=0.1,p=0.5)which indicates that throughout the course, external factors have positively contributed in the drop of the overall wellbeing of the subjects and needs further investigation of every feature contributing to the overall wellbeing.Fig.4.is the correlation matrix which computes the correlation coefficient between every variable within the Pre-test dataset. The correlation coefficient ranges from -1 to 1. There is an appreciable correlation between Sleep Scores and Stress Scores and Wellness scores respectively (0.38,0.56,0.84) in Pre-test data. But Stress Score strongly contributes to predicting the well-being of the individual (0.84) and this is also been the topic of many studies on Stress and Sleep study among students[5], [40]. Though there is an appreciable association between mental stress levels and the quality of sleep, its relationship with well-being can largely be related to other attributes like personality traits, the presence of environmental activities, and also other emotional indicators[6].

Among the many studies that have been conducted in the interest of students to find the relationship between Mental stress and Sleep health, a study was conducted by Sano et al.on nursing students to recognize academic performance based on Stress level and sleep quality. This study found a strong association between PSS and PSQI scale[41].

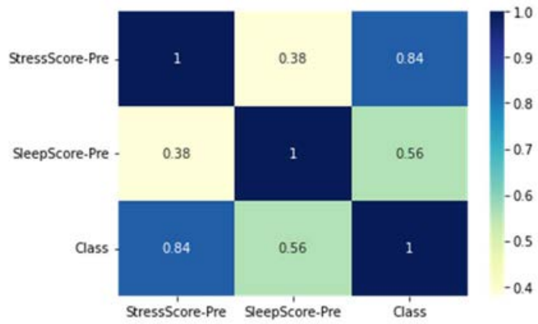

Fig. 4. Correlation matrix of StressScores and SleepScores of PreTest Data

Fig 5. is the correlation matrix of individual features in the Post-test dataset. There exists a weak relationship between Stress and Sleep Score from the post dataset, but both PSS score and PSQI score together have a significant association (0.11,0.36,0.86) which is used further for classification machine learning algorithms to classify the subjects into different Well-being categories. This analysis can be further extended to understand the feature rank of every item which positively or negatively contributes to estimating the well-being score of the individual.

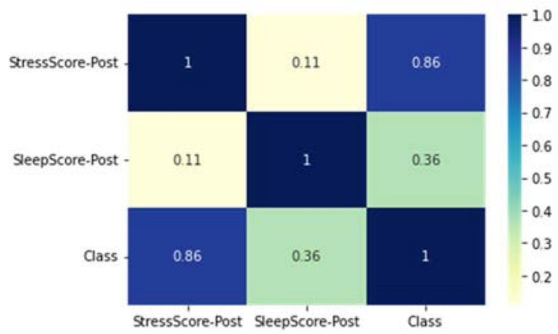

Fig. 5. Correlation matrix of StressScores and SleepScores of PostTest Data

Correlation analysis was further extended for visualization of the different classes of Well-being based on Stress Scores and Sleep scores. Fig 6. is the box plot representation of different classes of Well-being based on Stress scores during the Pre-test. Class 0 indicates Good,1: Average,2: Stressful. While the responses from the Stress Score from the Pre-test followed the normal distribution of responses and hence the Stress Scores were normally distributed across three well-being classes. Whereas the Sleep Score data from Pre-test had a non-normal distribution of data and the presence of outliers is more likely to contribute to the overfitting of the classification models.

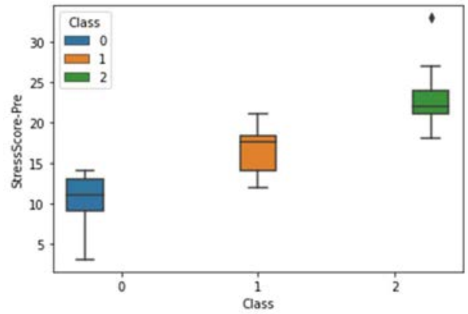

Fig. 6. Box-plot representation of the classification of well-being from Pre-test Stresscore

As observed in the correlation matrix there is no strong association between Sleep Score and well-being as the students with more stress or moderate stress continue to get a good quality nighttime sleep as they have understood a mechanism to cope with stress and are resilient to subjective changes which could cause an adverse impact over their overall wellbeing [24].

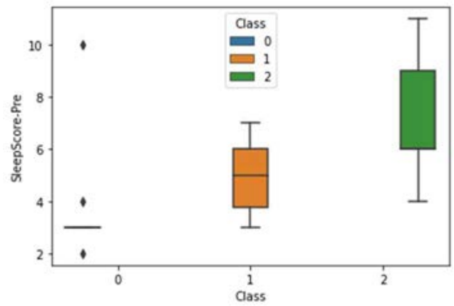

Fig. 7. Box-plot representation of the classification of well-being from Pre-test SleepScore

Fig.7.and Fig.8.shows the representation using a box plot as to how the Stress Score and Sleep score are classified into different Well-being classes.

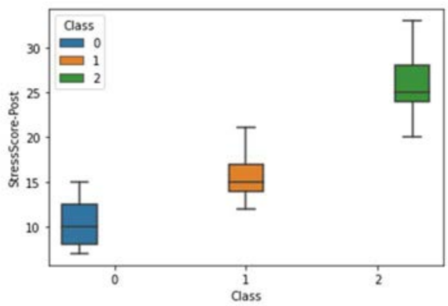

Fig. 8. Box-plot representation of the classification of well-being from PostTest StressScore

It can be visualized from the box plot representation that over 10 weeks, there is a variation in the stress scores and sleep quality. As students face different academic and non-academic challenges there is a clear categorization of the well-being of the students as many students have low stress and good quality sleep and over the period stress levels increases and sleep quality drops accordingly. However, the StudentLife dataset had only 30 samples for both pre-test and post-test analysis which is quite small, and the response-to-item mapping with the PSS scale and PSQI scale might have led to an introduction to biases in the results. Further exploration of every feature response is needed to better analyze the correlation among the features thereby contributing in making better predictions.

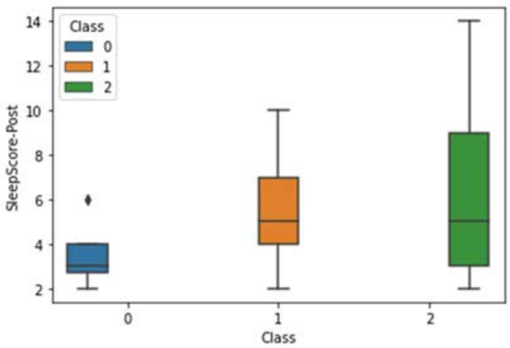

Fig. 9. Box-plot representation of the classification of well-being from PostTest SleepScore

A. *Classification Performance*

Decision Tree Classifier (DT), Support Vector Machine Classifier (SVMC), and K-Nearest Neighbours(K-NN) are the three main Multiclass Classification algorithms that have been applied for classifying the well-being of the students from the StudentLife dataset. Table I has the results from the classification report on these three classifiers.

From the results obtained, SVM performed the best in terms of accuracy (96%) for the Pre-Test dataset whereas K-Nearest Neighbours (89%) gave the best results for this classification problem and can be seen from Table I. Other algorithms though have contributed significantly to the classification of Students' well-being, the same can be improved upon with large datasets and various pre-processing techniques. All three classifiers had more or similar metrics scores among precision, recall, and F1- scores.

TABLE I. PERFORMANCE METRICS OF CLASSIFICATION ALGORITHMS OF PRE AND POST-TEST DATA

Pre-Test Dataset					
No.	***Classification Algorithm***	***Accuracy***	***Precision***	***Recall***	***F1-score***
1	Decision Trees	0.89	0.75	0.80	0.89
2	Support Vector Machine(SVM)	0.96	0.95	0.94	0.92
3	K-Nearest Neighbors	0.87	0.80	0.58	0.67
Post-Test Dataset					
No	***Classification Algorithm***	***Accuracy***	***Precision***	***Recall***	***F1-score***
1	Decision Trees	0.67	0.71	0.72	0.63
2	Support Vector Machine(SVM)	0.75	0.78	0.89	0.78
3	K-Nearest Neighbors	0.89	0.83	0.94	0.86

The above results demonstrate that Machine Learning Techniques can be implemented on the StudentLife dataset and there is a need to further dive into this dataset as this can be further explored for predicting another psychosocial well-being of the subjects. Research studies employing the analysis or predictions of Stress or Sleep health can further analyze this dataset for various other predictions.

CONCLUSIONS

Detection of stress levels and sleep quality is mostly conducted to understand the rising levels of stress and increasing cases of students subjected to insomnia which in turn is causing other serious health issues. Exploring various features contributing to psychological distress among students is very crucial in current times. And StudentLife study helps in understanding the pattern of students' overall well-being, academic performance, mental health, and behavioral traits over the semester. Students started the semester with high energy due to low stress and good quality sleep which eventually deteriorated as students lost interest in the subjects, some students even dropped out from the course during the 10-week semester. This dataset can be used in the interest of students to further understand the interrelation among different components which contribute to the mental well-being of the students. PSS and PSQI questionnaires though are found in most research studies on stress and sleep health of diverse subjects both in the area of clinical and non-clinical studies, this study is one of its kind which attempts to apply machine learning techniques to understand the pattern which thereby helps to make future predictions of the wellbeing of the students. The inclusion of Linear regression helped in understanding the correlation between the individual predicting components. An increase in PSS score resulted in low-quality sleep which further helped in finding the correlation of the factors contributing to students' overall Wellness. Through the current state of technology and best-known techniques there is a need to implement various Machine Learning Techniques in the Mental Health Predictions of students in specific, which thereby helps in preventing any irreversible damage to them both psychologically and emotionally.

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