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Prediction of University Students' Subjective Well-Being with Sleep and Physical Activity Data using Classification Algorithms

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Abstract

Daily activities affect mental health. One of the most used scales is "subjective well-being (SWB)", which is a self-reported questionnaire. This study aimed to predict SWBs using step count, heart rate and sleep duration data from sensors instead of questionnaires. NetHealth data from the University of Notre Dame[1] has been used. Attributes included average daily steps, average heart rate, heartbeat standard deviation, average sleep duration, and sleep duration deviation. Preprocessing, processing, classification, and evaluation followed. Naive Bayes, K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Ensemble classifiers were used. Performance metrics include accuracy, precision, recall, F1-Score, and ROC (Receiver Operating Characteristic) curves. Model accuracy was 62%. This indicates that machine learning could be beneficial in detecting SWB levels using sensor data.

Keywords: Subjective well-being, physical activity, sleep, classification, machine learning.

[1] NetHealth project, conducted in University of Notre Dame and which is publicly accessible via the following URL: http://sites.nd.edu/nethealth/data-2/.

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1. Introduction

When the word "well-being" is mentioned, a large portion of society thinks of monetary well-being. Although financial well-being affects a person's overall well-being, research has shown that monetary profits are not always the most convenient factor [1]. For centuries, philosophers and scientists debated well-being and happiness, attempted to understand its origins, struggled with its quantifiability, and advanced numerous theories. From psychological perspective, human happiness and well-being is defined as the satisfaction of a lifestyle, the frequency of good feelings, and the absence of bad feelings [2]. Different approaches have been tried to measure it [7]. Self-report assessments, such as the Positive and Negative Affect Scale (PANAS), a psychological scale, are the most popular approaches [8, 9]. In addition, significant organizations worldwide such as Gallup, the British Household Panel, and Eurobarometer utilize their measures to assess people's happiness and well-being. After the measurement methods were developed, studies were conducted on the factors affecting these results. Scientists in the field of SWB noticed that achieving a high level of satisfaction and living a healthy lifestyle are the primary motivations for each person's choices and activities, these will lead to happiness [1, 35]. Furthermore, there has been ample research demonstrating a link between daily activities and well-being [4] [5].

Today, technological gadgets geared up with sensors consisting of mobile phones, smartwatches, and wristbands which enable the tracking of physical activity, are actively used. These tools are also used within the discipline of analysis because data that may be accrued are diverse and easily collectable compared to the previous methods [3]. Physical activity here, refers to any movement that causes the body's skeletal system and skeletal muscles to waste energy, and physical activities can be used for various purposes in daily life. An important usage area of these tools is SWB detection. It has been proved that being in motion has a built-in positive impact and is a meaningful and rewarding activity in and of itself [14]. In a study conducted in an office, it was revealed that the well-being of employees who participate in physical activity in the office environment is higher than the control group [37, 38, 39, 40]. Furthermore, it has been discovered that engaging in physical activities regularly for a while reduces the risk of depression [15, 41, 42, 43] and anxiety [16, 44, 45]. On the other hand, physical activity that lasts less than ten weeks has been shown to have a lower impact on SWB and mental well-being than prolonged activities [17].

Another factor that scientifically affects quality of life and SWB, is sleep. Besides physical activities, sleep is one of the main activities of life. There is numerous research suggesting that sleeplessness reduces emotional well-being. For example, an individual who sleeps between 4 and 6 hours for 14 consecutive days, i.e. with increasing cumulative wakefulness, has been observed to have a considerably lower cognitive performance in all activities [18]. Also, researching the association between obesity and insomnia, it has been discovered in some studies that insomnia also impacts mental health status, generating stress and depression and triggering chronic sleep problems [19, 20, 21]. As a result of these and comparable investigations, it can be stated that sleep duration has both direct and indirect impacts on SWB [22]. As stated before, technological devices equipped with sensors are used in the collection of sleep data.

Self-regulation is a character aspect often related to one's self-control. Much research demonstrates that one of its physiological markers is heart rate variability (HRV), and there is a significant link with self-regulation [23]. Self-regulation also directly affects personal or professional accomplishments [24]. Additionally, some studies proved that HRV is a promising biomarker of mental health resilience as well as indicates autonomous response of stress [36]. Since stress resilience effects mental well-being, it has a direct impact on a person's degree of well-being [25, 46, 47].

In this study, estimation of SWB using machine-learning algorithms is proposed. A model was developed for determining SWB level based on physical activity and sleep data with 285 entities. It has been found that sleep and physical activity (heart rate and step number) could be used to predict SWB. Compared to previous research in the literature, this study aims to obtain comparable results using data from low-cost and widely available devices such as smartwatches, wristbands, and mobile phones [26].

As shown in the Figure 1, "daily average and daily standard deviation of heart rate, number of steps and sleep duration" were used as estimators. These were computed using the average and standard deviation of the daily values within the data set over one year.

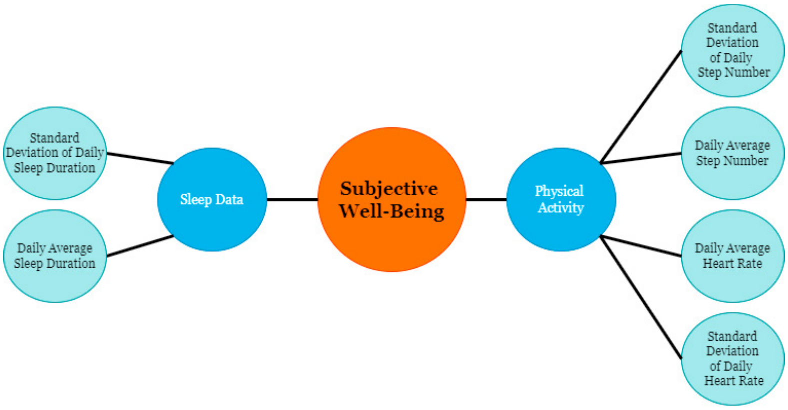

Fig. 1. Summary of the data set.

2. Methods

2.1. Dataset

The data set [6] used was collected between 2015 and 2019 at the University of Notre Dame and covered information such as activity recorded via Fitbit Charge HRs. As the scope of NetHealth study is so broad and includes a variety of contexts, a sort of elimination procedure was used to narrow the scope. Since it was difficult to maintain the participation of all 700 undergraduate students over time, the project's participation rates dropped during study. Data on social networking, physical activity, and sleep were just a few of the information gathered from the students who took part in the study. Other types of information gathered included questionnaires about physical and mental health and information about their socio-psychological conditions and habits.

2.2. Classifiers

Different models have been used in prediction studies. These models can be categorized under three main sets: statistical, intelligent and hybrid/ensemble models. In this study, one from each set was selected and applied. The methods previously employed for psychological inventory such as mental health, stress, bipolar disorder, mood etc. prediction include: Naive Bayes [49, 50, 51], SVM [52, 53], KNN [54, 55, 56], Ensemble [57, 58, 59, 60]. Hence, the data classification was performed using Naive Bayes, KNN, SVM, and ensemble classifiers. Bayesian network classifiers are a major supervised classification paradigm. A well-known Bayesian network classifier is the Naive Bayes' classifier is a probabilistic classifier based on the Bayes' theorem, considering Naive (Strong) independence assumption [33]. Bayes classifier enables practical learning techniques but also knowledge and observed data may be linked. The starting point is the Bayes' theorem for conditional probability, saying that, for a given data point x and class C, shown as equation 1 [34]:

$$P\left(\frac{C}{x}\right) = \frac{P\left(\frac{x}{C}\right)}{P(x)} \quad (1)$$

Furthermore, by assuming that for a data point x = {x1,x2,...xj}, the likelihood of each of its characteristics being in a particular class is independent, we may estimate the probability of x as follows and illustrated as equation

2 [34]:

$$P\left(\frac{C}{x}\right) = P(C).\prod P\left(\frac{x_i}{C}\right) \tag{2}$$

KNN is a sort of instance-based learning or slow learning where the function is only estimated locally, and all computation is held until classification. It is also a non-parametric supervised classification technique that determines a point's KNN by minimizing a similarity measure such as the Euclidean distance. The unidentified item is then categorized using either majority voting (the neighborhood's dominant class) or a weighted majority, in which points closer to the unlabeled object receive a higher weight [28, 29, 30].

SVM is a pattern recognition approach that avoids local optimization and provides optimum statistical classification using decision functions [31]. There are numerous critical components to the SVM approach. The first is the kernel function, which transfers the input vector to hyperspace with a high dimension. After examining the Gaussian, Linear, Quadratic, and Cubic kernel functions, the Gaussian kernel function has been chosen for our research. Following that, we looked for the optimum box constraint, which is a parameter that regulates the highest penalty applied on observations that violate the margin, so preventing overfitting (regularization).

Adaptive Boosting (AdaBoost) is an ensemble method in supervised machine learning [48]. It works by iteratively updating an ensemble of classifiers constructed from weak learners to be stronger. Each succeeding learner, except for the first, transformed into a strong learner.

2.3. Performance Measures

First performance measure used was accuracy which is a metric to evaluate classification models. It is the fraction of predictions that model made right. As second metric, precision was used gives the proportion of positive labels identified correctly. Third metric used was recall and it gives the proportion of actual positives identified correctly [61]. As fourth metric, F1 score used which had been developed rely on both precision and recall scores

Accuracy	Precision	Recall	F1 Score
$\frac{TN+TP}{TN+FP+TP+FN}$	$\frac{TP}{TP+FP}$	$\frac{TP}{TP+FN}$	$2*\frac{Precision*Recall}{Precision+Recall}$

and calculated by weighted average of these two metrics [62]. Table 1 shows the formulation for each metric.

Table 1. Performance measures.

Other metrics are ROC curve and AUC (Area Under Curve). ROC is a graph showing the performance at all classification thresholds and has two parameters as True Positive Rate (recall) and False Positive Rate. TPR vs. FPR is plotted on a ROC curve at various categorization levels. Lowering the classification threshold causes more items to be classified as positive, which increases both False Positives and True Positives [61] and AUC provides an aggregate measure of performance across all possible classification thresholds by summing up the area under ROC curve both are shown within the Figure 2.

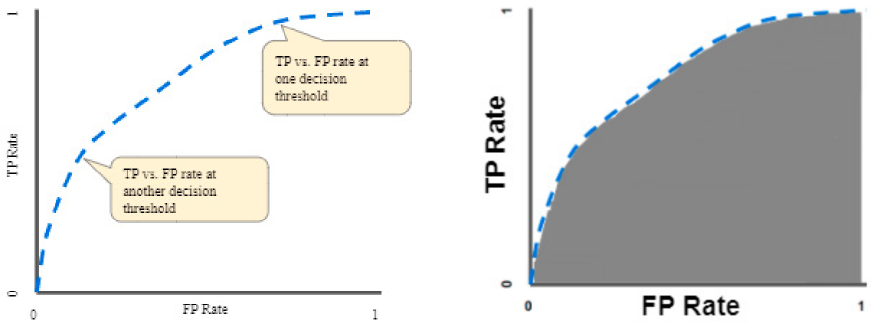

Fig. 2. ROC curve and AUC [61].

3. Implementation and Results

As there was no SWB questionnaire within the data, it was formed by combining some other survey results. Previous studies have shown a positive correlation between SWB and "happiness, health, and health satisfaction scales" [10, 11, 12, 13]. Hence, an SWB scale was formed using these scales. The applied model had a total of six features. Four separate classifiers were trained using these six features, and the SWBs of the dataset's participants were predicted to be high or low using these classifiers. To construct a balanced (homogeneously distributed) dataset, the threshold value was chosen as the median for low/high labelling. Thus, the dataset was separated into two equal portions, with 147 low SWBs and 147 high SWBs.

The MATLAB "Classification Learner" module was used to apply these methods. These four classifiers are also often used in the literature and perform well in solving classification problems [27]. The validation challenge was solved using eight-fold cross-validation. The data set was separated into equal halves with an equal number of targets, and all data except that needed to test the model was utilized for training; the remaining data was used for testing. Thus, all produced elements were used in the model's training.

3.1 Data Preprocessing

As mentioned earlier, NetHealth data was used in the study. The timeframe from 2015 to 2016 was chosen, and a total of about 52 weeks was covered throughout this paper. Since the quantity of the sensor data from the FitBit is fewer than the survey data and thus creates a bottleneck, data filtering began with the sensor data from the FitBit. During the period studied, 594 unique FitBit participants were recorded.

It was noticed that the number of days that all 594 participants actively utilized Fitbit during the year varied. The data size was reduced to 307 individuals after filtering out users who participated in the "Health, Happy, and HSS" questionnaires and those who had sensor data. Another bottleneck identified during the data analysis stage was data loss caused by individual factors such as not wearing the wristbands when sleeping, running out of energy, or synchronization issues [6]. As a result, when users with no sleep time data were filtered out, the data set's dimension was reduced to 303. Those who wore Fitbits during sleep for at least 180 days of the year, or half of the year, were filtered out to confirm compliance with the data.

Finally, the data was normalized. This ensured that each feature contributes equally to the overall range and satisfies the requirements of the algorithms to be used. Also, any outliers were removed at the final stage. As a result of this, a total of 285 persons left. The process is schematized in Figure 3.

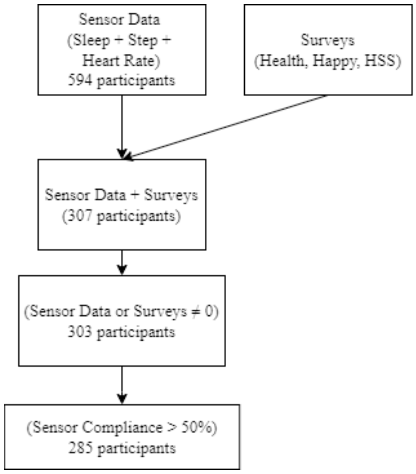

Fig. 3. Data cleaning and filtration process.

3.2 Model Application and Performance

Different performance indicators were utilized to assess the performance of four different classifiers with separate model parameters. The tested parameters and the hyperparameters that produced the best outcomes are compared in Table 1.

Table 2. Classifiers applied.

Model Name	Tested Hyperparameters	Optimum Hyperparameters	Training Time	Accuracy	Precision	Recall	F1-Score
(1) Naive Bayes	**-Distribution names:** Gaussian, Kernel **-Kernel type:** Gaussian, Box, Epanechnikov, Triangle	**-Distribution names:** Kernel **-Kernel type:** Gaussian	37.406 sec	56.3%	56.6%	62.1%	59.2%
(2) SVM	**-Multiclass method:** One-vs-All, One-vs-One **-Box constraint level:** 0.001-1000 **-Kernel scale:** 0.001-1000 **-Kernel function:** Gaussian, Linear, Quadratic, Cubic	**-Kernel function:** Gaussian **-Kernel scale:** 0.1587 **-Box constraint level:** 3.9439 **-Multiclass method:** One-vs-One	22.091 sec	59.9%	61.0%	59.3%	60.1%
(3) KNN	**-Number of neighbors:** 1-147 **-Distance metric:** City block, Chebyshev, Correlation, Cosine, Euclidean, Hamming, Jaccard, Mahalanobis, Minkowski (cubic), Spearman **-Distance weight:** Equal, Inverse, Squared inverse	-**Distance metric:** Cosine **-Distance weight:** Equal **-Standardize data:** true	19.824 sec	58.8%	59.7%	59.3%	59.5%

(4) Ensemble	**-Ensemble method:** Bag, GentleBoost, LogitBoost, AdaBoost, RUSBoost **-Number of learners:** 10-500 **-Learning rate:** 0.001-1 **-Maximum number of splits:** 1-293 **-Number of predictors to sample:** 1-4	**-Ensemble method:** AdaBoost **-Maximum number of splits:** 24 **-Number of learners:** 13 **-Learning rate:** 0.54611	59.564 sec	57.7%	59.3%	55.2%	57.1%

Table 2 shows the findings for the models that were used. While the SVM classifier performed best in terms of Accuracy, Precision, and F1-Score, Naive Bayes performed best in terms of Recall. As a result, the following conclusions can be drawn:

- If the aim is to properly identify all persons with low and high well-being, SVM has the highest Accuracy.
- If the aim is to accurately identify those with high well-being while keeping the false positive (FP) ratio low, SVM has the highest Precision.
- If the goal is to correctly identify those with high well-being while keeping the false negative (FN) ratio low, Naive Bayes has the highest Recall rate.
- Since this sort of model may be utilized in processes such as recommendation and intervention, assistance to an individual with low SWB should also be prioritized. As a result, it is critical for the model to maintain a low FP ratio and to avoid inaccurate prediction of persons with low SWB. As a result, Precision rate prioritized as performance metric.

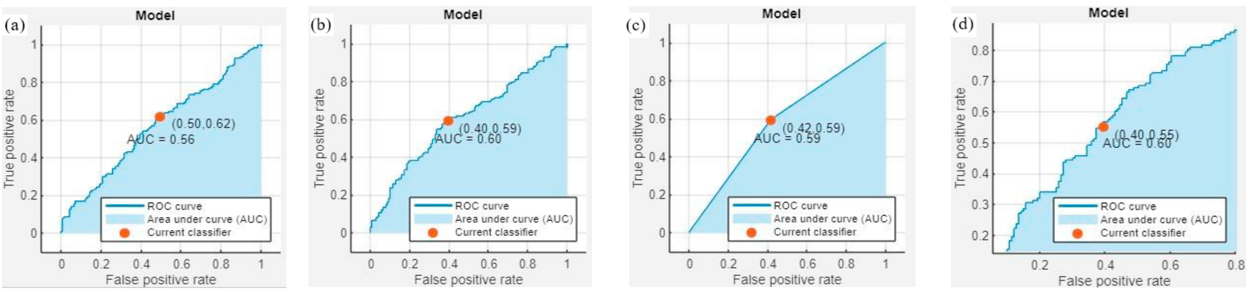

Fig. 5. ROC Curves for (a) first model – naive bayes; (b) second model – SVM; (c) third model - KNN; (d) fourth model – Ensemble.

Figure 5 illustrates the ROC curves and area under curve (AUC) for each model to predict response. The curve depicts the likelihood of an SWB estimation as high or low.

4. Conclusion

This paper presents work on the significance of sensor data for the purposes of predicting subjective well-being of a person. While existing research works detecting SWB by questionnaires and surveys, it is a novel way to apply using sensor data and analyzing it with machine learning to predict people's SWB levels. Also, several challenges have been encountered in the questionnaires used for SWB identification, both in terms of time, cost, and other restraints and interfering with the flow of natural life during implementation. Therefore, the measurability of people's SWB levels was examined by utilizing sensors, apps, and so on to prevent such difficulties and introduced an alternative method. In this study, first time period was specified, sleep duration and physical activity data from sensors selected as attributes related with SWB. After that, noise and outliers cleaned within data preprocessing phase and remained 285 entities. Consequently, the selected algorithms that had been used within the literature applied. SWB levels predicted with 59.9% accuracy, 61.0% precision, and 60.1% F1-Score by SVM classifier, 62.1% recall by Naive Bayes. Given the scores among these models, sleep duration and physical activity be considered as a measure of informing one's subjective well-being.

Future work should focus on improving the developed approach by studying with other aspects that may differ from person to person, such as personality traits, social media usage, and communication network behavior. Also, data size can be enlarged to obtain better predictions with better performance rates.

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