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Uncovering the Link between Sleep, Alexithymia, and Overweight Status: A Machine Learning Approach

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Excessive weight, including obesity and overweight statuses, has been identified as a significant risk factor for a wide range of severe health problems and the severity of psychiatric symptoms associated with various psychiatric diseases. Our primary objective was to predict overweight status using comprehensive data on sleep-related factors and alexithymia. We employed advanced machine learning models, specifically random forest (RF) and neural networks (NN), to identify the most influential predictive factors in this context. The Stockholm Brain Study focuses on functional brain imaging data obtained from two distinct age groups: participants aged 20-30 years and older individuals aged 65-75 years. In order to assess overweight and obesity status, participants' body mass index (BMI) was calculated using the World Health Organization's defined cut-off points for overweight and obesity. Additionally, the study incorporates alexithymia data to further investigate its role in predicting overweight status. The results showed that RF ML model predicted overweight status with an accuracy of 72 % (sensitivity: 100 %, specificity:30%). The area under curve (AUC) value was 95. Furthermore, NN found that overweight status was predicted with the accuracy of 93 % in the train data and the accuracy of 56 % in the test data (sensitivity:80%, specificity:20%). To validate our results, the cross-validation was performed based on algorithms of RF, and NNs, and resulted in an average accuracy score of 0.70 ± 0.12, 0.54±0.11, respectively. The study findings revealed that the prediction of overweight status exhibited remarkable accuracy, surpassing 70 percent, through the utilization of a RF model.

Keywords: Obesity, Overweight Status, Sleep, Severity of Alexithymia, Severity of Symptoms, Machine Learning

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Childhood overweight has been identified as a significant predictor of various health parameters, including an increased risk of developing conditions such as heart disease (Janssen et al., 2005) and metabolic disorders like diabetes. Therefore, it is vital to calculate relevant risk factors associated with being overweight such as sleep and alexithymia. This research topic is relevant as overweight and obesity are significant public health concerns, and there is a growing interest in using machine learning (ML) to develop predictive models for various health outcomes. Sleep patterns and alexithymia have been identified as potential risk factors for overweight and obesity, and therefore, incorporating these variables in a predictive model may improve its accuracy.

Sleep disorders are widespread (Hauri, 2021), while insufficient sleep may lead to specific psychological symptoms, such as cognitive symptoms (Killgore, 2010). In addition, sleep deprivation is common among individuals and associated with health costs (Goel, Rao, Durmer, & Dinges, 2009). Furthermore, restricted sleep may lead to excessive daytime sleepiness and altered mood, and sleep loss to hormonal changes that could result in obesity (Vorona et al., 2005). Similarly, a different study found that sleep duration was inversely related to being overweight in young males (Eisenmann, Ekkekakis, & Holmes, 2006). Moreover, additional research confirmed that short sleep duration is a risk factor for both overweight and obesity statuses in children (Chaput et al., 2011).

Besides sleep-related factors, alexithymia is a disturbance in emotional processing shown by difficulties in recognizing feelings (Martínez-Sánchez, Ato-García, & Ortiz-Soria, 2003) and is associated with more light sleep (Bazydlo, Lumley, & Roehrs, 2001). Furthermore, the analysis indicates a significant association between overweight status and impaired emotional recognition, with the data suggesting that individuals with severe obesity face greater challenges in accurately discerning their emotions compared to the control group (Da Ros, Vinai, Gentile, Forza, & Cardetti, 2011).

Collectively, the role of both alexithymia and sleep quality on overweight status is unclear. Therefore, our study goal was to predict overweight status using random forest (RF) and neural networks (NN) models using sleep and alexithymia data.

Method

Subjects

The data from a previous study (Nilsonne et al., 2016) (The Stockholm Brain Study) was used to conduct this study.

The participants (n=83) were recruited to the MR center at the Karolinska University Hospital. Younger (20-30 years) and older (65-75 years) healthy participants were recruited (Stockholm city). The participants completed rating scales at their homes using Google Forms. To ensure confidentiality, participants used a provided code instead of revealing their identities. No online forms had any missing responses. All paper-based responses were entered into spreadsheets and later verified by another investigator to ensure accuracy.

Overall, our study included the following variables to predict weight status: age, Karolinska Sleep Questionnaire (KSQ) Overall Sleep Quality, KSQ_Morning or Evening Person, Toronto Alexithymia Scale-20 (TAS20) Total score, TAS20 subscale of DIF, TAS20 subscale of DDF, TAS20 subscale of EOT, were used to predict overweight status.

Participants were paid around 280 Euro. As mentioned in the previous article, participants who participated in the Zürich prosocial game could gain additional money and be offered taxi travel (Nilsonne et al., 2016). The data collection spanned two periods: from December 4, 2012, to March 27, 2013, and from October 24, 2013, to April 29, 2014.

Instruments

Calculating Body Mass Index

Body mass index (BMI) (kg/m2) was calculated from weight and height data. Participants were grouped into the following categories of BMI: overweight (25—29.9), and obese (30—34.9) (Organization, 2000).

Toronto Alexithymia Scale

Toronto Alexithymia Scale-20 (TAS-20) 14 was used to calculate alexithymia levels in participants and was translated into Swedish (Simonsson-Sarnecki et al., 2000).

Random Forest Model

Random Forest (RF) model is a standard machine learning (ML) model frequently used to solve prediction problems in psychology, neurology, and psychiatry. It is a kind of ensemble learning method that consists of multiple decision trees to make predictions.

Random Forest Model Parameters

Default parameters of the Scikit-learn package of Python (Pedregosa et al., 2011) were used to implement the RF model. The random state value was set to 10. The maximum depth value was set to 4, while the test-size was set to ‘’0.3‘’.

Neural Networks (NN)

Neural Networks (NN) is one of the recently applied ML methods. NN are considered black boxes, due to their complex working mechanism (Alber et al., 2019).

Neural Networks Parameters

Default parameters of the Scikit-learn package of Python (Pedregosa et al., 2011) were used to implement NN model. This network has neurons in the 30 input layer. We use 50 hidden neurons as well as 30 output neurons. The random state value was set to ‘’10’’.

Statistical Analysis

We compared demographic and clinical variables between patients with and without overweight status using the chi-square test for categorical variables. Independent sample T-test and Mann Whitney U test were used for non-categoric variables according to the normality of the variables. Python 3.8.8. version was used to conduct analysis related to machine learning (ML), while SPSS version 17 was used to perform statistical analysis related to descriptive statistics (e.g., mean and standard deviation). In addition, the Kolmogorov-Smirnov test was used to test the normality of the data. There was no missing data in our study.

Ethical Approval

All procedures performed in studies involving human participants were following the ethical standards of the institutional and national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. Also, informed consent was obtained from all patients.

As mentioned in the previous study (Nilsonne et al., 2016) this study was registered to clinicaltrials.gov (NCT02000076). In addition, a list of hypotheses was uploaded to the Open Science Framework (https://osf.io/bxfsb/. Further, the study was approved by the Regional Ethics Review board of Stockholm (2012/1098-31/2, amended as 2012/1565-32 and 2012/1870-32), mainly including permission for open publication of de-identified data.

Results

Descriptive Statistics

The participants (n=83) were between (20-30 years) and (65-75 years). Forty-six were in the younger age group, while 47 were in the older age group. Most of them were males (n=42). In addition, three obese patients with over the 30 body mass index (BMI) were excluded.

Table 1

Precision and Recall of Random Forest and Neural Networks

	Random Forest	Neural Networks
Precision	65	50
Recall	64	50
F1 Score	25	48

Table 2

Confusion Matrix according to Random Forest

$$\begin{bmatrix} 15 & 7 \\ 0 & 3 \end{bmatrix}$$

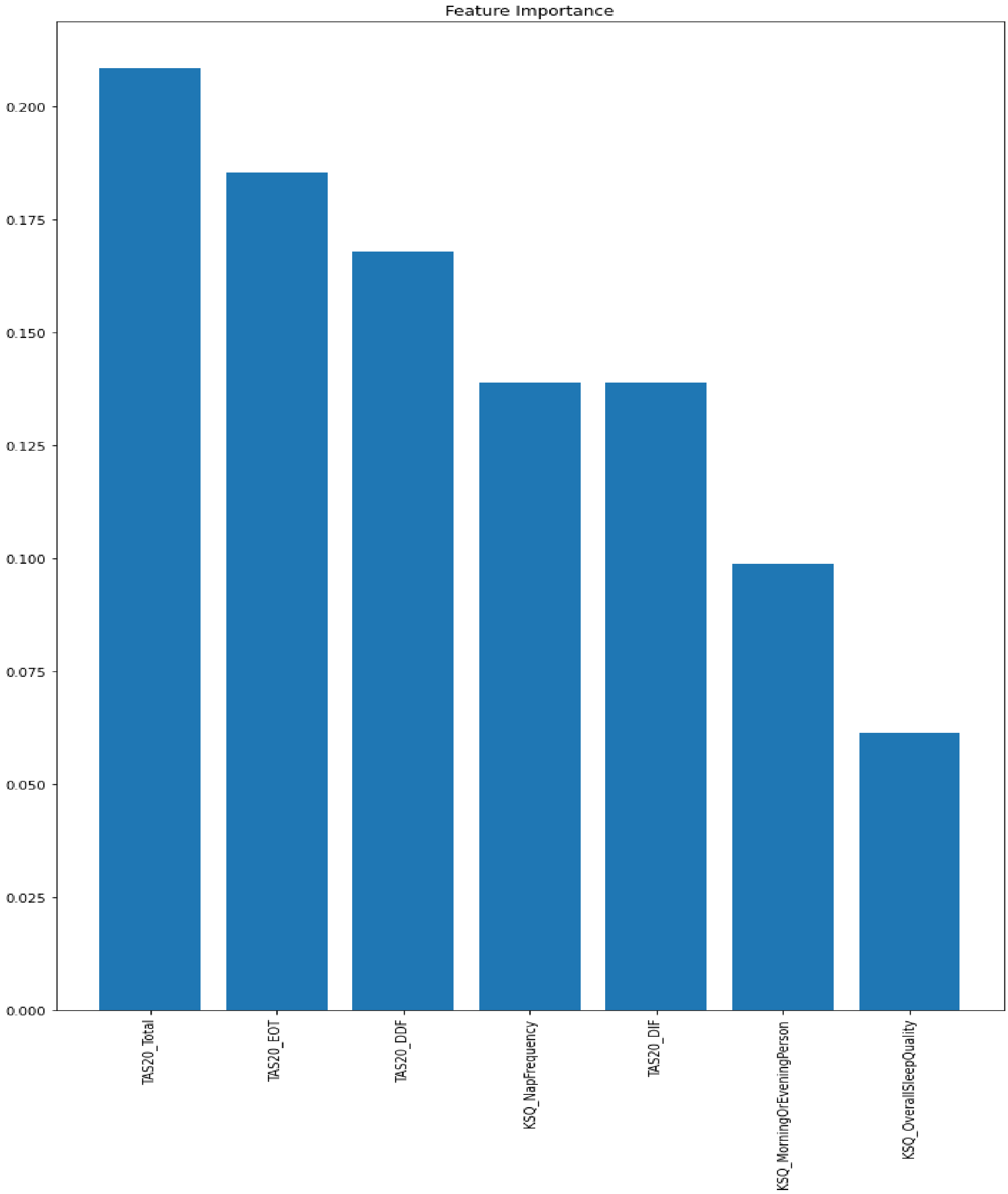
Table 3

Confusion Matrix according to Neural Networks

$$\begin{bmatrix} 12 & 8 \\ 3 & 2 \end{bmatrix}$$

Figure 1

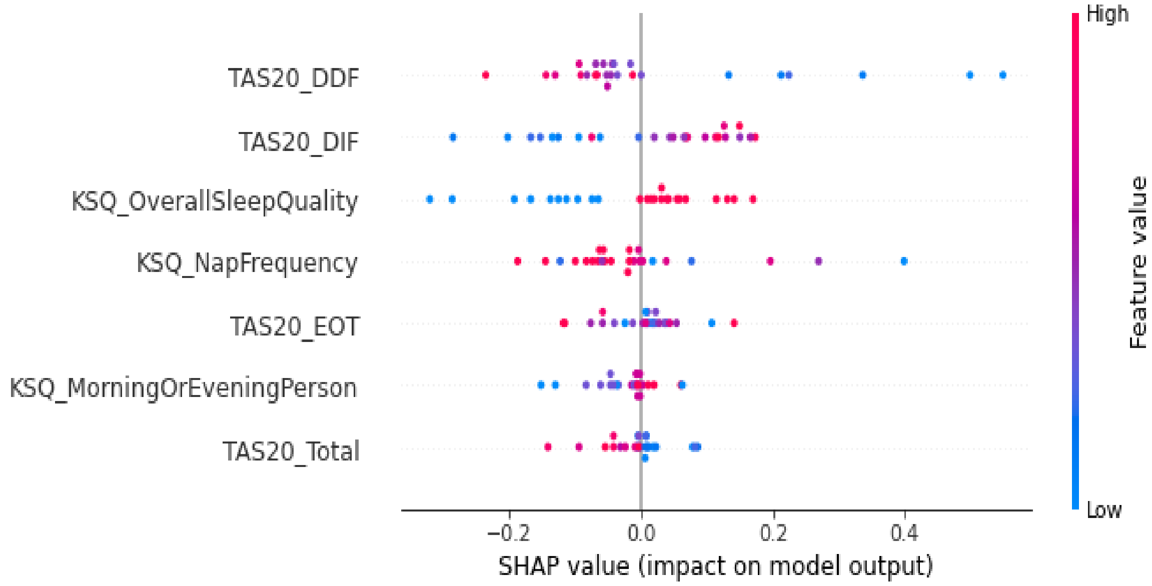
Most Predictive Factors according to Random Forest Model



TAS 20 total score, TAS 20 EOT, TAS 20 DDF, KSQ Nap frequency TAS 20 DIF KSQ morning evening person, KSQ overall sleep quality.

Figure 2

Most Predictive Factors, according to Neural Networks Model



TAS 20 DDF, TAS 20 DIF , KSQ overall sleep quality, KSQ nap frequency, TAS 20 EOT, KSQ morning or evening person, TAS 20 total

Random Forest Machine Learning Model Results

Random Forest (RF) model found that in the training set the accuracy was 72 (sensitivity:100%. specificity:30%). The area under curve (AUC) value was 95. The most predictive factors were Toronto Alexithymia Scale-20 scores (TAS) 20 total score, TAS 20 EOT, TAS 20 DDF, Karolinska sleep questionnaire (KSQ) nap frequency, TAS 20 DIF KSQ morning-evening person, KSQ overall sleep quality respectively.

To validate our ML results, the cross-validation was performed based on algorithms of RF, and NNs, and resulted in an average accuracy score of 0.70 ± 0.12, 0.54±0.11, respectively.

Neural Networks Machine Learning Model Results

Neural Networks (NN) model found that in the training set the accuracy was 93 while in the test set the accuracy was 56% (sensitivity:80%. specificity:20%). The most predictive factors were TAS 20 subscale of DDF, TAS 20 subscale DIF , KSQ overall sleep quality, KSQ subscale of nap frequency, TAS 20 subscale of EOT, KSQ morning or evening person, and TAS 20 total, respectively.

Discussion

Our study's main findings indicate that overweight status can be predicted using random forest (RF) and neural networks (NN) machine learning (ML) models. The RF model demonstrated a training accuracy of 93%, testing accuracy of 56%, sensitivity of 100%, specificity of 30%, and an area under the ROC curve (AUC) of 95%. Meanwhile, the NN model exhibited a training accuracy of 80%, testing accuracy of 20%, sensitivity of 100%, specificity of 30%.

Both the RF and NN models consistently identified alexithymia parameters as the most influential predictors of overweight status. In particular, the RF model highlighted the following factors as highly predictive: Toronto Alexithymia Scale-20 (TAS-20) total score, TAS-20 subscale of Externally Oriented Thinking (EOT), TAS-20 subscale of Difficulty Identifying Feelings (DIF), Karolinska sleep questionnaire (KSQ) nap frequency, TAS-20 subscale of Difficulty Describing Feelings (DDF), KSQ morning-evening person, and KSQ overall sleep quality.

Similarly, the NN model identified TAS-20 subscale of DDF, TAS-20 subscale of DIF, KSQ overall sleep quality, KSQ nap frequency, TAS-20 subscale of EOT, KSQ morning or evening person, and TAS-20 total score as the most influential factors for prediction.

These results collectively highlight the significant role of alexithymia parameters in predicting overweight status, emphasizing the importance of emotional regulation and sleep quality in relation to weight regulation.

According to the literature, obesity, excessive daytime sleepiness, and self-reported short sleep duration may increase, while there is evidence that obesity and sleep disorders are connected (Vgontzas, Bixler, Chrousos, & Pejovic, 2008). In addition, it is worth noting that sleep deprivation has been linked to a pattern of centripetal distribution of fat (De Bernardi Rodrigues et al., 2016). In addition, there is a complex relationship among alexithymia, overweight status, and sleep quality. Therefore, creating prediction models using sleep-related and alexithymia parameters may help predict overweight status. Considering that being overweight is detrimental to overall health, predicting the risk can be beneficial.

In the literature, variations in the defined cut-off points for obesity and overweight status can contribute to discrepancies observed in studies concerning obesity. Furthermore, our research identified heterogeneous variables, including age and gender, as potential confounding factors that may influence the outcomes.

Association between Alexithymia and Overweight Status

The literature consistently found that alexithymia is associated with overweight status. For example, the data suggest severely obese patients have more difficulty recognizing their emotions than controls (Da Ros et al., 2011). Similarly, findings supported having a substantial alexithymic element among severely obese patients compared to their counterparts (Clerici, Albonetti, Papa, Penati, & Invernizzi, 1992). Another study interestingly suggests that the improvement in weight-related attitudes following stable weight loss may differ in alexithymic and non-alexithymic obese patients (Franco Adami, Campostano, Ravera, Leggieri, & Scopinaro, 2001). Further, an additional study found that alexithymia was associated with a more severe binge eating disorder (Carano et al., 2006).

The existence of overweight status was associated with higher emotional dysregulation than normal weight conditions (Casagrande, Boncompagni, Forte, Guarino, & Favieri, 2020). Moreover, a different study found that alexithymia and psychopathology are correlated among obese patients seeking treatment (Pinna et al., 2011). Our study findings demonstrate that parameters related to alexithymia hold potential for predicting overweight status.

Association between Alexithymia and Sleep

It is essential to understand the association between alexithymia and sleep, as our study included alexithymia-related factors. The results of the meta-analysis study found a link between alexithymia and sleep problems (Alimoradi et al., 2021). In addition, further research confirmed the relationship between alexithymia and poor sleep quality (Murphy, Wulff, Catmur, & Bird, 2018). Any association between alexithymia and sleep complaints disappears when the contribution of depression is partialled out by multiple regressions, and only the well-known relationship between depression and impairment of sleep quality is confirmed (De Gennaro, Martina, Curcio, & Ferrara, 2004).

Also, dreaming has a specific manifestation in the case having alexithymia (Obrębska & Rohoza, 2021). Additionally, the findings of a different study suggest a consistent relationship between alexithymia and dreaming components that offer processes regulating emotion during dreaming (Nielsen, Levrier, & Montplaisir, 2011). Similarly, a study showed a higher incidence of nightmares and the association of nightmares with alexithymia (Godin, Montplaisir, Gagnon, & Nielsen, 2013). The association between alexithymia and overweight status highlights the importance of considering psychological factors in the prevention of overweight and obesity. By addressing emotional regulation and promoting healthy eating behaviors, interventions may be able to effectively target both alexithymia and overweight status, and improve overall health and well-being.

Conclusion

This study concluded that overweight status might be predicted using sleep-related and alexithymia data.

Limitations

We have used only BMI to measure obesity and overweight status. Many studies have relied on self-report measures of alexithymia and overweight status, which may be subject to inaccuracies. Also, small sample size is one of the limitations of the study. One of the limitations of this study is that the data collection was conducted during two distinct periods.

Suggestions for Further Studies

Future studies should measure various overweight status-related parameters and associated risk factors. In addition, an integrated approach to promote emotional regulation may reduce the risk of being overweight (Casagrande et al., 2020). Future research endeavors may delve into exploring potential mediators such as emotional eating or other maladaptive coping strategies to better understand the underlying mechanisms linking emotional regulation and weight regulation. Additionally, investigating neural or physiological pathways could shed light on the intricate connections between these two domains.

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