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Exploring the influence of lifestyle on sleep health based on deep learning

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Abstract. Sleep plays a crucial role in maintaining overall health. However, various lifestyle factors significantly influence sleep quality and duration. Understanding the relationship between lifestyle choices and sleep health is crucial for individuals seeking to improve their sleep patterns. The purpose of this study is to provide valuable insights into the causes and effects of sleep disorders in order to help individuals make informed decisions to optimize their sleep health. This article implements the CatBoost gradient algorithm for predictive modeling. Among various models including K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Xtreme Gradient Boosting (XGBoost), Gradient Boosting Decision Tree (GBDT), Random Forest (RF), Decision Tree (DT), Logistic Regression (LR), Deep Neural Network (DNN), CatBoost shows better overall performance with an accuracy of 0.93, an Fl-score of 0.925, and a recall of 0.95. Through data analysis, Blood-pressure-Systolic, Blood-Pressure-Diastolic, and Stress Level are found to have the greatest impact on the model's output.

Keywords: Deep Learning, Lifestyle Sleep Health, CatBoost, Influence.

1. Introduction

In recent years, the sleep quality of Chinese residents has been progressively declining, a phenomenon that has garnered widespread attention from both the government and society. Consequently, sleep has become a societal focal point for maintaining people's health. However, various lifestyle factors significantly influence sleep quality and duration [1]. Understanding the relationship between lifestyle choices and sleep health is crucial for individuals seeking to improve their sleep patterns. Over the past decade, as society has continued to develop and the pace of life has accelerated, there has been an upward trend in the decline of sleep quality [2-5]. Surveys have shown that chronic sleep deprivation can lead to a range of physiological impairments. Currently, the decreasing sleep quality affecting an increasing number of people poses a serious threat to their health [6,7]. Therefore, our study investigates the impact of lifestyle on sleep quality, aiming to provide a more accurate basis for people to make better decisions.

We employed various models, including Categorical Boosting, K-Nearest Neighbors, Support Vector Machine, Extreme Gradient Boosting and Deep Neural Network, to identify the most suitable approach.

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By evaluating and comparing these models, we can pinpoint the most appropriate model to study the influence of lifestyle on sleep health. The specific parameters and feature selection of these models can be adjusted and optimized according to actual needs and data characteristics. Combining data visualization and deep learning methods allows us to gain a more comprehensive understanding of the impact of lifestyle on sleep health, thus providing more accurate foundations for related decisions.

2. Method

2.1. Data visualization analysis

Data visualization is the process of representing data through charts, graphs, and other visual elements to facilitate a more accessible understanding and analysis of data. By transforming data into visual forms, data visualization aids users in recognizing patterns, trends, and correlations, thereby supporting decision-making and communication. In our analysis, we examined the impact of factors such as body mass index, stress levels, and occupation on sleep quality (Figure 1).

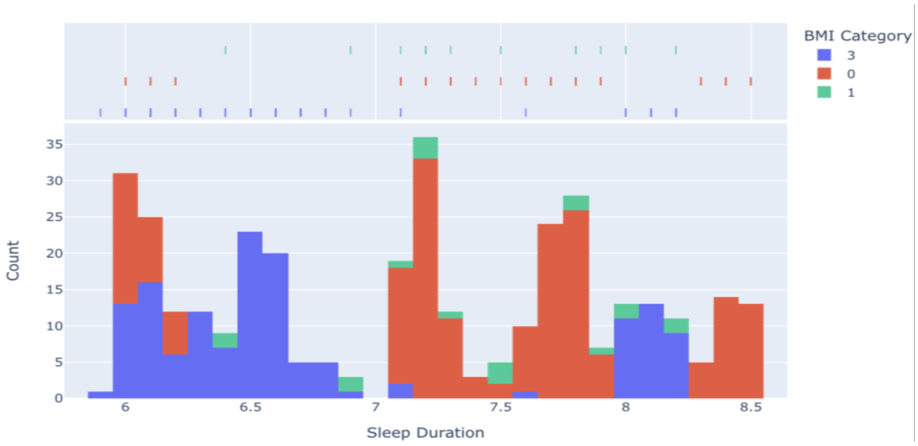

Figure 1. Relationship Between Body Mass Index Categories and Duration of Sleep.

From a research perspective, when considering body mass index (BMI), individuals with a BMI falling within the 0 and 1 categories tend to have longer sleep durations (Figure 1). To enhance sleep quality, individuals should aim to maintain their BMI within the range of 0 to 1.

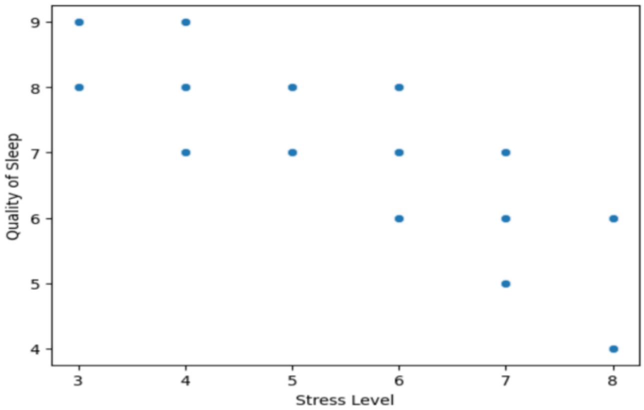

Figure 2. Relationship Between Sleep Quality and Stress Levels.

In terms of stress levels, the higher the stress level, the poorer the sleep quality (Figure 2); indicating that lower stress levels are associated with higher sleep quality [8].

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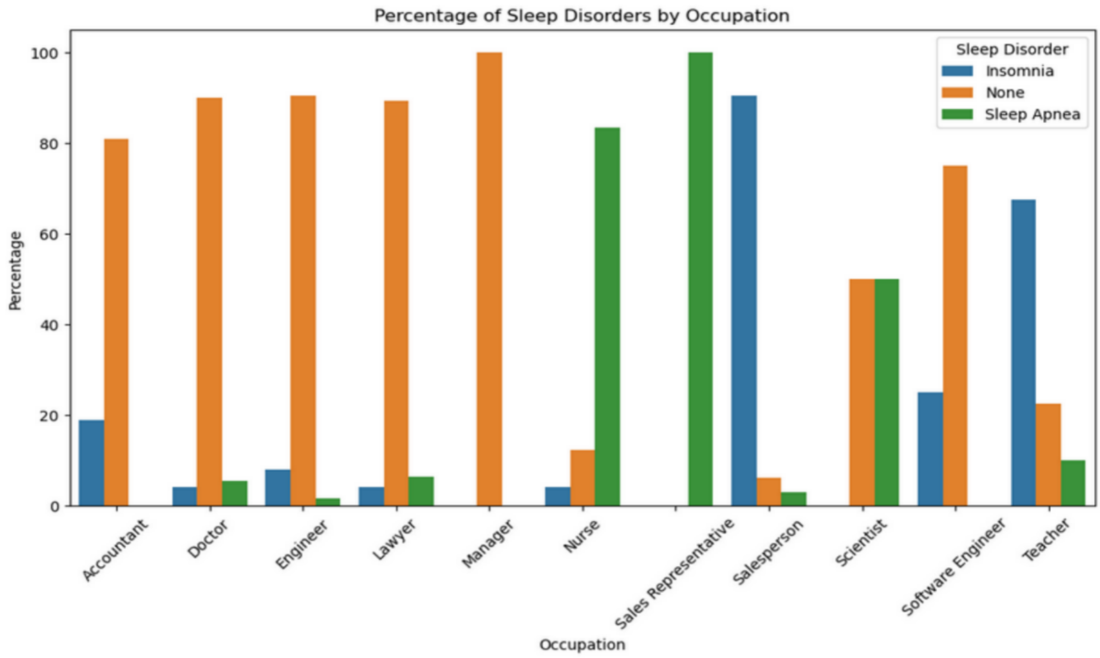

Figure 3. Relationship Between Sleep Disorders and Occupations.

From an occupational perspective, we can observe that bank tellers, doctors, engineers, lawyers, teachers, and executives mostly experience normal sleep patterns (Figure 3). In contrast, nurses, salespersons, scientists, software engineers exhibit poor sleep quality, with instances of sleep apnea and a higher prevalence of insomnia. Based on these findings, we can make informed career choices that align with our preferences for sleep quality.

2.2. Analysis of Catboost Algorithm Principles

Catboost is a model based on Gradient Boosting Decision Tree algorithm. Its principle is mainly based on the principle of gradient boosting tree and the optimization strategy of categorical feature processing. Gradient Boosting Decision Tree is an ensemble learning method that combines multiple decision tree models for prediction. Catboost improves the traditional gradient boosting tree algorithm by introducing handling of categorical features [9].

Catboost utilizes specific encoding rules to handle categorical features more effectively. For each category of each feature, Catboost calculates weights based on reducing the loss of the objective function. This allows Catboost to better utilize the information from categorical features and improve model accuracy. In addition to handling categorical features, Catboost also introduces a technique called Ordered Target Statistics to address overfitting [10]. This technique sorts the training data based on the values of the objective function and computes cumulative statistical information of the sorted objective function values.

In the context of regression tasks, the mean value of the labels is calculated as the prior value. For binary classification tasks, the probability of occurrence for the positive class is used as the prior value. α represents the weight coefficient for priority, which is used to smooth the impact of low-frequency features. Without this operation, when a feature has only one sample, its feature encoding would be 1, which poses a risk of overfitting. This method is known as Ordered Target Statistics numerical encoding method, which effectively solves the problem of prediction drift.

3. Result

3.1. Experimental details and performance indicators

- **Experimental details**

Experimental configuration: In this study, all models were implemented in a Python 3.8 environment using Pandas, Scikit-Learn, and XGBoost packages.

Hardware configuration includes 4.30GHz i3-12100 CPU, RX 5700XT GPU and 16GB RAM The hyperparameter for training is blood pressure, stress level

Training times :1000

- **Performance indicators**

Accuracy: Accuracy refers to the ratio of the number of samples correctly predicted by the classifier to the total number of samples. It measures the overall performance of the classifier, i.e. the ability of the classifier to correctly classify the sample.

Precision: Precision is the %age of samples that the classifier predicts to be positive cases that are actually positive cases. It measures the accuracy of the classifier in the sample predicted to be a positive example.

Fl-score: The Fl-score Accuracy and recall are two metrics commonly used in binary classification problems, where accuracy measures the classifier's accuracy in predicting positive examples, and recall measures the classifier's ability to correctly find positive examples. Which is a weighted harmonic average of the accuracy and recall rates. The Fl-score can be used to combine the accuracy and recall of the classifier.

Recall: Recall is the %age of true positive cases that the classifier correctly predicts to be positive. It measures the classifier's ability to correctly find positive instances.

These measures play an important role in assessing the performance of a classifier or model and can help researchers or practitioners understand how accurate and biased its classification or prediction task is.

3.2. Analysis of experimental results

Based on the experimental results given, we can compare and analyze the various methods. The following Table 1 is a detailed analysis of each method:

Table 1. Experiment results data table.

Methods	ACCURACY	PRECISION	FL-SCORE	RECALL
KNN	92%	92%	90%	88%
SVM	91%	88%	90%	92%
Catboost	96%	89%	93%	96%
XGBoost	94%	89%	92%	95%
GBDT	95%	89%	93%	96%
RF	95%	89%	93%	96%
DT	94%	90%	93%	93%
LR	88%	88%	90%	92%
DNN	87%	88%	89%	91%

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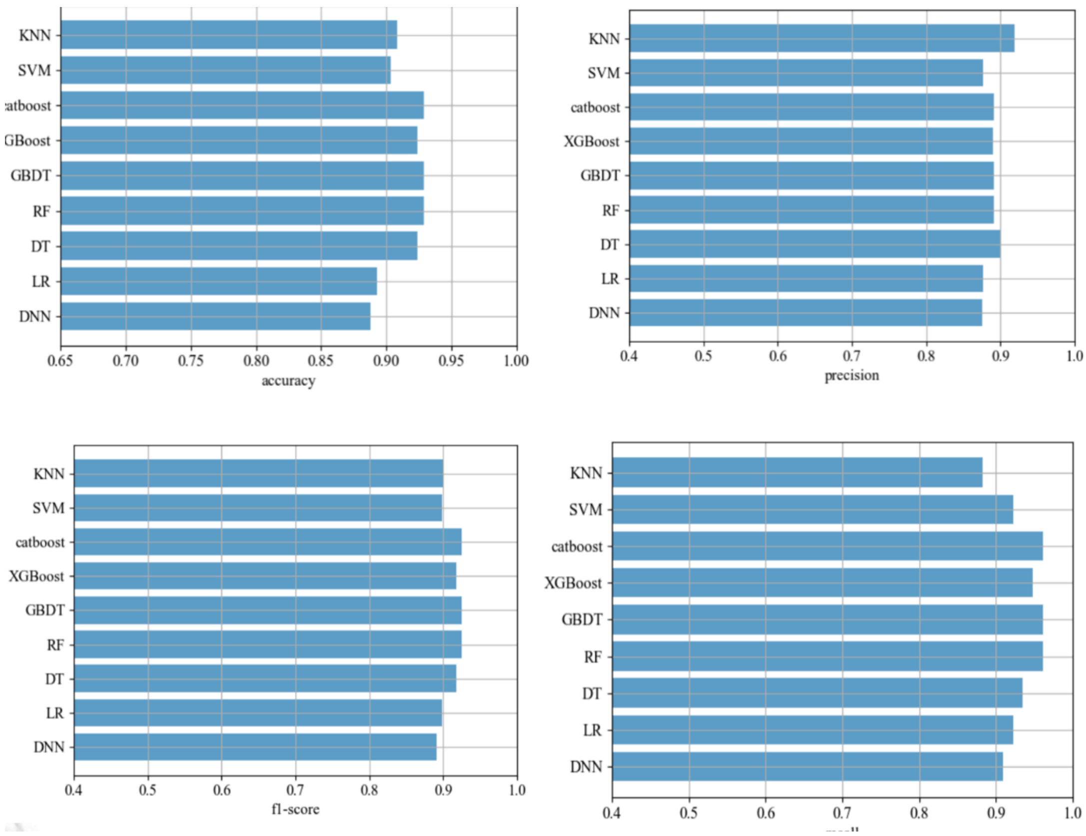

Figure 4. The results from different methods.

In evaluating the performance of different machine learning algorithms (Figure 4), accuracy is an important metric. In our experiments, we compared the accuracy of Catboost, XGBoost, GBDT, and RF algorithms on a given dataset. The results indicated that Catboost algorithm achieved the highest accuracy, with a remarkable 96 %. It outperformed other algorithms such as XGBoost, GBDT, and RF, which all achieved an accuracy of 95 %.

Furthermore, we examined accuracy in relation to specific algorithms such as KNN and LR. Both of these algorithms demonstrated the highest accuracy of 92 %. The DT algorithm followed closely with 90 % accuracy. Interestingly, the Catboost algorithm, along with SVM, XGBoost, GBDT, and RF algorithms, exhibited slightly lower accuracy at 89 %. This suggests a potential vulnerability of misclassifying some negative samples as positive within the Catboost method.

In addition to accuracy, we also considered the Fl score as a comprehensive metric, which captures the balance between precision and recall. Notably, the Catboost algorithm, GBDT algorithm, and RF algorithm demonstrated the highest Fl score of 93 %. Both XGBoost and DT algorithms achieved an Fl score of 92 %.

When examining the recall rate, which denotes the ability to identify all relevant instances, the Catboost algorithm, GBDT algorithm, and RF algorithm again showcased superior performance with a recall rate of 96 %. The SVN algorithm displayed a recall rate of 92 %, while the XGBoost and DT algorithms achieved a recall rate of 95 %. These findings underline the efficacy of the Catboost algorithm in achieving high accuracy and recall rates, especially when compared with other machine learning algorithms. However, further investigation is needed to understand the potential drawbacks and factors contributing to the algorithm's slightly lower accuracy in certain scenarios.

3.3. Discussion

In the experimental analysis, we conducted a thorough investigation and comparison of various machine learning algorithms, focusing on their performance in terms of accuracy, Fl score, and recall. Our findings reveal interesting insights into the performance of Catboost algorithm compared to other traditional machine learning algorithms.

Firstly, when evaluating the accuracy metric, we observed that the traditional machine learning algorithms achieved an accuracy range of 88% to 95%, with no significant differences among them. However, Catboost algorithm demonstrated a noteworthy advantage with an accuracy of 96%. This significant improvement suggests that Catboost algorithm is better suited for the given classification task, outperforming other algorithms.

Furthermore, considering the Fl score as a comprehensive metric that balances precision and recall, Catboost algorithm, GBDT algorithm, and RF algorithm displayed the highest Fl scores of 93%. On the other hand, XGBoost and DT algorithm both achieved an Fl score of 92%.

In terms of recall, which indicates the ability to identify all relevant instances, Catboost algorithm, GBDT algorithm, and RF algorithm again showcased exceptional performance with a recall rate of 96%. The SVN algorithm exhibited a recall rate of 92%, while XGBoost and DT algorithm achieved a recall rate of 95%.

Based on these results, it is evident that Catboost algorithm stands out in terms of accuracy and recall, demonstrating its effectiveness in achieving high accuracy rates and correctly identifying relevant instances. Additionally, Catboost algorithm also showcases strengths in handling classification features, missing values, and noisy or abnormal data. Its advantages of parallel training and high accuracy further solidify it as a preferable choice for machine learning models in this particular scenario.

4. Conclusion

This paper combines data visualization and deep learning methods to investigate the impact of lifestyle on sleep health. Various models, including Catboost, KNN, SVM, XGBoost, and DNN, were utilized to identify the most suitable approach. Catboost, a powerful algorithm for handling categorical features and missing values, showed excellent performance in analyzing the effects of postnatal lifestyle on sleep health. Traditional machine learning algorithms achieved an accuracy range of 88% to 95%, with no significant differences observed among them. In contrast, Catboost demonstrated a distinct advantage with an accuracy of 96%, as well as a superior Fl score (93%) and recall (96%). Overall, this study successfully explored the relationship between lifestyle and sleep quality using deep learning methods and obtained substantial research findings. To further enhance sleep quality improvements, collecting additional data to enhance the model's generalization ability to new data is recommended. Additionally, considering factors such as mood and environment, in addition to lifestyle, can contribute to a more comprehensive investigation of sleep quality. By pursuing further research, we can provide more accurate guidance and decision-making support for enhancing sleep health.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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