Sleep Evaluation:Inspired by My Bad Sleep

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1. Introduction

This project was inspired by my own poor sleep experiences and aims to provide an overall sleep quality score based on various factors. By combining data from sleep habits, lifestyle, and sleep posture, the system evaluates sleep quality and offers insights for improvement. Sleep quality is influenced by many factors, including lifestyle habits (e.g., screen time, caffeine intake, study or work schedule), physical activity, health conditions, and sleep environment. Additionally, sleep posture can affect comfort, spinal alignment, and breathing patterns, further impacting overall sleep quality. Therefore, the goal of this project is to evaluate sleep in a thorough and comprehensive way.

2. Dataset

I first categorized the data into three types to help me find the datasets: data related to sleep itself, data related to the human body, and images of sleep postures. Based on this categorization, i selected datasets that provided comprehensive information, including sleep duration, daily routines, demographic details, and images of different sleep positions. After collecting the data, I cleaned and organized it to ensure consistency and compatibility for model training. The datasets were chosen to cover a comprehensive range of sleep-related factors. Structured data provides insights into lifestyle and health influences, while images of sleep postures capture physical behaviors during sleep. Combining these sources allows for a more holistic evaluation of sleep quality than using a single type of data alone.

This project uses three data sources:

2.1 Sleep Health and Lifestyle Dataset

Link: https://www.kaggle.com/datasets/uom190346a/sleep-health-and-lifestyle-dataset

This dataset provides information about sleep, such as sleep habits, physical activity, and health-related indicators. It also includes basic demographic information like age and gender. With this data, we can evaluate sleep quality from different angles and understand how lifestyle and personal factors may affect sleep.

2.2 Student Sleep Patterns Dataset

Link: https://www.kaggle.com/datasets/arsalanjamal002/student-sleep-patterns

This dataset contains demographic information as well as details about the sleep situation. It also includes personal attributes of the sleeper, which enables a more comprehensive evaluation of sleep quality.

2.3 Sleep Poses Dataset

Link: https://universe.roboflow.com/sleep-pose/sleep-poses

This dataset contains images of various sleep positions (Back, Fetal, Side, Stomach). It is used to train a convolutional neural network (CNN) to recognize user sleep posture and assign posture scores, which are combined with tabular data for a comprehensive sleep quality score.

3.Models

3.1 Text Models

The tabular model was trained to predict Sleep Quality Scores from structured data. We used a Random Forest Regressor from scikit-learn, with 80% of the data for training and 20% for testing. To measure performance, we looked at the Mean Squared Error (MSE) and the R^2 score. I chose Random Forest here because it works well with non-linear relationships and can automatically find complex patterns in the data. It also doesn't need feature scaling because decision trees split data based on the order of values, not the exact numbers.

3.2 Image Model

A Convolutional Neural Network (CNN) was trained to classify sleep posture images. ResNet18 was chosen because it has already been trained on large image datasets, so it can recognize general image features such as edges and shapes. Using a pre-trained model helps the network learn faster and reduces the amount of data needed for training. Since our sleep posture dataset is relatively small, transfer learning with ResNet18 improves performance and helps prevent overfitting.

The CNN model was trained for 10 epoch.The batch size was set to 32. The learning rate was 1e-4, controlling the step size of parameter updates. Adam optimizer was used, which adaptively adjusts learning rates for each parameter and works well for small datasets and transfer learning. The loss function was CrossEntropyLoss, suitable for multi-class classification.

Each posture was assigned a corresponding pose score based on relevant research (Back: 8, Fetal: 6, Side: 10, Stomach: 5). The distribution was informed by findings from research papers and online sources, which generally suggest that side sleeping is the best, followed by back, fetal, and stomach positions. Therefore, I assigned the scores accordingly to reflect this ranking.

3.3 Combined Sleep Score

A weighted combination of predictions was used:

$$\text{Final Score} = \mathbf{0.4} \times \text{Score1} + \mathbf{0.4} \times \text{Score2} + \mathbf{0.2} \times \text{Pose Score}$$

This weighted sum allows us to combine information from different sources, giving more importance to the table-based scores while still including the influence of posture. I haven't found a precise method to determine the weights, so I chose them based on intuition.Full score is ten.

The **predict_sleep_score** function combines predictions from tabular data models and a sleep posture image model to calculate a comprehensive sleep quality score for a user. It takes three inputs: two sets of structured user data (user_input_1 and user_input_2) and an image of the user's sleep posture (image_path).

For the tabular data, each input is converted into a DataFrame and one-hot encoded to match the feature space of the pre-trained Random Forest models. Missing columns are automatically filled with zeros to ensure consistency. Each model then predicts a sleep quality score, which is clipped to the range 1–10 to maintain a standardized scale.

For the image input, a Convolutional Neural Network (CNN) model based on ResNet18 is used to classify the sleep posture into one of four categories: Back, Fetal, Side, or Stomach. Each posture is assigned a corresponding score based on research, reflecting its influence on sleep quality.

Finally, the function combines the predictions from the tabular models and the posture score using weighted sums: 40% from the first tabular model, 40% from the second, and 20% from the posture score. The final score is clipped to ensure it remains within the 1–10 range. The function returns the final comprehensive sleep score, the predicted sleep posture, and all intermediate scores for transparency.

3.4 LLM-based Recommendation

A Large Language Model (LLM) is used to generate the final user report. It takes as input the user's personal information (e.g., gender, age, lifestyle, and health indicators), the predicted scores from the models, and the combined final sleep score to provide personalized sleep advice.

3.5 Results

The tabular model achieved an excellent performance on the test set, with a mean squared error (MSE) of 0.02 and an R^2 score of 0.98.

5.Final Score

For the sample user, the tabular model predicted a sleep quality score of 1.23 and 1.41 individually. The CNN-based sleep posture classifier identified the user's posture as Side with a posture score of 10. Using the weighted combination (0.4 × old model + 0.4 × new model + 0.2 × posture), the final comprehensive sleep score is 3.06(full score is 10).

6.Future Work

1.Using a better method to evaluate pose scores.In this project, we currently assign scores to different sleep postures manually. In the future, we plan to adopt a more scientific approach to evaluate these scores, using objective measurements and consistent criteria to make the assessment of each posture more accurate and reliable. For example, we could use motion capture data or pressure sensor readings to measure how the body aligns in each posture, rather than relying on rough estimates(Some relevant datasets are publicly accessible and can be used for research on sleep postures or related tasks.).

2.Using a more advanced way to assign weights in the last step.Right now, we apply weights in a basic way, which may not fully reflect the importance of different posture features. In the future, we aim to implement more scientific weighting methods that consider multiple factors. For example, we could use feature importance from machine learning models or attention mechanisms in neural networks to automatically learn which aspects of a posture have the most impact on sleep quality, making the model more accurate and reliable.

3.I also plan to use visualization to better understand sleep patterns and model predictions in the future. For instance, we can plot key features like sleep duration, caffeine intake, and activity levels to see trends and relationships. These visualizations can make the model easier to interpret and help provide useful advice for improving sleep quality.

4 The current sleep evaluation does not support personalized assessment. In the future, each user could set their own ideal sleep standards, and the system could score their sleep based on these personal benchmarks.

7.Conclusion

In this project, we developed a system to evaluate overall sleep quality by combining information from sleep habits, lifestyle, and sleep posture. We used a Random Forest model for tabular data and a CNN to classify sleep posture images. By combining the predictions from these models with posture scores, we obtained a comprehensive sleep score for each user.

The results show that both models perform well, and the combined score provides a clear and meaningful evaluation of sleep quality. Future improvements could include using more scientific methods to calculate posture scores and applying advanced weighting methods to better reflect the importance of different posture features. Overall, this system provides a useful tool for understanding sleep quality and offering personalized advice for improvement.

Reference:

1.uom190346a. (2020). Sleep Health and Lifestyle Dataset [Data set]. Kaggle. https://www.kaggle.com/datasets/uom190346a/sleep-health-and-lifestyle-dataset

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4.Zhang, Y., Xiao, A., Zheng, T., Xiao, H., & Huang, R. (2022). The relationship between sleeping position and sleep quality: A flexible sensor-based study. Sensors, 22(16), 6220. https://doi.org/10.3390/s22166220