

Abstract

This study examined whether machine-learning models could predict sleep quality using age, sleep duration, and physical activity. Five methods were evaluated on the public Sleep Health and Lifestyle dataset. Decision-tree and random-forest models produced the lowest test errors, indicating that they were the most accurate among the methods tested.

Main findings

Tree-based methods produced the closest predictions, with average errors of 0.03 points for the best decision tree and 0.07 for the random forest. Nearest neighbours and linear regression made larger errors, while the neural network had the highest at 1.35 points.

These results show that greater complexity does not guarantee better predictions. Further tuning and testing on real data are needed to determine whether this pattern holds beyond the study.

Introduction

Poor sleep can affect concentration, daily functioning and overall health. Sleep quality is influenced by several factors, making it difficult to understand by looking at one factor alone.

This study explored whether machine learning could predict sleep quality from age, sleep duration and physical activity. Several models were compared to assess their accuracy and potential for sleep-health research.

Methods

Dataset and inputs

The Sleep Health and Lifestyle dataset contained 374 synthetic records. Three variables were selected as inputs: age, sleep duration and physical activity level. The models used these to predict the dataset’s sleep-quality score, defined on a 1–10 scale [1].

Model comparison

Five regression models were compared: Linear Regression, Decision Tree, Random Forest, K-Nearest Neighbours (KNN) and a Multilayer Perceptron (MLP) neural network. The study also explored an adaptive weighted average of four models, giving greater influence to smaller errors.

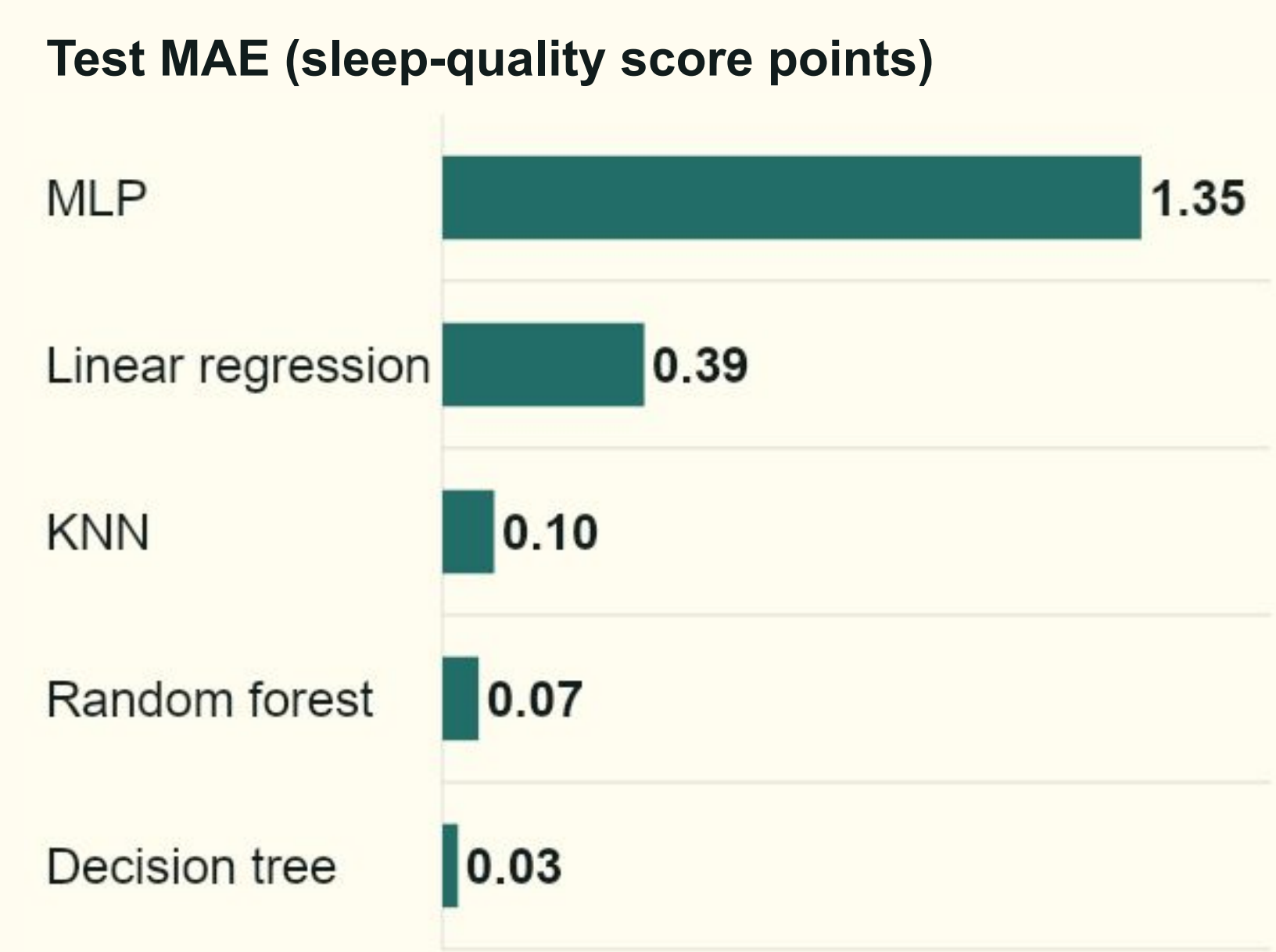
Training and evaluation

The data were randomly divided into 250 training records and 124 test records. Models learned from the training data before predicting scores for the test data. Performance was measured using mean absolute error (MAE), the average absolute difference between predicted and recorded scores, and mean squared error (MSE), which gives larger errors more weight. Lower values indicate better predictions.

Results

The decision tree had the lowest average error at 0.03 points, followed by the random forest at 0.07. KNN and linear regression had larger errors, while MLP had the highest at 1.35 points [2].

Increasing tree depth from 6 to 10 reduced the decision tree’s MSE from 0.04 to 0.03. The random forest’s reported MSE remained unchanged.



Model	Setting	MSE	MAE
Linear	—	0.25	0.39
Decision tree	depth 6	0.04	0.05
Decision tree	depth 10	0.03	0.03
Random forest	depth 6	0.03	0.07
Random forest	depth 10	0.03	0.07
MLP	500 iter.	3.42	1.35
MLP	50 iter.	3.42	1.35
KNN	k = 1	0.22	0.10
KNN	k = 10	0.22	0.10

Chart: tree depth 10, KNN k = 1, MLP 50 iterations.
Table: published test errors, rounded as reported.

Discussion

The stronger performance of tree-based models suggests that the relationships between the inputs and sleep quality were better captured by a series of decision rules than by a simple linear equation. [2].

KNN performed well on its training examples but less accurately on test records, suggesting overfitting: learning the examples too closely to predict new cases reliably. The neural network’s higher error may reflect the small dataset or insufficient tuning. These are possible explanations, rather than causes established by the study.

Limitations and improvements

The synthetic dataset and single training/test split limit how confidently these findings can apply to real people. Future work should use real sleep-health data, test different splits and refine model settings.

Scaling inputs may improve KNN and neural-network performance. Adaptive weighting needs separate evaluation because it used observed test scores to adjust later predictions.

Conclusion

Tree models gave the most accurate predictions in this study. Real world validation is needed before considering sleep-health applications.

References

[1] Tharmalingam, L. Sleep Health and Lifestyle Dataset. Kaggle. kaggle.com/datasets/uom190346a/sleep-health-and-lifestyle-dataset
[2] Yamanov, A. (2026). Artificial Intelligence in Sleep Medicine: Predicting Sleep Quality Using Lifestyle and Demographic Indicators. OJSS 4(1), pp. 249–260. Results: pp. 257–258.