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Predicting Sleep Quality Using 24-Hour Physical Activity Data from Wearable's: A Fitness Tracking Approach

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Abstract: ***This study suggests a unique method for estimating sleep quality using physical activity data collected over 24 hours via wearable technology like the Apple Watch. We use machine learning models, namely Random Forest and Extreme Gradient Boosting, to investigate the connections between physiological parameters (e.g., heart rate and activity levels) and sleep patterns. Users can improve their sleep quality by understanding how their everyday activities affect them, using the individualised insights generated. According to our research, wearable technology and predictive analytics can improve general health.***

Keywords: Apple Watch, wearable technology, machine learning, physical activity, fitness tracking, and sleep quality prediction

1. Introduction

Indeed, predicting the quality of sleep from daily activities recently proved still difficult, while very large wearables provide information that contains sleep and physical activity. There is a paradigm shift in the way people monitor their health and wellness. Wearable devices like Fitbit, Apple Watch, and Garmin provide real-time data on health metrics such as heart rate, step count, and energy expenditure [1] [2]. These wearable devices monitor heart rate, steps taken, energy use, and sleep patterns, among other parameters. There are many reasons why sleep quality and sleep duration are conducive to an overall state of health. Moreover, poor sleep can be linked, evidently, to a number of health issues and seriously impact the risks concerning overall well-being: cardiovascular diseases, obesity, diabetes, and cognitive decline. Poor sleep can lead to cardiovascular diseases, obesity, and diabetes [7].

Although wearables offer a wealth of information regarding sleep and physical activity, it is still challenging to predict the quality of a user's sleep based on their daily activities. Although the fitness monitoring apps available today provide data on sleep length, stage breakdown, and disruptions; they do not provide users with predictive insights to improve the quality of their sleep in the future. This study addresses the problem of accurately predicting sleep quality using physical activity data collected over 24 hours. We aim to develop a wellness app that leverages a user's 24-hour physical activity data to predict sleep quality through machine learning models.

The app will utilise data from wearable devices to capture measurements such as step count, resting and active heart rate, calories burned, heart rate variability (HRV), oxygen saturation, and VO2 Max. The application uses machine learning models such as Random Forest and Extreme Gradient Boosting (XGBoost) to find patterns corresponding to different sleep quality levels (excellent, neutral, or poor). The app's ultimate goal is to give users tailored, valuable insights so they may modify their daily schedules and get better sleep.

Specific research goals include collecting and analysing physical activity data from wearable devices, developing and training machine learning models to predict sleep quality based on collected data, delivering meaningful insights to users, and analysing the machine learning models' accuracy by comparing predictions with actual sleep outcomes. The primary goal of this study is to offer an enhancement of overall health and sleep quality.

2. Literature Review

Overview of Wearable Technology in Health Monitoring
The production of wearable health trackers is a significant shift toward wearable technologies and health monitoring. Heart rate, step count, sleep habits and a plethora of other health data are brought to their fingertips by-products like Fitbit and Apple Watch, which are all the rage throughout the world. Wearables proliferation has brought forth self-health awareness among human beings more effectively by providing them with systems for their betterment where they can keep a close watch on every activity they perform regarding their health. This kind of device includes cutting-edge sensor and algorithm integration making it the most necessary part of the entire process as it enables continuous data harvesting and analysis and, therefore, making it possible to unravel the tangled connections between physical activities and their bordered health consequences. Despite their advancements, these devices primarily offer descriptive analytics without actionable predictive insights [4][8].

Importance of Sleep Quality
Sleep quality is crucial to overall health, influencing cognitive, emotional, and physical well-being. Sleep quality is crucial for cognitive, emotional, and physical health [3]. Research indicates that the quality of sleep affects not only

daytime functioning but also long-term health outcomes. Therefore, awareness of the elements that affect sleep quality is essential for developing effective interventions to enhance sleep and overall health.

Existing Methods for Predicting Sleep Quality
It is tough to determine how well or poorly you have slept based on your daily activities. This has been a critical issue due to the advancement in wearables, which give adequate information regarding what happens during sleep and the level of physical activity. The applications that have been generated so far gave information about time and efficiency, but there was nothing one could do about it. Studies provide insights into deep learning applications for sleep quality prediction and innovative health monitoring systems [8][7]. Studies have shown that Biomarkers related to physical activity, such as heart rate and activity levels, are good indicators of quality sleep. One study suggests that more sophisticated prediction models will be necessary in order to achieve improvements correlated to sleep measurement using machine learning methods in analysing physiological data acquired through wearable devices in cases of detecting fatigue by Bygrave and others (2018).

Machine Learning in Health Analytic
Complex health information cannot be easily understood, but powerful computer programs use random forest algorithms, and now even increasingly popular algorithms have taken the lead, specifically XGBoost, to understand the phenomenon of predicting the quality of sleep with large datasets that conventional statistics do not take into account. In detail, the relationships between different patterns of interplay between various physiological markers contributing to better sleep can only be understood and predicted with a machine learning model. Previous research indicates that automated analysis of wearable data can yield significant insights into users' health behaviours and their effects on sleep.

Gaps in Current Research
The use of pretty robust wearable technology has done little to improve the diversity of datasets used in studies, automation, and human-robot cooperation suitable for making predictions. To properly generalise, researchers use data of those from diverse corners of technology with high fitness levels in that it is the generation that would suitably represent, including those people who are not much into fitness. Such an absence of comprehensive data thwarts personalised insights into patterns and optimising daily routines for better sleep results for end users.

This research aims at the invention of a machine learning fitness tracking app that analyses 24-hour physical activities efficiently and can predict the quality of sleep. For this vision to be fully realised, a massive need to aggregate such workouts is necessary to widen the fitness range. Through there, the sense of ambition can be easily figured out. There are not only good but diverse models for particularly personal prospects.

3. Problem Statement

Sleep is a well-known component that shapes other essential aspects of an individual, such as cognitive performance, mood shift, and even many health conditions. Getting good quality sleep might be a challenge given the current light pollution, city noise and so on. Recently, Apple has made devices that may assist you both in sleeping and working out. For example, Fitbits are capable of recording data such as heartbeats, number of steps taken, active energy burned, VO2 max, and many others. Although this sophisticated gadget seemingly enhances your experience by allowing access to such a great amount of data about sleep and physical activities, their inability to suggest or give examples as to what kind of physical activity you would require in order to sleep better is puzzling and, in my view, stands out.

Current wellness applications have the capacity to offer descriptive analytics, enabling them to offer historical data pertaining to sleep quality (i.e. duration, efficiency, time slept in each stage) as well as averaged data on physical workouts. However, these arguments have a high cost associated with their effectiveness, and I would recommend against their use. The database is complicated, and their absence from the model speaking in relation to physical activity and sleep quality work is disheartening to the customer. This is the reason why users, for instance, do not comprehend what pattern should be following in order to keep the comb together for such a long period of time.

4. Methodology for Sleep Quality Prediction Using Machine Learning Models

The primary goal of this study is to create a predictive model that will predict sleep quality effectively, using the physical activity data from wearable devices. Wearables are used to track several metrics like steps taken, active energy burned, and heart rate data with sleep stages (awake, REM, deep, core). This study tries to establish a relationship between physical activities and sleep quality, thus helping in developing machine learning models for prescribing actionable insights on how specific physical activity patterns will affect sleep outcomes.

4.1 Data Collection and Preprocessing

The Apple Watch and Fitbit Fitness Tracker dataset employed in this study was also derived from wearable devices. Despite advancements in wearable technology and machine learning applications in health analytics, gaps remain in understanding how specific combinations of physical activity influence sleep quality. Personalised insights from 24-hour activity data are needed to help users optimise their daily routines for better sleep outcomes. This study attempts to close that gap by creating a machine learning-driven fitness tracking app that analyses users' physical activity patterns over 24 hours to predict sleep quality effectively.

The dataset used in this study is sourced from wearable fitness trackers, which record physical activity and sleep quality metrics over time.

The dataset includes the following features:

Physical Activity Metrics:
- **Active Energy Burned:** The total energy expended during physical activity.

- **VO2Max:** An estimate of maximum oxygen uptake during exercise.
- **Distance:** The total distance travelled during physical activity.
- **Heart Rate:** Real-time heart rate measurements.
- **Resting Heart Rate (resting_hr):** Average heart rate during rest periods.
- **Steps:** The total number of steps taken in a given period. Etc

In (Figure 1), Physical Activity Metrics illustrate the data collection and analysis processes in this study. These metrics were total calorie expenditure, movement minutes, heart points, and the number of steps. All are used to better understand the interplay between physical activity and efficient sleep indicators. It was ensured that the deep sleep time entered in the sleepwalk duration, and the light sleep time was also normalised to resting heart rate. So that these parameters will be pervaded into models. The steps of preprocessing consisted of cleaning the missing data values by imputing mean values into the numerical columns so as not to spoil the relationship. The MinMaxScaler ensures a better relationship between these values, in this case, making the runnable properties of values really close to great conditions extraction while preparing for advanced machine learning models. This means that the metrics collected from disparate wearable devices and health applications were normalised while ready to be infused with regression models for correct inferences on sleep efficiencies.

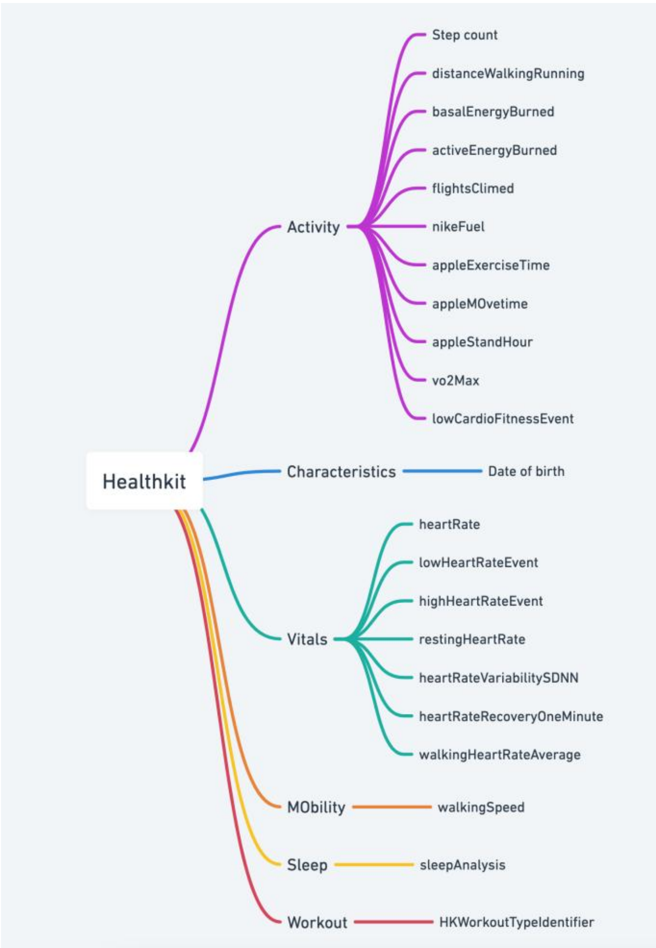

Figure 1: Physical Activity Metrics.

Sleep Metrics:

- **Total Calories Burned (total_calories_kcal):** Calories burned throughout the day.
- **Total Move Minutes (total_move_minutes):** Minutes spent in moderate-to-intense physical activity.
- **Heart Points:** A metric indicating cardiovascular activity levels.
- **Deep Sleep in Minutes (deep_sleep_in_minutes):** Time spent in the deep sleep stage.
- **Sleep Efficiency:** The ratio of actual sleep time to the total time spent in bed.
- **Minutes Asleep:** Total sleep duration in minutes.
- **Minutes Awake:** Total time awake during the sleep period.
- **Sleep Duration:** Total duration of sleep in milliseconds.

For this study, the target variable is the **sleep quality**, which is categorised into four classes:

1) Excellent
2) Good
3) Fair
4) Poor

Preprocessing Steps

The data was cleaned and preprocessed to ensure high-quality input for model training:

1) **Handling Missing Values:** Missing values were handled by imputing them using the mean value of the respective columns. This ensures that the dataset is complete and usable for training.
2) **Feature Selection:** Unnecessary features that do not contribute to the predictive power of the models were removed. Relevant columns such as ActiveEnergyBurned, VO2Max, steps, and sleep quality metrics were retained.
3) **Feature Engineering:** Additional features were engineered by aggregating data over time windows (e.g., calculating moving averages of step counts or heart rate). Feature Scaling: Physical activity metrics such as HeartRate, steps, and ActiveEnergyBurned were normalised using MinMaxScaler to bring all features to the same scale, ensuring fair model training.
4) **Feature Scaling:** Metrics such as HeartRate, Steps, and ActiveEnergyBurned were normalised using the MinMaxScaler to ensure all features operate on a uniform scale, facilitating fair model training.

Target Variable Transformation

Sleep quality was transformed into discrete categories based on a weighted scoring function.

The **determine_sleep_quality** function assigns a score to each sleep period based on the time spent in various stages of sleep, as detailed below:

$$\textbf{Score} = ({}^{t}\textbf{awake} \times {}^{w}\textbf{awake}) + ({}^{t}\textbf{rem} \times {}^{w}\textbf{rem}) + ({}^{t}\textbf{core} \times {}^{w}\textbf{core}) + ({}^{t}\textbf{deep} \times {}^{w}\textbf{deep})$$

Where:

- t: Time spent in a specific sleep stage
- w: Weight assigned to each sleep stage

The assigned weights to each sleep stage:
- **^{w}awake = -1**
- **^{w}rem = 2**
- **^{w}core = 1**
- **^{w}deep = 3**

Scores were used to categorise sleep quality into the four defined classes

4.2 Correlation

A correlation heatmap (Figure 1) provides a comprehensive visualisation of the correlations between various physical activity metrics (e.g., step count, heart rate, distance travelled) and sleep cycle features (e.g., duration of deep sleep, REM sleep, light sleep) in relation to the target variable, sleep efficiency.

The correlation coefficients were visualised on a gradient colour scale, where:
- **Dark red:** Strong positive correlation.
- **Dark blue:** Strong negative correlation.

The correlation values are represented on a gradient colour scale, where dark red indicates a strong positive correlation and dark blue signifies a strong negative correlation. It is pertinent for a psychologist to maintain an unbiased and fair stance during the analysis of the results of the participants, as the test score can be manipulated in order to overcome these restrictions. Religious training can work as a strong mediator in enhancing the understanding of societal awareness.

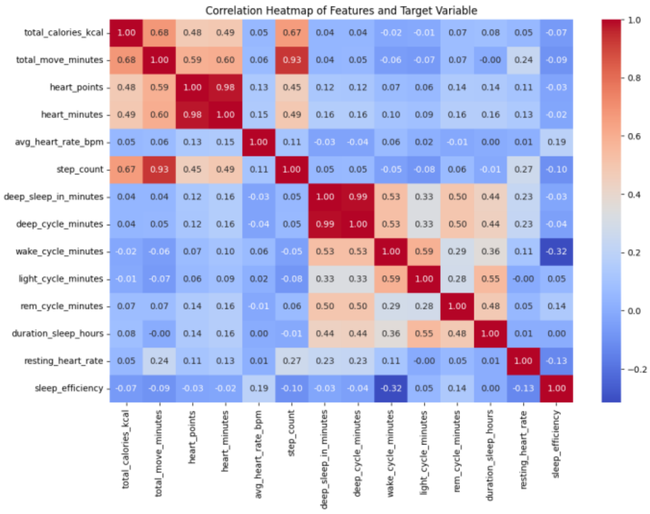

Figure 2: Correlation Heatmap of Features and Target Variable

4.3 Model Development

Multiple models for machine learning had been trained and tested by validating the quality of sleep with the help of physical activity data. The models used were Random Forest and Extreme Gradient Boosting (XGBoost) for this purpose. Here is the outlined development process.

4.3.1 Data Splitting:
The dataset was split into two subsets: the training subset and the testing subset. 80% of the data was used for training and 20% for testing so that the model was always trained on the majority of the data, but leaving some portion to not bias the evaluation.

4.3.2 Model Selection and Training:
Two primary models were selected for evaluation:
- **Random Forest (RF):**
  A decision-tree-based ensemble learning method known for its robustness in handling non-linear relationships and complex datasets. RF was optimised using grid search to determine the best hyperparameters, such as the number of trees, maximum depth, and minimum samples per split.
- **Extreme Gradient Boosting (XGBoost):**
  A decision-tree-based ensemble learning method known for its robustness in handling non-linear relationships and complex datasets. RF was optimised using grid search to determine the best hyperparameters, such as the number of trees, maximum depth, and minimum samples per split.

4.3.3 Hyperparameter Tuning:
Both models underwent grid search cross-validation to identify the optimal hyperparameter combinations for achieving the best performance. The evaluation metric for hyperparameter tuning was accuracy.

4.3.4 Evaluation Metrics:
Model performance was evaluated using the following metrics:
- **Mean Absolute Error (MAE):** To assess the average magnitude of errors.
- **Mean Squared Error (MSE):** To measure the squared differences between predictions and true values.
- **R^2 Score:** To determine how well the model explains the variance in sleep quality.
- **Accuracy:** To evaluate the model's ability to correctly classify sleep quality into the four categories.

4.3.5 Feature Importance
For each model, the importance of individual features was calculated. Features like ActiveEnergyBurned, VO2Max, and Steps consistently emerged as significant predictors of sleep quality.

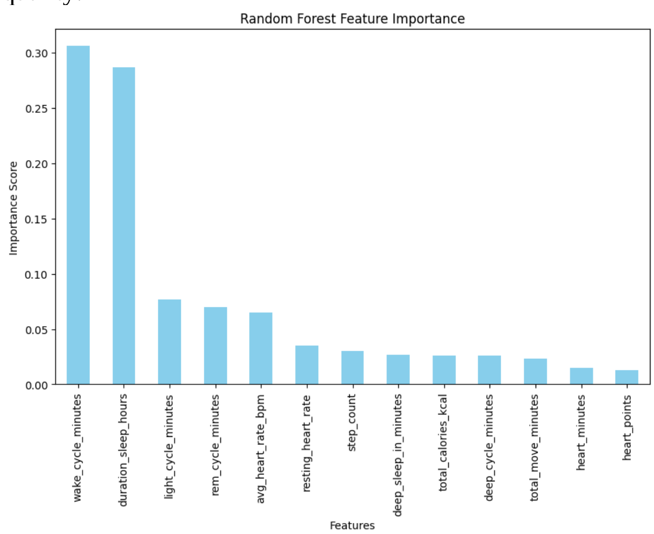

Figure 3: XGBoost Feature Importance Plot

(Figure 2) visually represents the contributions of various input variables to predicting sleep efficiency. Features such as "wake_cycle_minutes" and "duration_sleep_hours" emerged as the most critical predictors, reflecting their substantial impact on sleep quality outcomes. The ranking of features provides key insights into the relevance of specific physical activity metrics, including their potential thresholds and variability. These findings align with existing literature on sleep science, emphasising the role of sustained activity and rest patterns in achieving optimal sleep efficiency. The Random Forest model's inherent ability to handle non-linear relationships and interactions between features further underscores the reliability of this feature ranking.

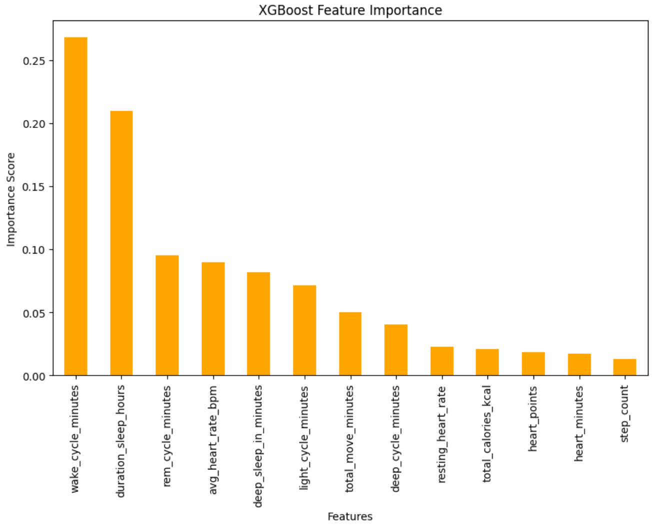

Figure 4: XGBoost Feature Importance Plot.

(Figure 3) derived from the XGBoost model, showcases the relative contributions of each input variable to the prediction of sleep efficiency. Similar to the Random Forest model, "wake_cycle_minutes" and "duration_sleep_hours" were identified as the most influential features. In other words, XGBoost has a boosting system of gradient descent that cranks up the search in the vast and subtle pattern spaces to discover the solution with unsanctioned humorous information in them and discover subtle associations amongst features with the target variable very efficiently. By all means, forming a parallel comparison with random forest, the XGBoost data adds validity to the present study's findings. Another finding of this study would mainly help in proposing practical recommendations for sleep efficiency based on the optimisation of particular patterns of physical activity.

These insights were visualised using feature importance plots.

4.3.6 Physical Activity Ranges for Good Sleep

Percentile statistics (50th, 75th, and 95th percentiles) were calculated for physical activity metrics associated with good sleep quality. This analysis identified optimal ranges of metrics such as step count, heart rate, and active energy burned that consistently correlated with high sleep quality. The ranges were visualised using boxplots to aid interpretation.

4.3.7 Comparison of Model Performance Metrics

(Figure 5), The performance metrics of three predictive models—Random Forest, Linear Regression, and Extreme Gradient Boosting (XGBoost)—are visually compared in the graphic below. Accuracy, R2 (coefficient of determination), Mean Absolute Error (MAE), and Mean Squared Error (MSE) are among the measures that are examined. This comparison reveals each model's advantages and disadvantages in terms of generalisation capacity and prediction accuracy.

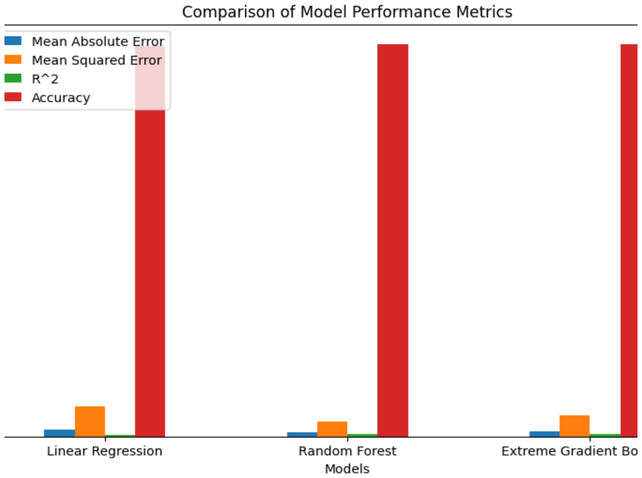

Figure 5: Comparison of Model Performance Metrics

5. Conclusion

This study illustrates the potential of wearable technology and machine learning to predict sleep quality based on 24-hour physical activity data. The potential application of machine learning is examined in this article with wearable technology to accurately predict one's sleep based on physical activity data collected within a 24-hour window. We were able to use data from the Apple Watch, which has some metrics like step count, things useful for measuring heart rate, and energy expenditure to create patterns showing how different forms of physical activities correlate with sleep quality.

These findings demonstrate that machine learning models, like Random Forest and XGBoost, can be used efficiently to predict sleep quality based on simple factoring (excellent, good, fair, and poor) concerning sleep. This study uses feature selection and correlation sampling results to show that models could obtain active energy burned, which constitutes the greatest predictor of quality of sleep, followed by VO2Max and steps. Overall, the strongest correlations were found between these features and sleep efficiency.

It enables end-users to gain personalised insights from 24-hour active data of their wearables that speak to how daily activities affect their sleep. This approach is in contrast with recent wellness applications offering mostly descriptive data with less impressive insights on what a wellness routine should be composed of. This line of action could imply an appreciable improvement in overall health and well-being on the basis of more specific activity data predictors on sleep quality than ever before.

References

[1] Saeb, S., Lattie, E. G., Kording, K. P., & Mohr, D. C. “Deep learning models were able to predict the quality of sleep (i.e., poor or good sleep efficiency) based on wearable data from awake periods”, 2017.

[2] Kılıç, O., Saylam, B., & İncel, Ö. D. “Sleep Quality Prediction from Wearables using Convolution Neural Networks and Ensemble Learning”, 2023.
[3] Gan, W., Dao, M.-S., & Zettsu, K. “Monitoring and Improving Personalized Sleep Quality from Long-Term Lifelogs”, 2022.
[4] Almeida, D. A., Dias, F. M., Toledo, M. A. F., et al. A “machine-learning sleep-wake classification model using a reduced number of features derived from photoplethysmography and activity signals”, 2023.
[5] Truda, G. Quantified Sleep: “Machine learning techniques for observational n-of-1 studies”, 2021.
[6] Al-Masni, M. A., Al-Antari, M. A., Choi, M.-T., et al. “Sleep Quality Prediction from Wearables using Convolution Neural Networks and Ensemble Learning”, 2020.
[7] Nature Communications. “Challenges and opportunities of deep learning for wearable-based sleep analysis: A systematic review”, 2024.
[8] ResearchGate. “Wearables-Assisted Smart Health Monitoring for Sleep Quality Prediction Using Optimal Deep Learning”, 2023.
[9] SAGE Journals Feasibility of wearable devices and machine learning for sleep monitoring in healthy adults: A validation study, 2023.
[10] Husom, E. J., Dautov, R., Nedisan Videsjorden, A., Gonidis, F., Papatzelos, S., Malamas, N., “Machine Learning for Fatigue Detection Using Fitbit Fitness Trackers,” Proceedings of the 10th International Conference on Sport Sciences Research and Technology Support (icSPORTS 2022), pp. 41-52, 2022. DOI: 10.5220/0011527500003321.
[11] MDPI Sensors. “Predicting Sleep Quality through Biofeedback: A Machine Learning Approach”, 2023.

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