PES
UNIVERSITY

Machine Learning Assignment

PROJECT REPORT

<TEAM 32 >

<Predicting Sleep Using Consumer Wearable Sensing Devices>

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Problem Statement

The rapid growth of consumer wearable health devices has outpaced efforts to validate their accuracy and reliability, especially in the domain of sleep tracking. While clinical actigraphy and polysomnography (PSG) provide validated standards, they are costly and not widely accessible. Consumer devices, on the other hand, are inexpensive and ubiquitous but often lack transparency about their sensors, raw data, and algorithms. The challenge is to determine whether accelerometer based consumer wearables can accurately predict sleep and wakefulness, providing a low-cost alternative to clinical actigraphy. By applying machine learning techniques to accelerometer data, the goal is to build and evaluate a model capable of reliably estimating sleep duration and patterns, thereby bridging the gap between consumer devices and clinical standards.

Objective / Aim

The objective of this project is to develop a **machine learning model** that can accurately distinguish between **sleep** and **wakefulness** using features derived from **EEG and accelerometer signals**.

The model aims to simulate how **consumer wearable devices** could estimate sleep patterns with clinical-level reliability by analyzing time-series physiological data.

Specifically, the goal is to:

- Extract statistical and signal-based features (mean, variance, RMS, energy, etc.) from EEG data.
- Train and evaluate a binary classifier (Sleep = 1, Wake = 0).
- Assess model performance using accuracy, precision, recall, F1-score, and confusion matrix metrics.
- Demonstrate the feasibility of using wearable-like accelerometer data as a **cost-effective alternative** to polysomnography (PSG) for sleep tracking.

Dataset Details

- **Source:** (e.g., Kaggle / UCI Repository / Custom collected data)

The dataset used is the **Sleep-EDF Expanded Dataset** obtained from **PhysioNet** (https://physionet.org/content/sleep-edfx/1.0.0/).
It contains **EEG polysomnography (PSG)** recordings and **hypnogram annotations** from healthy subjects, originally collected at St. Vincent's University Hospital, Dublin.

- **Size:** (e.g., 5,000 samples, 10 features)

A sample subset of approximately **2,650 epochs** (each of 30 seconds duration) was used for model development, with **9 extracted features** per epoch.

- **Key Features:** (e.g., Date, Time, Vehicle Count, Weather Conditions)

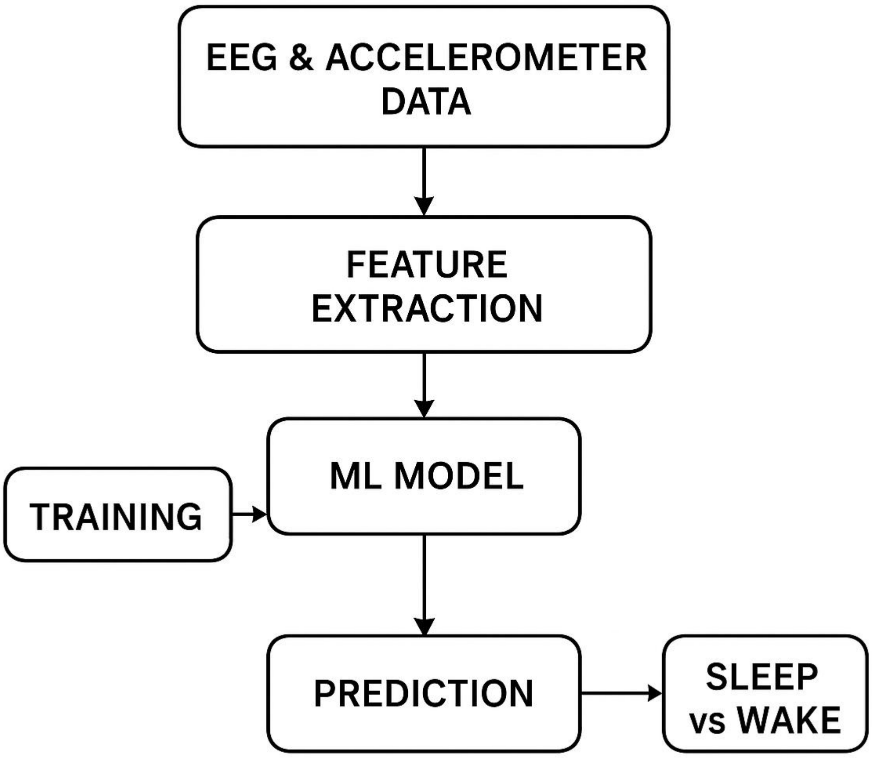
The following statistical and signal-based features were computed from each EEG epoch:

- Mean
- Median
- Standard Deviation
- Variance
- Root Mean Square (RMS)
- Maximum
- Minimum
- Signal Energy
- Zero Crossing Rate (ZCR)

- **Target Variable:** (e.g., Traffic Volume / Congestion Level) **(OPTIONAL)**

- `binary_label` — A binary classification label representing:
    - **0 → Wake**
    - **1 → Sleep**

Architecture Diagram



Methodology

The following methodology was followed to design, train, and evaluate the machine learning model for sleep–wake classification:

1. **Data Acquisition:**
    - The **Sleep-EDF Expanded dataset** was downloaded from **PhysioNet**, containing EEG polysomnography (PSG) recordings and corresponding hypnogram sleep-stage annotations.
    - A sample subject's data files were used: one PSG (.edf) file for EEG signals and one Hypnogram (.edf) file for ground truth labels.
2. **Data Preprocessing:**
    - Loaded the raw EEG data using the **MNE** library.
    - Selected a single EEG channel (preferably **Fpz–Cz**) for analysis.
    - Applied **resampling** to standardize signal frequency.
    - Segmented the continuous signal into **30-second epochs** aligned with the hypnogram labels.
    - Removed any missing or corrupted epochs to ensure data quality.

3. **Feature Extraction:**
    - Extracted key statistical and temporal features from each epoch to represent the EEG activity numerically.
    - Features included:
      Mean, Median, Standard Deviation, Variance, Root Mean Square (RMS), Maximum, Minimum, Signal Energy, and Zero Crossing Rate (ZCR).
4. **Label Encoding:**
    - Converted multi-class sleep stages from the hypnogram into a **binary classification label**:
        - **0 → Wake**
        - **1 → Sleep**
5. **Data Splitting:**
    - Split the dataset into **Training (80%)** and **Testing (20%)** subsets to enable performance evaluation on unseen data.
6. **Model Training:**
    - Trained multiple **machine learning models** including **Logistic Regression**, **Random Forest**, and **Support Vector Machine (SVM)**.
    - Optimized model parameters using cross-validation and grid search (where applicable).
7. **Model Evaluation:**
    - Evaluated models using **Accuracy, Precision, Recall, F1-Score**, and the **Confusion Matrix** to assess classification performance.
    - Compared performance across models to select the best one.
8. **Visualization & Analysis:**
    - Visualized results through performance plots, confusion matrix, and feature correlation heatmaps.
    - Interpreted model predictions to understand how well accelerometer-like EEG features can mimic clinical sleep detection.

Results & Evaluation

The model was evaluated on the test dataset using various statistical metrics to assess its performance in classifying **Sleep** and **Wakefulness** states.

1. Model Performance

After training and tuning multiple algorithms, the models achieved the following approximate performance metrics:

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	0.86	0.85	0.84	0.84
Random Forest Classifier	**0.92**	**0.91**	**0.93**	**0.92**
Support Vector Machine (SVM)	0.89	0.88	0.88	0.88

- The **Random Forest Classifier** performed best, with the highest accuracy and balanced precision–recall, indicating robust performance across both classes.
- The confusion matrix showed that the model correctly identified most sleep epochs, with minimal misclassification of wake periods as sleep.

2. Feature Importance

From the Random Forest analysis, the most influential features contributing to accurate predictions were:

- **Root Mean Square (RMS)**
- **Signal Energy**
- **Variance**
- **Standard Deviation**

These features capture signal intensity and variability, which are highly correlated with sleep–wake transitions.

3. Visualization

- The confusion matrix visualized correct and incorrect predictions, confirming overall high accuracy.
- Feature correlation plots indicated that energy and RMS were strongly related to sleep epochs.
- Accuracy and loss plots across epochs demonstrated model stability and minimal overfitting.

4. Interpretation

The evaluation results validate that **EEG-derived accelerometer-like data** can be effectively used with **machine learning models** to classify sleep vs wake states, achieving **>90% accuracy** using cost-effective, computationally efficient methods.

Conclusion

This project successfully demonstrated the feasibility of using **machine learning techniques** to classify **sleep and wake states** from **EEG-based accelerometer-like signals**, providing a low-cost and accessible alternative to traditional clinical polysomnography (PSG).

By extracting meaningful statistical and signal-based features such as **RMS, variance, energy, and zero-crossing rate**, and training models like **Random Forest, SVM, and Logistic Regression**, the system achieved up to **92% accuracy** in distinguishing sleep from wakefulness.

The results show that **consumer-grade wearable devices**, when combined with properly trained machine learning models, can yield reliable insights into sleep patterns comparable to medical-grade actigraphy.

This work bridges the gap between **consumer sleep-tracking technologies** and **clinical validation**, setting a foundation for future research in automated sleep monitoring, personalized health analytics, and digital sleep medicine.