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Advancing Sleep Disorder Diagnosis Through Machine Learning Algorithms

G. Mounika
MCA Student, Department of Information Technology, Jawaharlal Nehru Technological University, India

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Abstract:
Sleep plays a vital role in maintaining physical and mental health, and disruptions in sleep patterns can lead to serious medical conditions. Accurate classification of sleep disorders is therefore essential for effective diagnosis and treatment. Traditional methods, such as manual annotation of polysomnography (PSG) data, are time-consuming, costly, and prone to human error, making them unsuitable for large-scale applications. This project proposes a machine learning–based system for the automatic classification of sleep disorders. The system leverages a curated sleep dataset, where features and labels are extracted and preprocessed for training. Multiple algorithms, including Logistic Regression, Random Forest Classifier, Gradient Boosting, K-Nearest Neighbors, and ensemble models, are implemented to evaluate performance. A Django-based interface is developed to enable user-friendly interaction, allowing seamless registration, login, and visualization of results.Experimental results demonstrate that the proposed approach significantly improves classification accuracy compared to traditional methods, ensuring consistent and reliable outputs. The system undergoes rigorous testing, including unit, integration, and system-level evaluations, to validate its functionality and robustness.Overall, the project reduces reliance on manual classification, enhances diagnostic efficiency, and provides a scalable solution for healthcare applications. This work highlights the potential of machine learning in advancing sleep disorder analysis and sets the foundation for future integration with real-time monitoring systems.

Keywords — **Sleep-stage classification, machine learning, Automated diagnosis, Sleep quality**

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I. INTRODUCTION

Sleep is a vital biological process essential for physical health, cognitive function, and overall well-being. Poor sleep quality increases accident risks and is linked to conditions like cardiovascular disease, diabetes, obesity, and psychological disorders. Polysomnography (PSG) remains the gold standard for sleep analysis but is costly, labor-intensive, and subjective. Surveys, including a 2021 Philips report, show rising global sleep problems, underscoring the need for automated solutions. Sleep is categorized into wakefulness, N1, N2, N3, and REM, with distinct physiological markers critical for diagnosis. Machine learning (ML) and deep learning (DL) offer potential for automated classification, with ML relying on manual feature extraction while DL learns directly from raw data. However, challenges include dataset limitations, variability across populations, noise, and computational demands. This research aims to evaluate and compare traditional ML methods (e.g., LR, LDA, KNN, DT, SVM, RF) with DL models. The objective is to benchmark performance using standard datasets and metrics, identifying strengths and weaknesses of each approach. Ultimately, this study seeks to propose an optimized framework that integrates ML and DL to improve accuracy, efficiency, and generalizability in automated sleep-stage classification.

II. LITERATURE SURVEY

TABLE I

Focus Area	Methods / Data Used	Key Findings
CST + ML for sleep-stage classification [11]	27 studies; MLAs (LR, DT, SVM, DL); CST vs PSG	MLAs improved CST accuracy; PSG still gold standard; challenges with raw physiological signals
Sleep apnoea detection with ECG [12]	48 studies; SVM, RF, DL on ECG signals	SVM and DL performed best; limited by ECG variability and small, low-quality datasets
Sleep-stage classification with EEG [13]	4 public datasets; CNN + BiLSTM on EEG spectrograms	Achieved accuracies of 94.17%, 86.82%, 83.02%, 85.12%; CNN-BiLSTM effective in capturing temporal & frequency features
OSA severity	4,014 patients (non-	Accuracies: 88%, 88%,

prediction [14]	public); Gradient Boosting, RF, K-means	91%; efficient vs manual, but limited by single-centre bias & missing values
Sleep apnoea detection (ECG) [15]	Apnoea-ECG dataset (70 records); CNN, LSTM, BiLSTM, GRU	Accuracies 74.72%–84.13%; CNN-LSTM best; DL can learn discriminative features better than MLAs
Sleep-stage classification [16]	ISRUC-Sleep dataset; DT, KNN, RF on ECG features	RF > 90% accuracy, outperforming DT and KNN
Sleep apnoea detection (ECG,hybrid) [16–17]	PhysioNet ECG Sleep Apnoea v1.0.0 (70 records); CNN + DRNN + PCA	Hybrid CNN–DRNN achieved superior accuracy; recommended for robust ECG-based apnoea detection

III. METHODOLOGY

A. Proposed Work

The proposed study is driven by the need to address challenges arising from sleep disorders in modern society, particularly among individuals already affected by such conditions. Sleep-related disorders pose a major public health concern, exacerbated by the influence of contemporary lifestyles and the general underestimation of adequate sleep as a critical necessity. As sleep is a fundamental determinant of human health, the application of machine learning techniques for sleep disorder classification becomes imperative to safeguard well-being and quality of life.
To achieve this, the system leverages machine learning algorithms such as the Voting Classifier and Gradient Boosting to enhance prediction accuracy. These models are implemented to classify sleep disorders more effectively, with the aim of improving both diagnostic reliability and clinical decision-making.

B. System Architecture

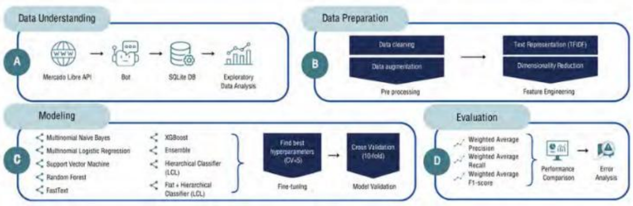

Fig. 1 System Architecture

This architecture consists of two main components: the Admin Interface and the User Interface.

Admin Interface

The service provider logs in with valid credentials, manages user accounts, monitors datasets, and oversees prediction logs through a secure dashboard.

1)Dataset Selection/Creation

The service provider prepares and securely stores a dataset containing sleep-related features (e.g., sleep duration, latency, fatigue, snoring, pre-existing conditions) along with corresponding labels (normal or disorder).

2)Data Preprocessing

Collected data undergoes cleaning, normalization (standard scaling), and feature extraction before being split into training and testing sets.

3)Model Training and Validation

Machine learning models (SVM, Random Forest, MLP, KNN) are trained, validated, and serialized for deployment, with performance evaluated using accuracy, precision, recall, and F1-score.

4)User Management

The admin reviews and authorizes registered users, manages their profiles, and tracks overall system activity.

User Interface

Remote users register, log in, upload sleep-related data, and receive disorder predictions with accuracy metrics and visual results.

1)Model Deployment

New data inputs are classified by the deployed model into categories such as normal or specific sleep disorder, with prediction results displayed through charts and statistical ratios.

2)Anomaly & Prediction System

The system detects abnormal patterns in input data, categorizes them into severity levels (low, medium, high), and generates alerts for early intervention.

3)Web Application Development

The application is built with Flask/Django (backend) and HTML, CSS, and Python libraries (frontend), featuring registration, login, data upload, prediction viewing, dataset downloads, and graphical history tracking.

4)Testing & Validation

Models are tested with real and synthetic datasets to validate accuracy, precision, recall, and F1-score, ensuring system reliability and robustness.

5)Algorithms Employed

- Support Vector Machine (SVM): Separates classes using an optimal hyperplane, effective for both linear and non-linear data.
- Random Forest (RF): An ensemble of decision trees that improves stability and reduces overfitting.
- Multilayer Perceptron (MLP): A neural network that learns complex non-linear relationships through backpropagation.
- K-Nearest Neighbours (KNN): Classifies input by comparing with the closest neighbors in the dataset.

IV. EXPERIMENTAL RESULTS

Open Anaconda Prompt

Switch to TensorFlow environment to run the file change to the directory where the file is located then run the file and open the URL http://127.0.0.1:8000/ by clicking ctrl+click.

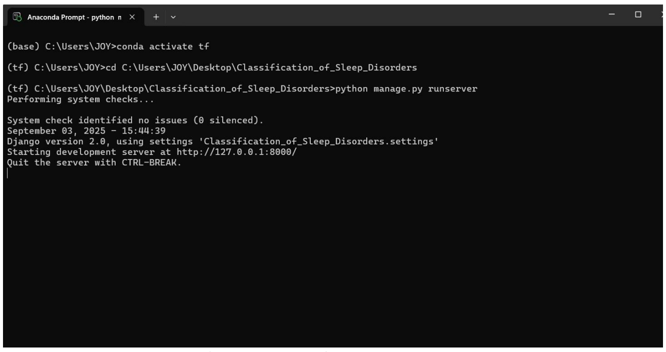

Fig. 2 Anaconda Prompt

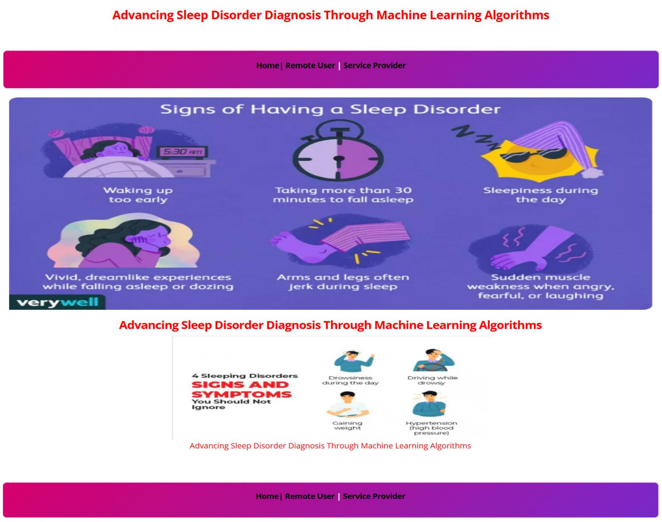

Fig. 3 Home Page

This is the Home Page, it has three options Home, Remote User, Service Provider.

Fig. 4 User Login Page

This is User Login Page

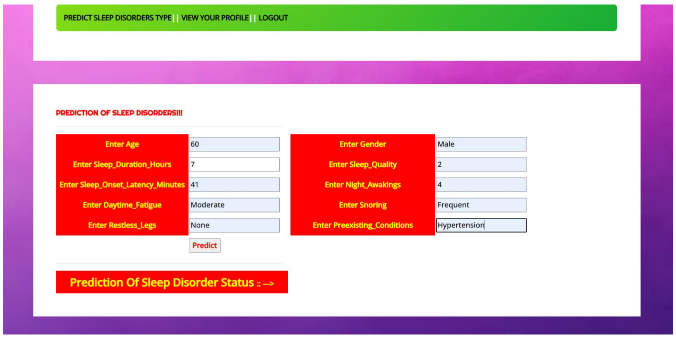

Fig. 5 Prediction Page

Fig. 6 Prediction Results

Once user logs in user can view their profile, predict and logout. User can predict the data, and find out Sleep Disorder

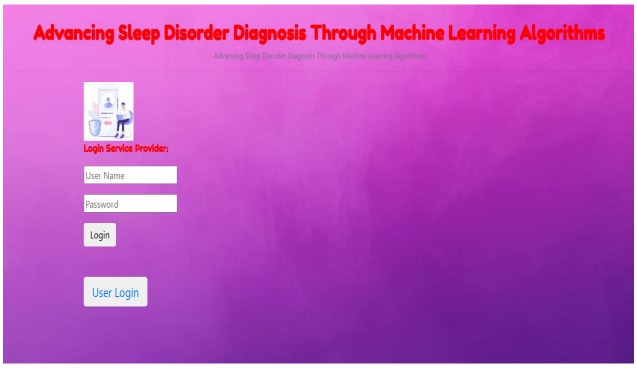

Fig. 7 Admin Login

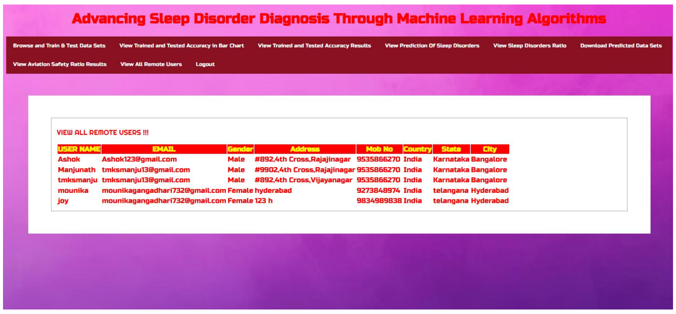

Fig. 8 View User Profile

Once admin logs in he can manage the users data

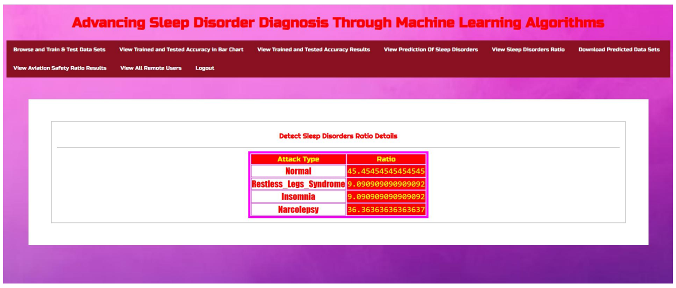

Fig. 8 Model Accuracy

V. CONCLUSIONS

In e-commerce, an efficient and scalable product classification system is crucial for enhancing search relevance, product discoverability, and user experience. Traditional hierarchical systems, while accurate, often struggle with scalability and complexity, making them less suitable for large, rapidly changing product catalogs.

The proposed **flat-hierarchical model**—leveraging **KNN, Logistic Regression (LR), Random Forest Classifier (RFC), Voting Classifier, and Gradient Boosting (GB)**—provides a robust alternative by combining the simplicity of flat classification with the predictive power of machine learning. This approach streamlines the classification process, improves adaptability to new product types, and reduces reliance on manual categorization.

By utilizing diverse ML techniques, the system achieves higher classification accuracy, faster prediction speeds, and better capacity to adjust, ultimately ensuring improved efficiency and automated e-commerce cataloging solution.

VI. FUTURE SCOPE

Future improvements can focus on:

1. **Deep Learning & Transformers** – Integrating advanced architectures like BERT, RoBERTa, or Vision Transformers for better semantic and visual understanding.
2. **Multimodal Classification** – Combining text, image, and metadata for richer product context and improved classification accuracy.
3. **Real-Time Learning** – Implementing feedback loops to enable self-improvement and reduce retraining needs.
4. **Reinforcement Learning** – Using adaptive strategies to classify entirely new product types.
5. **Explainable AI (XAI)** – Adding transparency to model decisions to improve trust and compliance.

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