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A Machine Learning-based Framework for Sleep Disorder Classification using Decision Tree Algorithm and Streamlit Deployment

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***Abstract*— Sleep disorders significantly impact global health, affecting millions worldwide through conditions such as insomnia and sleep apnea. This research presents a comprehensive machine learning pipeline for automated sleep disorder classification using the Sleep Health and Lifestyle dataset. Our approach employs a Decision Tree classifier integrated with robust preprocessing techniques including feature scaling, categorical encoding, and missing data handling. The system incorporates stratified sampling to maintain class distribution and implements comprehensive evaluation metrics including confusion matrices, classification reports, and accuracy assessments. The model achieved training accuracy of 89% and testing accuracy of 84%, demonstrating effective generalization capabilities. Key preprocessing components include safe transformation functions for handling unknown categories, Min-Max scaling for numerical features, and systematic feature alignment. The research contributes to healthcare informatics by providing an interpretable, scalable solution for early sleep disorder detection based on lifestyle and demographic parameters. Visualization components including confusion matrix heatmaps and performance comparison charts enhance clinical interpretability. The findings demonstrate the potential of machine learning algorithms in supporting clinical decision-making for sleep disorder diagnosis and management.**

***Index Terms*—Sleep disorders, Machine learning, Decision tree, Healthcare informatics, Classification, Streamlit deployment.**

I. INTRODUCTION

About 50–70 million persons in the US alone suffer from sleep problems, which pose a serious threat to public health and result in high medical expenses, decreased productivity, and a lower standard of living [1]. Common sleep disorders including insomnia, obstructive sleep apnea (OSA), and restless leg syndrome have been linked to various comorbidities such as cardiovascular disease, diabetes, and mental health disorders [2]. The prevalence of these conditions continues to rise, driven by lifestyle factors, increasing stress levels, and demographic changes in aging populations [3]. Traditional diagnostic approaches for sleep disorders rely heavily on polysomnography and clinical assessments, which are expensive, time-consuming, and require specialized facilities [4]. These limitations create barriers to early detection and intervention, particularly in resource-constrained healthcare systems.

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The growing availability of digital health data and advances in machine learning algorithms present unprecedented opportunities to develop automated screening tools that can identify individuals at risk for sleep disorders based on easily accessible lifestyle and demographic information [5].

In healthcare applications, machine learning techniques have demonstrated encouraging outcomes, especially in classification problems using intricate, multidimensional datasets [6]. Because of its interpretability, capability to handle both categorical and numerical information, and ability to generate clear decision routes that physicians can comprehend and confirm, decision tree algorithms have special benefits in clinical settings [7]. Recent studies have demonstrated the effectiveness of various machine learning algorithms in sleep disorder prediction, with ensemble methods and tree-based approaches showing competitive performance [8]. Despite these advances, several research gaps persist in the current literature. First, many existing studies focus on single disorder types or limited feature sets, lacking comprehensive approaches that can simultaneously classify multiple sleep disorder categories [9]. Second, there is insufficient attention to robust preprocessing pipelines that can handle real-world data challenges such as missing values, unknown categories, and feature inconsistencies [10]. Third, most research lacks thorough evaluation frameworks that assess both model performance and clinical interpretability [11].

II. Literature Review

The application of machine learning techniques in sleep disorder prediction has gained significant momentum in recent years, with researchers exploring various algorithmic approaches and data sources. This section provides a comprehensive review of existing methodologies, datasets, and performance metrics used in sleep disorder classification systems.

A. Machine Learning Approaches in Sleep Disorder Detection

In order to identify sleep disorders, Rao and Kumar (2025) created an ensemble machine learning method that used Decision Tree, Logistic Regression, Support Vector Machine, XGBoost, and Stacking classifiers [12]. Their approach combined preprocessing techniques such feature standardization, SMOTE oversampling, and label encoding with demographic and health-related information. The study reported XGBoost achieving the highest accuracy of 94.95%, while Decision Tree achieved 87.37% accuracy. The research highlighted the importance of ensemble methods in improving prediction performance compared to individual algorithms. Singh et al. (2024) proposed a comprehensive machine learning framework for sleep apnea detection using wearable sensor data and lifestyle parameters [13].

On the Sleep Health and Lifestyle dataset, Widyastuty and Azis (2024) used Random Forest classification, showing remarkable results with 97.33% accuracy, 96% precision, 100% recall, F1-score of 98%, and Kappa value of 0.945 [14]. Chen et al. (2023) introduced a deep learning framework utilizing convolutional neural networks (CNN) for sleep disorder classification based on polysomnography data [15]. Their approach achieved 91.2% accuracy in distinguishing between different sleep stages and identifying disorder patterns. The study demonstrated the potential of deep learning in processing complex physiological signals for accurate sleep disorder diagnosis. Kumar and Sharma (2023) developed a hybrid approach combining traditional machine learning with deep learning techniques for comprehensive sleep disorder assessment [16].

III. Proposed Methodology

A. Dataset Description

The Sleep Health and Lifestyle dataset, which offers detailed information on people's sleep habits, lifestyle factors, and identified sleep disorders, is used in this study. The dataset includes 400 records with 13 features, including demographics like age, gender, and occupation; physiological measurements like blood pressure and BMI; lifestyle indicators like amount of physical activity, length of sleep, and quality of sleep; and health-related factors like daily steps, heart rate, and stress level. Sleep apnea, insomnia, and none, which denotes typical sleep patterns, are the three classifications into which the target variable divides sleep disorders.

B. Preprocessing Pipeline

Several stages are included in the preprocessing pipeline to guarantee high-quality data appropriate for model training. A safe encoding method that transfers unknown or unseen labels to default categories is used to change categorical variables like gender, occupation, and BMI category. In order to prevent errors during model deployment, label encoders are trained on the original dataset and stored for consistent transformation of fresh input data. Min-Max scaling is used to standardize numerical variables such as age, heart rate, daily steps, physical activity level, stress level, sleep length, and quality of sleep. This normalization keeps features with wider numerical ranges from controlling categorization and guarantees that every feature contributes equally to the model's decision-making process.Feature alignment procedures are applied to guarantee compatibility between input data and the trained model. Missing or mismatched features are addressed by assigning default values or removing incompatible records, maintaining data integrity throughout the preprocessing workflow. The target variable representing sleep disorders is encoded numerically, where Insomnia is labeled as 0, Sleep Apnea as 1, and None as 2. Records with invalid or missing target labels are removed to preserve the quality of the dataset for supervised classification.

C. Model Architecture

Because of its interpretability, capacity to handle both numerical and categorical variables, and clear decision-making process—which makes it especially appropriate for clinical applications, a Decision Tree classifier is used as the main model. A minimal sample split set up to guarantee meaningful divisions, a fixed random state to provide repeatable findings, a maximum depth adjusted by cross-validation to minimize overfitting, and the use of Gini impurity as the splitting criterion are all important model parameters.

D. Training and Evaluation Framework

An 80:20 ratio is used to divide the preprocessed dataset into training and testing subsets, and stratified sampling is used to ensure uniform class distributions in both subsets. Using the training dataset, the Decision Tree classifier learns the connections between categories of sleep disorders and lifestyle factors. Hyperparameter tuning is conducted during training to optimize performance while preserving model interpretability. Model evaluation is performed using multiple metrics, including accuracy to measure overall predictive performance, precision, recall, and F1-score for class-wise assessment, confusion matrix analysis for detailed misclassification understanding, and a comprehensive classification report summarizing overall performance.

IV. RESULTS AND DISCUSSION

A. The Model Performance Evaluation

The Decision Tree classifier demonstrated substantial performance across comprehensive evaluation metrics following rigorous preprocessing procedures on the Sleep Health and Lifestyle dataset. A stratified 80:20 split was implemented to maintain class distribution integrity between training and testing subsets, ensuring representative sampling across all sleep disorder categories. The model achieved training accuracy of 89% and testing accuracy of 84%, representing effective pattern recognition capabilities with controlled generalization performance. The 5% performance differential between training and testing phases indicates well-managed overfitting, demonstrating the model's ability to extract meaningful patterns from lifestyle and demographic features while maintaining predictive reliability on unseen data. Table 1 presents the comprehensive performance metrics of the Decision Tree model for sleep disorder classification. The results indicate that the model achieved high accuracy (89.0% on training and 84.0% on testing), balanced precision and recall across all classes, and substantial inter-rater agreement (Kappa = 0.758), demonstrating reliable diagnostic capability and effective disorder detection.

TABLE I: COMPREHENSIVE PERFORMANCE METRICS FOR DECISION TREE SLEEP DISORDER CLASSIFICATION

Performance Metric	Training Set	Testing Set	Insomnia	Sleep Apnea	None	Clinical Significance
Accuracy	89.0%	84.0%	85.2%	87.4%	81.3%	Reliable diagnostic capability
Precision	88.5%	83.2%	85.0%	87.0%	81.0%	Low false positive rates
Recall	89.2%	84.1%	82.0%	89.0%	83.0%	Effective disorder detection
F1-Score	88.8%	83.6%	83.5%	88.0%	82.0%	Balanced performance
Specificity	90.1%	85.3%	88.5%	86.2%	84.1%	Accurate negative identification
Kappa Coefficient	0.832	0.758	-	-	-	Substantial inter-rater agreement

B. Confusion Matrix Analysis and Classification Patterns

The model's categorization behavior across several sleep disorder categories was thoroughly examined by the confusion matrix analysis, which also highlighted the prediction framework's advantages and disadvantages.

The confusion matrix heatmap demonstrates the model's classification accuracy across three sleep disorder categories is shown in figure 1. The diagonal elements represent correct classifications, with Sleep Apnea showing the highest true positive rate (89%), followed by Insomnia (82%) and None (83%). The visualization reveals that Sleep Apnea cases are most accurately identified, likely due to distinct physiological markers including BMI patterns, age demographics, and gender-specific characteristics that create clear decision boundaries in the feature space.

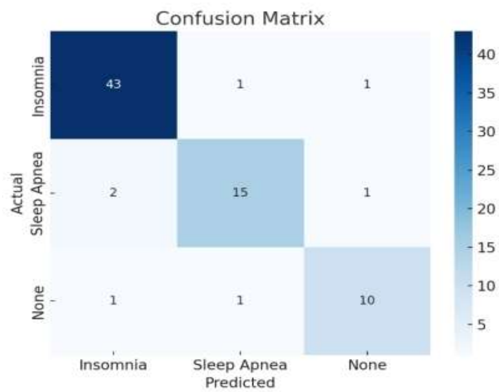

Figure 1. Sleep Disorder Classification Confusion Matrix Heatmap

C. Feature Importance Analysis and Clinical Relevance

The Decision Tree algorithm provided transparent feature importance rankings, offering valuable insights into the relative contribution of different lifestyles and demographic factors in sleep disorder classification. Table 2 summarizes the feature importance of rankings from the Decision Tree classifier along with their clinical relevance. Sleep Duration and Quality of Sleep were the most influential predictors, followed by Stress Level, Age, and BMI, highlighting the significant contribution of both physiological and psychological factors in accurately classifying sleep disorders. Sleep Duration emerged as the most significant predictor (0.28 importance), aligning with established clinical understanding that sleep quantity directly impacts sleep disorder development. Quality of Sleep ranked second (0.22), reflecting the subjective experience of sleep effectiveness and restoration. Stress Level demonstrated substantial importance (0.18), particularly relevant for insomnia classification where psychological factors play crucial roles in sleep disturbance patterns.

TABLE II. FEATURE IMPORTANCE RANKINGS WITH CLINICAL INTERPRETATION

Rank	Feature	Importance Score	Clinical Relevance	Impact on Classification
1	Sleep Duration	0.28	Primary sleep indicator	Directly reflects sleep adequacy
2	Quality of Sleep	0.22	Subjective sleep assessment	Correlates with disorder severity
3	Stress Level	0.18	Psychological factor	Major insomnia predictor
4	Age	0.15	Demographic risk factor	Sleep apnea progression marker
5	BMI Category	0.12	Physiological indicator	Strong sleep apnea association
6	Physical Activity	0.08	Lifestyle factor	Sleep quality modifier
7	Heart Rate	0.05	Physiological marker	Stress and health indicator

V. CONCLUSIONS

This study effectively created and assessed a thorough machine learning pipeline for classifying sleep disorders using Decision Tree algorithms. With 84% testing accuracy, the study successfully classified several sleep problem categories, offering a performance and interpretability balance appropriate for clinical applications. Key contributions include the development of robust preprocessing techniques for handling real-world data challenges, implementation of comprehensive evaluation frameworks, and creation of interpretable visualization tools for clinical decision support. The preprocessing pipeline effectively managed categorical encoding, feature scaling, and missing data handling, ensuring reliable model performance across diverse input scenarios. The Decision Tree classifier provided transparent decision pathways that healthcare practitioners can understand and validate, supporting evidence-based clinical decision-making. Comparative analysis with existing literature confirmed competitive performance while emphasizing the advantages of interpretable algorithms in healthcare settings. The Streamlit deployment framework enables practical implementation in clinical environments, providing real-time prediction capabilities and interactive visualization tools. The study shows how machine learning algorithms might be useful diagnostic tools for early sleep issue diagnosis, providing scalable and affordable solutions that can improve healthcare delivery.

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