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RestSure AI: An Intelligent Web-Based System for Sleep Disorder Detection Using Machine Learning

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***Abstract*—Sleep disorders, including insomnia and sleep apnea, have a profound impact on physical health, cognitive functioning, and overall quality of life. However, they are often difficult to detect early because diagnosis typically relies on clinical evaluations and polysomnography, which can be costly and not widely available. This paper introduces RestSure AI, a web-based intelligent platform designed to predict prevalent sleep disorders using lifestyle and physiological information gathered through structured questionnaires. The system combines a Django powered web interface with a machine learning backend based on a soft voting ensemble classifier. User-provided data—such as sleep duration, stress levels, physical activity, BMI, and vital signs—are processed and analyzed to classify sleep disorder types. Experimental results show that the proposed system yields accurate predictions and provides interpretable health guidance, making it a practical tool for initial sleep health screening.**

***Index Terms*—Sleep Disorder Detection, Machine Learning, Ensemble Learning, Django, Health Informatics**

I. Introduction

Sleep is essential for sustaining both physical and mental well-being. Conditions like insomnia and sleep apnea are becoming more common, driven by contemporary lifestyle factors such as stress, lack of physical activity, and inconsistent sleep patterns. Conventional diagnostic approaches often depend on clinical assessments and specialized devices, which restrict broad access to timely detection.

With recent progress in machine learning, it is now possible to perform predictive analysis using non-invasive data sources. This study focuses on developing and deploying a scalable, easy-to-use web application that utilizes machine learning models to forecast sleep disorders from everyday lifestyle habits and health-related metrics.

II. Related Work

Recent progress in artificial intelligence has played a substantial role in advancing sleep monitoring and the detection of sleep disorders. A comprehensive review from December 2022 examined how consumer-grade sleep technologies—such as wearable devices and smartphone-based sensors—are being combined with AI methods for sleep stage classification. The review emphasized the increasing importance of inexpensive, non-clinical data sources and showcased how machine learning and deep learning models can be effectively applied in realistic, everyday sleep tracking contexts. At the same time, it identified important limitations, including lower clinical accuracy compared to polysomnography (PSG) and inconsistent performance across various consumer devices.

A separate research direction has concentrated on classifying sleep disorders using structured lifestyle and health data. For example, a study released in August 2023 used the Random Forest algorithm on the Sleep Health and Lifestyle dataset to identify conditions such as insomnia and sleep apnea. The researchers showed that Random Forest models work particularly well for tabular health datasets because they can model complex, non-linear relationships and offer

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interpretable measures of feature importance. However, the study also found that the model's performance was strongly influenced by the quality of the dataset, and its ability to generalize to clinical settings was still constrained.

To better manage uncertainty and ambiguity in medical diagnosis, a new neutrosophic-based machine learning framework was proposed in January 2025. This method integrated fuzzy reasoning with conventional classifiers to strengthen decision support for predicting sleep disorders. The research demonstrated greater robustness when dealing with vague or incomplete datasets. Nonetheless, the intricate nature of the neutrosophic logic framework led to significant computational overhead and made the system harder to interpret for users without specialized expertise.

In addition, ensemble integration-focused methods have been investigated to boost the accuracy of sleep disorder detection. A January 2025 study concentrated on improving standard machine learning models through sophisticated feature engineering and hyperparameter featuring, such as grid search. These refined models produced higher classification accuracy than their baseline counterparts. Yet, longer training durations and an elevated risk of overfitting emerged as key limitations of these ensemble model-centric strategies.

Ensemble learning has gained traction as an effective strategy for boosting predictive performance in sleep disorder detection. A study published in January 2025 introduced a multi-layer ensemble framework integrated with advanced data balancing methods, including the Synthetic Minority Oversampling Technique (SMOTE). The findings showed notable gains in prediction accuracy, especially when dealing with imbalanced datasets. Nonetheless, this ensemble design led to higher computational demands and diminished overall model interpretability.

Building on ensemble-oriented methods, another study from January 2025 utilized stacked classifiers alongside ensemble balancing techniques to better capture minority classes. The proposed approach achieved higher sensitivity for rare sleep disorders and delivered strong classification results across multiple evaluation metrics. However, the increased architectural complexity of the stacked ensemble required more extensive training data and greater computational power, which constrained its scalability.

In July 2025, a systematic review offered an extensive assessment of AI-based approaches for sleep stage classification and sleep disorder detection. It encompassed diverse techniques, including traditional machine learning, deep learning, and hybrid models applied to both PSG and wearable sensor data. Although the review successfully highlighted prevailing research directions and existing gaps, it did not provide experimental validation and was limited by the coverage of the databases used for literature selection.

Deep learning-based techniques have also been extensively explored for sleep stage classification. In a study from January 2023, convolutional neural networks (CNNs) and long short-term memory (LSTM) networks were applied to multi-modal physiological signals, including EEG, ECG, and EMG. This method achieved high accuracy by automatically extracting intricate temporal and spatial patterns. Nevertheless, its dependence on large annotated datasets and substantial computational power restricted its use in resource-limited settings.

In another investigation from April 2023, several machine learning algorithms were compared for predicting the severity of obstructive sleep apnea syndrome. The study underscored the strong potential of machine learning models for early diagnosis based on clinical and physiological variables. However, it also reported that the models' performance was highly dependent on the specific dataset and that they were not readily applicable in real-time clinical environments.

Finally, a 2024 study examined traditional machine learning methods—such as Support Vector Machines, Decision Trees, and Random Forests—for classifying different sleep disorders using health and lifestyle information. The authors highlighted that these models are straightforward, interpretable, and relatively easy to deploy. Despite these advantages, they showed lower accuracy than deep learning models and encountered scalability issues when applied to larger, more complex datasets.

TABLE I
SUMMARY OF RELATED WORK IN SLEEP DISORDER PREDICTION

Ref	Year	Dataset Used	Technique Applied	Key Focus	Performance Level
1	2022	Consumer sleep device data	ML and AI models	Sleep classification	Medium
2	2023	Sleep Health & Lifestyle data	Random Forest	Disorder classification	High
3	2025	Clinical sleep data	Neutrosophic ML	Decision support	High
4	2025	Lifestyle and clinical data	ensemble ML models	Diagnosis improvement	High
5	2025	Imbalanced sleep dataset	Ensemble learning	Disorder detection	Very High
6	2025	Balanced sleep dataset	Multi-layer ensemble	Accuracy improvement	Very High
7	2025	PSG and wearable data	AI-based review	Survey study	–
8	2023	EEG, ECG, EMG signals	Deep Learning	Sleep stage classification	Very High
9	2023	Clinical parameters	Multiple ML models	OSA severity estimation	High
10	2024	Health and lifestyle data	ML algorithms	Disorder classification	Medium–High

III. METHODOLOGY

This section describes the materials, dataset, experimental setup, machine learning algorithms, and evaluation metrics employed in the proposed RestSure AI system for sleep disorder classification.

A. Materials and Methods

The proposed methodology integrates data-driven machine learning techniques with a web-based health assessment plat-

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form to predict common sleep disorders. The system processes lifestyle, physiological, and demographic parameters collected through structured questionnaires and applies supervised learning models to classify sleep disorders into predefined categories.

All experiments were conducted using the Python programming language and relevant scientific computing libraries. The system workflow consists of data preprocessing, feature encoding, model training, evaluation, and deployment within a Django-based web application for real-time inference

B. Real Sleep Health and Lifestyle Dataset

The proposed system employs the Sleep Health and Lifestyle Extended Dataset from Kaggle, which offers detailed information on lifestyle, health, and sleep gathered from a heterogeneous group of individuals. This dataset combines self-reported lifestyle indicators with physiological data that are linked to sleep habits and sleep quality. It includes variables such as age, gender, occupation, total sleep time, perceived sleep quality, physical activity level, stress level, body mass index (BMI), blood pressure, heart rate, and daily step count.

This extended dataset expands on existing health records by adding a wider array of demographic and behavioral attributes, enabling more comprehensive modeling of sleep health trends and classification of sleep disorders. In contrast to strictly clinical datasets, it captures everyday lifestyle factors that affect sleep outcomes, making it well-suited for non-invasive predictive modeling.

The dataset is rigorously preprocessed before model training. This procedure entails encoding categorical attributes, converting continuous measurements into standardised formats, and eliminating missing and inconsistent entries. To preserve numerical stability during training, continuous characteristics like daily steps, heart rate, and sleep duration are normalised. Label encoding or one-hot encoding are used to transform categorical variables like gender and occupation according to their respective cardinalities.

Sleep disorder labels, such as No Sleep Disorder, Insomnia, and Sleep Apnoea, make up the target variable. When dividing the dataset into training and evaluation subsets, stratified sampling is used to guarantee balanced representation. Class proportions are maintained by this partitioning technique, which is essential for generating accurate performance metrics in multi-class classification tasks. All things considered, the Sleep Health and Lifestyle Extended Dataset offers a wealth of behavioural, physiological, and demographic information that facilitates efficient supervised learning for the identification of sleep disorders. The development of models that generalise well beyond controlled or clinical environments is supported by its real-world scope.

C. Experimental Design

This study uses a two-phase experimental framework to evaluate the effectiveness of machine learning algorithms for the classification of sleep disorders using lifestyle and physiological data. Prior to applying optimisation and feature refinement techniques to enhance predictive performance, the primary objective of this design is to analyse baseline model behaviour.

During the first stage, the dataset is split 70:30 into training and testing subsets. The training subset is used to fit a number of machine learning classifiers without the need for ensemble classification or hyperparameter optimisation. During this stage, which serves as a baseline evaluation, the models can learn directly from the original feature space. Performance is assessed using an unseen testing subset to investigate generalisation capacity and identify intrinsic constraints such as noise sensitivity, feature redundancy, and parameter dependency.

Using an optimised learning strategy, the second phase aims to improve classification performance. To guarantee consistency and numerical stability, the dataset is preprocessed before training. A Voting Classifier combined with machine learning classifiers is used for ensemble classification and parameter tuning. An ideal subset of features and matching model parameters that maximise classification performance are found using the Voting Classifier.

The dataset is split into 0.70 training and 0.30 testing subsets once more during this optimised phase. By combining feature subsets and classifier parameter configurations, the Voting Classifier-based optimisation process iteratively assesses potential solutions. In order to ensure fair evaluation across various sleep disorder classes, a fitness function is defined based on classification accuracy and F1-score.

The Voting Classifier-selected feature subsets are used to train the optimised classifiers, which are then assessed on the testing data to gauge gains over baseline performance. This experimental approach makes it possible to compare non-ensemble and Voting Classifier-enhanced models, offering insights into how ensemble classification and parameter tuning affect the accuracy of sleep disorder classification. The baseline learning phase and the Voting classifier ensemble learning phase are highlighted in Fig. 1, which depicts the overall workflow of the suggested experimental design. This methodical approach guarantees a thorough assessment of both raw and optimised machine learning models, assisting in the creation of a precise and comprehensible sleep disorder detection system.

D. Performance Metrics

To evaluate the effectiveness of the proposed sleep disorder classification models, several standard performance metrics were employed. These metrics provide a comprehensive assessment of classification accuracy, class-wise prediction quality, and robustness, particularly in multi-class and imbalanced dataset scenarios.

Let TP, TN, FP, and FN denote *True Positives*, *True Negatives*, *False Positives*, and *False Negatives*, respectively.

1) Accuracy: Accuracy measures the proportion of correctly classified instances among the total number of samples and is defined as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

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Although accuracy provides an overall measure of model performance, it may be misleading when class imbalance is present.

2) Precision: Precision evaluates the correctness of positive predictions by measuring the proportion of true positives among all predicted positives:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

A higher precision value indicates a lower false positive rate, which is critical in reducing incorrect sleep disorder diagnoses.

3) Recall (Sensitivity): Recall, also known as sensitivity, measures the model's ability to correctly identify actual positive instances:

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

High recall ensures that a larger proportion of sleep disorder cases are correctly detected.

4) F1-Score: The F1-score represents the harmonic mean of precision and recall and provides a balanced evaluation metric:

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

This metric is particularly effective for evaluating classification performance on imbalanced datasets.

5) Specificity: Specificity measures the model's ability to correctly identify negative instances:

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{5}$$

A high specificity value indicates that individuals without sleep disorders are correctly classified.

6) Confusion Matrix: The confusion matrix is a tabular representation that summarizes prediction outcomes. For binary classification, it consists of four elements: TP, TN, FP, and FN. In multi-class classification, the matrix is extended to represent all classes and allows detailed per-class performance analysis.

7) Macro-Averaged Metrics: For multi-class sleep disorder classification, macro-averaging is employed to ensure equal contribution from each class. The macro-averaged metrics are defined as:

$$\text{Macro Precision} = \frac{1}{C} \sum_{i=1}^{C} \text{Precision}_i \tag{6}$$

$$\text{Macro Recall} = \frac{1}{C} \sum_{i=1}^{C} \text{Recall}_i \tag{7}$$

$$\text{Macro F1-score} = \frac{1}{C} \sum_{i=1}^{C} \text{F1-score}_i \tag{8}$$

where C denotes the total number of classes.

E. Classification Algorithms

To categorize sleep disorders using health, lifestyle, and physiological attributes, multiple supervised machine learning classifiers were implemented in this study. The selected algorithms were chosen based on their classification capability, interpretability, and suitability for structured tabular data. Each model was trained using preprocessed features and evaluated under a multiclass sleep disorder prediction framework.

1) Logistic Regression: Logistic Regression (LR) is a probabilistic classification technique widely used for baseline performance evaluation. The model estimates the likelihood of class membership by applying a logistic function to a linear combination of input features. For multiclass sleep disorder prediction, a one-versus-rest strategy is employed. Owing to its low computational complexity and ease of interpretation, LR provides an effective benchmark for comparing more complex models.

2) Decision Tree: Decision Tree (DT) classifiers construct a hierarchical structure by recursively splitting the dataset based on feature values that maximize information gain. Each internal node represents a decision condition, while leaf nodes correspond to predicted classes. In the proposed sleep disorder prediction system, DTs enable transparent rule-based learning and effectively capture nonlinear relationships among health and lifestyle parameters. However, excessive tree growth may lead to overfitting, which is mitigated through depth constraints.

3) Random Forest: Random Forest (RF) is an ensemble learning technique that integrates multiple decision trees to enhance predictive performance and generalization capability. Each tree is trained on a bootstrapped subset of the data with randomly selected feature subsets. The final classification is obtained through majority voting. RF demonstrates high robustness to noise, feature interactions, and class imbalance, making it well-suited for sleep disorder classification tasks.

4) K-Nearest Neighbors: K-Nearest Neighbors (KNN) is an instance-based learning algorithm that assigns class labels based on the dominant class among the k closest samples in the feature space. Distance measures such as Euclidean distance are used to evaluate similarity. The choice of k is ensemble experimentally to balance bias and variance. KNN is effective in identifying local data patterns but is sensitive to feature scaling and computationally intensive for large datasets.

5) Support Vector Machine: Support Vector Machine (SVM) is a margin-based classifier that constructs an optimal decision boundary by maximizing the separation between classes. Kernel functions, including linear and radial basis function (RBF) kernels, enable SVM to model complex nonlinear relationships. In this project, SVM effectively captures intricate dependencies between sleep-related attributes and disorder classes, offering strong generalization performance.

F. Feature Importance

Feature importance analysis was conducted to identify the most influential parameters contributing to sleep disorder prediction. Tree-based models, particularly the Random Forest

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classifier, were used to compute feature importance scores based on impurity reduction.

Results indicated that sleep duration, stress level, quality of sleep, physical activity level, BMI category, and daily steps were among the most significant predictors. This analysis enhances model interpretability and provides valuable insights into lifestyle factors affecting sleep health.

G. Correlation Coefficient Analysis

Correlation analysis was performed using the Pearson correlation coefficient to examine the relationships between input features and the target variable. This analysis helped identify redundant features and multicollinearity within the dataset.

Strong correlations were observed between sleep duration and sleep quality, as well as between physical activity and daily step count. Features exhibiting high correlation were carefully evaluated to prevent redundancy and improve model efficiency.

H. Voting Classifier Ensemble

To enhance prediction reliability, both hard and soft voting ensemble strategies were implemented. The ensemble combines heterogeneous base learners to leverage their complementary strengths.

Hard Voting: The final class label is determined by majority voting among base classifiers.

Soft Voting: The predicted class probabilities from individual classifiers are averaged, and the class with the highest aggregated probability is selected.

Soft voting is particularly effective in healthcare datasets where class boundaries overlap and probabilistic confidence is essential.

Hard voting was used for comparative analysis, while soft voting was selected as the final deployment model due to superior probabilistic performance.

I. Design and Implementation

This section describes the architectural design and implementation details of the proposed sleep disorder detection system. The framework integrates data preprocessing, machine learning classification, Voting Classifier-based web-based deployment platform to enable real-time sleep disorder assessment.

1) System Architecture: The overall system architecture follows a modular pipeline consisting of data acquisition, preprocessing, classification, and deployment. The design ensures scalability, interpretability, and real-time usability. Figure **??** illustrates the high-level workflow of the proposed system.

The architecture is composed of four main layers:

- Data Layer: Responsible for dataset ingestion and preprocessing.
- Learning Layer: Performs classification using machine learning algorithms.
- Application Layer: Provides a web-based interface for user interaction and prediction delivery.

2) Data Preprocessing and Encoding: The Sleep Health and Lifestyle Extended dataset was preprocessed to ensure data quality and consistency. Missing values were removed, and categorical attributes such as gender, occupation, and sleep disorder labels were encoded using label encoding techniques. Continuous features were normalized using standard scaling to ensure uniform feature contribution during training.

BMI values were converted into categorical classes (underweight, normal, overweight, obese) to align with clinical interpretation. The final feature vector consisted of demographic, lifestyle, and physiological attributes.

3) Model Design: Multiple machine learning algorithms were employed to classify sleep disorders, including Logistic Regression, Decision Tree, Random Forest, and an ensemble-based soft voting classifier. The ensemble model combined predictions from individual classifiers to improve generalization and reduce model bias.

Each model was trained using a supervised learning approach, with sleep disorder category as the target variable. The ensemble classifier served as the primary prediction model due to its superior performance.

4) Voting Classifier Framework: A hard voting ensemble strategy was adopted in this work to enhance the robustness and predictive stability of the sleep disorder classification system. In hard voting, each base classifier independently predicts a class label for a given input instance, and the final output is determined by majority consensus among all classifiers. This decision-level fusion mechanism is particularly effective for healthcare applications, as it reduces the influence of isolated misclassifications and promotes consistent predictions across diverse patient profiles.

To construct a heterogeneous ensemble, five supervised machine learning algorithms were selected as base learners: Logistic Regression (LR), Decision Tree (DT), Random Forest (RF), K-Nearest Neighbors (KNN), and Support Vector Machine (SVM). These classifiers were chosen to represent diverse learning paradigms, including linear models, instance-based learning, tree-based reasoning. The heterogeneity of the ensemble ensures that different aspects of the underlying data distribution are captured, thereby improving generalization capability.

Logistic Regression contributes to the ensemble through its linear decision boundary and probabilistic modeling framework. It effectively captures global trends between lifestyle variables—such as sleep duration, stress level, and physical activity—and sleep disorder classes. Although LR has limited capacity to model complex nonlinear relationships, its stable and interpretable predictions provide a reliable baseline that strengthens the ensemble's consensus mechanism.

Decision Tree and Random Forest classifiers enable the ensemble to model nonlinear interactions and hierarchical feature dependencies. The Decision Tree learns interpretable decision rules by recursively splitting the feature space based on information gain, making it suitable for capturing threshold-based clinical patterns. Random Forest extends this capability by aggregating multiple decision trees trained on bootstrapped

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data samples and random feature subsets, thereby reducing overfitting and variance. Within the hard voting ensemble, Random Forest contributes robust predictions that are resilient to noise and class imbalance.

The K-Nearest Neighbors classifier adds a local, instance-based perspective to the ensemble. By assigning class labels based on the majority class among the nearest data points in the feature space, KNN effectively captures neighborhood-level similarities between individuals with comparable lifestyle and physiological characteristics. While KNN is sensitive to feature scaling and computationally expensive for large datasets, its inclusion enhances the ensemble's ability to model localized patterns that may be overlooked by global classifiers.

Support Vector Machine further strengthens the ensemble through its margin-based optimization framework. By constructing an optimal separating hyperplane in a high-dimensional feature space, SVM is capable of handling complex class boundaries, particularly when nonlinear kernel functions are employed. Its strong generalization performance complements the probabilistic and tree-based models in the ensemble, ensuring balanced decision-making across diverse sleep disorder classes.

Overall, the hard voting ensemble integrates linear, nonlinear, probabilistic, instance-based, and margin-based classifiers into a unified framework. The majority voting mechanism ensures that the final prediction reflects collective agreement among heterogeneous learners, reducing individual model bias and variance. This ensemble strategy significantly improves classification reliability and stability, making it well-suited for real-world sleep disorder detection in a web-based healthcare application.

5) Experimental Implementation: The implementation was carried out using Python and popular machine learning libraries. The dataset was divided into training and testing subsets using a 70:30 ratio. Five-fold cross-validation was applied to the training data to evaluate model stability.

Two experimental configurations were implemented:

- Baseline Model: Trained without feature selection or optimization.
- ensemble Model: Trained using Voting Classifier-selected features and ensemble parameters.

Performance metrics were computed for both configurations to analyze improvement.

6) Web-Based Deployment: The ensemble ensemble model was serialized and deployed within a Django-based web application. A multi-step questionnaire interface was designed to collect user inputs related to sleep habits, lifestyle, and health parameters.

User responses were processed in real time, transformed into model-compatible feature vectors, and passed to the trained classifier. The system generated instant predictions along with personalized sleep health recommendations, enhancing user engagement and practical applicability.

J. System Deployment and Integration

The ensemble machine learning model was serialized using standard Python model persistence techniques and integrated into a Django-based web application. This deployment architecture enables real-time interaction between the user interface and the trained classification model.

User data collected through the multi-step questionnaire interface are processed dynamically within the application layer. Input features undergo the same preprocessing and encoding steps used during model training to ensure consistency. The processed feature vector is then passed to the deployed model to generate predictions in real time.

The system outputs the predicted sleep disorder category along with personalized health recommendations based on the classification results. This seamless integration of machine learning inference within a web framework ensures scalability, accessibility, and responsiveness, making the proposed proposed system suitable for real-world sleep health assessment applications.

IV. Results and Discussion

The experimental results demonstrate that ensemble learning significantly enhances sleep disorder classification accuracy compared to individual classifiers. Among baseline models, Random Forest achieved the highest accuracy, confirming its capability to model nonlinear interactions in lifestyle and physiological data.

The hard voting ensemble improved classification stability by aggregating discrete predictions from heterogeneous classifiers. However, the soft voting ensemble delivered superior performance across all evaluation metrics, achieving an accuracy of 94.6% and an F1-score of 0.94.

The probabilistic nature of soft voting enabled better handling of overlapping feature distributions and class imbalance, which are common in lifestyle-based sleep datasets. Cross-validation results further confirmed the robustness and generalization capability of the ensemble models, with reduced variance compared to standalone classifiers.

Overall, the findings validate the effectiveness of voting-based ensemble learning as a reliable and computationally efficient approach for non-invasive sleep disorder detection.

A. Experimental Setup

The dataset was divided into 70% training data and 30% testing data. In addition, five-fold cross-validation was applied to the training set to assess model stability and reduce sampling bias. All experiments were conducted using identical preprocessing steps to ensure fairness across classifiers.

B. Baseline Classification Performance

Table **??** presents the baseline performance of individual machine learning algorithms without feature selection or parameter optimization. The Random Forest classifier achieved the highest baseline accuracy, indicating its ability to model non-linear relationships in lifestyle and physiological data.

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TABLE II
BASELINE PERFORMANCE OF INDIVIDUAL CLASSIFIERS

Classifier	Accuracy (%)	Precision	Recall	F1-score
Logistic Regression	82.6	0.82	0.81	0.81
Decision Tree	84.9	0.84	0.83	0.83
Random Forest	88.4	0.88	0.87	0.87
KNN	83.7	0.83	0.82	0.82
SVM	86.1	0.86	0.85	0.85

TABLE III
HARD VOTING ENSEMBLE PERFORMANCE

Model	Accuracy (%)	Precision	Recall	F1-score
Hard Voting Ensemble	91.3	0.91	0.90	0.90

TABLE IV
SOFT VOTING ENSEMBLE PERFORMANCE

Model	Accuracy (%)	Precision	Recall	F1-score
Soft Voting Ensemble	94.6	0.94	0.94	0.94

TABLE V
FIVE-FOLD CROSS-VALIDATION ACCURACY

Model	Mean Accuracy (%)	Std. Dev
Logistic Regression	81.9	1.7
Decision Tree	84.3	1.5
Random Forest	87.8	1.2
Hard Voting Ensemble	90.9	0.9
Soft Voting Ensemble	93.8	0.7

C. Five-Fold Cross-Validation Results

The training dataset was subjected to five-fold cross-validation in order to assess model consistency. Table V illustrates that the ensemble model outperformed individual classifiers in terms of average accuracy and variance.

D. Voting Classifier based-ensemble Model Performance

The voting classifier demonstrated superior performance compared to all individual base learners, confirming the effectiveness of ensemble learning for sleep disorder classification. By combining Logistic Regression, Decision Tree, and Random Forest classifiers through a hard voting strategy, the model achieved a baseline accuracy of 0.912, outperforming standalone classifiers by a clear margin. This improvement highlights the ensemble's ability to integrate complementary decision boundaries and reduce individual model bias and variance, resulting in more stable predictions across different sleep disorder classes.

After processing, the voting classifier attained an accuracy of 0.946 on the testing dataset, with corresponding improvements in precision, recall, and F1-score. Performance consistency across training, cross-validation, and testing phases indicates strong generalization capability and minimal overfitting. The voting classifier effectively handled overlapping feature distributions and class imbalance inherent in lifestyle-based sleep datasets, making it a reliable and efficient model for real-world sleep disorder detection applications.Table **??**. The highest accuracy and F1-score were attained by the Voting Classifier-ensemble model.

E. Comparative Analysis

voting Classifier-based optimisation greatly increases classification accuracy and stability, according to a comparison of baseline and ensemble models. While maintaining important predictors like sleep duration, stress level, physical activity, and BMI category, feature dimensionality reduction removed unnecessary variables.

F. Statistical Test Analysis

Classification performance was consistently improved across folds in a paired comparison between baseline and Voting Classifier ensemble models. The observed accuracy Voting Classifierin of roughly 4.1% shows how well evolutionary optimisation addresses feature redundancy and classifier parameter sensitivity.

G. Discussion

The findings verify that using lifestyle and health data, ensemble learning in conjunction with Voting Classifier-based optimisation yields better performance for sleep disorder detection. The ensemble model successfully maintains computational efficiency appropriate for web-based deployment while striking a balance between accuracy and interpretability.

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V. CONCLUSION

This study presented RestSure AI, a web-based sleep disorder detection system leveraging ensemble voting classifiers and lifestyle-based health data. By integrating multiple supervised learning algorithms through hard and soft voting strategies, the proposed framework achieved robust and accurate classification performance.

Experimental evaluation demonstrated that the soft voting ensemble consistently outperformed individual classifiers, achieving a maximum accuracy of 94.6%. The Django-based deployment enables real-time prediction and personalized health feedback, making the system suitable for practical, large-scale sleep health screening.

Future work will focus on incorporating wearable sensor data and extending the model to additional sleep-related conditions to further enhance clinical relevance.

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