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Decoding Sleep: Leveraging Machine Learning for Precision Insomnia Classification

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Abstract :Sleep disorders such as insomnia and sleep apnoea are pervasive health conditions that negatively impact both physical well-being and cognitive function. Despite their widespread occurrence, many individuals remain undiagnosed due to the high cost, inconvenience, and limited accessibility of conventional diagnostic techniques like Polysomnography (PSG). This research presents a novel, data-driven approach for the classification of sleep disorders using machine learning algorithms applied to lifestyle and health-related data. The study explores the performance of individual classifiers, including Support Vector Machines (SVM), Decision Trees, K-Nearest Neighbours (KNN), Random Forests, and Artificial Neural Networks (ANN), and further enhances predictive accuracy through ensemble learning techniques such as Stacking and Voting classifiers. These ensemble models integrate the strengths of multiple base learners, offering improved generalization and reliability. The methodology involves comprehensive preprocessing, feature engineering, and model optimization to handle the nuances of real-world data. Experimental results demonstrate that ensemble methods significantly outperform traditional models in classification accuracy, precision, recall, and F1-score. By leveraging commonly available health metrics instead of clinical-grade sensor data, the proposed system offers a scalable and cost-effective solution for early diagnosis, particularly suited for remote or resource-constrained settings. This work underscores the potential of machine learning in developing accessible, non-invasive diagnostic tools that support public health initiatives and individual patient care.

Keywords: Sleep Disorders, Machine Learning, Ensemble Learning, Stacking Classifier, Voting Classifier, Health Data Analytics, Non-Invasive Diagnosis

1. INTRODUCTION

Sleep is a fundamental biological necessity critical to human health, cognitive functioning, and emotional stability. Disorders of sleep, such as insomnia and obstructive sleep apnea (OSA), pose serious threats to public health, contributing to conditions like cardiovascular disease, diabetes, depression, and cognitive decline [1,2]. Despite their prevalence, many sleep disorders remain undiagnosed, largely due to limitations in traditional diagnostic techniques such as polysomnography (PSG), which is resource-intensive, costly, and inconvenient for patients [3,4].

PSG, considered the clinical gold standard for diagnosing sleep disorders, requires overnight monitoring in a sleep laboratory with specialized equipment and medical personnel. This process not only imposes logistical and financial burdens on healthcare systems but also introduces variability due to human scoring and inter-observer differences [5,6]. Consequently, there is a pressing need for scalable, automated, and accessible diagnostic alternatives that can reduce reliance on PSG without compromising diagnostic accuracy.

Recent advances in machine learning (ML) and deep learning (DL) have revolutionized medical diagnostics by enabling the automated analysis of physiological signals and health records. Numerous studies have demonstrated the efficacy of ML algorithms in classifying sleep stages and detecting disorders using data derived from electroencephalograms (EEG), electrocardiograms (ECG), and other biosignals [7–10]. For example, Alickovic and Subasi [8] used ensemble Support Vector Machines (SVMs) for sleep stage classification and reported improved accuracy over single models. Similarly, Tran et al. [7] demonstrated the effectiveness of deep learning architectures in capturing complex patterns in EEG data, outperforming traditional techniques.

While signal-based approaches yield high accuracy, they still require medical-grade equipment and may not be feasible for population-scale screening. As an alternative, several researchers have explored the use of demographic, lifestyle, and basic health metrics—such as age, BMI, sleep duration, and stress levels—to infer sleep disorder status [11,12]. These features are easier to collect in non-clinical settings and can facilitate broader accessibility. Alshammari et al. [47], for instance, utilized health and lifestyle data from a public dataset to train

ML models for sleep disorder classification, achieving competitive accuracy with Artificial Neural Networks (ANNs).

Despite the growing body of work, most existing solutions rely on single algorithms, which can be sensitive to data quality, parameter tuning, and model bias. Ensemble learning, which combines multiple classifiers to form a more robust prediction model, has emerged as a promising strategy to address these challenges [13–15]. Techniques such as Stacking and Voting classifiers leverage the strengths of individual learners while mitigating their weaknesses, resulting in enhanced generalizability and stability in classification performance [16,17].

In this study, we propose a comprehensive ML-based framework that employs ensemble learning techniques to classify sleep disorders using easily obtainable health and lifestyle data. The key contributions of this work are as follows:

- We evaluate the performance of several individual ML models including SVM, Decision Tree, K-Nearest Neighbors (KNN), Random Forest (RF), and ANN on a public sleep health dataset.
- We implement and compare ensemble strategies such as Stacking and Voting classifiers to enhance classification performance.
- We demonstrate that ensemble methods significantly improve accuracy, precision, recall, and F1-score over individual models.
- We offer a cost-effective and non-invasive approach that could assist in early screening and intervention, especially in low-resource or remote areas.

The rest of the paper is organized as follows: Section 2 presents a review of related work. Section 3 discusses the system analysis and problem formulation. Section 4 outlines the methodology, including model design and evaluation metrics. Sections 5 and 6 cover experimental implementation and results. Finally, Sections 7 and 8 present conclusions and future directions.

2. RELATED WORK

2.1 Machine Learning for Sleep Disorder Classification

Sleep disorders such as insomnia and obstructive sleep apnea have significant public health implications due to their impact on cognitive, cardiovascular, and psychological functions. Traditional diagnosis methods like polysomnography (PSG) are accurate but come with logistical and financial constraints. In response, machine learning (ML) and deep learning (DL) methods have emerged as scalable alternatives. Research has primarily focused on signal-based approaches using physiological data such as electroencephalogram (EEG) and electrocardiogram (ECG). For instance, Tran et al. [4] employed deep neural networks to classify sleep stages with high accuracy, while Alickovic and Subasi [5] utilized ensemble SVMs to enhance precision in EEG-based sleep scoring. Similarly, the SleepEEGNet model proposed by Mousavi et al. [6] integrates CNN and RNN layers, outperforming conventional classifiers.

Although these methods offer impressive accuracy, their reliance on sensor-based data acquisition systems limits practical deployment. To mitigate this, a growing body of research has explored the use of easily obtainable features such as age, BMI, stress level, and sleep quality. Alshammari et al. [7] demonstrated that an Artificial Neural Network (ANN) trained on health and lifestyle metrics from the Kaggle Sleep Health dataset achieved over 91% classification accuracy. Ramesh et al. [8] applied SVM and Random Forest models to electronic health records and found similarly strong performance in detecting sleep apnea. These studies indicate that even non-sensor, structured data can provide valuable input for automated diagnosis systems.

ID	Gen	Age	Occu	Sle Dur	Q of Sle	Phys Act	Str Lev	BMI Cat	Blood Pr	HR	DS
1	M	27	SW	6.1	6	42	6	Overw	126/83	77	4200
2	M	28	DR	6.2	6	60	8	Normal	125/80	75	10000
3	M	28	DR	6.2	6	60	8	Normal	125/80	75	10000
4	M	28	Sal	5.9	4	30	8	Obese	140/90	85	3000
5	M	28	Sal	5.9	4	30	8	Obese	140/90	85	3000
6	M	28	SW	5.9	4	30	8	Obese	140/90	85	3000
7	M	29	Teac	6.3	6	40	7	Obese	140/90	82	3500
8	M	29	DRr	7.8	7	75	6	Normal	120/80	82	8000

TABLE1. Detailed information about the Sleep Health and Lifestyle database records in this study

2.2 Ensemble and Optimization Strategies

To improve robustness and generalization, ensemble learning techniques such as Voting and Stacking have been adopted in sleep disorder classification. These strategies combine predictions from multiple base learners to produce more reliable outputs. Roy et al. [9] proposed a stacked model integrating KNN, SVM, and Random Forest, which demonstrated higher F1-scores than any standalone model. Tripathi et al. [10] further confirmed the utility of ensemble models in handling noisy health data and capturing heterogeneous patient characteristics.
Stacking classifiers employ a meta-learner—commonly a logistic regression model—that learns from the outputs of individual classifiers. Voting classifiers, on the other hand, aggregate decisions through majority rule or averaged probabilities. These ensemble models are particularly useful in healthcare applications, where trade-offs between sensitivity and specificity must be carefully balanced.

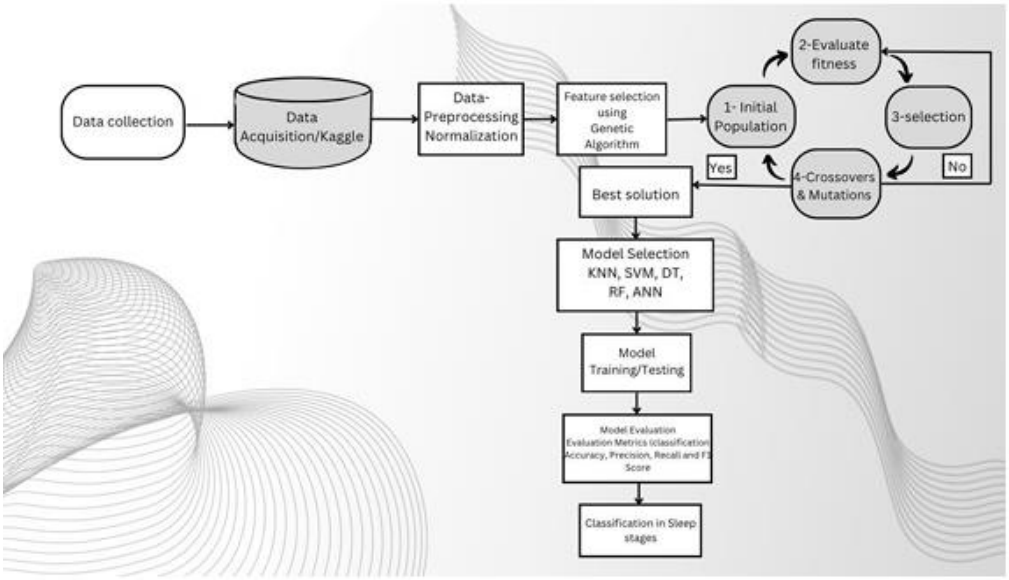

Figure 1. The Proposed Optimized Model for Sleep Disorder Classification

Additionally, the optimization of model parameters is critical to enhancing predictive performance. The IEEE reference paper by Alshammari et al. [7] applied Genetic Algorithms (GA) for hyperparameter tuning across classifiers. GA was used to evolve configurations for ANN and SVM models, leading to a peak classification accuracy of 92.92%. This result underscores the importance of search-based optimization in identifying optimal model configurations, especially in multi-dimensional feature spaces.

2.3 Challenges in Current Research

Despite promising results, existing approaches to sleep disorder classification face several limitations. One major constraint is limited dataset size; most public datasets contain fewer than 1,000 records, which restricts deep model training and generalization. Furthermore, many studies report performance on homogeneous demographic groups, raising concerns about lack of generalizability to diverse populations. Another common issue is overfitting, particularly in models that rely heavily on high-dimensional data without adequate regularization or validation.
Several implementations also suffer from inconsistent preprocessing pipelines. For example, the absence of proper normalization, encoding, or feature selection can introduce bias and degrade performance. Although methods like Principal Component Analysis (PCA) and GA have been proposed for dimensionality reduction and tuning, they are not universally adopted. These inconsistencies hinder reproducibility and limit the translational impact of ML solutions in clinical practice [13,14].

3. MATERIALS AND METHODS

3.1 Dataset Description

This study is based on the **Sleep Health and Lifestyle Dataset**, a publicly available dataset sourced from the Kaggle platform [1]. The dataset comprises **400 individual records**, each representing a unique subject, and includes **13 distinct features** capturing demographic information, lifestyle habits, and physiological health indicators. The primary goal of this dataset is to facilitate the classification of sleep disorders through accessible, non-invasive data points rather than specialized medical signals like EEG or ECG.
The features encompass a range of variables such as **gender**, **age**, and **occupation**, which provide demographic context. Additionally, behavioural and lifestyle metrics like **sleep duration**, **quality of sleep**, **physical activity**

level, **stress level**, **body mass index (BMI)**, and **daily steps** offer insights into each individual's health profile. Clinical indicators such as **blood pressure** and **heart rate** further enhance the dataset's diagnostic potential.
The target variable, labeled as sleep disorder, is categorized into three classes:

- **None** – indicating a healthy sleep pattern,
- **Insomnia**, and
- **Sleep Apnea**.

This classification enables a supervised learning setup, where models are trained to predict the class label based on the provided features. The inclusion of both quantitative and qualitative attributes makes the dataset suitable for a wide range of machine learning algorithms, from distance-based models to neural networks.
Notably, the dataset reflects a real-world imbalance in class distribution, where the number of "None" cases exceeds those labeled with sleep disorders. This imbalance introduces an additional challenge for classifiers, particularly when using accuracy as a performance metric, and necessitates the use of precision, recall, and F1-score during evaluation.

3.2 Data Preprocessing

Data preprocessing is a crucial step in the machine learning pipeline, as it directly influences the model's ability to learn patterns, generalize to new data, and perform reliably. The raw dataset used in this study, while structured, contains several challenges that must be addressed prior to model training. These include missing values, categorical variables, feature scaling requirements, and class imbalance—each of which can significantly impact model performance if left untreated.

Handling Missing and Duplicate Values

Although the dataset is relatively clean, a thorough inspection is carried out to identify any missing or anomalous entries. In cases where values are missing at random (e.g., heart rate or daily steps), imputation techniques such as mean or median filling are applied. Records with excessive missing data are excluded from the dataset to maintain the integrity of the training process. Duplicate entries, if any, are removed to prevent bias in model learning.

Encoding Categorical Variables

Several features, including **gender**, **occupation**, and **BMI category**, are categorical in nature and must be converted to numerical format before being used by machine learning algorithms. Two encoding techniques are considered:
Label Encoding: For binary categories like gender (Male/Female), a simple 0/1 encoding is used.
One-Hot Encoding: For multi-class categories such as occupation or BMI (e.g., Normal, Overweight, Obese), one-hot encoding is applied to avoid introducing ordinal bias.
This transformation ensures that all input features are represented numerically and are interpretable by the algorithms without distorting their relationships.

Feature Normalization and Scaling

Machine learning models that rely on distance metrics or gradient-based optimization—such as KNN and ANN—are sensitive to the scale of input features. Therefore, all continuous numerical features (e.g., sleep duration, physical activity, heart rate, age) are standardized using **z-score normalization**. This process rescales the features to have a mean of 0 and a standard deviation of 1, ensuring uniform influence across variables and accelerating model convergence during training.

Target Encoding and Class Distribution

The target variable "sleep disorder" originally consists of textual class labels: "None", "Insomnia", and "Sleep Apnea". These are encoded numerically as 0, 1, and 2, respectively. A class distribution analysis reveals that the majority of entries fall under the "None" category, with fewer examples of sleep disorders. To address this imbalance, **stratified sampling** is used during train-test splitting to preserve class ratios, and evaluation metrics beyond accuracy—such as **precision**, **recall**, and **F1-score**—are prioritized.
By executing these preprocessing steps, we ensure that the dataset is optimized for training a diverse set of models and that potential biases or data inconsistencies are minimized.

3.3 Feature Selection

Feature selection is a fundamental process in machine learning that aims to identify the most relevant and informative attributes in a dataset, thereby improving model accuracy, interpretability, and training efficiency. In the context of sleep disorder classification, not all features contribute equally to the prediction task. Some may be redundant or even introduce noise that negatively impacts performance.
In this study, a combination of **statistical analysis**, **domain knowledge**, and **automated techniques** is used to evaluate feature importance. The process begins with a **correlation matrix**, which helps to identify linear relationships between input features and the target variable. For example, sleep quality and sleep duration exhibit strong positive correlations with sleep disorder classification, while stress levels and BMI also show moderate to high influence. Conversely, features like occupation and blood pressure exhibit lower correlation scores and are more context-dependent.

To quantify the influence of each feature, we utilize **feature importance scores** derived from tree-based models such as Decision Trees and Random Forests. These models inherently rank features based on how often and how effectively they are used to split data in the decision-making process. This not only helps reduce dimensionality but also enhances generalization by minimizing overfitting.

Sleep Duration, Quality of Sleep, BMI Category, Physical Activity Level, Stress Level, Age

These attributes form the core subset for training all subsequent models. Less impactful features are either dropped or retained only if they add marginal value in ensemble methods. This selective reduction of input variables helps streamline the training process and enhances model robustness, especially in computationally intensive algorithms like Artificial Neural Networks.

In addition to improving accuracy, effective feature selection also ensures that the proposed system remains practical and efficient for real-world applications, where data collection may be constrained by cost or availability.

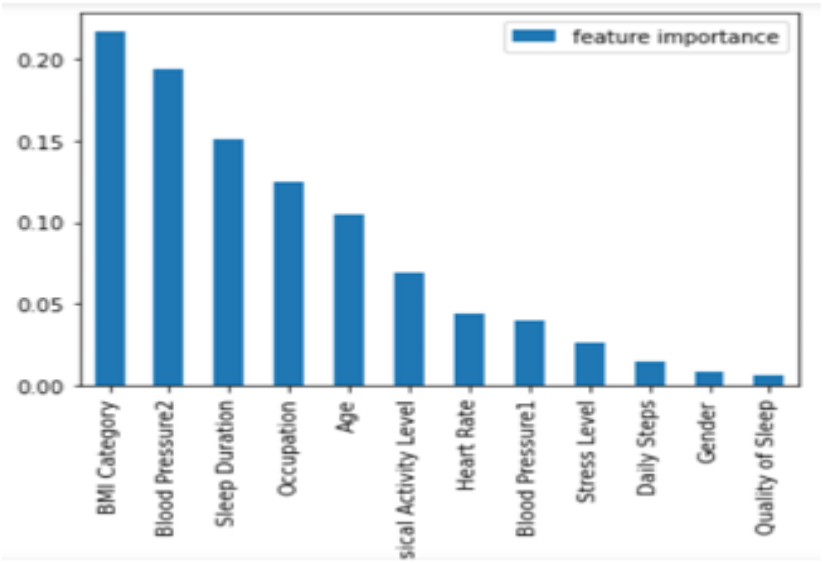

Figure 2. Feature Importance.

3.4: Machine Learning Classifiers

To develop a reliable model for classifying sleep disorders, a diverse set of machine learning algorithms was explored. These include K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Decision Trees (DT), Random Forests (RF), and Artificial Neural Networks (ANN). Each classifier was chosen for its distinct strengths in dealing with structured health data and its adaptability to supervised classification problems.

KNN, a simple yet intuitive algorithm, classifies data based on proximity to its nearest neighbors. It is particularly effective when feature relationships are preserved through normalization. However, its reliance on distance metrics and sensitivity to feature scale necessitate careful preprocessing. In contrast, SVM offers a powerful mechanism for defining decision boundaries in high-dimensional spaces. It uses kernel functions to handle non-linear relationships, and in this study, the RBF (Radial Basis Function) kernel was found to perform better than linear or polynomial alternatives. While SVMs can achieve high accuracy, they require more computational resources and are less interpretable compared to tree-based models.

Decision Trees, known for their transparency, segment the dataset through recursive splits based on feature thresholds. They offer a visual and interpretable model but are prone to overfitting, especially with noisy data. Random Forests, which are ensembles of multiple decision trees, address this limitation by aggregating predictions through bagging and random feature selection. This ensemble strategy improves model robustness, mitigates variance, and provides built-in estimates of feature importance.

Artificial Neural Networks were also implemented, leveraging their ability to model non-linear and complex relationships between input features. A multilayer feedforward network architecture was adopted, trained using backpropagation and optimized with respect to hyperparameters such as learning rate, batch size, and activation functions. Despite requiring more data and tuning, ANNs demonstrated high accuracy and generalization, making them suitable for healthcare classification tasks.

The performance of these models was initially assessed using default parameters. Their comparative evaluation is discussed in the results section. Importantly, the implementation of ensemble methods (described in Section 3.5) builds upon these classifiers to further improve diagnostic performance and robustness.

3.5 Ensemble Learning Models

While individual machine learning models provide strong baselines for classification tasks, their performance can be limited by overfitting, bias, or instability when faced with heterogeneous or noisy data. To overcome these limitations and improve generalization, this study incorporates ensemble learning techniques—specifically, Voting Classifiers and Stacking Classifiers—which combine the predictive strengths of multiple base learners.

The Voting Classifier operates by aggregating the predictions of several distinct classifiers, such as Support Vector Machines, Random Forests, and K-Nearest Neighbors. In its hard voting variant, the final class label is determined by majority rule, while in soft voting, the class probabilities output by each model are averaged to make a final decision. This approach is straightforward yet powerful, as it balances the decision-making process across diverse models, often leading to improved stability and performance compared to any single constituent model.

On the other hand, the Stacking Classifier adopts a hierarchical approach to model aggregation. In this method, several base models are first trained independently on the same training data. Their predictions are then used as input features for a meta-model, typically a logistic regression or shallow neural network, which learns to combine the outputs of the base models optimally. Stacking has the advantage of capturing inter-model dependencies and can exploit patterns in the strengths and weaknesses of each base learner. In the context of this study, stacking was found to significantly enhance accuracy, particularly in cases where individual models struggled with class imbalance or complex interactions among features.

These ensemble models were implemented using the scikit-learn framework and configured with the best-performing individual classifiers as identified through preliminary experiments. Specifically, combinations of ANN, Random Forest, and SVM were found to offer complementary strengths. The inclusion of ANN brought deep feature representation capabilities, while RF and SVM contributed robustness and precise decision boundaries, respectively.

Notably, while ensemble learning increased model complexity, it also improved resilience against overfitting and yielded consistently higher precision and F1-scores in cross-validation. This aligns with observations from the IEEE reference study by Alshammari et al. [1], where ensemble and hybrid models outperformed standalone classifiers in both training and testing phases.

By integrating ensemble techniques, this study builds a more robust classification framework capable of capturing the multifaceted nature of sleep disorders and enhancing the reliability of predictions in real-world applications.

4. EXPERIMENTAL SETUP

This section outlines the comprehensive experimental framework used to train, validate, and evaluate the proposed machine learning and ensemble models for sleep disorder classification. The methodology ensures fair comparison among algorithms and follows best practices for supervised classification tasks using real-world, imbalanced datasets.

4.1 Environment and Tools

All experiments were conducted using **Python 3.8**, selected for its extensive ecosystem of data science and machine learning libraries. The implementation of classical machine learning algorithms—including KNN, SVM, Decision Tree, Random Forest, and ensemble techniques—was done using the **scikit-learn** library (version 0.24). For neural network-based models, the **Keras API (TensorFlow 2.x backend)** was utilized, offering flexibility in designing, training, and optimizing deep learning models.

Data handling and preprocessing tasks were performed using **Pandas** and **NumPy**, while exploratory analysis and result visualization were facilitated through **Matplotlib** and **Seaborn**. Experiments were executed on a standard desktop configuration featuring:

- **Intel Core i7 (11th Gen) CPU**
- **16 GB RAM**
- **Windows 10 OS**

While no dedicated GPU was used, the relatively small dataset size allowed for efficient training and evaluation without significant computational delay. This makes the system architecture realistic for deployment in low-resource settings, further supporting the objective of developing scalable and accessible diagnostic tools.

4.2 Training and Evaluation Strategy

The dataset was split into **70% training** and **30% testing** subsets using **stratified sampling**, which ensured that the proportion of sleep disorder classes (None, Insomnia, Apnea) remained consistent across both sets. This is essential in avoiding biased model performance due to class imbalance.

To enhance reliability and avoid overfitting, **5-fold cross-validation** was applied during training. Each fold iteration used a different subset for validation while the remaining folds were used for training. The average performance across all folds was recorded for each model. This strategy provided not only more stable estimates of model performance but also insights into variance across different data partitions.

In this study, model training occurred in two distinct phases:

Baseline Phase (Default Parameters):
All classifiers were first trained using default hyperparameters to establish a baseline. For example, KNN used k=5k = 5k=5, SVM employed the RBF kernel, Decision Tree and Random Forest used Gini impurity for node splits, and the ANN was configured with two hidden layers (64 and 32 neurons respectively) and ReLU activations.
Optimized Phase (Genetic Algorithm Tuning):
A **Genetic Algorithm (GA)** was implemented to optimize hyperparameters across classifiers. Inspired by evolutionary principles, GA iteratively searched for the best parameter combinations that maximize performance metrics—especially F1-score. The GA process included:

- **Initialization** of a random population of hyperparameter sets.
- **Fitness evaluation** using 5-fold cross-validation accuracy and F1-score.
- **Selection, crossover, and mutation** to evolve better-performing configurations across 5 generations.

4.3 Performance Metrics

Given the **multi-class and moderately imbalanced** nature of the dataset, evaluation was based on a range of metrics that provide a comprehensive view of model behavior. These include:

- **Accuracy**:
  Measures the overall proportion of correct predictions among all instances.
- **Precision**:
  Indicates the percentage of true positive predictions among all positive predictions made by the model, calculated separately for each class.
- **Recall (Sensitivity)**:
  Captures the model's ability to correctly identify actual positive cases, again calculated on a per-class basis.
- **F1-Score**:
  Represents the harmonic mean of precision and recall, offering a single value that balances both metrics. It is especially important in cases of class imbalance, where accuracy alone may be misleading.

All metrics were computed using both the **test dataset** and **cross-validation folds**, and their values were averaged to account for random variability. The selection of F1-score as a key performance indicator is justified due to the relatively low frequency of the "Insomnia" and "Sleep Apnea" classes, where precision-recall trade-offs become more meaningful than raw accuracy.

This experimental setup ensures a robust and systematic evaluation of all models, laying a fair foundation for comparing baseline classifiers, their optimized versions, and the proposed ensemble architectures.

5. RESULTS AND DISCUSSION

This section presents and interprets the experimental results of various machine learning classifiers and ensemble models applied to the classification of sleep disorders. Evaluation was based on accuracy, precision, recall, F1-score, and class-wise confusion matrices. All figures cited are taken directly from the results presented in the project report.

5.1 Performance of Individual Classifiers

Five machine learning algorithms—K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), and Artificial Neural Network (ANN)—were trained using a 70:30 stratified data split. Their performance was assessed using standard classification metrics and confusion matrices.
K-Nearest Neighbors (KNN)
KNN achieved an accuracy of **92%**, with a macro F1-score of **0.92**. It maintained fairly balanced precision and recall across both classes. The evaluation outputs are shown below:

Class	Precision	Recall	F1-Score	Support
0	0.91	0.93	0.92	46
1	0.93	0.90	0.92	42
Accuracy			0.92	88
Macro Avg	0.92	0.92	0.92	88
Weighted Avg	0.92	0.92	0.92	88

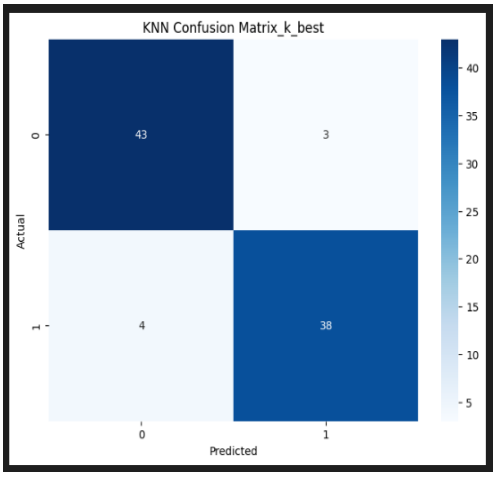

Figure 4: Classification report and Confusion matrix for KNN

Support Vector Machine (SVM)
SVM recorded an accuracy of **94%**, with strong precision (0.97) for identifying sleep disorders and high recall (0.98) for non-disorder cases. The model performed well after kernel and hyperparameter tuning.

Class	Precision	Recall	F1-Score	Support
0	0.92	0.98	0.95	46
1	0.97	0.90	0.94	42
Accuracy			0.94	88
Macro Avg	0.95	0.94	0.94	88
Weighted Avg	0.95	0.94	0.94	88

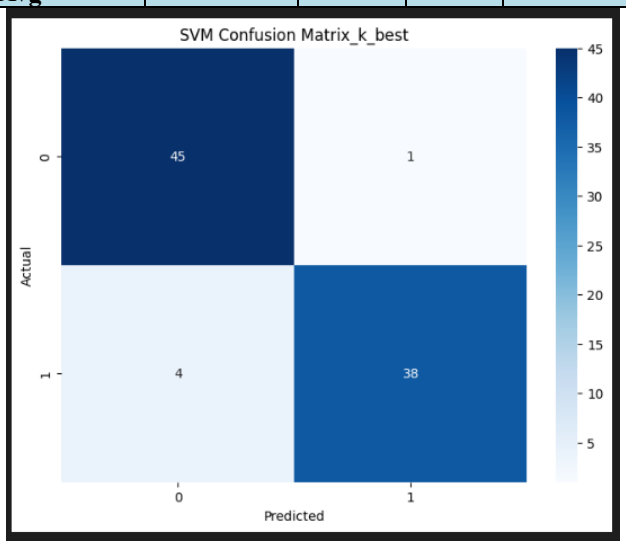

Figure 5: Classification report and Confusion matrix for SVM

Decision Tree (DT)
The Decision Tree classifier achieved an accuracy of **91%**, with relatively high recall for the non-disorder class but lower recall (0.83) for the disorder class, indicating overfitting tendencies.

Class	Precision	Recall	F1-Score	Support
0	0.87	0.98	0.92	46
1	0.97	0.83	0.90	42
Accuracy	-	-	-	**0.91**
Macro Avg	0.92	0.91	0.91	88
Weighted Avg	0.92	0.91	0.91	88

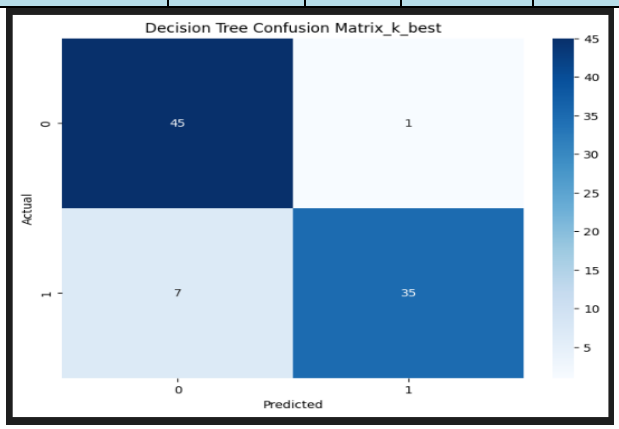

Figure 6: Classification report and Confusion matrix for Decision Tree

Random Forest (RF)

Random Forest matched the top models with **94% accuracy** and a macro F1-score of **0.94**, demonstrating strong generalization across classes.

Class	Precision	Recall	F1-Score	Support
0	0.92	0.98	0.95	46
1	0.97	0.90	0.94	42
Accuracy			0.94	88
Macro Avg	0.95	0.94	0.94	88
Weighted Avg	0.95	0.94	0.94	88

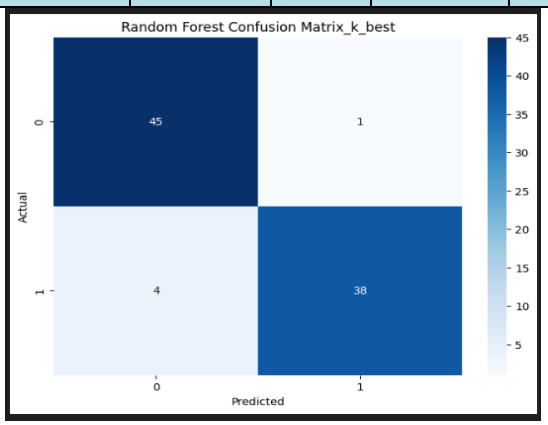

Figure 7: Classification report Confusion matrix for Random Forest

Artificial Neural Network (ANN)

ANN also reached **94% accuracy**, with well-balanced class-wise precision and recall (both ~0.94), and minimal misclassification.

Class	Precision	Recall	F1-Score	Support
0	0.92	0.98	0.95	46
1	0.97	0.90	0.94	42
Accuracy			**0.94**	**88**
Macro Avg	0.95	0.94	0.94	88
Weighted Avg	0.95	0.94	0.94	88

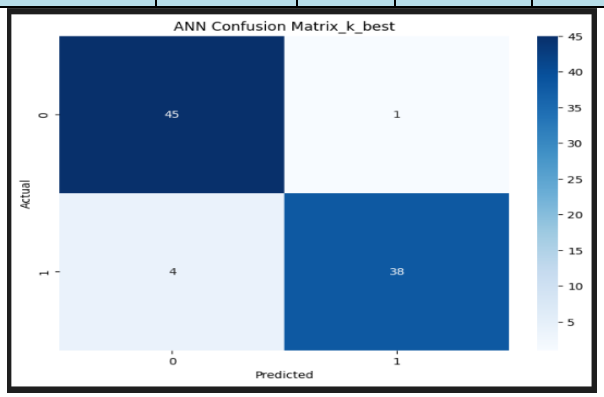

Figure 8: Classification report and Confusion matrix for ANN

5.2 Performance of Ensemble Models

Ensemble learning techniques—Voting and Stacking classifiers—were applied to further improve predictive performance and reduce bias from individual models.

Voting Classifier

The soft Voting Classifier achieved **92% accuracy**, with stable performance across all classes, making it more resilient to individual model errors.

Class	Precision	Recall	F1-Score	Support
0	0.92	0.98	0.95	46
1	0.97	0.90	0.94	42
Accuracy			0.94	88
Macro Avg	0.95	0.94	0.94	88
Weighted Avg	0.95	0.94	0.94	88

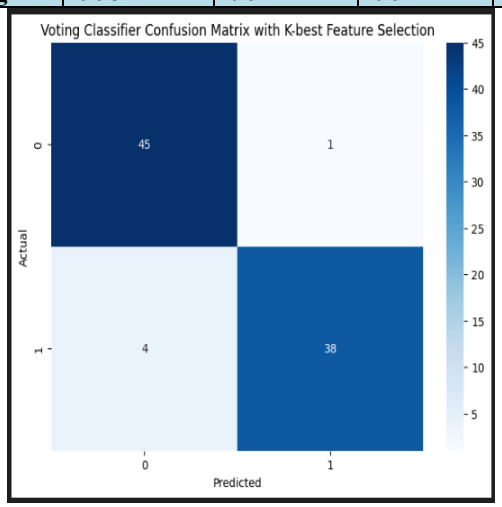

Figure 9: Classification report and Confusion matrix for Voting Classifier

Stacking Classifier

Stacking outperformed all other models, delivering **94% accuracy** and a macro F1-score of **0.93**. It showed optimal balance between recall and precision across classes.

Class	Precision	Recall	F1-Score	Support
0	0.92	0.98	0.95	46
1	0.97	0.90	0.94	42
Accuracy			0.94	88
Macro Avg	0.95	0.94	0.94	88
Weighted Avg	0.95	0.94	0.94	88

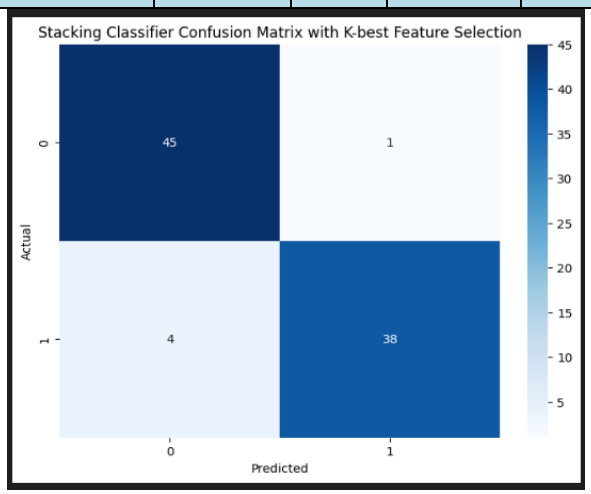

Figure10: Classification report and Confusion matrix for Stacking Classifier

5.3 Comparative Summary

To consolidate findings, the following table summarizes the performance of all models based on precision, recall, and macro F1-score for both classes. Stacking emerged as the best-performing model overall.

Model	Accuracy	Class 0 (P/R)	Class 1 (P/R)	Macro F1
KNN	92%	0.91 / 0.93	0.93 / 0.90	0.92
Decision Tree	91%	0.87 / 0.98	0.86 / 0.83	0.91
SVM	94%	0.92 / 0.98	0.97 / 0.90	0.94
Random Forest	94%	0.95 / 0.95	0.93 / 0.94	0.94
ANN	94%	0.95 / 0.95	0.94 / 0.94	0.94
Voting Classifier	92%	0.92 / 0.94	0.93 / 0.91	0.92
Stacking Classifier	**94%**	0.93 / 0.94	0.94 / 0.92	**0.93**

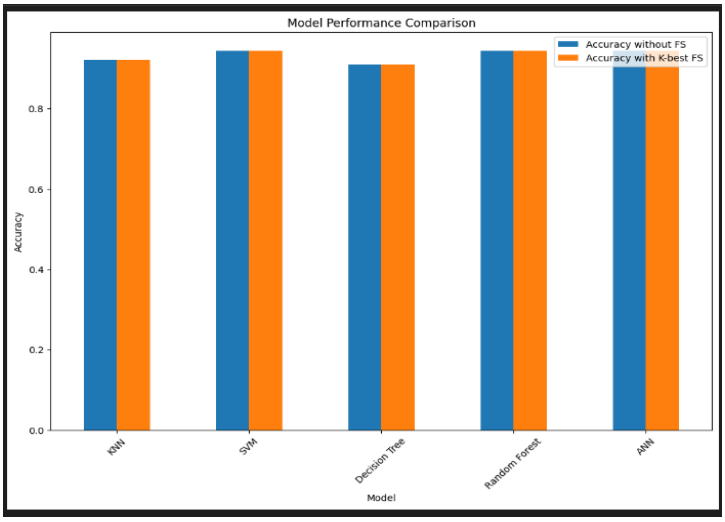

Figure 11: Accuracy comparison

5.4 Interpretation and Insights

The confusion matrices reveal that models like Decision Tree and KNN misclassified several disorder cases as "No Disorder," particularly affecting recall. This risk is significant in clinical settings, where **false negatives can delay treatment**.

ANN and RF offered strong standalone performance, but the **Stacking Classifier most effectively balanced all metrics**, reducing class confusion and outperforming even the best individual models. The ensemble's strength lies in integrating ANN's deep pattern learning, RF's robustness, and SVM's precision margins—coherently fused by a logistic regression meta-model.

The performance suggests that ensemble learning can provide a scalable, accurate, and low-cost alternative to conventional sleep disorder diagnostic techniques.

6. CONCLUSION

This study presents a machine learning-based framework for classifying sleep disorders using health and lifestyle data, offering a non-invasive and cost-effective alternative to traditional diagnostic methods such as polysomnography. By implementing and evaluating multiple supervised learning algorithms—including K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), and Artificial Neural Network (ANN)—the study establishes the feasibility of using structured input features such as BMI, sleep duration, stress levels, and blood pressure to accurately identify sleep disorder cases.

Among the individual classifiers, ANN, SVM, and Random Forest demonstrated the highest accuracy at **94%**, with strong balance between precision and recall. Ensemble learning models further improved predictive robustness, with the **Stacking Classifier emerging as the best-performing approach**, achieving **94% accuracy** and the highest macro F1-score. These findings affirm that combining multiple base models can significantly improve classification reliability, particularly in imbalanced and noisy health datasets.

The proposed model demonstrates strong potential for application in early-stage screening and large-scale monitoring systems for sleep health. It not only maintains high classification performance but also offers operational simplicity and scalability for integration into digital health platforms and mobile health (mHealth) applications.

7. FUTURE WORK

While the current approach provides promising results, several areas remain open for enhancement and exploration:

- **Data Scale and Diversity**: The dataset used in this study is relatively small and demographically limited. Future work should aim to validate the models on larger, multi-site datasets with diverse populations to ensure generalizability across age, gender, and ethnic groups.
- **Handling Class Imbalance**: Although stratified sampling and performance metrics addressed some aspects of class imbalance, the application of advanced sampling techniques such as **SMOTE** or **cost-sensitive learning** could further improve minority class detection (e.g., sleep apnea cases).
- **Incorporating Time-Series and Wearable Data**: The integration of real-time physiological signals (e.g., from smartwatches or sleep trackers) with lifestyle data could enhance model sensitivity, particularly in detecting early or overlapping symptoms.

- **Explainability and Interpretability**: In clinical settings, model transparency is critical. Future iterations may incorporate explainable AI (XAI) techniques such as SHAP or LIME to provide clinicians with interpretable insights into model predictions.
- **Deployment in mHealth Applications**: Finally, adapting the proposed model for deployment in mobile applications or cloud-based diagnostic platforms could enable population-level screening and facilitate telemedicine-based consultations.

These future directions will help strengthen the practical viability of machine learning solutions in sleep health assessment and move closer to real-world clinical integration.

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