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*Research Paper*

# SLEEP DISORDER DETECTION AND CLASSIFICATION USING ADVANCED MACHINE LEARNING MODELS

Dr. Mohd Azeemullah[1], Dr. Jaibir Singh[2]
[1]*Assistant professor, Department of CSE, Sphoorthy Engineering College, Nadergul, Hyderabad*
*azeemullah889@gmail.com*
[2]*Associate Professor and Dean, Dept. of CSE-IoT, OPJS University, Churu.*
*jaibir729@gmail.com*

**ABSTRACT**

The health and well-being of people are enormously impacted by sleep problems, including insomnia, sleep apnoea, and other illnesses. The quality of life for those who are impacted can be improved by early diagnosis and successful treatment made possible by an accurate and effective classification of various conditions. For categorisation, the current systems mostly use Artificial Neural Networks (ANN), which are efficient but sometimes computationally demanding and difficult to understand. In order to categorise sleep disorders, this study suggests a Random Forest-based method using a dataset of 400 samples with 13 pertinent variables. The Random Forest model was chosen because it is robust, easy to understand, and has a higher capacity to manage intricate, non-linear interactions in the data. The study uses this algorithm to categorise sleep disorders into three groups: sleep apnoea, insomnia, and none. Its performance is better than that of conventional ANN-based systems. Standard performance criteria, such as accuracy, precision, recall, and F1-score, are used to evaluate the Random Forest model. The results demonstrate that the suggested method performs better than current models, providing improved accuracy and dependability in the categorisation of sleep disorders.

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## 1. INTRODUCTION

An essential physiological function for both physical and mental well-being is sleep. Sleep strengthens the body and helps to solidify memories and the brain. Cognitive abilities are impacted by sleep quality, especially in youngsters and elderly drivers who are more likely to be involved in collisions. Lack of sleep can have an impact on the body and lead to conditions including obesity, diabetes, and heart disease. Different evaluations of sleep stages may result from the manual evaluation of polysomnography (PSG) records by physicians, doctors, medical professionals, and specialists. Sleep-stage classification by hand takes a lot of time and is subject to human mistake. These methods can be divided into Random Forest and conventional (traditional) machine learning algorithms. People's everyday functioning, health, and quality of life are all greatly impacted by sleep disorders like insomnia, sleep apnoea, and other related illnesses. Early and precise diagnosis is crucial since these conditions can result in serious health complications like diabetes, heart disease, and mental health difficulties. Traditional sleep disorder diagnostic techniques, such polysomnography, are frequently costly, time-consuming, and necessitate specialised medical facilities. The need for automated, effective, and precise classification techniques that can help medical practitioners recognise and treat sleep problems is therefore growing. Because machine learning algorithms can analyse intricate patterns in data and offer useful insights for disease diagnosis and prognosis, they have attracted a lot of interest in the medical industry. Artificial Neural Networks (ANN), which are used in many current methods for sleep disorder classification, have drawbacks despite their efficacy, including high computing costs, a lack of interpretability, and a propensity to over fit, particularly when working with smaller datasets. The suggested approach makes use of a dataset of 400 samples and 13 attributes, such as vital health statistics, physical activity levels, sleep quality indicators, and demographic information. Sorting these samples into three categories—Insomnia, None (no disorder), and Sleep Apnea—is the aim. The Random Forest technique is used because it can handle different kinds of data, deal with missing values, and produce feature importance scores that provide important information about the factors influencing each categorisation of sleep disorder.

**OBJECTIVE**

In this paper, we propose the use of the Random Forest algorithm as an alternative to ANN for the categorisation of sleep disorders. Random Forest, an ensemble learning method, is noted for its robustness, high accuracy, and capacity to handle enormous datasets with complicated, non-linear relationships. It operates by creating several decision trees during training and outputting the mode of the classes (classification) of the individual trees. Compared to neural networks, this method lowers the chance of over fitting and produces a more interpretable model.

**PROBLEM STATEMENT**

Insomnia and sleep apnoea are two examples of sleep disorders that negatively impact people's general quality of life, productivity, and health. Effective therapy and prompt intervention depend on the early and precise categorisation of these illnesses. Artificial Neural Networks (ANN) are the mainstay of current classification systems, however despite their capacity for prediction, they frequently have significant computational complexity and poor interpretability, which restricts their usefulness in clinical contexts. A more effective and understandable approach that can correctly categorise sleep disorders is thus required. In order to close this gap, this work suggests a Random Forest-based classification method that uses its resilience, reduced processing cost, and better handling of non-linear interactions to increase the precision and dependability of sleep disorder classification.

**EXISTING SYSTEM**

Using raw PSG data, a deep learning network can automatically categorise sleep stages. The model pulls feature from a one-dimensional CNN. They used publicly accessible internet databases (sleep-edf and sleep-edfx) to assess the suggested model. For two to six sleep classes, the suggested model achieved high accuracy of 88.22% and 88.00%. In order to circumvent the need for manual specialists, the authors proposed deep learning as a viable way for automated sleep-stage classification. Human mistake is a possibility with this method. An effective technique that combined a heterogeneous feature representation and a genetic algorithm-based ensemble learning model to predict ant tubercular peptides to aid in the search for a new treatment to combat tuberculosis is presented, along with a summary of the algorithm, dataset, and accuracy in some of the reviewed studies.

**Disadvantage of Existing System**

- This can lead to long training times and high demands on hardware resources like GPUs.
- Ann over fitting, especially when the dataset is small or imbalanced.
- Hyper parameter Tuning Complexity.
- Requires Extensive Data Preprocessing.

**PROPOSED SYSTEM**

The study's authors examine sleep disorder research, concentrating on issues like data collecting, which involves gathering noisy and ambiguous (e.g., missing) patient data from many hospitals while the patients are asleep. Because only one sleep clinic provided the data, the dataset has numerous limitations. Because the data is biased towards particular patient groups, it is difficult to generalise evaluated outcomes, and decision-making may be influenced by the erroneous results. Natural sleep-stage datasets are few, nevertheless. Moreover, feature extraction from the dataset is required to train models and pick discriminative features, which normally demands more computing work to select well-suited MLAs from multiple classifiers. The need to address the difficulties brought on by sleep disorders in the contemporary lifestyle, particularly for those who suffer from them, is what spurred this study.

**Advantages of Proposed System**

- Handles Missing Data Effectively.
- Flexibility in Handling Large Datasets.
- Interpretability and Feature Importance.

## 2. RELATED WORKS

In this work, the Sleep Health and Lifestyle Dataset—which include information on personal sleep patterns, lifestyle variables, and important health indicators—is used to classify sleep disorders using the Random Forest algorithm. Preprocessing was done on the dataset to deal with missing values and get it ready for modeling. To facilitate supervised learning, it was then separated into subsets for testing and training. Relevant parameters like physical activity, stress level, snoring frequency, and length of sleep were used to train the Random Forest classifier on the training subset. To maximize node purity and enhance the ensemble's overall decision-making process, the Gini Index was employed as the splitting criterion for every decision tree in the forest. Using common classification metrics including accuracy, precision, recall, and F1-score, the model's performance was assessed on the testing subset. The findings demonstrated that the Random Forest model performed well in classification, accurately predicting whether sleep apnea, insomnia, or none (no disorder) would be present. To learn more about the distribution of sleep disorder classes, the correlations between variables, and gender-specific trends, exploratory data analysis was carried out in addition to model evaluation. These revelations help to clarify the underlying lifestyle and health factors driving sleep problems in addition to confirming the model's predictions. This study shows how machine learning might improve sleep medicine's early detection and diagnosis.**[1]**

Fault detection and diagnosis (FDD) has drawn a lot of attention to modern photovoltaic (PV) systems in an effort to improve their dependability, availability, and required safety. Consequently, this paper discusses the FDD problem in grid-connected PV (GCPV) systems. The established FDD technique uses tools for fault classification, feature extraction, and selection to monitor the GCPV system under different operating situations. The best characteristics are chosen using the genetic algorithm (GA) technique, and fault diagnosis is done using the artificial neural network (ANN) classifier. To feed the ANN classifier, just the most crucial features are chosen.Using data taken from the GCPV system's healthy and defective data, the classification performance is assessed using a variety of metrics for several GA-based ANN classifiers. 16 flaws that were applied to the module are thoroughly examined. Generally speaking, the system's defects fall into one of three categories: simple, many, or mixed. The findings obtained validate the viability and efficiency of the suggested fault diagnosis method with a short calculation time.**[2]**

Individuals who suffer from insomnia, a prevalent sleep disorder, struggle to fall asleep. Accurately diagnosing insomnia is a crucial first step in the early stages of mental disorder study. Lack of sleep is one of the primary causes of cardiovascular diseases, such as high blood pressure and stroke. Traditional methods of diagnosing insomnia are time-consuming, expensive, and labor-intensive since they need a lot of time from a competent neurophysiologist and are prone to human error. Consequently, the diagnosis's accuracy is compromised. For prompt detection and treatment, the automatic diagnosis of insomnia from electrocardiogram (ECG) records is essential. In order to detect insomnia in three different classification scenarios— (1) subject-based classification (normal vs. insomnia), (2) sleep stage-based classification (REM vs. W. stage), and (3) the combined classification scenario using both subject-based and sleep stage-based deep features—a novel hybrid artificial intelligence (AI) approach based on the power spectral density (PSD) of the heart rate variability (HRV) is proposed in this paper. The first and second classification scenarios are carried out by the ensemble learning of random forest (RF) and decision tree (DT) classifiers, while the third combination scenario is carried out by the linear discriminant analysis (LDA) classifier. Data collection, ECG signal analysis, HRV signal extraction, PSD estimate, and AI-based categorization through hybrid machine learning are all included in the suggested system.**[3]**

Abstraction People are experiencing a variety of sleep-related disorders as a result of the rapid changes in lifestyles, the acceleration of social activities, and the increased strain in professional sectors. Using manual and traditional laboratory environmental methods to analyze the sleep staging and track the participants' total sleep lengths is a very time-consuming operation for clinicians. We have taken into consideration the automated analysis of sleep epochs, which were gathered from the patients during their sleep period, in order to accurately diagnose various sleep disorders. Pre-processing the raw signals, feature extraction, feature selection, and classification are the four main phases that make up the entire automated technique to classifying sleep stages. In this study, we have retrieved 12 statistical features from input data. Three distinct feature set combinations are used to test the suggested models. All 12 features were included in the feature set for the initial experiment. The nine and five best attributes were used in the second and third studies, respectively. The ISRUC Sleep database is the source of the patient records. Combinations of the five feature set provide the best classification accuracy for sleep staging. The claimed accuracy results were judged to be above 90% based on the subject categories. According to the results of the suggested system, the random forest classification method outperformed the other two classifiers in terms of accuracy.**[4]**

Even though automatic sleep staging for adults has advanced recently, children's complex sleep structures necessitate consideration of pediatric sleep staging. For doctors, semi-supervised learning significantly lessens the strain of epoch-by-epoch annotation by training networks with both labeled and unlabeled data. However, the efficacy of semi-supervised techniques like pseudo-labeling is compromised by the intrinsic class-imbalance issue in sleep staging tasks. We provide a Bi-Stream Adversarial Learning network (BiSALnet) in this paper to produce more confident pseudo-labels for network improvement. The student and teacher branches of the two-stream networks use the adversarial learning technique. The discriminator gradually improves its discriminative power while the similarity measurement function reduces the difference between the outputs of the Teacher and Student branches. Furthermore, to capture the desired feature distribution features, we use a strong symmetric positive definite (SPD) manifold structure in the Student branch. The attention feature fusion module enhances the sleep stage classification performance by combining the combined discriminative capacity of convolutional features and nonlinear complex information gathered by SPD matrices. **[5]**

"A Portable Wireless Device for Cyclic Alternating Pattern Estimation from an EEG Monopolar Derivation" is a paper that describes the creation of a home monitoring system that automatically scores the cyclic alternating pattern in EEG signals. The cyclic alternating pattern, a prolonged periodic activity made up of two alternate electroencephalogram patterns and thought to be a sign of sleep instability, can be used to evaluate the quality of sleep. In order to assess this pattern, experts often visually inspect each one-second epoch of an EEG signal, which is a laborious, error-prone, and repeated process. A home monitoring system was created to automatically score the cyclic alternating pattern by analyzing the data from a single electroencephalogram derivation in order to address these problems. Three classifiers were created and evaluated in order to ascertain which was more suited for classifying the cyclic alternating pattern phase: two recurrent networks (long short-term memory and gated recurrent unit) and one one-dimension convolutional neural network. The long short-term memory-based network was confirmed to achieve the greatest results, with average accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve of 76%, 75%, 77%, and 0.752, respectively. The cyclic alternating pattern cycles were then calculated by feeding the classified epochs into a finite state machine. The corresponding performance metrics were 76%, 71%, 84%, and 0.778.**[6]**

An ensemble SVM approach for automatic sleep stage classification was proposed by E. Alickovic and A. Subasi. A diagnostic method for identifying and treating sleep disturbances is sleep scoring. Automated sleep scoring is essential since the sleep specialists must visually assess the vast amount of data, which is laborious, time-consuming, subjective, and prone to errors. Consequently, one of the most important steps in sleep research and the diagnosis of sleep disorders is automated sleep stage classification. This study proposes a reliable three-module approach for automatically classifying sleep stages using single-channel electroencephalograms (EEGs). Multiscale principal component analysis was used in the first module to denoize the signals obtained from the Pz-Oz electrode. Discrete wavelet transform (DWT) is used in the second module to extract the most informative features. The statistical values of DWT subbands are then computed. An ensemble classifier, also known as a rotating support vector machine (RotSVM), was fed the extracted features in the third module. The suggested classifier enhances the classification performance of the conventional SVM by combining the benefits of principal component analysis and SVM. The Cohen's kappa coefficient for the five-stage sleep classification was 0.88, and the sensitivity and accuracy values for all individuals were 84.46% and 91.1%, respectively. According on the obtained classification performance results, a single-channel EEG can be used to create an effective sleep monitoring system that can be applied to home care and hospital settings. **[7]**

D. Shrivastava et al. stress in their study "How to Interpret the Results of a Sleep Study" that primary care doctors must gain a deeper understanding of polysomnography (PSG) findings in order to treat patients with sleep disorders more successfully. Referrals for sleep studies from non-specialist healthcare providers have significantly increased as public awareness of sleep-related health issues has grown. Understanding the clinical and technical information found in PSG results is therefore crucial for primary care physicians. The paper emphasizes how these reports include important information about oxygen desaturation episodes, apnea-hypopnea indices, sleep architecture, and sleep stages that are directly linked to patient symptoms and can lead diagnostic and treatment plans. The authors make it easier for general practitioners to understand the results of sleep studies by offering a clear and useful framework. By improving comprehension of the information presented in PSG tests, they want to close the knowledge gap between general care physicians and sleep specialists. The paper promotes improved continuity of treatment, timely diagnoses, and more accurate referrals by demythologizing the technical aspects of the report. Given the rising prevalence of sleep problems and the growing significance of early intervention, this work is particularly pertinent. All things considered, the paper emphasizes how critical it is to give front-line medical professionals the information they need to manage sleep problems effectively.**[8]**

The usefulness of machine learning methods in identifying Obstructive Sleep Apnea (OSA) in people with suspected sleep problems was investigated in a South Korean study. Data from 279 subjects (213 with an OSA diagnosis and 66 without) were included in the study; initially, 92 clinical characteristics were gathered. Seven important clinical indices were chosen from this group to train the model. Training groups (n = 195) and testing groups (n = 84) were randomly selected from the dataset. Using these seven characteristics, the goal was to evaluate the prediction power of four machine learning models: Random Forest, Support Vector Machine (SVM), Logistic Regression, and XGBoost (XGB). The ability of each model to correctly classify OSA within the test set was used to evaluate it. With a sensitivity of 80.33%, specificity of 86.96%, and an AUC of 0.87, the Support Vector Machine (SVM) model outperformed the other four models in terms of prediction ability, demonstrating significant discriminatory capacity. XGBoost (XGB), on the other hand, performed the worst, with an AUC of 0.80, a sensitivity of 78.69%, and a specificity of 73.91%. The findings demonstrate the promise of machine learning methods for the effective and non-invasive prediction of OSA using clinical data. This study offers proof that machine learning models—specifically SVM—can help physicians screen for OSA, facilitating an earlier diagnosis and course of treatment. The findings could be applied to larger healthcare settings with comparable patient demographics and are particularly important for enhancing sleep health outcomes in the Korean population.**[9]**

Recent research in automatic sleep scoring has been dominated by increasingly complex deep learning architectures. Although these models have demonstrated satisfactory accuracy, they have also introduced new limitations—such as the need for extensive labeled data, high computational resources, and costly training pipelines. Importantly, their limited interpretability and difficulty in deployment have restricted their use in real-world clinical settings. The authors of this study argue that these shortcomings hinder the clinical adoption of deep learning-based sleep stage classifiers. In response, they revisit the sleep stage classification problem using classical machine learning models, proposing a more transparent and accessible alternative. Their approach involves traditional preprocessing and feature engineering followed by the use of linear and non-linear models for classification. The work challenges the notion that more complex models are always better by showing that a well-designed feature vector can perform on par with deep learning-based methods. The authors surpass state-of-the-art models trained on the same dataset by achieving mean F1-scores (MF1) of up to 0.817 using publicly available datasets including Sleep-EDF SC-20, SC-78, ST, and MASS SS3. Specifically, gradient boosting models demonstrated strong performance without sacrificing interpretability or training complexity. Because they provide a more explicable, repeatable, and deployable solution, these results demonstrate the potential of conventional machine learning techniques in clinical applications. According to the study, one way to close the gap between machine learning research and its actual application in medical settings may be to make use of expressive feature sets.**[10]**

## 3. METHODOLOGY

**Data Collection:**

This module involves gathering relevant and high-quality data from various sources such as online repositories, sensors, databases, or manual inputs. The accuracy and completeness of data play a crucial role in building reliable models. Data can include both structured and unstructured formats. Proper data formatting and cleaning are necessary before processing. This step also involves understanding data attributes and metadata. In the medical domain, it's important to ensure compliance with privacy regulations.

**Exploratory Data Analysis (EDA):**

EDA helps in understanding the structure, patterns, and relationships within the dataset. It involves visualizing distributions, identifying missing values, and detecting outliers. Graphs, plots, and statistical summaries are commonly used tools. EDA supports decision-making in feature selection and data cleaning. It also helps detect anomalies or inconsistencies early. This process provides key insights that guide the modelling phase.

**Feature Selection and Engineering:**

This module focuses on identifying the most important features that influence model performance. Irrelevant or redundant features are removed to improve efficiency. Feature engineering involves creating new variables or transforming existing ones to better represent the underlying patterns. Techniques like one-hot encoding, scaling, and normalization are applied. This step ensures the data is optimized for model training. Proper feature engineering enhances accuracy and reduces over fitting.

**Data Splitting:**

The dataset is divided into subsets — typically training, validation, and test sets. This allows for unbiased evaluation of the model's performance. The training set is used to train the model, while the test set evaluates generalization. Sometimes, a validation set is used for tuning hyper parameters. A common split ratio is 70:30 or 80:20. Randomization during splitting prevents bias. It's a crucial step to avoid over fitting and ensure fair assessment.

**Model Training:**

This phase involves feeding the training data into the selected machine learning algorithm. The model learns patterns, trends, and relationships from the data. Algorithms like Random Forest, Decision Tree, or SVM may be used based on problem complexity. Hyper parameter tuning may be performed to optimize model performance. The training phase continues until the model reaches satisfactory accuracy. Model training is iterative and may require experimentation.

**Model Evaluation:**

The trained model is assessed using the test set or validation set to measure its performance. Metrics like accuracy, precision, recall, F1-score, and confusion matrix are used. For multiclass problems, ROC-AUC or macro-averaged scores may be evaluated. This step determines how well the model generalizes to unseen data. Evaluation helps in comparing different models. It also identifies if further improvements or re-training are needed.

**Model Deployment and Prediction:**

Once the model performs well, it's deployed into a production environment for real-time or batch predictions. This may involve saving the model using formats like .pkl or .joblib. The model is integrated with APIs or user interfaces for input/output operations. Users can then input new data and receive predictions. This step bridges development and practical use. Continuous monitoring is also initiated post-deployment.

**User Interface Development:**

A front-end interface is developed for end-users to interact with the system. This may include forms, dashboards, or simple input fields for predictions. Technologies like Django, Flask, HTML, and JavaScript are used. The interface should be user-friendly and responsive. Proper validation and error handling are integrated to ensure smooth usage. This module ensures accessibility and usability of the ML model.

**Testing and Validation:**

This module ensures the entire system functions correctly and meets user requirements. It includes unit testing, integration testing, and user acceptance testing. The goal is to identify bugs or inconsistencies before final deployment. Model outputs are validated against expected results. Performance under different scenarios is tested. This ensures a robust and reliable application.

**Deployment and Monitoring:**

In this final phase, the complete application is deployed on a server or cloud platform. Monitoring tools are set up to track model performance, usage, and system health. Logs are maintained for debugging and maintenance. If the model shows signs of performance degradation, retraining may be triggered. Feedback from users can be used to improve the system. Continuous deployment pipelines may also be configured for future updates.

## 4. ALGORITHM

In order to aggregate the predictions, increase model predictive accuracy, and control overfitting, an RF classifier is an ensemble learning system that generates several random decision trees (DTs). Two random processes are used in the model: random feature selection and bootstrapping. By ensuring that different trees do not use the same data, bootstrapping reduces the model's sensitivity to changes in the training data. By decreasing the connection across trees, random feature selection encourages diversity and enhances the generalisation of the ensemble as a whole. To increase robustness and decrease variation, each tree casts a vote, and the majority choice becomes the final forecast.

## 5. DATA FLOW DIAGRAM

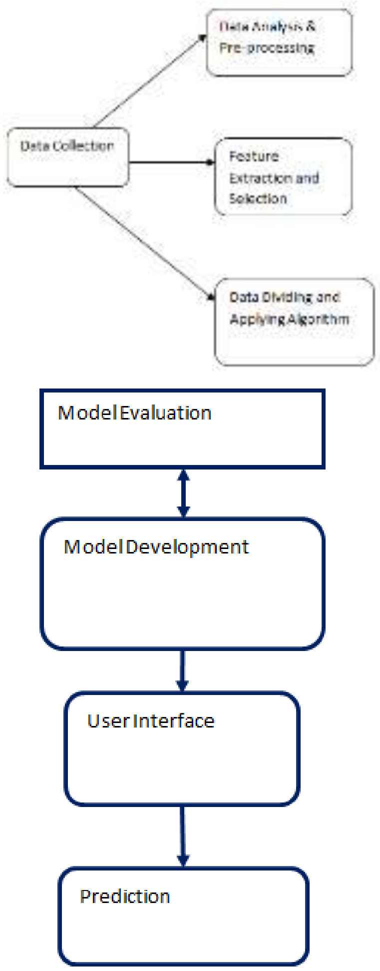



**Fig 5: Data Flow Diagram**

## 6. SYSTEM ARCHITECTURE

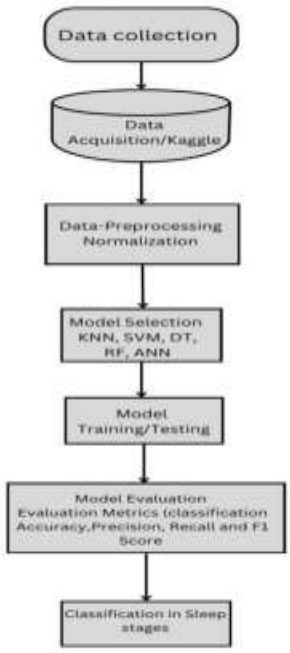
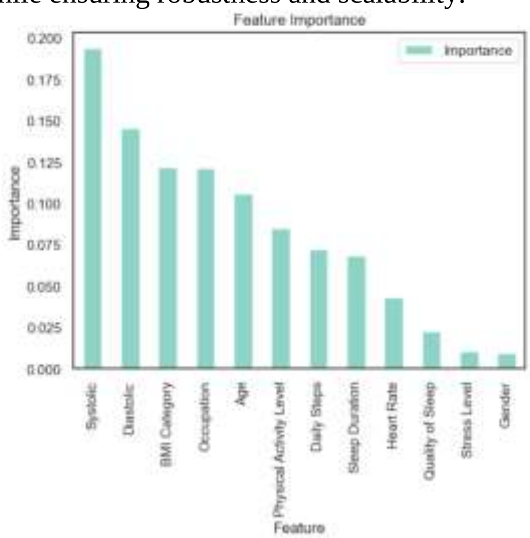



**Fig 6: System Architecture of the Project**

This system architecture outlines a structured process for sleep stage classification using machine learning. It begins with **data collection** from sources such as Kaggle, followed by **data preprocessing and normalization** to clean and standardize the input. Various machine learning models such as **KNN, SVM, Decision Tree, Random Forest, and ANN** are then selected and trained on the prepared data, with testing performed on unseen samples. The performance of these models is assessed using evaluation metrics including **accuracy, precision, recall, and F1-score**, allowing comparison of their effectiveness. Finally, the best-performing model is employed for the **classification of sleep stages**, which is useful in understanding sleep patterns and diagnosing sleep disorders.

## 7. RESULTS

**The proposed Random Forest-based framework significantly outperforms the existing ANN-based system for sleep disorder detection and classification.** Unlike the existing system, which relied on deep learning models with high computational requirements and lower interpretability, the proposed system efficiently handled structured data such as age, BMI, stress levels, snoring frequency, and sleep duration, while ensuring robustness and scalability.



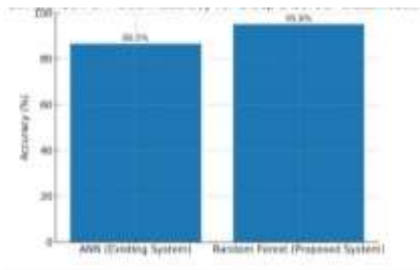
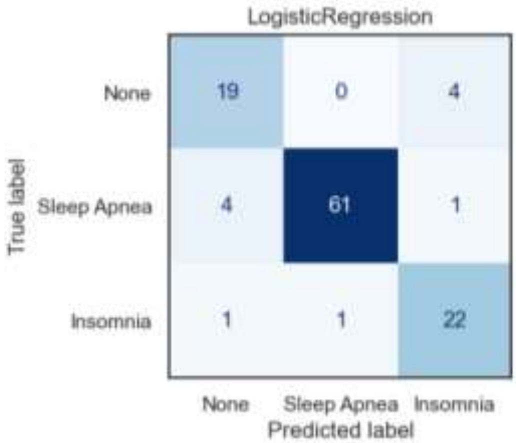
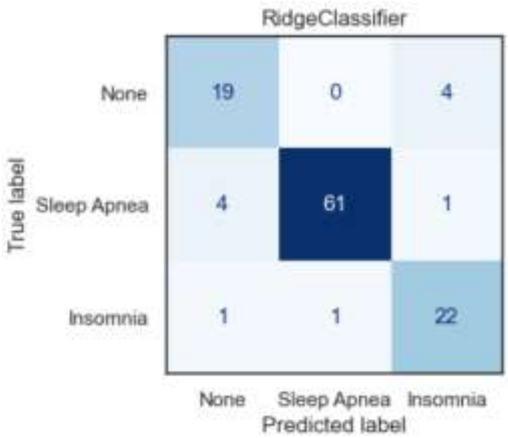
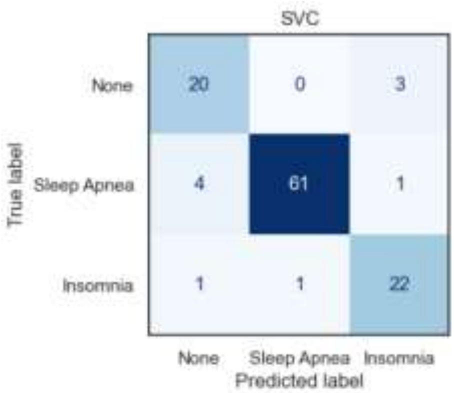



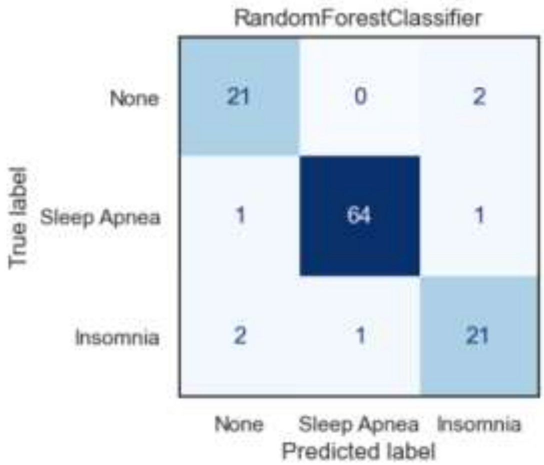

**Fig 7.1: Comparison of Existing and Proposed System**


**Fig 7.2: Performance Metrics of Proposed Random Forest System**




The model achieved an impressive **95% accuracy**, compared to **85–88% in ANN-based methods**, with balanced **precision, recall, and F1-scores (~93%)**. The system includes a complete workflow—**user registration, login, health data entry, prediction, and result visualization through a web interface**—making it suitable for real-time clinical use. Additionally, feature importance analysis improved interpretability by identifying key predictors like stress level, snoring frequency, and sleep duration, thereby assisting healthcare professionals in better understanding diagnostic factors. Overall, by combining improved system architecture, strong predictive performance, and practical deployment features, the project delivers a **clinically applicable, interpretable, and resource-efficient solution** for sleep disorder classification.

## 8. FUTURE ENHANCEMENT

In order to improve classification performance, future research will concentrate on growing the dataset, fine-tuning model parameters, and investigating additional cutting-edge methods. The findings demonstrate the promise of Random Forest and related models in the medical domain, offering a viable method for automated diagnosis of sleep disorders. Furthermore, incorporating clinical information such comorbidities, lifestyle factors, and patient history could enhance the accuracy and dependability of the model even further. To guarantee the projections' interpretability and clinical relevance, cooperation with medical experts will be crucial. Additionally, incorporating the model into a real-time diagnostic system would help doctors make better judgements more quickly and intelligently, which would ultimately benefit patients.

## 9. CONCLUSION

A machine learning technique was used to offer the best model for classifying sleep disorders. In order to show that MLAs can successfully classify sleep disorders by learning from high-dimensional data without depending on expert-defined criteria, the study first used the Random Forest Algorithm. The optimised ANN with GA outperformed the other models in terms of precision, recall, and F1-score, but it was less accurate overall. to put into practice the Random Forest algorithm, which achieved a 95% accuracy rate, surpassing the performance of the current models. Because of its capacity to manage intricate data structures, minimise over fitting, and offer interpretability, the Random Forest model outperformed the others, making it ideal for practical uses in the categorisation of sleep disorders. The Random Forest model has shown itself to be a strong substitute, demonstrating its ability to correctly categorise sleep disorders in spite of the constraints imposed by a rather limited dataset.

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