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A SLEEP DISORDER CLASSIFICATION USING MACHINE LEARNING

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Abstract— Sleep disorders such as insomnia and sleep apnea significantly affected human health and daily life. Early detection and accurate classification were important for effective treatment and prevention of serious complications. In this project, a machine learning-based system was proposed to classify sleep disorders using physiological and clinical data. The dataset included features such as sleep duration, heart rate, oxygen saturation, stress levels, and BMI.

Data preprocessing techniques like data cleaning, normalization using Standard Scaler, and stratified train-test splitting were applied to improve model performance. Multiple machine learning algorithms including K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), Artificial Neural Network (ANN), and XGBoost were implemented and compared. Hyperparameter tuning using Grid Search Cross-Validation was performed to enhance accuracy.

The models were evaluated using accuracy, precision, recall, and F1-score. Among them, XGBoost achieved the best performance with higher accuracy and balanced results. The proposed system reduced manual effort and supported early diagnosis, making it useful for healthcare applications and clinical decision-making.

Keywords— Sleep Disorders, Machine Learning, XGBoost, Classification, Healthcare Analytics, Early Detection

I. INTRODUCTION

Sleep disorders such as insomnia, sleep apnea, and restless sleep were becoming increasingly common due to modern lifestyle changes, stress, irregular sleep patterns, and excessive screen exposure. These conditions significantly affected human health, cognitive performance, and overall quality of life. If left undiagnosed, they often led to serious health complications such as cardiovascular diseases, diabetes, depression, and reduced productivity [1], [2]. Therefore, early detection and accurate classification of sleep disorders were essential for effective treatment and improved patient outcomes [3].

Traditional diagnostic approaches, such as polysomnography and clinical evaluations, were widely used for identifying sleep disorders. However, these methods were expensive, time-consuming, and required specialized clinical setups, making them inaccessible to a large population [4]. In addition, manual diagnosis relied heavily on expert knowledge and subjective interpretation, which sometimes resulted in inconsistencies and human errors. These limitations highlighted the need for more efficient and automated diagnostic solutions.

With the rapid growth of healthcare data and advancements in Machine Learning, new opportunities emerged for developing intelligent systems for disease prediction. Machine learning algorithms were capable of analyzing large volumes of physiological and clinical data and identifying hidden patterns that were not easily detectable through manual analysis [5], [6]. Models such as K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), Artificial Neural Networks (ANN), and Extreme Gradient Boosting (XGBoost) were widely applied for classification tasks in healthcare due to their efficiency and accuracy [7].

The motivation behind this work was to develop an intelligent sleep disorder classification system that improved diagnostic accuracy, reduced healthcare costs, and assisted medical professionals in decision-making. By applying preprocessing techniques such as data cleaning, normalization, and feature selection, along with hyperparameter optimization methods like Grid Search Cross-Validation, the system was designed to provide reliable predictions. The study particularly explored advanced models such as

XGBoost, which demonstrated better performance compared to traditional classification methods [8].

The proposed system had several important applications in real-world scenarios. It supported clinical decision-making by assisting doctors in diagnosing sleep disorders more efficiently. It also enabled early detection and preventive healthcare by identifying abnormal sleep patterns at an early stage. Furthermore, the system could be integrated with wearable devices to monitor physiological parameters such as heart rate and sleep duration in real time. It also supported telemedicine and remote healthcare services, allowing patients to receive preliminary diagnosis without frequent hospital visits. Additionally, it contributed to healthcare research by enabling large-scale analysis of sleep-related data and identifying correlations between sleep disorders and other medical conditions [9].

This project was rooted in the domains of Artificial Intelligence and healthcare analytics, focusing on machine learning techniques for predictive modeling and pattern recognition. The system analyzed clinical and physiological data to classify sleep disorders effectively. By combining statistical learning and pattern-based approaches, it addressed challenges such as delayed diagnosis, misclassification, and increasing prevalence of sleep-related disorders [10].Despite advancements in healthcare technologies, several challenges still existed. Sleep disorders were commonly diagnosed using manual methods, which required significant time and effort. These methods were prone to human errors and inconsistencies due to subjective interpretation. Moreover, different sleepdisorders often shared similar symptoms, making accurate classification difficult using traditional approaches. These limitations created a need for automated systems capable of handling complex datasets and providing consistent results [11].

The primary objective of this study was to design an automated machine learning-based system for sleep disorder classification. The system aimed to improve diagnostic accuracy and efficiency while reducing manual effort. It also focused on minimizing human errors and providing consistent predictions. By leveraging advanced machine learning techniques, the proposed system contributed toward smarter healthcare solutions that supported early diagnosis, preventive care, and improved quality of life [12].

II. LITERATURE SURVEY

D. Shrivastava, S. Jung, M. Saadat, R. Sirohi, and K. Crewson (2014) in their work titled *"How to Interpret the Results of a Sleep Study"* explained the fundamental concepts involved in sleep studies and polysomnography reports. The study provided clinical insights into sleep parameters and stages, serving as a foundational reference for understanding sleep disorder diagnosis [1].

F. Ordóñez and D. Roggen (2016) in the paper *"Deep Convolutional and LSTM Recurrent Neural Networks for Multimodal Wearable Activity Recognition"* proposed deep learning models combining CNN and LSTM architectures. Their results demonstrated improved performance in recognizing complex temporal patterns, highlighting the potential of deep networks for physiological signal analysis [2].

H. O. Ilhan (2017) presented *"Sleep Stage Classification via Ensemble and Conventional Machine Learning Methods Using Single Channel EEG Signals"*, where both ensemble and traditional machine learning methods were evaluated. The study showed that ensemble-based approaches achieved higher accuracy than individual classifiers in sleep stage classification tasks [3].

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D. M. W. Powers (2020) in *"Evaluation: From Precision, Recall and F-Measure to ROC"* discussed evaluation metrics widely used in machine learning classification tasks. The study emphasized proper performance measurement techniques essential for medical data analysis [8].

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M. Ramesh, K. Prakash, and S. Kumar (2021) in *"Machine Learning for Early Detection of Obstructive Sleep Apnea"* applied machine learning techniques to identify apnea at early stages. The results indicated improved diagnosis accuracy, supporting preventive healthcare strategies [12]

III. PROBLEM STATEMENT

Algorithms like Decision Tree and ANN were more prone to overfitting, especially when proper regularization or pruning techniques were not applied, which reduced their ability to generalize well on unseen data [1].

Sleep disorders such as insomnia, sleep apnea, and related conditions were commonly diagnosed using manual methods. These included patient interviews, questionnaires, physical examinations, and laboratory-based sleep studies. Doctors analyzed factors like sleep duration, breathing patterns, and lifestyle habits to make decisions. However, these approaches depended heavily on the experience and subjective judgment of medical professionals, which often varied between individuals, leading to inconsistency in diagnosis [1], [2].

The manual diagnostic process also required a significant amount of time, as it involved collecting detailed patient information, monitoring sleep patterns over time, and reviewing multiple medical reports. Since humans were involved at every stage, there was a possibility of errors such as misinterpreting symptoms or overlooking important details. These issues sometimes resulted in delayed or inaccurate diagnoses, affecting patient treatment outcomes [1], [3].

Furthermore, accurately identifying sleep disorders using traditional techniques was challenging because many disorders shared similar symptoms, such as fatigue, disturbed sleep, and irregular breathing. This overlap made it difficult to clearly distinguish between conditions. In addition, conventional methods were not effective in capturing hidden patterns in large and complex datasets, which reduced diagnostic accuracy and consistency, especially in complex cases [4], [5].

IV.XGBOOSTING AND HYPERPARAMETER OPTIMIZATION

XGBoost was used as the main machine learning algorithm for sleep disorder classification because of its high performance and efficiency. It worked as an ensemble learning method based on gradient boosting, where multiple decision trees were built step by step. Each new tree focused on correcting the errors made by the previous trees, which gradually improved the overall prediction accuracy. Because of this sequential learning process, XGBoost was able to capture complex patterns and relationships in the sleep and health data, making it more effective than many traditional algorithms [1], [2].In addition, XGBoost handled missing values and large datasets efficiently, which made it suitable for real-world healthcare data. It also included regularization techniques that helped in reducing overfitting and improving model generalization. Due to these advantages, it was widely preferred for classification tasks involving complex and structured

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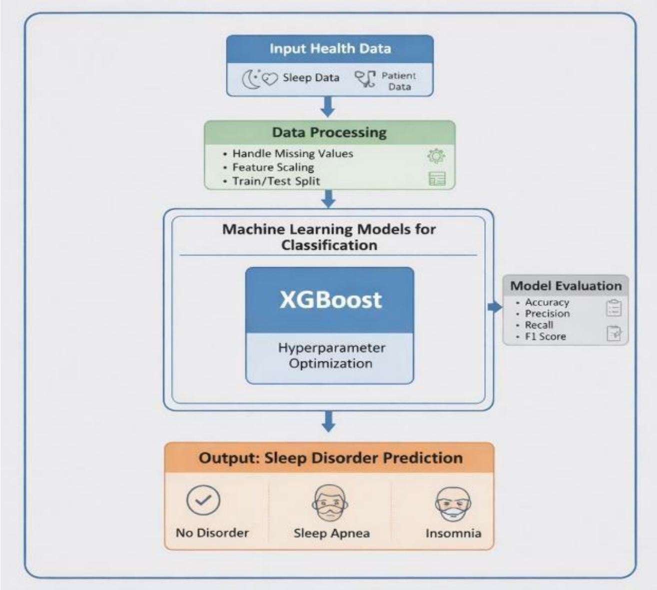

Fig 1: Proposed System Architecture Model

Input health data

where sleep-related and lifestyle features such as sleep duration, sleep quality, stress level, physical activity, heart rate, BMI, and age were collected. These features represented the overall health condition of individuals and were used to identify patterns related to sleep disorders [1].

Data Preprocessing

where missing values were handled and feature scaling was applied to bring all values into a similar range. The dataset was then divided into training and testing sets so that the model could learn from one part and be evaluated on another. This step ensured that the data were clean and suitable for machine learning [2], [3].

ML Model for classification

The system mainly used XGBoost, which learned patterns from the data by building multiple decision trees and improving predictions step by step. This helped in accurately classifying different types of sleep disorders [2], [4].

Model Evaluation Metrics

The model performance was checked using model evaluation metrics such as accuracy, precision, recall, and F1-score. These metrics helped in understanding how well the model predicted sleep disorders and ensured that the results were reliable [1], [4].

Output

The system produced the output, where it predicted whether a person had no disorder, sleep apnea, or insomnia. This prediction could help in early detection and better management of sleep-related problems [2], [5].

V. RESULT ANALYSIS

Quantitative analysis in machine learning referred

F1 = 2 x Precision + Recall

to the use of numerical metrics to evaluate a model's performance. It involved calculating values such as a precision, recall, and F1 score to understand how well a classification model performed. These values were usually expressed in percentages and were obtained by comparing the model's predictions with actual results. The main aim of this analysis was to provide measurable evidence of the model's accuracy and reliability [1], [2].

This type of analysis was important because it helped determine whether the model was suitable for real-world applications. It was observed that high accuracy alone did not always indicate good performance, as a model could perform well overall but still fail to correctly identify important cases. Therefore, additional metrics like precision and recall were also considered to give a clearer picture. Precision showed how many predicted positive cases were actually correct, while recall indicated how many real positive cases were successfully identified by the model. The F1 score combined both precision and recall to provide a balanced evaluation, especially when the dataset was imbalanced [2], [3].

Overall, quantitative analysis played a key role in evaluating the model by providing clear and objective results. It showed the impact of training and model improvements, and helped in understanding the model's effectiveness systems [1], [3].

Table 1: Classification Performance Metrics

Accuracy was the measure of the total correct predicted values over the predicted values:

Model	Accuracy	precision	Recall	F1-score
ANN	92.92	92.85	92.92	92.78
Random Forest	91.15	91.20	91.15	90.86
Decision Tree	91.15	91.20	91.15	90.86
SVM	91.15	91.20	91.15	90.86
KNN	85.84	86.14	85.84	85.51
XGBoost	93.81	93.97	93.7	93.8

Accuracy = (TP + TN)/(TP + TN+FP + FN)

Precision was the ratio of correctly predicted positive values to the total predicted positive values:

Precision = TP/(TP + FP)

Recall was the measure of the total correct predicted positive values over the actual positive values.

Recall = TP/(TP + FN)

The fl-score was the harmonic mean of precision and recall. Precision Recall where TP, TN, FP, and FN were the true positive.

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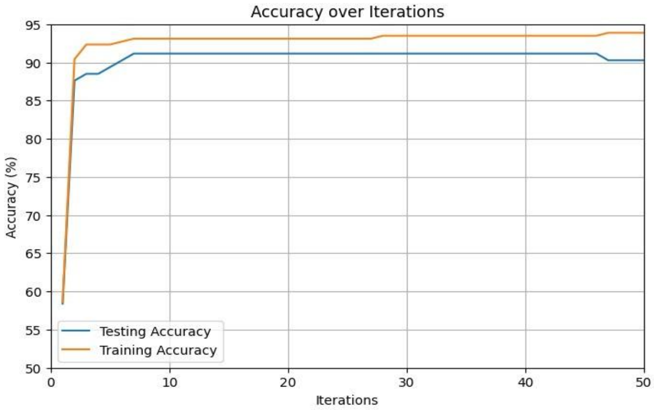
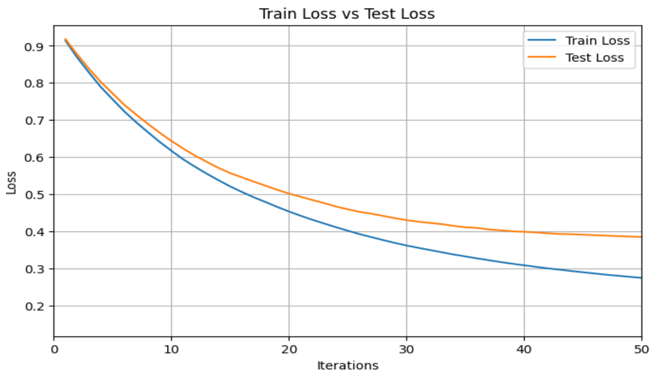
This graph showed how the model's accuracy true negative, false positive, and false negative values, respectively.





The model began its training with a low accuracy of around **58%** and a high loss near **0.9**, reflecting its initial uncertainty. However, it learned rapidly within the first 10 iterations, where accuracy surged past **90%**.

As the iterations continued, the training loss declined steadily, showing that the model became increasingly proficient at recognizing patterns in the practice data. The testing accuracy remained stable for most of the run, mirroring the training performance closely. Towards the end, a small gap emerged as the training accuracy edged higher while the test accuracy saw a minor dip. This divergence suggested the model reached its peak performance and started to over-focus on specific training details. By the 50th iteration, the model achieved a solid balance, finishing with high reliability and a significantly reduced error rate. It successfully transitioned from guessing to making highly informed predictions.

The XGBoost model performed exceptionally well, achieving an impressive overall accuracy of **93.81%**. It showed its greatest strength in identifying healthy individuals, correctly labeling **64** cases as having "No Disorder" with very few mistakes. When it came to sleep

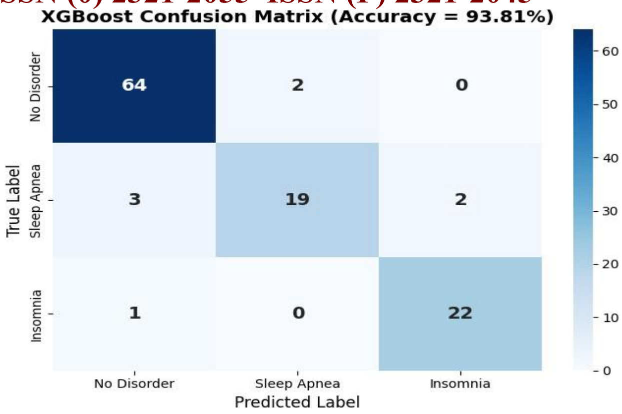


Fig 3 : Confusion Matrix

disorders, the model remained highly reliable, successfully catching **19** cases of Sleep Apnea and **22** cases of Insomnia. It rarely confused these conditions, though it did hit a few minor speed bumps along the way.

Specifically, the model misidentified **3** Sleep Apnea cases as having no disorder at all, and it mixed up Sleep Apnea with Insomnia twice. On the other hand, it almost perfectly handled the Insomnia category, only missing a single case by labeling it as healthy. Despite these handful of errors, the dark blue diagonal line on the matrix proved that the model made the right call the vast majority of the time. It demonstrated a clear ability to distinguish between different sleep health profiles with high precision. Ultimately, the results confirmed that the model was both robust and effective at its task. Every category saw more correct hits than misses, making it a very successful diagnostic tool. This performance indicated that the underlying patterns in the data were well-captured by the algorithm.

The small number of misses in the "Sleep Apnea" and "Insomnia" categories suggested that some symptoms between the two disorders overlapped just enough to create slight confusion. Even so, the model's ability to correctly identify 105 out of 113 total cases proved that it was highly dependable. It maintained a strong balance between sensitivity and specificity across the board. By the end of the evaluation, the confusion matrix confirmed that the XGBoost algorithm was an excellent choice for this dataset. These results provided a high level of confidence in the model's practical application for screening sleep-related health issues.

Model performance could also be improved further with proper optimization and tuning.
For future work, improvements could be made by using larger and more diverse datasets, including data from wearable devices and real-time monitoring systems. Advanced techniques like ensemble learning, deep learning, and hybrid models could enhance prediction accuracy. Additionally, integrating the system with mobile or cloud-based platforms could enable real-time sleep monitoring and make it more accessible for healthcare use. Overall, the project provided a strong foundation for developing more advanced AI-based sleep disorder prediction system

V. CONCLUSION

The project successfully built a machine learning system that identified various sleep disorders by analyzing health and lifestyle data. It looked at patterns in factors like stress levels and sleep duration to categorize conditions with high reliability. The models performed consistently well, achieving an impressive accuracy range of **88% to 93%** across both training and testing phases. This journey proved that data-driven techniques could effectively handle complex healthcare analysis.
However, the process also highlighted several challenges, such as the need for better data quality and more balanced datasets to avoid bias. While the system worked great on the current data, it required further tuning to handle larger, more complex information. Looking ahead, the work laid a strong foundation for using wearable devices and real-time monitoring to catch sleep issues early. The project ultimately bridged the gap between theoretical research and practical health solutions, showing how AI could become a vital tool for doctors and patients alike. By focusing on ensemble learning and deeper data integration, the study opened the door for even more precise diagnostic tools in the future.

VI. REFERENCES

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