iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: V Month of publication: May 2025

DOI: https://doi.org/10.22214/ijraset.2025.70996

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue V May 2025- Available at www.ijraset.com

Sleep Disorder Classification and Cause Analysis using Deep Learning

Mr. Raveendra Naick Bhogya[1], Navitha Arigela[2], Geethika Desineni[3], Madhu Sudhan Reddy Sangana[4], Mohan Krishna Girinadula[5]
Department of Computer Science and Engineering(AI/ML), Sree Vidyanikethan Engineering College, Tirupati, A.P

Abstract: Sleep disorders common in aging populations impact not only physical but also mental health. Early identification and knowledge about the root factors play an important role in enhancing quality of life as well as avoiding lasting health complications. In this study introduces a hybrid deep learning approach to not just classify sleep disorders like insomnia and sleep apnea but also determine the responsible factors. A hybrid Convolutional Neural Network (CNN) with Gated Recurrent Units (GRU) model with an attention mechanism is used to extract spatial as well as temporal features from structured health records. SMOTE (Synthetic Minority Over-sampling Technique) is applied in the model to treat class imbalance, allowing for better classification. LIME (Local Interpretable Model-Agnostic Explanations) is also applied to offer insights into the most influencing factors behind the predicted sleep disorder for every sample, allowing for individualized suggestions. Upon prolonged training and through these methodologies combined, the model scores over 90% accuracy, providing an efficient tool to diagnose sleep disorders with high accuracy. This also opens doors to discover the interrelationship among different physiologic and lifestyle factors, thus leading to tailored treatment plans for individuals facing sleep disorders.
Keywords: Sleep Disorders, Hybrid model, CNN-GRU, Attention Mechanism, LIME, SMOTE, Deep Learning, Sleep Apnea, Insomnia, Factor Analysis, EarlyStopping, Hyperparameter Tuning.

I. INTRODUCTION

Sleep is an essential bodily function to restore physical and mental health. Sleep is important to repair, memory consolidation, and brain processing. Not surprisingly, though, quantity and quality of sleep tend to be compromised by an array of sleep disorders, one of this world's major health challenges. Insomnia, sleep apnea, restless leg syndrome, and drowsiness throughout the day comprise a broad group of illnesses known as sleep disorders, all of which have serious consequences on an individual's quality of life. These afflictions not only abound in developed countries but also increasingly pervade populations in developing countries, including India. As an example, research has found that 61% of Indians get less than six hours in bed per day, reflective of the common rate of sleeping disorders and sleep deficiency. Prevalence is high, as research has indicated that nearly 30% of all U.S. adults report insomnia, and 26% have sleep apnea. In India too, 25.7% of people have insomnia, while 37.4% have obstructive sleep apnea (OSA). These are more prevalent in urban populations as well as people with chronic disorders like diabetes and cardiovascular disease. The effects of sleep disorders do not stop with tiredness but are linked with severe health ailments like cardiovascular disease, obesity, diabetes, impairment of cognitive ability, and conditions of the mental state like depression and anxiety. The prevalence of this condition at the global level is evident by the fact that countries like the USA, the UK and Northern Ireland, Germany, and Japan have seen high rates of prevalence of sleep disorders, thereby necessitating effective diagnosis and treatment guidelines. Diagnosis and sleep disorder classification have historically involved visual examination of polysomnography (PSG) recordings, which is laborious and prone to human interpretation error. Quality of sleep is heavily associated with the body's natural process through the various stages of physiology, distributed between rapid eye movement (REM) and non-rapid eye movement (NREM) sleep. NREM is in three phases: N1 (Light Sleep) Transitional stage from wakefulness, during which theta waves emerge in EEG traces.N2 (Intermediate Sleep) Sleep spindles and K complexes in EEG, is essential for memory consolidation. N3 (Deep Sleep) Delta waves, which are essential for body restoration. REM Sleep is marked reduced muscle tone, and sawtooth waves in EEG. This stage is closely linked to dreaming and cognitive processing. Disturbances in these stages of sleep—such as decreased deep sleep (N3) or fragmented REM sleep—are linked to disorders such as insomnia, sleep apnea, and narcolepsy. Polysomnography (PSG) is gold standard of sleep, combining several physiological signals (EEG, ECG, EOG, EMG, respiratory effort) to study sleep patterns and identify abnormalities. For instance, EEG (Electroencephalogram) Monitors brain wave activity, showing neural oscillations that underlie various stages of sleep.

ECG (Electrocardiogram) Records HRV (heart rate variability), offering information on autonomic nervous system changes during sleep transition and disease, i.e., apnea-related HRV abnormalities.

A number of physiological and life-style variables come into the incidence and severity of sleep disorders. Age, for example, affects sleep significantly, with older people having shorter sleep duration and more nocturnal awakening. Gender also comes into play, with women being susceptible to insomnia and men being susceptible to sleep apnea. Occupational stress, non-day work shifts, and physical inactivity also interfere with the quality of sleep, as do other factors like BMI(Body mass index), heart rate, and amount of physical exercise. For instance, increased BMI and obesity are strong predictors of sleep apnea, whereas a consistent regimen of physical exercise enhances the quality of sleep.

Improvements in machine learning (ML) and deep learning (DL) algorithms can potentially address automated sleep-stage classification and enhanced diagnostic accuracy. Conventional ML algorithms, though effective with small datasets, involve extensive feature engineering, whereas DL algorithms can learn intricate patterns from high-dimensional datasets without any human intervention, hence very suitable for sleep disorder classification tasks. Noisy and biased datasets, lack of natural sleep-stage data, and the requirement of computational efficiency remain the significant challenges to the progress in this field.

This study aims to overcome these weaknesses by a detailed analysis of recent literature on sleep disorder classification and comparison of performance between traditional ML and DL methods in this application. By employing intricate computational algorithms, this research seeks to contribute meaningfully to more effective and precise diagnosis and treatment methods of sleeping disorders and eventually enhance the life quality of sleeping disorder patients. The subsequent parts of this paper provide the related work, methods, and results of this research, and demonstrate to what extent ML and DL can revolutionize sleeping disorder classification.

II. RELATED WORK

Sleep disorders like insomnia and sleep apnea are an international public health issue. Traditional diagnosis via polysomnography (PSG) is costly, inconvenient, and not available to most. Emerging methods for the detection and diagnosis of the disorders have arisen with recent developments in ML and DL. This review summarizes few recent studies that employ ML and DL techniques to diagnose insomnia, sleep apnea, or neither, explaining their methods, results, and limitations.

Anitha et al. gave a summary of ML-based sleep apnea monitoring systems such as sensor types, feature extraction, and classifiers. The study outlined wearable sensor integration with ML for real-time monitoring. The study did not involve discussion regarding dataset biases, validation metrics, and real-world issues such as sensor noise and user compliance[1].

Kusmakar et al. suggested a two-level model to detect chronic insomnia from actigraphy data. The study used standard ML models since the dataset was small and the model was unable to detect complex sleep patterns. The dataset was also not heterogeneous, and the model was not cross-validated with clinical PSG data, which raised questions about diagnostic accuracy[2].

Singh et al. made comparisons between DL and ML classifiers for predicting sleep apnea with HRV and ECG signals and concluded in favor of the former. They did not employ SpO2-type multi-modal data, small dataset sizes, and clinical annotation, which would be different from real-world implementations[3].

Bazoukis et al. assessed ML models for sleep apnea diagnosis prediction from ECG, pulse oximetry, and audio signals. Although the models were highly accurate, the research was conducted on low-quality retrospective data with low-quality labels. It also failed to consider DL model explainability and scalability issues in low-resource environments[4].

Abd-Alrazaq et al. meta-analyzed wearable AI for sleep apnea screening, its real-time utility for tracking. Yet, heterogeneity between studies, absence of long-term validation, and omission of comorbidities restricted its use for complicated cases[5].

Alshammari applied ML models to forecast sleep disorders from a lifestyle dataset. While highly accurate, the study did not examine causal causes (e.g., genetics, stress) and did not correlate findings with clinical diagnoses, and thus is not as useful for individual treatment[6].

C.-H. Su et al. research explores the connection between pre-sleep stress and slow-wave sleep (SWS) deficiency through electroencephalography (EEG). Stress influences sleep, but its direct effect on SWS is unknown. The research derives pre-sleep EEG-based stress-related neural characteristics like beta/delta correlation, alpha asymmetry, and entropy measures. The findings show that EEG activity related to stress is greater in SWS deficiency subjects, i.e., higher beta/delta correlation and FuzzEn values. Supervised learning algorithms, for example, RF(Random Forest) and SVM(Support Vector Machines), were employed to classify SWS deficiency with a balanced mean accuracy of over 0.75. The work hypothesizes that EEG stress biomarkers can be integrated into personalized sleep monitoring systems to initiate early intervention protocols for sleep disorders[7].

Tripathi et al. presents a new hybrid artificial intelligence (AI) approach tailored specifically for automatic diagnosis of insomnia based on analysis of electrocardiogram (ECG) signals. Traditional techniques for detection of insomnia are time-consuming, error-prone, and costly, and thus an automated technique is highly desirable. The approach of interest is designed for the extraction of HRV features from ECG signals and utilizes power spectral density (PSD) analysis for classification of sleep stages and insomnia states. Three classification scenarios have been compared in the research: 1. normal vs. Insomnia (subject-based), 2. REM vs. wake stage (sleep stage-based), and a 3. hybrid approach. The ensemble learning approach includes RF (Random Forest), DT (Decision Tree), and LDA (Linear Discriminant Analysis), with excellent accuracy rates of 96% for subject-based and sleep stage classification, and 99% for hybrid approach. This paper points to the possibility of mobile-based real-time monitoring systems for detection of insomnia, a great advancement in diagnosis of sleep disorders[8].

Beard showed "smart pajamas" that could track sleep with 98.6% accuracy. Testing was conducted in the lab only, however, and problems with fabric deformation, washing resistance, and cost restrict their utility. designations[9].

Despite advancements in ML and DL for sleep disorder classification, key gaps remain. Existing models (CNNs, LSTMs, SVMs, RF) achieve high accuracy but fail to identify underlying causes, limiting personalized treatment. Most studies rely on physiological signals (ECG, actigraphy) while neglecting environmental, psychological, and lifestyle factors. Short-term datasets hinder long-term trend analysis, and models lack generalizability across diverse populations. Additionally, hybrid approaches for improved feature extraction and sequential pattern recognition remain underexplored. Addressing these gaps through causal analysis, diverse datasets, and improved interpretability will enhance DL-driven sleep disorder diagnosis and intervention.

III. PROPOSED SYSTEM

This approach blends deep learning to classify sleep disorders and identify their root causes based on organized health and lifestyle data. The steps begin with data preprocessing and gathering, where missing values are handled, categorical features are encoded, and class imbalances are rectified using SMOTE[10]. High-quality input for model training is thereby guaranteed.

A CNN-GRU hybrid model with attention[11] is used for classification. CNN learns spatial features, and GRU learns sequential dependencies in sleep data. Attention mechanism improves learning by concentrating on important features that influence sleep disorders. The model is optimized and tested on basis of accuracy, precision, recall, specificity, and F1-score.

For enhancing interpretability, LIME[12] is employed to interpret the top three factors responsible for each classification of sleep disorders. In case no disorder is found, the system verifies a healthier condition. Otherwise, it identifies major risk factors like BMI, stress levels, or habits.

This method ensures equity, reproducibility, and applicability in everyday life, offering a transparent and clinically relevant solution. It facilitates early intervention, allowing individuals and clinicians to make decisions for better sleep health.

A. Dataset

The Sleep-Health and Lifestyle Dataset is feature-labeled and is engaged to explore the interrelationship of sleep disorders with other lifestyle factors. It contains 357 samples and 13 features, extracting demographic, health, lifestyle, and sleep disorder labels. It is employed to train ML models to recognize sleep disorders and to discover potential risk factors.

This information gives the general picture of the interaction between sleep health and lifestyle factors. Statistical and machine learning-based etiological and severity research for sleep disorders is feasible with this information. Trends can be identified by researching this information to enhance the initial diagnosis, optimize the intervention, and encourage healthier sleep hygiene practices.

TABLE I
SCHEMA AND DESCRIPTION OF THIS DATASET

Attribute	Type	Description
Person ID	Categorical	Unique Identifier
Gender	Categorical	Male or Female
Age	Numerical	Age of the person
Occupation	Categorical	Job type
Sleep Duration	Numerical	Sleep per night in hours
Quality of Sleep	Numerical	Subjective rating (1-10)

Physical Activity	Categorical	Activity frequency
Stress Level	Categorical	Self-reported stress level (1-10)
BMI Category	Numerical	BMI classification (Underweight, Normal, Overweight, Obese)
Blood Pressure	Categorical	Originally recorded as "Systolic/Diastolic", later split into separate columns
Heart Rate	Numerical	Beats per minute (BPM)
Daily Steps	Numerical	Average number of steps taken per day
Sleep Disorder	Categorical	Target variable (No disorder, Insomnia, Sleep Apnea)

B. Preprocessing

Before the use of ML models, preprocessing is performed to make the data accurate and data consistency.

- The blood pressure readings are separated in two columns are Systolic_BP, Diastolic_BP to better analyze them. Categorical columns like Gender, Occupation, BMI Category, and Sleep Disorder are label-encoded to enable proper interpretation by the model.
- Numerical columns (Sleep Duration, Age, Heart Rate, Daily Steps) are scaled by StandardScaler to improve gradient-based model performance.
- NONE values are replaced with “No” in the Sleep Disorder to make the data consistent.
- SMOTE[10] also handles class imbalance by developing artificial examples for underrepresented groups.Class distribution balancing avoids the injection of bias. This stops the models from developing biases to majority classes and thus makes the prediction more reliable.

C. Model Building

In order to classify sleep disorders properly and identify the causes, a Hybrid CNN-GRU model with an Attention Mechanism is adopted. The model incorporates the advantages of CNNs(Convolutional Neural Networks) for extracting spatial features and GRUs(Gated Recurrent Units) for the detection of sequential patterns and employs an attention mechanism for enhanced accuracy and explainability.

The CNN module is used to extract spatial features from physiological time-series data. Parameters of sleep like heart rate, blood pressure, daily steps, and oxygen saturation have local patterns that play a pivotal role in interpreting sleep disorders. CNN layers are efficient at identifying these local relationships between significant parameters such as sleep duration, oxygen levels, and blood pressure variations, and the model will be able to identify small relationships, e.g., how disrupted sleep duration affects heart rate variation. CNNs identify local dependencies by utilizing convolutional filters, which enables us to better grasp sleep health.

GRU for Sequencial Dependencies Modeling While CNNs are good at learning spatial relationships, GRUs are proposed to capture the sequential dependencies of sleep data. Sleep patterns change with time—sleeping time, physical activity, and lifestyle all vary over a few weeks and days. GRUs handle this temporal data very well, performing better than the other conventional Long Short-Term Memory (LSTM) networks by minimizing computational complexity without losing long-term dependencies that are essential. This enables the model to detect trends, for instance, how decreased physical activity over a few days is related to poor sleep quality.

Attention Mechanism for Feature Prioritization To further improve the classification process, an Attention Mechanism is used. Instead of assigning equal importance to all the input features, the attention mechanism assigns greater importance to the most descriptive features resulting in sleep disorders. For instance, while occupational status and BMI influence sleep well-being, sleep duration, stress, and oxygen saturation parameters would be more representative of conditions like insomnia and sleep apnea. Selective feature weighting of the most informative features by the attention mechanism improves interpretability as well as classification performance.

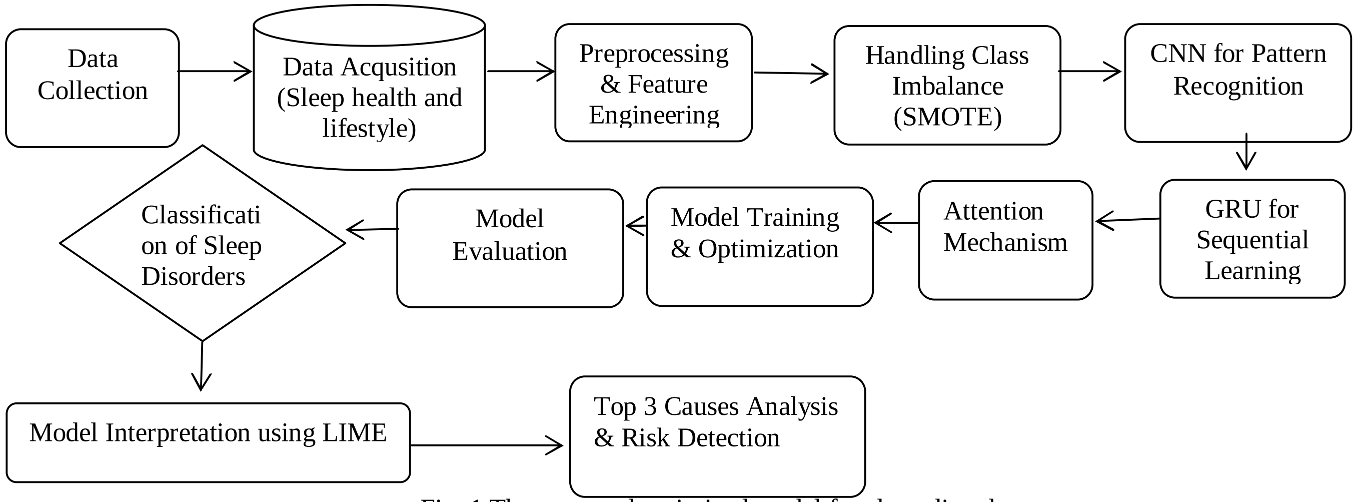


Fig. 1 The proposed optimized model for sleep disorder

While the Attention Mechanism improves feature importance at training-time, LIME provides interpretation of a single prediction after classification. Interpretability is provides as we know what features were used to make a particular prediction. LIME assists:

• Explain the reason a sample was classified with a specific sleep disorder.

• Confirm feature significance discovered by the Attention Mechanism.

• Identify model biases and ensure fair and reliable predictions.

D. Classification and Cause analysis

The Hybrid CNN-GRU-Attention model forecasts sleep disorders through learning high-level representations from multi-dimensional lifestyle and sleep information. The CNN module learns initial local spatial patterns among features like heart rate, blood pressure, and short sleep duration. The patterns provide vital micro-signals—like short sleep duration and elevated heart rate—pertaining to the identification of deviant sleep behavior.

Then, the GRU module temporalizes spatial information, recording how sleep wellness varies over weeks or days. This is an important role to capture fine-grained temporal trends such as off-time sleeping patterns to help produce sub-optimal sleep. Stacked GRU and CNN layers generate information-dense feature embeddings that learn current and past trends.

The Attention Mechanism selectively highlights most salient attributes. On each prediction, it assigns weights to parameters such as sleep duration, stress level, or BMI differently, depending upon their relative salience to an individual's specific disorder. It thus differentiates between disorders such as Insomnia (sleep hygiene- and stress-related) and Sleep Apnea (BMI-related).

For cause analysis, attention weights create an overall importance across the data set. To further customize insights, LIME is applied subsequent to prediction. LIME breaks down each prediction to contributory features, confirming which variables—like occupational stress or sedentary behavior—were most important for an individual's diagnosis. This two-pronged approach not only predicts that disorder exists but specifies why it exists, enabling such transparent, actionable insights for clinical decision-making as well as self-awareness.

E. Performance Evaluation Measures

Model performance measurement for sleep disorder classification must incorporate several performance measures to promote reliability and clinical utility. The following are the major metrics that give a general overview of model strengths and weaknesses:

??. Accuracy: It gives you the ratio of true positive and true negative classified samples to samples. High accuracy informs you that you have high-quality classification, but accuracy is deceptive in the case of imbalanced instances when one class is dominant.

$$\text{Accuarcy} = \frac{TP + TN}{TP + TN + FP + FN}$$

??. Precision(Positive Predictive Value): It refers to the measurement of true positive predictions and plays a key role in eliminating false positives. Measurement of high precision avoids misdiagnosis of healthy individuals for sleep disorders and avoidable medical procedures are avoided.

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

??. Recall: It measures model's ability to detect actual sleep disorder cases and is critical when false negatives are costly (e.g., failing to diagnose a patient with sleep apnea). A high recall score ensures that most sleep disorder cases are correctly identified, reducing the risk of missed diagnoses.

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

??. Specificity (True Negative Rate): It refers to model's capacity to accurately classify healthy individuals. High specificity prevents false alarms and misdiagnosis and unwarranted anxiety in healthy individuals.

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

??. F1-Score: This is one such measure that balances precision with recall and is an apt choice if false negatives or false positives have serious consequences. This is used to ensure that the model is indeed good at making correct predictions without over-classifying.

$$\text{F1} = 2 * \frac{Precison * Recall}{Precison + Recall}$$

I. RESULTS AND DISCUSSIONS

The Hybrid CNN-GRU Model with Attention Mechanism was cross-validated and trained over the preprocessed dataset for lifestyle and sleep-health. Model performance on classification of sleeping disorders and identification of their causes was computed against standard classification metrics: accuracy, precision, recall, specificity, and F1-score.

??. Comparison with other models:

??The highest classification performance among all the metrics was achieved by the hybrid CNN-GRU with Attention model, demonstrating that it is capable of identifying patterns in lifestyle and behavioral factors affecting sleep disorders.

TABLE II
THE PERFORMANCE COMPARISON OF DIFFERENT MODELS

Model	Accuarcy (%)	Precision (%)	Recall (%)	Specificity(%)	F1-score (%)
Logistic Regression[13]	78.5	74.2	68.9	80.1	71.4
Random Forest[14]	85.2	81.4	79.6	86.7	80.5
XGBoost [15]	90.3	87.5	85.3	90.9	86.4
CNN-GRU	90.6	90.5	90.6	90.6	90.5

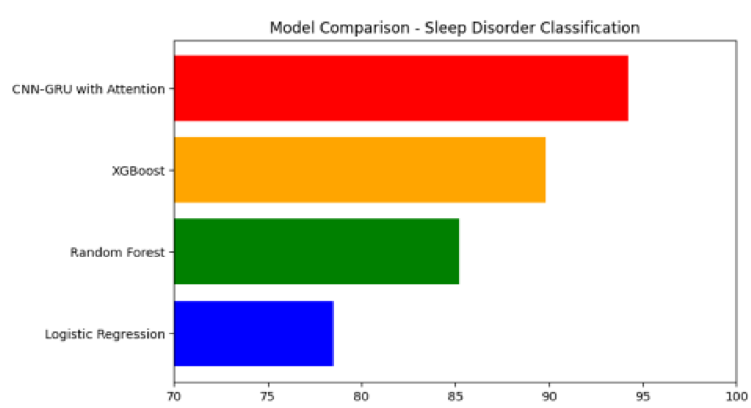


Fig. 2 Comparison of Models

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue V May 2025- Available at www.ijraset.com

Confusion Matrix and ROC Analysis:

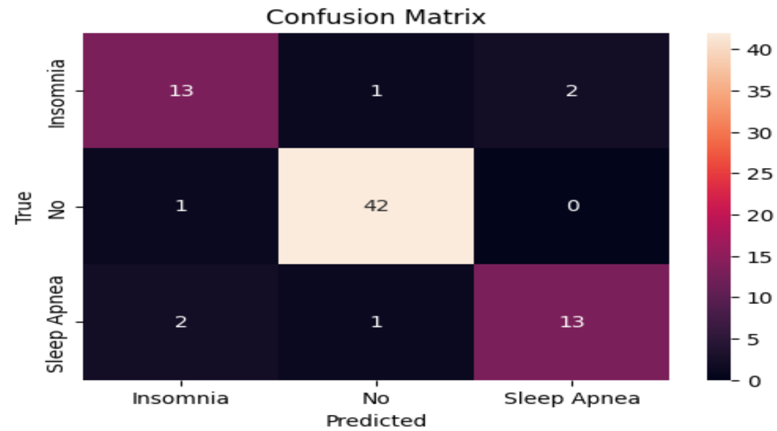


Fig.3 Confusion matrix of CNN-GRU with attention

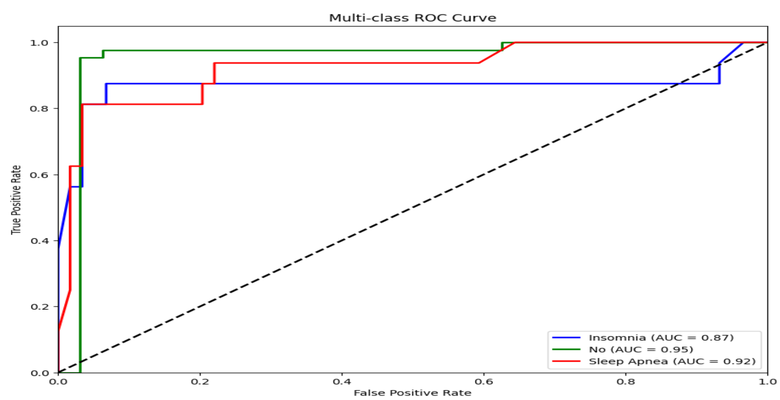


Fig. 4 ROC Curve for sleep Disorder Classification

Possible Causes for Sleep Disorders:
Along with classifying sleep disorders (Sleep Apnea, Insomnia, No Disorder), the model is tested for determining potential causes. The primary features responsible for it were determined by feature importance from LIME.

Main Factors Affecting Sleep Disorders:
Sleep Duration: Sleeping less than 6 hours substantially increased the risk for insomnia.
1. Level of Stress: High stress was the cause behind distressed sleep and reduce sleep quality.
??. Body Mass Index (BMI): Those who were obese as well as overweight were more related to Sleep Apnea.
3. Physical Activity: inactive or sitting living was linked to risk for sleep disorders

IV. CONCLUSION & FUTURE WORK

This research has effectively introduced a deep learning-based technique for classifying sleep disorders and identifying their causes using a hybrid CNN-GRU model with an Attention Mechanism and LIME interpretation. The model is able to extract both spatial and temporal features from a dataset on sleep health and lifestyle, leading to improved classification accuracy and causes detection and analysis. Using several deep learning techniques, this system successfully determined the important risk factors related to the sleep dysregulation that should be addressed for personalised care. After, evaluate metrics on this model such as accuracy, precision, recall, AUC-ROC. showed that in comparison to classical ML algorithms this model performed efficiently.
The attention mechanism also enhanced interpretability by highlighting important features such as sleep duration, level of stress, and BMI those parameters that are major contributors to diseases such as Insomnia, Sleep Apnea, and No Disorder. These results identify the potential of AI-based solutions in healthcare for early detection and personalized treatment plans.

Future Work:

While much progress has been achieved in this study, there are also various areas that hold promise for further improvements:

??. Dataset Expansion – Incorporating greater, more diverse datasets from multiple demographics and the integration of real-time wearable data to create even more robust features.

??. Edge AI Deployment – Running the model on low-power edge hardware or mobile platforms for real-time, non-clinical diagnosis of sleep disorders.

??. Personalized Recommendations – Designing an adaptive system that recommends customized lifestyle changes according to one's own sleep habits.

4. Integration with Smart Home Systems – Linking AI models with IoT-enabled smart home devices to adjust environmental factors (e.g., lighting, temperature) for better sleep quality.

REFERENCES

[??] R. Anita and A. Karuppiah, “A Survey on Recent Advances in Machine Learning Based Sleep Apnea Detection Systems,” Healthcare, vol. 9, no. 7, p. 914, Jul. 2021, doi: https://doi.org/10.3390/healthcare9070914.

[??] S. Kusmakar et al., “A machine learning model for multi-night actigraphic detection of chronic insomnia: development and validation of a pre-screening tool,” Royal Society Open Science, vol. 8, no. 6, p. 202264, Jun. 2021, doi: https://doi.org/10.1098/rsos.202264.

[??] N. Singh and R. H. Talwekar, “Comparison of Machine Learning and Deep Learning Classifier to Detect Sleep Apnea Using single-channel ECG and HRV: a Systematic Literature Review,” Journal of Physics: Conference Series, vol. 2273, no. 1, p. 012015, May 2022, doi: https://doi.org/10.1088/1742-6596/2273/1/012015.

[??] G. Bazoukis et al., “Application of Artificial Intelligence in the Diagnosis of Sleep Apnea,” Journal of Clinical Sleep medicine: JCSM: Official Publication of the American Academy of Sleep Medicine, vol. 19, no. 7, pp. 1337–1363, Jul. 2023, doi: https://doi.org/10.5664/jcsm.10532.

[??] Alaa Abd-Alrazaq et al., “Detection of Sleep Apnea Using Wearable AI: Systematic Review and Meta-Analysis,” Journal of Medical Internet Research, vol. 26, no. 10, pp. e58187–e58187, Sep. 2024, doi: https://doi.org/10.2196/58187.

[??] Talal Sarheed Alshammari, “Applying Machine Learning Algorithms for the Classification of Sleep Disorders,” IEEE Access, pp. 1–1, Jan. 2024, doi: https://doi.org/10.1109/access.2024.3374408.

[??] C.-H. Su et al., “Extracting Stress-Related EEG Patterns from Pre-Sleep EEG for Forecasting Slow-Wave Sleep Deficiency,” IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 32, pp. 1817–1827, 2024, doi: https://doi.org/10.1109/tnsre.2024.3394471.

[??] P. Tripathi et al., “Ensemble Computational Intelligent for Insomnia Sleep Stage Detection via the Sleep ECG Signal,” IEEE Access, vol. 10, pp. 108710–108721, Jan. 2022, doi: https://doi.org/10.1109/access.2022.3212120.

[??] M. Beard, “Smart Pajamas Can Monitor Sleep Apnea and Other Disorders at Home and Send the Results to Your Smartphone,” New York Post, Feb. 21, 2025. https://nypost.com/2025/02/21/health/smart-pajamas-can-monitor-sleep-disorders-at-home/

[??] J. Brownlee, “SMOTE for Imbalanced Classification with Python,” Machine Learning Mastery, Jan. 16, 2020. https://machinelearningmastery.com/smote-oversampling-for-imbalanced-classification/

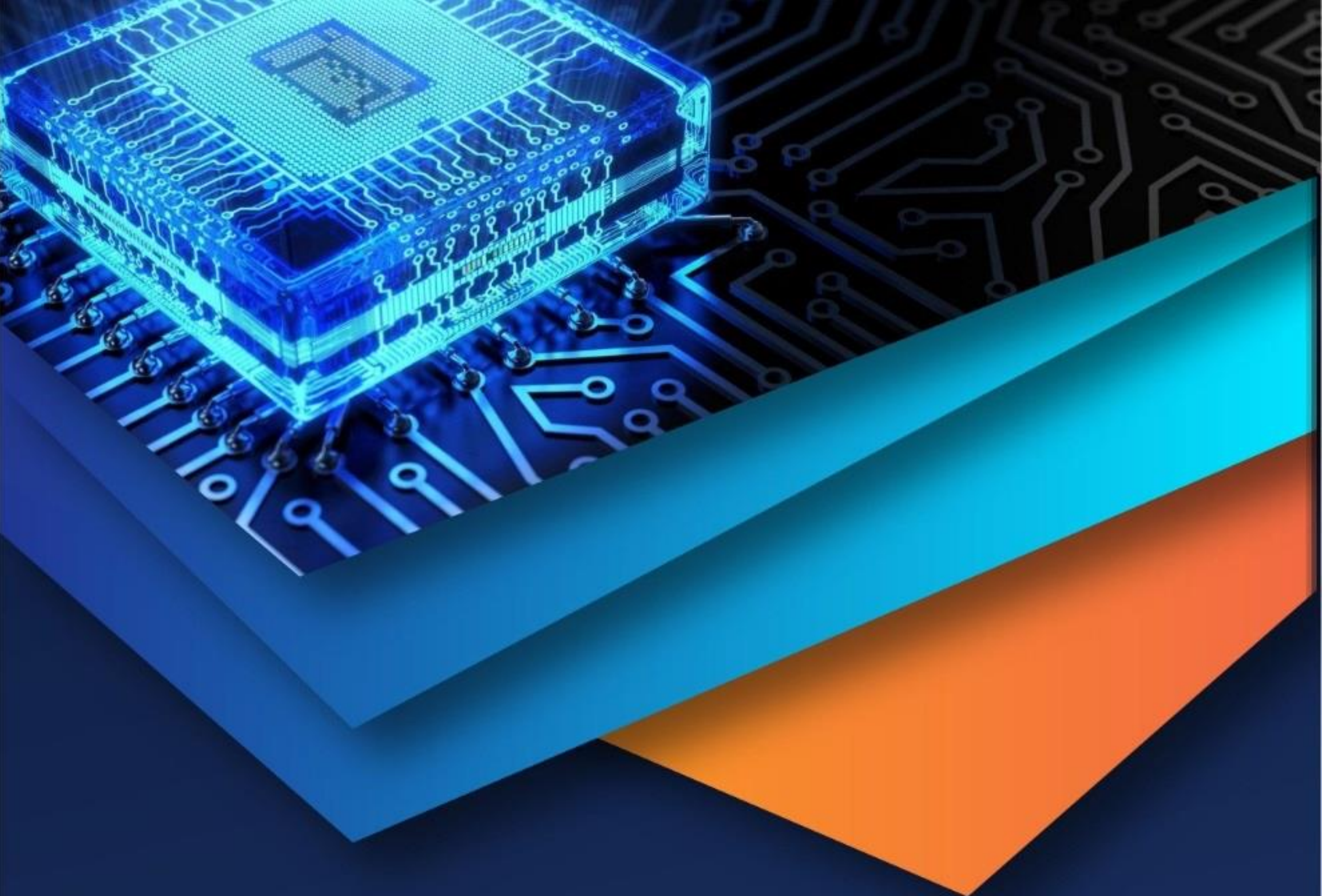
[????] C. Li, D. Liu, M. Wang, H. Wang, and S. Xu, “Detection of Outliers in Time Series Power Data Based on Prediction Errors,” Energies, vol. 16, no. 2, p. 582, Jan. 2023, doi: https://doi.org/10.3390/en16020582.

[????] Christoph Molnar, “5.7 Local Surrogate (LIME) | Interpretable Machine Learning,” Github.io, Sep. 18, 2019. https://christophm.github.io/interpretable-ml-book/lime.html

[????] T. Soni, “Enhancing Accuracy of Sleep Disorder with Logistic Regression Model | IEEE Conference Publication | IEEE Xplore,” ieeexplore.ieee.org, Sep. 30, 2023. https://ieeexplore.ieee.org/document/10295230

[????] I. A. Hidayat, “Classification of Sleep Disorders Using Random Forest on Sleep Health and Lifestyle Dataset,” Journal of Dinda : Data Science, Information Technology, and Data Analytics, vol. 3, no. 2, pp. 71–76, Aug. 2023, doi: https://doi.org/10.20895/dinda.v3i2.1215.

[15] N. Malik, V. Gupta, and V. Sharma, “Predictive Analysis of Sleep Disorders Using Machine Learning: a Comprehensive Analysis,” 2024 International Conference on Trends in Quantum Computing and Emerging Business Technologies, pp. 1–4, Mar. 2024, doi: https://doi.org/10.1109/tqcebt59414.2024.10545120



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