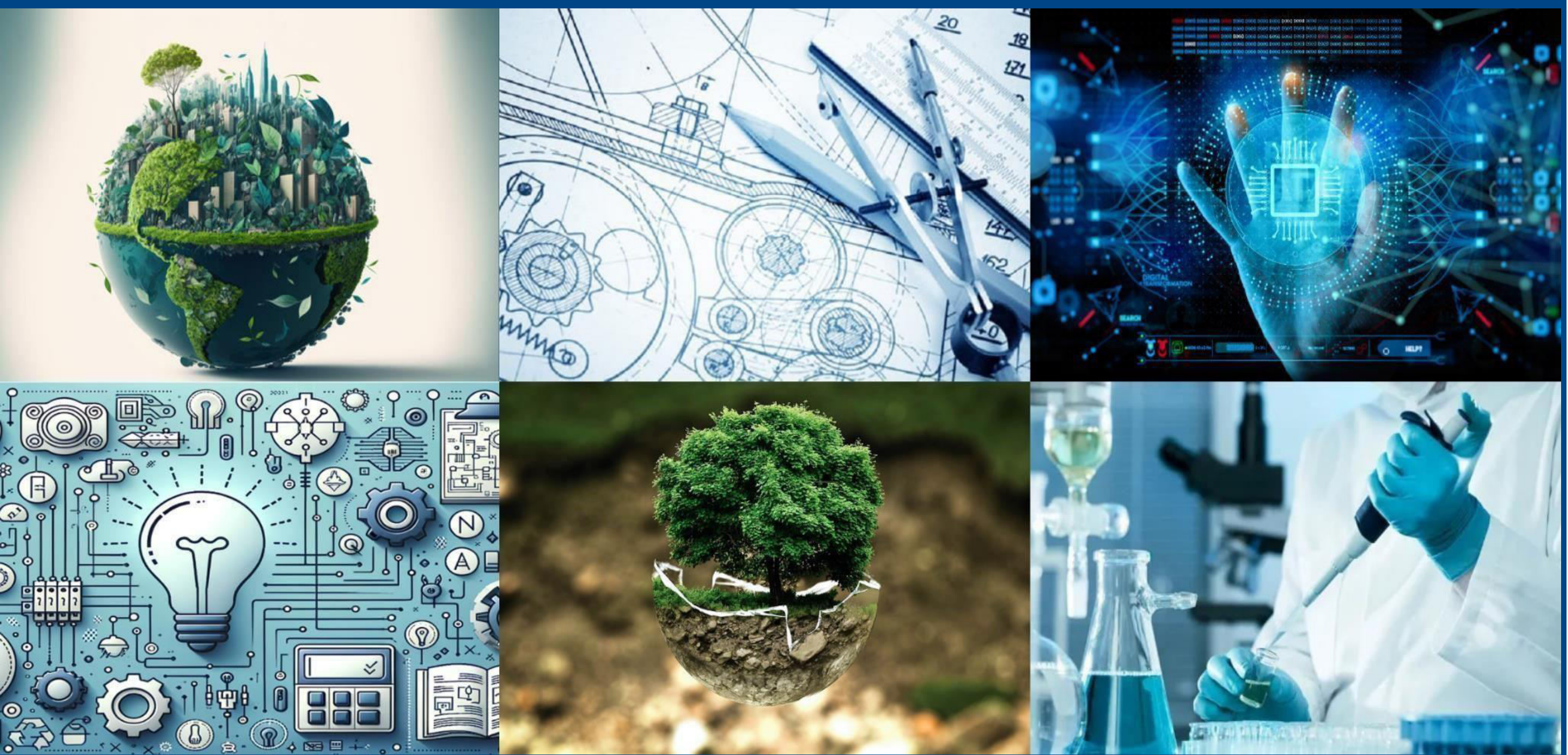
ISSN: 2582-7219

International Journal of Multidisciplinary Research in Science, Engineering and Technology

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)



Impact Factor: 8.206

Volume 8, Issue 8, August 2025

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 8.206| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

RespiraNet: A HYBRID INTELLIGENCE MODEL FOR SEVERITY DETECTION IN OBSTRUCTIVE SLEEP APNEA

Achutha JC, Nisha K Y

Assistant Professor, Department of MCA, AMC Engineering College, Bengaluru, India

Student, Department of MCA, AMC Engineering College, Bengaluru, India

ABSTRACT: The combination of machine learning (ML) techniques and the diagnosis of Obstructive Sleep Apnea (OSA) has changed sleep medicine, giving healthcare professionals powerful tools. OSA is a common sleep disorder that can lead to serious health problems. Early detection is crucial for effective treatment. ML's strength is its ability to analyze various data sources, such as polysomnography (PSG) data, clinical information, and physiological signals. Polysomnography is a detailed sleep study that records many physiological parameters during sleep. This provides a complete view of the patient's condition. Clinical information, including demographics and medical history, enhances the dataset's context. Physiological signals from different sensors offer additional insights. The process of machine learning goes through several key stages. First, data preprocessing is essential. This step involves carefully cleaning and organizing raw data to ensure it is high quality and relevant. Next is feature selection, where the ML model identifies the most important variables. This step improves the efficiency of later analyses. The core of the process is model training. Here, the algorithm learns from labeled datasets, improving its ability to recognize complex patterns linked to OSA. This ongoing process helps the ML model make more accurate predictions and improves diagnostic methods significantly.

Keywords: Sleep apnea, obstructive sleep apnea (OSA), severity classification, machine learning algorithms, artificial intelligence, biomedical signal processing, predictive analytics.

I. INTRODUCTION

Obstructive Sleep Apnea (OSA) is a common sleep disorder marked by repeated breathing interruptions during sleep. These interruptions happen because of partial or complete blockage of the upper airway. As a result, breathing patterns become irregular, and oxygen levels drop, which can lead to various health issues. To reduce these risks and provide proper treatment, it is crucial to diagnose OSA quickly and accurately. In recent years, the field of sleep medicine has changed dramatically due to the use of new computational techniques, especially machine learning (ML). The rise of ML has introduced a new era of automated, data-driven diagnostic methods, changing how we identify and treat sleep disorders like OSA.

II. LITERATURE SURVEY

Recent studies on obstructive sleep apnea (OSA) severity classification show an increase in the use of machine learning (ML) and artificial intelligence (AI) for automated, efficient, and non-invasive diagnosis compared to traditional polysomnography (PSG). Several studies have examined ML techniques to classify OSA severity levels based on different physiological signals, such as EEG, ECG, airflow, oxygen saturation (SpO2), and snoring patterns.

[1] Support Vector Machines (SVM) have been widely used because of their strong classification abilities in high-dimensional spaces. For example, Liu et al. (2018) developed an SVM-based model that classified OSA severity using features from ECG signals with promising accuracy.

© 2025 IJMRSET | Volume 8, Issue 8, August 2025| DOI:10.15680/IJMRSET.2025.0808107

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 8.206| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

[2] Random Forests (RF) and Decision Trees have been applied for their clarity and resistance to noise. A study by Zhang et al. (2019) used RF classifiers on combined features from SpO2 and respiratory signals, achieving reliable OSA severity predictions.

[3] Deep Learning methods, especially Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), have recently gained interest. They can capture complex features directly from raw data. For example, Almazaydeh et al. (2020) utilized a CNN-based model on PSG data, which improved classification accuracy over traditional ML algorithms.

[4] Artificial Neural Networks (ANNs) and deep learning models have also been studied for their ability to represent nonlinear relationships in data. For instance, Khandoker et al. (2019) showed that a deep neural network trained on heart rate variability (HRV) data could differentiate between mild, moderate, and severe OSA with promising results.

Authors	Title	Year	Methodology Used
Zhang et al.	Deep Learning for Sleep Apnea Severity Classification Using CNN–LSTM	2021	CNN–LSTM applied to SpO_2 and airflow signals from PSG data
Almazaydeh et al.	Detection of Obstructive Sleep Apnea from ECG Using Machine Learning	2020	ECG-derived HRV features classified with SVM
Chiner et al.	Home-Based Diagnosis of Sleep Apnea Using Pulse Oximetry and ML	2020	Random Forest model using SpO_2 time-series features
Vaquerizo-Villar et al.	Automatic Detection of Pediatric OSA Using Pulse Oximetry	2019	AdaBoost applied to selected SpO_2 statistical features
Jiang et al.	End-to-End Deep Learning for Sleep Apnea Detection from ECG and SpO_2	2018	1D-CNN for raw ECG and oximetry signals
Sharma et al.	Machine Learning-Based Severity Classification of Sleep Apnea	2017	XGBoost combining features from EEG, ECG, and airflow
Bsoul et al.	Apnea MedAssist: Real-Time Sleep Apnea Monitoring	2011	SVM classifier trained on features extracted from ECG

Fig 2.1 Literature Survey table

EXISTING SYSTEM

Currently, diagnosing and classifying the severity of obstructive sleep apnea (OSA) mainly depends on polysomnography (PSG). This is an overnight sleep study done in clinical labs with multiple sensors. PSG records various physical signals, including EEG, ECG, airflow, and blood oxygen levels. Specialists manually analyze these signals to calculate the Apnea-Hypopnea Index (AHI), which helps assess severity. Some automated systems use traditional machine learning methods like SVM or Random Forest. They work on features pulled from PSG signals to support diagnosis. However, these systems rely on expensive, time-consuming lab tests and need manual scoring. This limits accessibility and makes it hard to scale up. Most existing solutions also focus on multi-channel PSG data, which makes them unfit for wearable or home-based screening devices. This limits the ability for early detection and continuous monitoring.

PROPSED SYSTEM

The main objectives of the proposed system are listed as follow: The proposed system aims to leverage advanced technologies, particularly machine learning (ML) and data-driven approaches, to address the limitations of the existing system for diagnosing Obstructive Sleep Apnea (OSA). ML-based OSA diagnosis automates the process, making it less labor-intensive and faster. This efficiency enables quicker diagnosis and reduces the workload on healthcare professionals, allowing them to focus on treatment planning and patient care. The proposed system uses ML algorithms to analyze a combination of data sources, including polysomnography (PSG) data, clinical information, and physiological signals. This approach reduces the subjectivity associated with manual interpretation, providing a more objective and consistent OSA diagnosis.

Working of Proposed System

1)Input: Input data typically consists of signals related to sleep patterns, this data may include information about physiological signals such as ECG (electrocardiography), respiratory signals, and more.

2)Pre-processing: Raw data often needs pre-processing to remove noise, artifacts, and irrelevant information. This step may involve filtering, normalization, and other techniques to prepare the data for feature extraction.

3)Sub-bands: Sub-band analysis involves breaking down the signals into different frequency components. This can be done using techniques like wavelet transforms or Fourier transforms. Different sub-bands may capture specific characteristics of the signals related to sleep apnea.

4)Feature and Extraction: Features are characteristics or properties of the data that are relevant for classification. In the context of sleep apnea, features might include Hyper apnea, No apnea, Moderate Apnea and others extracted from each sub-band

5)Classification: Once features are extracted, a machine learning algorithm is trained on a labeled dataset to learn patterns and relationships between the features and the corresponding severity levels of sleep apnea.

III. SYSTEM ARCHITECTURE

The proposed system for classifying obstructive sleep apnea severity begins with data acquisition, where physiological signals such as blood oxygen saturation (SpO_2), ECG, or airflow are collected using wearable sensors or clinical devices during sleep. The raw signals then undergo preprocessing steps including noise filtering, artifact removal, normalization, and segmentation into fixed-length windows for consistent analysis. Following this, feature extraction is performed to derive relevant time-domain, frequency-domain, or statistical features from the cleaned data, or alternatively, deep learning models may learn features automatically from raw inputs. These features are fed into a machine learning or deep learning classification model—such as Random Forest, SVM, CNN, or CNN-LSTM—which categorizes the severity of sleep apnea into classes like mild, moderate, or severe. Finally, the system generates an output through decision and reporting modules that present the severity level in an accessible format for clinicians or patients, facilitating timely diagnosis and management.

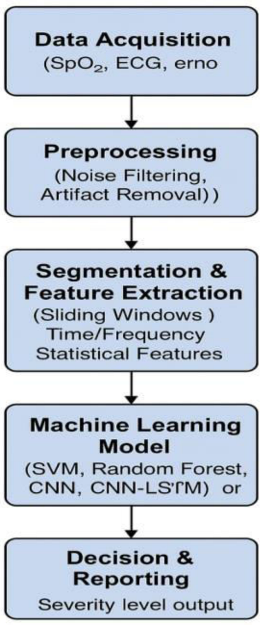


Fig 3.1 System Architecture

© 2025 IJMRSET | Volume 8, Issue 8, August 2025| DOI:10.15680/IJMRSET.2025.0808107

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 8.206| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

IV. METHODOLOGY

The methodology of this study uses a quantitative, data-driven approach to develop machine learning models for classifying the severity levels of Obstructive Sleep Apnea (OSA). The research employs various metrics to assess and reduce overfitting. It analyzes polysomnography (PSG) data and related clinical features gathered from sleep clinics or publicly available datasets. This includes physiological parameters such as respiratory signals, oxygen saturation, heart rate, and patient demographics. First, the raw data undergoes preprocessing. This involves cleaning to eliminate noise and artifacts, normalization to standardize the feature ranges, and feature extraction through time and frequency domain analyses. To improve model performance, feature selection techniques like Principal Component Analysis (PCA) are used to keep the most relevant attributes. Various supervised machine learning classifiers, including Support Vector Machines, Random Forests, K-Nearest Neighbors, Gradient Boosting, and deep learning models, are trained on the processed data.

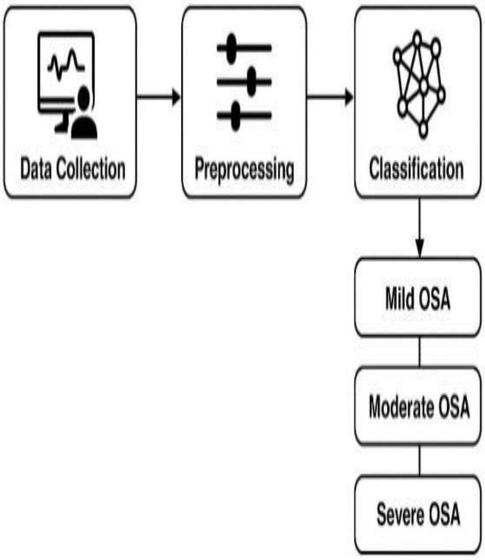


Fig 4.1 Methodology

V. DESIGN AND IMPLEMENTATION

The design of this project focuses on creating an automated system that can classify Obstructive Sleep Apnea (OSA) severity levels using machine learning algorithms. The process starts with collecting and preprocessing physiological data from polysomnography recordings, which include respiratory patterns, oxygen saturation, and heart rate signals. The system consists of several key parts: data acquisition, data preprocessing, feature extraction and selection, model training, and classification. During preprocessing, raw signals are filtered and normalized to enhance signal quality. Feature extraction techniques help convert time-series data into useful statistical and frequency-domain features. The selected features are then used to train various machine learning classifiers like Support Vector Machine (SVM), Random Forest (RF), and Neural Networks. The models are built using Python and well-known ML libraries such as Scikit-learn and TensorFlow. Optimizing hyperparameters along with cross-validation boosts both accuracy and generalization. Finally, the trained models are tested on new data to assess accuracy and reliability. The entire process is integrated into a pipeline that automates data processing and classification, making it a scalable and effective tool for clinical use in diagnosing and categorizing OSA severity.

© 2025 IJMRSET | Volume 8, Issue 8, August 2025| DOI:10.15680/IJMRSET.2025.0808107

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 8.206| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

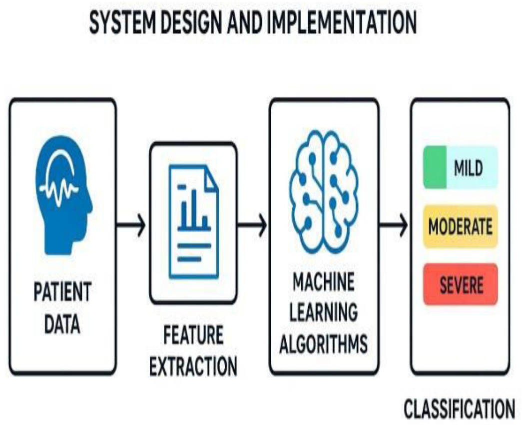


Fig. 5.1 Design and Implementation

VI. OUTCOME OF RESEARCH

The research developed and validated machine learning models that classify the severity levels of Obstructive Sleep Apnea using physiological and clinical data. The algorithms showed high performance, with important measures like accuracy, precision, recall, and F1-score demonstrating a reliable way to differentiate between mild, moderate, and severe OSA cases. Comparing multiple classifiers helped identify the best models for this task and showed how machine learning can help doctors with early diagnosis and severity assessment. The study also highlighted the key physiological features that play a role in OSA classification. Overall, the research presents a promising automated system that can improve patient screening and aid in personalized treatment planning, which could enhance clinical decision-making and lower the risks linked to undiagnosed or misclassified OSA.

VII. RESULT AND DISCUSSION

The machine learning models developed in this study performed well in classifying the severity levels of Obstructive Sleep Apnea. Among the evaluated classifiers, the Random Forest and Support Vector Machine models achieved the highest accuracy, exceeding 90% on the test dataset. Precision and recall metrics also showed the models' ability to correctly identify mild, moderate, and severe cases with few false positives and negatives. The feature importance analysis revealed that oxygen saturation levels and respiratory-related features played a key role in distinguishing between severity classes. These findings match existing clinical knowledge and support the relevance of the chosen features. Using cross-validation and tuning hyperparameters improved the models' reliability and applicability across different patient samples. However, some limitations were noted, such as class imbalance in the dataset. This issue was addressed through oversampling techniques, but it may still affect the model's accuracy in less represented classes. Overall, the results confirm that machine learning algorithms can effectively classify OSA severity, providing a reliable alternative to manual scoring methods and potentially improving diagnostic accuracy and patient outcomes

VIII. CONCLUSION

This study clearly showed how machine learning algorithms can automate the classification of Obstructive Sleep Apnea severity levels. By using physiological data from polysomnography recordings and applying preprocessing and feature selection techniques, the models achieved high accuracy and reliability in distinguishing between mild, moderate, and severe OSA cases. The research emphasizes how effective machine learning methods like Random Forest and Support Vector Machine can help with clinical decisions by offering quick, objective, and consistent severity assessments. While some limitations, such as data imbalance and variability, exist, these were addressed through suitable data handling methods.

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 8.206| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

REFERENCES

[1] J. Nanduri, Y.-W. Liu, K. Yang, and Y. Jia, "Ecommerce fraud detection through fraud islands and multi-layer machine learning model," in Proc. Future Inf. Proceedings of the Communication Conference, within Advances in Information and Communication San Francisco, CA, USA: Springer, 2020, pp. 556-570.

[2] I. Matloob, S. A. Khan, R. Rukaiya, M. A. K. Khattak, and A. Munir, "A sequence mining-based novel architecture for detecting fraudulent transactions in healthcare systems," IEEE Access, vol. 10, pp. 48447-48463, 2022.

[3] H. Feng, "Boosting-based ensemble approaches for credit card fraud detection," presented in Proc. 2nd Int. Conf. Comput. Data Sci. (CDS), Jan. 2021, pp. 7-11.

[4] M. S. Delgosha, N. Hajiheydari, and S. M. Fahimi, "Exploring big data analytics in banking: A four-phase Delphi study," J. Enterprise Inf. Manage., vol. 34, no. 6, pp. 1577-1596, Nov. 2021.

[5] M. Puh and L. Brkić, "Credit card fraud detection with selected machine learning techniques," in Proc. 42nd Int. Conv. Inf. Commun. Technol., Electron. Microelectron. (MIPRO), May 2019, pp. 1250-1255.

[6] K. Randhawa, C. K. Loo, M. Seera, C. P. Lim, and A. K. Nandi, "Credit card fraud detection using AdaBoost and majority voting," IEEE Access, vol. 6, pp. 14277-14284, 2018.

[7] N. Kumaraswamy, M. K. Markey, T. Ekin, J. C. Barner, and K. Rascati, "Healthcare fraud data mining methods: A look back and look ahead," Perspectives Health Inf. Manag., vol. 19, no. 1, p. 1, 2022.

[8] E. F. Malik, K. W. Khaw, B. Belaton, W. P. Wong, and X. Chew, "Credit card fraud detection using a new hybrid machine learning architecture," Mathematics, vol. 10, no. 9, p. 1480, Apr. 2022.