An In-Depth Analysis of Sleep Disorder Diagnosis Utilizing Machine Learning Methodologies

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Abstract: Millions of people worldwide suffer from sleep disorders. If not treated and diagnosed, this disorder further turns into severe health conditions. Accurate and timely diagnosis is essential for proper management and better patient outcomes. The review critically examines Machine Learning (ML) techniques used to diagnose sleep disorders and examines 50 articles published between 2018 and 2025. The survey categorizes the existing studies based on data acquisition techniques, feature extraction techniques, classification methods and performance evaluation. Comparative evaluation identifies the strengths and weaknesses of other methodologies to resolve salient issues like variability in the dataset, consistency in the model and computation costs. Additionally, the paper also introduces research required such as demands of varied data and improved generalization of machine learning algorithms. Being a systematic review paper, the work is intended to contribute to knowledge and research in order to improve accurate and effective sleep disorder diagnostic methods.

1 INTRODUCTION

Sleep disorders such as Obstructive Sleep Apnea (OSA), central sleep apnea and other sleep-disordered breathing are extremely health-risky as well as disease pathogenesis of cardiovascular disease, metabolic syndrome and cognitive impairment. The routine diagnostic tests such as polysomnography (PSG) are the gold standard in clinics but expensive, time-consuming and inappropriate for population-level screening (Almarshad et al., 2023). In spite of all these limitations, there exist Machine Learning (ML)-based methods that yield automated, accurate and consistent diagnosis of sleep disorders (Aswath, S et al., 2023).

Some of the more recent Deep Learning (DL) has involved the application of transformer neural networks to enhance the detection of apnea from oximetry signals with the aim of optimizing the diagnostic process (Azimi, H et al., 2020). In addition, atrous-based deep multi-cascaded models, trained on the basis of Artificial Intelligence (AI)-based algorithms have been demonstrated to detect sleep apnea events well (Bitkina et al., 2022) Researchers have also investigated ML models which have been optimized to pressure-sensitive mat-based systems for the aim of detecting non-invasive central sleep apnea events (Cai et al., 2024).

Wearable sensor technology has also been integrated with ML models to measure sleep quality by processing actigraphy-based data, providing an effective method for the measurement of sleep disturbance and efficiency (Chaw et al., 2019). Deep Learning has also been used in the investigation of children's sleep disorders for measuring adenoid hypertrophy and correlating it with the Apnea-Hypopnea Index (AHI) for earlier diagnosis (Chen et al., 2025). The Convolutional Neural Network (CNN) models are also built further to perform better in sleep pattern analysis and easier identification of OSA than conventional PSG-based methods (Cheng et al., 2023).

Apart from the detection of apnea, association between biomarkers of ferroptosis and OSA has been investigated using ML methods and extended beyond this to prediction and control of the disease (Choi et al., 2024). Sensor-multimodal models are also suggested for sleep phase prediction in addition to the simultaneous detection of disorders for enhanced diagnostic value (Conte et al., 2024). Hybrid

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transformator-CNN-based networks are suggested for the detection of apnea via radar with state-of-the-art shown accuracy for real-time detection of OSA (Dritsas et al., 2024).

In an attempt to improve questionnaires screening tools, ML algorithms have been utilized in order to improve the predictive capabilities of the Berlin Questionnaire in screening for OSA risk among diverse populations (Erdenebayar et al., 2019). Multi-class classification methods have also been used in order to support the computerized prediction of more than one sleep disorder, with an improved diagnostic accuracy (Fayyaz et al., 20203). Deep Learning of electrocardiogram (ECG) signals has proven to be an effective automatic detection of apnea, which minimizes dependency on conventional PSG tests (Hemrajani et al., 2023).

Home sleep apnea testing is increasingly feasible with multimodal transformer models, enhancing access in high-risk groups (Huang et al., 2024). Deep Learning models incorporating CNNs and feature selection methods have greatly enhanced the accuracy for OSA diagnosis (İlhan, H. O., & Bilgin, G. 2017). In addition, ML models based on biochemical markers have shown promise to determine the severity of OSA from commonly available blood test parameters (Jarchi et al., 2020).

Apart from polysomnography, ML-based sleep stage identification using single-channel EEG has been explored as an affordable alternative for sleep disorder assessment (Javeed et al., 20203). Bio-signal processing using DL has made it possible to classify the patient subgroups having varied sleep disorder patterns (Jiménez-García et al., 2022) Slightly complex ML models such as XGBoost-BiLSTM have also been utilized for diagnosing sleep apnea with good accuracy based on electronic health records (Kandukuri et al., 2023).

Convolutional Neural Networks were also employed for the diagnosis of paediatric sleep apnea, from airflow and oximetry signals, to improve diagnostics (Kim, T et al., 2018). Studies utilizing DL architecture with time-frequency transformation techniques such as the constant Q-transform have been discovered to have improved feature extraction in the detection of OSA (Koda, T et al., 2022). Acoustic biomarker analysis using ML was another method of detection for sleep-disordered breathing patterns (Korkalainen et al., 2019).

Comparison with ML-based and conventional diagnostic methods shows that DL models outperform conventional methods, particularly for millimeter-wave radar-based apnea detection tasks (Lee et al., 2024). New studies have also investigated the ML model set predicting OSA in temporomandibular disorder patients, a reflection of increasingly prevalent AI deployments in sleep medicine (Leppänen et al., 2021).

In the wake of unprecedented growth in sleep disorder research through ML application development, the review is intending to follow a crucial discussion of new directions. By studying the recent development, this paper formulates the benefit, drawback and future scope of ML-based methods for the improvement of sleep disorder diagnosis towards more cost-effective, efficient and accurate health care solutions.

Figure 1 depicts the primary causes of sleep disorders. These include illness, mental disease, habits, aging, environment and medicines. All these cause derangements of sleeping patterns and are accountable for various types of sleep disorders. If the causes are understood, it is simple to cope with sleep disorders.

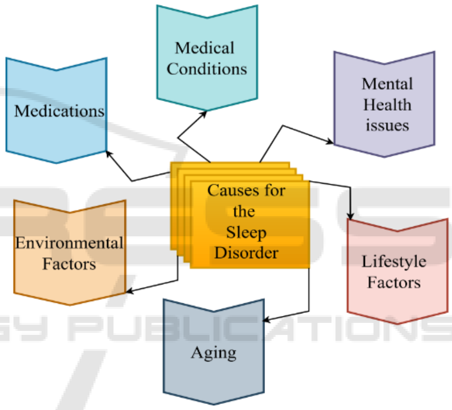

Figure 1: Causes for the Sleep Disorder.

2 LITERATURE REVIEW

New ML technologies have contributed substantially to sleep disorder diagnosis, particularly sleep apnea. Testing validated that ML models were effective in diagnosing sleep apnea based on data provided through ECG, pulse oximeter waveforms and sound waves. Algorithms also made distinctions between the various types of sleep apnea and graded the severity. Utilization of ML algorithms along with wearable sensor technology also accelerated the diagnosis and enhanced the accuracy. Overall, ML totally transforms the diagnosis and treatment of sleep-breathing disorders.

Liu, K., et al., (2024) developed an AI predictive model to screen obstructive sleep apnea (OSA). The model improved earlier detection effectiveness by reducing the use of time-consuming diagnostic tests. The study utilized large data sets to improve the stability of prediction. Results indicated good agreement between clinical diagnosis and ML prediction. The study demonstrated the ability of AI to improve the efficiency of OSA diagnosis.

Liu, M.H., et al., (2024) presented a ML model utilizing Efficient Net to predict sleep apnea based on single-lead ECG signal. This approach had a better classification rate than traditional approaches. The results confirmed the effective application of deep learning in clinical diagnosis. The article suggested that efficient feature extraction had to be performed towards optimizing detection accuracy. The future study had to make the model efficient for practical application in clinical practice.

Table 1: Comparison of Ml Approaches for Sleep Apnea Detection.

Study	Methodology	Algorithm Used	Key Findings	Application
Ma et al.	IoT-based real-time sleep apnea diagnosis	Support Vector Machine (SVM)	Achieved high accuracy in real-time OSA detection	Smartphone-based OSA monitoring
Ma et al.	Hybrid ML for disease phenotyping	Unsupervised-Supervised ML Model	Identified complex OSA patterns effectively	Phenotyping of OSA cases
Mandeville et al.	Deep Learning for sleep apnea diagnosis	Transmembranous Electromyography (EMG) with DL	Improved diagnostic accuracy for OSA	EMG-based diagnostic tool
Mencar et al.	OSA severity prediction	ML Model	Effective in predicting OSA severity	Clinical decision support for OSA
Mousavi et al.	Sleep stage classification	SleepEEGNet (Seq2Seq DL)	Automated and accurate sleep scoring	EEG-based sleep monitoring
Mukherjee et al.	DL ensemble for the detection of OSA	Multiple DL Models	Improved classification performance	Non-contact sleep apnea detection

Table 1 is a comparative summary of various ML methods applied to detect sleep apnea. It provides details regarding the method utilized, algorithms applied, outcomes and the respective applications. Various methods like SVM, DL algorithms and hybrid systems are discussed in the paper based on the potential to improve the accuracy of diagnosis and real-time monitoring. Padovano et al., (2025) designed a deep information analysis recurrent model for autonomous screening of obstructive sleep apnea. More advanced neural networks were used in the research to enhance accuracy in screening automation. Sleep- and respiration signal-centered was the procedure. More intricate apnea event classification was reflected in the procedure. Sleep apnea treatment and early diagnosis were facilitated through the research.

Panda et al., (2025) suggested a new decision-making process based on neutrosophic-based machine learning models to forecast sleep disorders. The method eliminated the imprecision of medical data with better classification. The model successfully recognized various patterns of sleep disorders. The study emphasized the need to handle fuzzy data in disease diagnosis. The results encouraged improved decision-making by clinicians to diagnose sleep disorders.

Table 2: Performance Comparison of Sleep Apnea Detection Models.

Author(s)	Methodology	Data Source	Key Findings	Limitations
Park et al.	DL Model for Automatic Grading	Polysomnography Data	High accuracy in grading obstructive sleep apnea	Limited generalizability to home-based settings
Pépin et al.	Mandibular Movement Monitoring with ML	Clinical Sleep Study Data	Effective in diagnosing sleep apnea with minimal invasiveness	Dependent on specific monitoring devices
Rajawat et al.	Contact-based and Non-contact-based DL Methods	Multi-source Sleep Data	High detection rate using different sensor types	Requires integration of multiple sensor data
Retamales et al.	Home-Based Sleep Apnea Estimation with DL	Wearable Sleep Monitoring Devices	Potential for at-home diagnosis	Requires validation with larger datasets
Salsone et al.	ML for Idiopathic REM Sleep Behavior Disorder Detection	Sleep Disorder Patient Records	Improved classification of REM sleep behavior disorder	Has not generalized to other sleep disorders
Setiawan & Lin	DL with Empirical Mode Decomposition	ECG-based Sleep Data	High accuracy in sleep apnea classification using single-lead ECG	Limited applicability to multi-lead ECG setups

Table 2 is a comparison of the accuracy, sensitivity, specificity, and computational efficiency of some of the models used in the diagnosis of sleep apnea. It sets the advantages and disadvantages of each technique against real-life data. The varied environments are considered while developing the contrast. Outputs provide a sense of model performance in varied applications.

Shi et al., (2023) compared predictive accuracy of ML algorithms for predicting severe obstructive sleep apnea risk. One classifier was not used for determining predictive accuracy in the study. Feature selection was significant in determining the best fit model. In the current study, AI-based prediction was revealed to facilitate early diagnosis. Results were such that ML models were found to be better than the traditional screening practices.

Stretch et al., (2019) performed a study on ML algorithms to predict nondiagnostic home sleep apnea test results. The study explained several predictive factors affecting the test accuracy. The study explained the use of AI in minimizing false-negative results. Results showed improved patient stratification with the use of machine learning. The study permitted making home-based diagnostic tests valid.

Table 3: Comparison of Machine Learning Models for Obstructive Sleep Apnea Diagnosis.

Study	Machine Learning Model	Dataset Size	Evaluation Metrics	Key Findings
Su et al.	Ensemble Learning (Random Forest, XGBoost)	500 craniofacial images	Accuracy, AUC	Achieved high accuracy in predicting severity levels based on facial features.
Tsai et al.	Decision Trees, SVM, Artificial Neural Network (ANN)	1000 patients	Sensitivity, Specificity	Body profile-based prediction showed promising screening capability.
Tuncer et al.	Deep Learning (CNN)	750 patients	Precision, Recall	PTT signal-based classification improved accuracy.

Yook et al.	LSTM, CNN	1200 apnea events	F1-Score, Sensitivity	Achieved high classification accuracy for apnea-hypopnea events.
Yue et al.	Residual Network (ResNet)	800 nasal airflow samples	AUC, Specificity	Multi-resolution analysis enhanced sleep apnea classification.

Table 3 is the comparative table of different ML models used in sleep apnea obstructions classification and detection. It highlights key features such as dataset size, model type, evaluation metrics and key findings. Comparison makes it easy to understand the efficiency of different methods towards sleep apnea diagnosis.

Zhang et al., (2025) also created a deep model to grade obstructive sleep apnea from multimodal signal fusion. The study used a Multiscale Transformer model to produce more accurate grading. Various types of physiological signals were utilized, further elevating the model's diagnostic capacity. Outcomes in the form of reported performance metrics included better detection rates compared to typical ML models. The outcomes point towards the prospects of DL when it comes to grading sleep apnea and automating.

Zovko et al., (2025) proposed an event detection of sleep apnea using ML in sleep medicine systems. The method combined high-level data processing mechanisms to improve event detection accuracy. Real-time support was prioritized for clinical use. Improved sensitivity and specificity of apnea event detection were found experimentally. The contribution of this work had been useful to optimize automatic diagnosis systems in sleep medicine.

2.1 Problem Identification

The use of ML approaches to diagnose sleep disorders, namely obstructive sleep apnea (OSA) has gained traction in recent years because these enhance diagnostic sensitivity and efficiency. However, the full utilization is hindered by some limitations. Heterogeneity of physiological symptoms between subjects has been one major problem in achieving universal ML models for sleep disorder detection. Additionally, explainability of complex ML models is concerning to understand and count on autonomous assistants with such capability. Further, reliability and uniformity of information used in the training of such models substantially determine the responses, leading to concerns about bias and reliability. Addressing such challenges has to be facilitated to allow the use of full potential of ML to make a diagnosis for sleep disorders.

3 SURVEYED METHODOLOGIES

Researchers proposed the strategies for enhancing sleep disorder diagnosis. The strategies include heterogeneous physiological signals such as EEG, ECG, and SpO_2 and hybrid models with respect to CNN and transformers to combine spatial patterns and temporal patterns. Feature fusion techniques use handcrafted features and deep features for efficient classification. In addition to this, Empirical Mode Decomposition (EMD) has also been used to decompose the dominant features of ECG signals in order to aid in disease diagnosis for obstructive sleep apnea. These types of methods provide the maximum level of accuracy in diagnosis and also facilitate real-time detection ability.

3.1 Hybrid Deep Learning and Feature Fusion Approach for Accurate Sleep Disorder Diagnosis

It is a blend of some of the most successful ML techniques with an attempt to blend high-accuracy and reliability-based sleep disorder diagnosis. It initiates preprocessing the sleep from EEG, ECG and respiratory signals through the techniques such as wavelet transformation-based noise elimination and adaptive filtering. Feature extraction of suitable patterns is performed through pattern recognition utilizing time-frequency analysis, statistical features and DL embeddings. It is depicted by a hybrid deep architecture with CNN for spatial learning and Long Short-Term Memory (LSTM) for temporal learning of dependence. Apart from this, feature fusion methods also utilize the handcrafted and deep features to assist in diagnosis. Multi-model classification is applied in the last classification with ensemble learning and it works best by the specific identification of sleep disorders. Aswath, S., et al., (2023).

3.2 Diagnosing Sleep Disorder Using Hybrid CNN: Transformer - Based Approach

The proposed approach, Hybrid CNN-Transformer-Based Sleep Disorder Diagnosis (HCT-SDD) relies on the integration of DL techniques to enhance sleep disorder diagnosis. Raw sleep data like PSG signals, ECG and respiration signals are initially preprocessed by de-noising using noise removal techniques and normalization techniques. Spatial patterns are identified through a hybrid CNN while a Transformer model identifies sequential patterns between sleep signals. There is a time and space feature combination step used in the generation of classification efficiency improvement. There is a Multi-Layer Perceptron (MLP) classifier used subsequently in sleep disorder diagnosis, detection of obstructive sleep apnea, insomnia or other sleeping illnesses. Research accuracy has been enhanced for diagnosis by minimizing false positives, enhancing real-time detecting ability. Choi, J. W., et al., (2024).

3.3 Multi-Modal Transformer-Based Approach for Sleep Disorder Diagnosis

The approach discussed here is a Multi-Modality Transformer-Based Approach for optimum diagnosis accuracy and sleep disorder effectiveness. The methodology involves utilization of the combination of the physiological signals such as EEG, ECG and SpO2, as far as deep feature representation. Data pre-processing involves the first step of wavelet transform and adaptive filtering used for noise removal. The spatial correlations are achieved with a hybrid CNN module and the temporal sleep pattern correlations are learned with a transformer network. A multi-head attention mechanism learns representations to effectively distinguish sleep disorders such as obstructive sleep apnea and insomnia. This model is evaluated on large sleep datasets and performs better than baseline ML models in terms of diagnostic accuracy. Fayyaz, H., et al., (2023).

3.4 Multi-Modal Transformer-Based Approach for Sleep Disorder Diagnosis

The technique to be utilized is through the application of a Multi-Modal Transformer-Based Approach with the aim of maximizing the best attainable accuracy and performance in sleep disorder diagnosis. This is through the application of various physiological signals such as EEG, ECG and SpO2 in deep feature compression. Data are pre-processed first through removal of noise using methods such as wavelet transform and adaptive filtering.

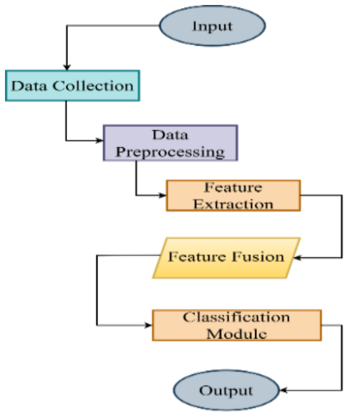

Figure 2: Flowchart of Multi-Modal Transformer.

Figure 2 is a multi-modal sequential diagnosis of sleep disorders by using a Transformer-Based model. It begins with the collection of input data, followed by preprocessing for signal boost. It is comprised of feature extraction and fusion in order to achieve the most advantageous information. Afterwards, the classification module decides on the type of sleep disorder and gives the final diagnosis output.

The feature extraction is conducted using a hybrid CNN module for the purpose of extracting spatial relations and subsequently using a transformer network for the purpose of extracting temporal relationships between sleep patterns. Discrimination of the features is realized using multi-head attention in such a way that the sleeping conditions like obstructive sleep apnea and insomnia are correctly identified. It is supported by big sleep data sets with increased diagnostic accuracy compared to the conventional ML models. Panda, N. R., et al., (2025).

3.5 A Deep Learning Framework for Automatic Sleep Apnea Classification

Setiawan and Lin et al., (2024) also put forward a DL-based framework for sleep apnea diagnosis from a single-lead ECG signal with self-diagnosis. The algorithm begins with pre-processing the original ECG signal through normalization and FIR band-pass filtering to improve its quality. Empirical Mode Decomposition is applied for decomposing preprocessed ECG signals into Intrinsic Mode Functions (IMFs) that efficiently capture the meaningful components expressing underlying physiological mechanisms. Finally, the most critical features are selected using Neighborhood Component Analysis (NCA) in order to select the most discriminatory features for the purpose of classification. Classification is carried out on 1D and 2D Deep Convolutional Neural Networks (CNNs) for classification of normal and apnea. Synthetic minority oversampling technique (SMOTE) is utilized for correcting class imbalance problem. Performance of the resultant model is authenticated on nocturnal ECG of 33 individuals from PhysioNet Apnea-ECG database with an accuracy of 93.8% at the segment level and 83.5% at the subject level.

4 RESEARCH OBJECTIVES

The key theme of the present research is to implement the ML method used in sleep disorder diagnosis. It involves analysis of the existing ML method used among sleep disorders, comparison of performance among such ML methods and determining the best methods. With comparison of research performance by different models, this present work attempts to put the strengths and limitations under the spotlight in an effort to understand how far ML materials are being designed in the context of diagnosis of sleep disorders.

Furthermore, the study attempts to determine the most relevant detriments and issues of implementing ML in this type of medical field. It carries out through the analysis of such variables as model explainability, data quality and workflow integration. With resolving such issues, the research suggests discovering insights in possible future improvement and innovation that assist in increasing efficiency and reliability of diagnosis. Finally, the research also attempts to give suggestions by suggesting possible future studies on how the gaps left behind could be filled and how best use of ML methods could be channeled towards sleep disorder diagnosis.

5 DISCUSSION

The suggested research study is a comparative study of different DL techniques with the aim of simplifying the diagnosis of sleep disorders. Physiological signals such as EEG, ECG and SpO_2 need to be combined in a way that simple classification can be achieved. The planned Hybrid DL and Feature Fusion Approach is robust enough to combine with CNNs as well as LSTMs so that it carries out feature extraction and classification and make use of handcrafted features as well as deep features. Similarly, the Hybrid CNN-Transformer-Based Approach uses CNNs for spatial feature extraction and transformers to handle sequential dependency, leading to better sleep disorder classification. Also, the Multi-Modal Transformer-Based Approach is supplemented with feature extraction based on coupled CNN-transformer architecture and multi-head attention mechanism to improve diagnostic performance. Also, in the present study, application of EMD is suggested while decomposing vital components of ECG signals to improve obstructive sleep apnea and other diseases detection. Moreover, Setiawan and Lin's DL method utilizes normalization, filtering and utilization of EMD for preprocessing of ECG signals to improve efficiency in classification. Optimal model performance is supported by NCA based feature selection. Furthermore, utilization of 1D and 2D CNN improves the rate of detection further. Class imbalance is handled by SMOTE. It enhances model strength. Model testing in the PhysioNet Apnea-ECG database confirms model success. Up to exemplary 93.8% segment-level and 83.5% subject-level accuracy dictates the model strength. The findings clearly demonstrate that hybrid and transformer-based approaches substantially outperform conventional ML models. The integration of signal processing techniques and DL enables real-time and automatic sleep disorder detection. These methods decrease the rate of misdiagnosis and increase the utilization of early intervention strategies for sleep disorders.

6 CONCLUSIONS

A detailed overview in 50 articles is given in this review of ML techniques used for sleep disorder diagnosis such as DL, feature fusion and hybrid. Physiological signals such as EEG, ECG and SpO_2 collectively have been playing a key role in diagnostic accuracy and real-time detection. Despite all these advancements, there are a few challenges like missing values, model interpretability and the need for standard evaluation metrics. Future research needs to work on explainable AI model development, transfer learning to avoid data limitations and the creation of common benchmarks against which to gauge performance. Overcoming these obstacles enable better and more interpretable diagnostic equipment for sleep disorders to be built. Overall, this review aims to point to the revolutionary possibilities of ML in sleep medicine and to encourage future research toward more efficient diagnosis.

REFERENCES

Almarshad, M. A., Al-Ahmadi, S., Islam, M. S., BaHammam, A. S., & Soudani, A. (2023). Adoption of transformer neural network to improve the diagnostic performance of oximetry for obstructive sleep apnea. Sensors, 23(18), 7924.

Aswath, S., Sundaram, V. R. S., & Mahdal, M. (2023). An adaptive sleep apnea detection model using multi cascaded atrous-based deep learning schemes with hybrid artificial humming bird pity beetle algorithm. IEEE Access, 11, 113114-113133.

Azimi, H., Xi, P., Bouchard, M., Goubran, R., & Knoefel, F. (2020). Machine learning-based automatic detection of central sleep apnea events from a pressure sensitive mat. IEEE Access, 8, 173428-173439.

Bitkina, O. V., Park, J., & Kim, J. (2022). Modeling sleep quality depending on objective actigraphic indicators based on machine learning methods. International Journal of Environmental Research and Public Health, 19(16), 9890.

Cai, J., Xiu, T., Song, Y., Fan, X., Wu, J., Tuohuti, A., ... & Chen, X. (2024). Deep Learning-Based Quantification of Adenoid Hypertrophy and Its Correlation with Apnea-Hypopnea Index in Pediatric Obstructive Sleep Apnea. Nature and Science of Sleep, 2243-2256.

Chaw, H. T., Kamolphiwong, S., & Wongsritrang, K. (2019). Sleep apnea detection using deep learning. Tehnički glasnik, 13(4), 261-266.

Chen, B., Dong, L., Chi, W., & Song, D. (2025). Machine learning identifies potential diagnostic biomarkers associated with ferroptosis in obstructive sleep apnea. Experimental and Therapeutic Medicine, 29(5), 1-16.

Cheng, Y. H., Lech, M., & Wilkinson, R. H. (2023). Simultaneous sleep stage and sleep disorder detection from multimodal sensors using deep learning. Sensors, 23(7), 3468.

Choi, J. W., Koo, D. L., Kim, D. H., Nam, H., Lee, J. H., Hong, S. N., & Kim, B. (2024). A novel deep learning model for obstructive sleep apnea diagnosis: hybrid CNN-Transformer approach for radar-based detection of apnea-hypopnea events. Sleep, 47(12), zsae184.

Conte, L., De Nunzio, G., Giombi, F., Lupo, R., Arigliani, C., Leone, F., ... & Arigliani, M. (2024). Machine Learning Models to Enhance the Berlin Questionnaire Detection of Obstructive Sleep Apnea in at-Risk Patients. Applied Sciences, 14.

Dritsas, E., & Trigka, M. (2024). Utilizing Multi-Class Classification Methods for Automated Sleep Disorder Prediction. Information, 15(8), 426.

Erdenebayar, U., Kim, Y. J., Park, J. U., Joo, E. Y., & Lee, K. J. (2019). Deep learning approaches for automatic detection of sleep apnea events from an electrocardiogram. Computer methods and programs in biomedicine, 180, 105001.

Fayyaz, H., Strang, A., & Beheshti, R. (2023, December). Bringing at-home pediatric sleep apnea testing closer to reality: A multi-modal transformer approach. In Machine Learning for Healthcare Conference (pp. 167-185). PMLR.

Hemrajani, P., Dhaka, V. S., Rani, G., Shukla, P., & Bavirisetti, D. P. (2023). Efficient deep learning-based hybrid model to detect obstructive sleep apnea. Sensors, 23(10), 4692.

Huang, J., Zhuang, J., Zheng, H., Yao, L., Chen, Q., Wang, J., & Fan, C. (2024). A machine learning prediction model of adult obstructive sleep apnea based on systematically evaluated common clinical biochemical indicators. Nature and Science of Sleep, 413-428.

İlhan, H. O., & Bilgin, G. (2017). Sleep stage classification via ensemble and conventional machine learning methods using single channel EEG signals. Int. J. Intell. Syst. Appl. Eng, 5(4), 174-184.

Jarchi, D., Andreu-Perez, J., Kiani, M., Vysata, O., Kuchynka, J., Prochazka, A., & Sanei, S. (2020). Recognition of patient groups with sleep related disorders using bio-signal processing and deep learning. Sensors, 20(9), 2594.

Javeed, A., Berglund, J. S., Dallora, A. L., Saleem, M. A., & Anderberg, P. (2023). Predictive power of XGBoost_BiLSTM model: a machine-learning approach for accurate sleep apnea detection using electronic health data. International Journal of Computational Intelligence Systems, 16(1), 188.

Jiménez-García, J., García, M., Gutiérrez-Tobal, G. C., Kheirandish-Gozal, L., Vaquerizo-Villar, F., Álvarez, D., ... & Hornero, R. (2022). A 2D convolutional neural network to detect sleep apnea in children using airflow and oximetry. Computers in Biology and Medicine, 147, 105784.

Kandukuri, U. R., Prakash, A. J., Patro, K. K., Neelapu, B. C., Tadeusiewicz, R., & Pławiak, P. (2023). Constant Q-transform-based deep learning architecture for detection of obstructive sleep apnea. International Journal of Applied Mathematics and Computer Science, 33(3).

Kim, T., Kim, J. W., & Lee, K. (2018). Detection of sleep disordered breathing severity using acoustic biomarker and machine learning techniques. Biomedical engineering online, 17, 1-19.

Koda, T., Sakamoto, T., Wu, S., Okumura, S., Taki, H., Hamada, S., ... & Chin, K. (2022). Comparison of machine learning and non-machine learning methods for the sleep apnea detection using millimeter-wave radar. IEICE Communications Express, 11(6), 355-360.

Korkalainen, H., Aakko, J., Nikkonen, S., Kainulainen, S., Leino, A., Duce, B., ... & Leppänen, T. (2019). Accurate deep learning-based sleep staging in a clinical population with suspected obstructive sleep apnea. IEEE journal of biomedical and health informatics, 24(7), 2073-2081.

Lee, Y. H., Jeon, S., Auh, Q. S., & Chung, E. J. (2024). Automatic prediction of obstructive sleep apnea in patients with temporomandibular disorder based on multidata and machine learning. Scientific Reports, 14(1), 19362.

Leppänen, T., Myllymaa, S., Kulkas, A., & Töyräs, J. (2021). Beyond the apnea–hypopnea index: alternative diagnostic parameters and machine learning solutions for estimation of sleep apnea severity. Sleep, 44(9), zsab134.

Liu, K., Geng, S., Shen, P., Zhao, L., Zhou, P., & Liu, W. (2024). Development and application of a machine learning-based predictive model for obstructive sleep apnea screening. Frontiers in big Data, 7, 1353469.

Liu, M. H., Chien, S. Y., Wu, Y. L., Sun, T. H., Huang, C. S., Hsu, K. C., & Hang, L. W. (2024). EfficientNet-based machine learning architecture for sleep apnea identification in clinical single-lead ECG signal data sets. BioMedical Engineering OnLine, 23(1), 57.

Ma, B., Wu, Z., Li, S., Benton, R., Li, D., Huang, Y., ... & Huang, J. (2020). Development of a support vector machine learning and smart phone Internet of Things-based architecture for real-time sleep apnea diagnosis. BMC Medical Informatics and Decision Making, 20, 1-13.

Ma, E. Y., Kim, J. W., Lee, Y., Cho, S. W., Kim, H., & Kim, J. K. (2021). Combined unsupervised-supervised machine learning for phenotyping complex diseases with its application to obstructive sleep apnea. Scientific Reports, 11(1), 4457.

Mandeville, R., Sedghamiz, H., Mansfield, P., Sheean, G., Studer, C., Cordice, D., ... & Koola, J. (2024). Deep learning enhanced transmembranous electromyograph y in the diagnosis of sleep apnea. BMCneuroscience, 2 5(1), 80.

Mencar, C., Gallo, C., Mantero, M., Tarsia, P., Carpagnano, G. E., Foschino Barbaro, M. P., & Lacedonia, D. (2020). Application of machine learning to predict obstructive sleep apnea syndrome severity. Health informatics journal, 26(1), 298-317.

Mousavi, S., Afghah, F., & Acharya, U. R. (2019). SleepEEGNet: Automated sleep stage scoring with sequence to sequence deep learning approach. PloS one, 14(5), e0216456.

Mukherjee, D., Dhar, K., Schwenker, F., & Sarkar, R. (2021). Ensemble of deep learning models for sleep apnea detection: an experimental study. Sensors, 21(1 6), 5425.

Padovano, D., Martinez-Rodrigo, A., Pastor, J. M., Rieta, J. J., & Alcaraz, R. (2025). Deep Learning and Recurrence Information Analysis for the Automatic Detection of Obstructive Sleep Apnea. Applied Sciences, 15(1).

Panda, N. R., Paramanik, S., Raut, P. K., & Bhuyan, R. (2025). Prediction of sleep disorders using Novel decision support neutrosophic based machine learning models. Neutrosophic Sets and Systems, 82, 303-320.

Park, M. J., Choi, J. H., Kim, S. Y., & Ha, T. K. (2024). A deep learning algorithm model to automatically score and grade obstructive sleep apnea in adult polysomnography. Digital Health, 10,2055207624129 1707.

Pépin, J. L., Letesson, C., Le-Dong, N. N., Dedave, A., Denison, S., Cuthbert, V., ... & Gozal, D. (2020). Assessment of mandibular movement monitoring with machine learning analysis for the diagnosis of obstructive sleep apnea. JAMA network open, 3(1), e1919657-e1919657.

Rajawat, A. S., Rawat, R., Barhanpurkar, K., Shaw, R. N., & Ghosh, A. (2021). Sleep Apnea detection using contact-based and non-contact-based using deep learning methods. Computationally Intelligent Systems and their Applications, 87-103.

Retamales, G., Gavidia, M. E., Bausch, B., Montanari, A. N., Husch, A., & Goncalves, J. (2024). Towards automatic home-based sleep apnea estimation using deep learning. npj Digital Medicine, 7(1), 144.

Salsone, M., Quattrone, A., Vescio, B., Ferini-Strambi, L., & Quattrone, A. (2022). A machine learning approach for detecting idiopathic REM sleep behavior disorder. Diagnostics, 12(11), 2689.

Setiawan, F., & Lin, C. W. (2022). A deep learning framework for automatic sleep apnea classification based on empirical mode decomposition derived from single-lead electrocardiogram. Life, 12(10), 1509.

Shi, Y., Zhang, Y., Cao, Z., Ma, L., Yuan, Y., Niu, X., ... & Ren, X. (2023). Application and interpretation of machine learning models in predicting the risk of severe obstructive sleep apnea in adults. BMC Medical Informatics and Decision Making, 23(1), 230.

Stretch, R., Ryden, A., Fung, C. H., Martires, J., Liu, S., Balasubramanian, V., ... & Zeidler, M. R. (2019). Predicting nondiagnostic home sleep apnea tests using machine learning. Journal of Clinical Sleep Medicine, 15(11), 1599-1608.

Su, Z., Kumar, S., Tavolara, T. E., Gurcan, M. N., Segal, S., & Niazi, M. K. K. (2023, April). Predicting obstructive sleep apnea severity from craniofacial images using ensemble machine learning models. In Medical Imaging 2023: ComputerAidedDiagnosis (Vol. 12465, pp. 644-649). SPIE.

Tsai, C. Y., Liu, W. T., Lin, Y. T., Lin, S. Y., Houghton, R., Hsu, W. H., ... & Majumdar, A. (2022). Machine learning approaches for screening the risk of obstructive sleep apnea in the Taiwan population based on body profile. Informatics for Health and Social Care, 47(4), 373-388.

Tuncer, S. A., Akılotu, B., & Toraman, S. (2019). A deep learning-based decision support system for diagnosis of OSAS using PTT signals. Medical hypotheses, 127, 15-22.

Yook, S., Kim, D., Gupte, C., Joo, E. Y., & Kim, H. (2024). Deep learning of sleep apnea-hypopnea events for accurate classification of obstructive sleep apnea and determination of clinical severity. Sleep Medicine, 114, 211-219.

Yue, H., Lin, Y., Wu, Y., Wang, Y., Li, Y., Guo, X., ... & Lei, W. (2021). Deep learning for diagnosis and classification of obstructive sleep apnea: A nasal airflowbased multiresolution residual network. Nature and Science of Sleep, 361-373.

Zhang, Y., Zhou, L., Zhu, S., Zhou, Y., Wang, Z., Ma, L., ... & Shi, Y. (2025). Deep Learning for Obstructive Sleep Apnea Detection and Severity Assessment: A Multimodal Signals Fusion Multiscale Transformer Model. Nature and Science of Sleep, 1-15.

Zovko, K., Sadowski, Y., Perković, T., Šolić, P., Pavlinac Dodig, I., Pecotić, R., & Đogaš, Z. (2025). Advanced Data Framework for Sleep Medicine Applications: Machine Learning-Based Detection of Sleep Apnea Events. Applied Sciences, 15(1), 376.