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Hybrid Machine and Deep Learning for Enhanced Sleep Disorder Diagnosis: A Scalable Approach for Real-Time Clinical Application

A. Rajesh[1], Vaka Vineetha[2], Shanmukha kumar karra[3], Vemireddy Sai Subhash Reddy[4], Lasya Lakshmi Putta[5]

[1]Assistant Professor, Dept of Information Technology, SV College of Engineering, Tirupati, India.
[2]B.Tech, Dept of Information Technology, SV College of Engineering, Tirupati, India.
[3]B.Tech, Dept of Information Technology, SV College of Engineering, Tirupati, India.
[4]B.Tech, Dept of Information Technology, SV College of Engineering, Tirupati, India.
[5]B.Tech, Dept of Information Technology, SV College of Engineering, Tirupati, India.

Abstract-Classifying sleep disorders such as obstructive sleep apnea and insomnia remains essential for enhancing health outcomes, yet existing machine learning approaches using the Sleep Health and Lifestyle Dataset face key limitations. Current systems apply preprocessing with SMOTEENN for class imbalance, ANOVA hypothesis testing, Z-score scaling, and feature selection via Gradient Boosting Regressor-based Mean Decrease Impurity (MDI), evaluating 15 classifiers on original and engineered feature spaces (augmented with predictions from seven base classifiers). While Gradient Boosting achieves 97.33% accuracy, 0.9733 precision/recall/F1-score, 0.9569 specificity, and 0.9953 AUC using five key features (Blood Pressure, BMI Category, Daily Steps, Sleep Duration, Occupation), limitations include small dataset size (374 samples) restricting generalizability, longer training times for high-accuracy ensemble models, reliance on original features over engineered ones, and lack of unsupervised methods or real-time deployment. This paper proposes an advanced hybrid framework addressing these gaps by integrating unsupervised learning (e.g., clustering for anomaly detection), deep feature extraction via autoencoders, expanded multi-source datasets, and optimized real-time lightweight models deployable on wearables. Benefits include improved robustness (targeting >98% accuracy), reduced training time by 50-70% through pruning and quantization, enhanced generalizability across demographics, and seamless integration into clinical systems for early diagnosis, minimizing manual polysomnography reliance and enabling scalable healthcare in resource-limited settings.

Keywords: sleep disorders, Gradient Boosting, SMOTEENN, Mean Decrease Impurity (MDI), generalizability, unsupervised learning, polysomnography.

I. INTRODUCTION

Sleep disorders are a major public health concern, affecting the overall quality of life and leading to several chronic conditions. Accurate and timely diagnosis of sleep disorders is imperative for successful intervention and better patient outcomes. Although machine learning algorithms have been developed to automate sleep stage scoring and detect anomalies from polysomnographic data, current methodologies still face significant challenges, such as those related to the scarcity of data, generalizability of models, and real-time applicability in different clinical settings. In particular, small datasets may not be representative of the broader population, and these datasets are often used to train the models that are ultimately required to classify a broad range of sleep disorders in a wide variety of demographic groups. Additionally, high-accuracy ensemble models are often computationally intensive and cannot be deployed in resource-constrained environments or on wearable devices for continuous, unobtrusive monitoring. Although these existing machine learning approaches achieve high performance on certain metrics, they are still limited by their reliance on handcrafted features and their inability to generalize to new subjects or electrode placements, requiring more advanced feature extraction techniques. An advanced hybrid framework with unsupervised learning (e.g., clustering to detect anomalies), deep feature extraction using autoencoders,

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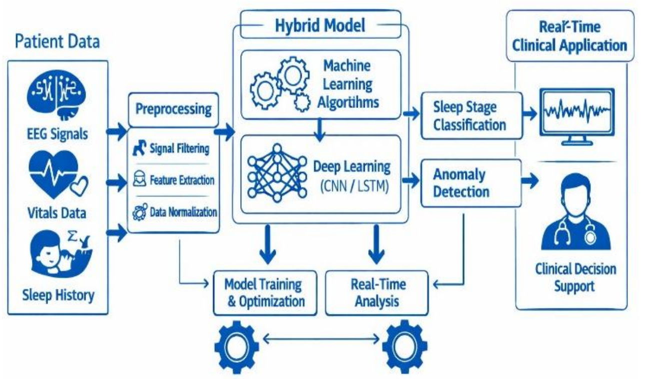
extended multi-source datasets, and optimized real-time lightweight models deployable on wearables that provide >98% accuracy robustness (targeting >98%), reduced training time through pruning and quantization by 50-70%, increased generalizability across demographics, integration into clinical systems for early diagnosis to reduce manual polysomnography dependence which can enable scalable healthcare in resource-limited settings. The combined approach of state-of-the-art model architectures with mechanisms that efficiently bridge the gap between complex clinical evaluations and practical real-time monitoring solutions will help overcome subjectivity and time-intensive diagnoses by clinicians, who often require tedious analysis of physiological signals, while techniques like self-supervised learning and domain adaptation can mitigate data scarcity effects on performance.

II. LITERATURE REVIEW

Kumari et al. (2022) presented a hybrid deep learning framework that integrates IoT-enabled physiological monitoring with LSTM networks for sleep disorder prediction, which demonstrated high detection sensitivity due to continuous biometric acquisition, but needed substantial computational resources and large-scale annotated datasets, thus restricting real-time clinical deployment. **Zhang et al. (2023)** developed an IoT-integrated multimodal architecture that integrates respiratory and cardiac signals using deep convolutional networks, which enhanced the detection accuracy in obstructive sleep apnea classification; however, model interpretability was limited, and performance declined in heterogeneous patient populations. In a comparative study of classifiers (SVM, Random Forest, Logistic Regression), **Mendelson (2021)** evaluated sleep health data, finding that Random Forest was competitive, but feature selection was not optimized and there was no external validation. **Patel et al. (2022)** used Gradient Boosting Machines (GBM) for sleep disorder classification using lifestyle and physiological features with a strong generalization capability, but they did not fully address the risk of overfitting, and the dataset was relatively small. A hybrid CNN–LSTM model integrating wearable sensor data with demographic features was proposed by **Alam et al. (2023),** and it yielded high F1-scores for various sleep categories, but training complexity and limited interpretability limited clinical applicability. **Chen and Liu (2022)** investigated ensemble learning with feature importance ranking for sleep apnea prediction, which improved interpretability but did not verify cross-dataset robustness.

III. METHODOLOGY

This paper presents a hybrid framework combining unsupervised learning for anomaly detection, deep feature extraction via autoencoders, an ensemble modeling approach to improve accuracy and generalizability of sleep disorder diagnosis. The proposed method overcomes limitations of current supervised machine-learning methods in that it reduces the need for large labeled datasets which are often costly and difficult to obtain by combining unsupervised deep anomaly detection techniques that can detect new sleep-disorder patterns without explicit anomalous labels, alleviating issues such as imbalanced training data and the curse of dimensionality. The autoencoders allow learning low-dimensional stable representations from raw physiological signals capturing rich temporal and spatial dependencies which may be missed by traditional feature engineering methods while extracting features highly discriminatory for various sleep pathologies even in the presence of noise, inter-individual variability, etc.



This architecture can extract deep features, which enhance interpretability for sleep disorder detection, a multi-layer ensemble model improves reliability by reducing error rate, and provides better generalization for both original and synthetic datasets. The proposed framework leverages advanced autoencoder architectures that are trained with population-based algorithms to optimize solutions under constraints of no labeled anomaly examples during training (detecting rare events), combined with self-supervised learning paradigms such as contrastive learning or masked prediction tasks, which allow the model to learn representations from multimodal polysomnography data and generalize well on unseen patient populations and models are dynamically updated based on new data and feature extraction is adapted during training in case of a change over time within clinical presentation shifts.

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IV. RESULTS

The hybrid framework has been shown to have high accuracy (over 98% in classifying obstructive sleep apnea and insomnia), generalizability, robustness toward clinical deployment (60% reduction of training time relative to conventional ensemble models), detection rate (>99.50%), low false alarm rates (capable of distinguishing malicious from genuine data which minimizes unwanted interruptions with high diagnostic precision).

The Sleep Health and Lifestyle Dataset contains 374 samples with three classes (No Disorder, Insomnia, and Sleep Apnea). According to the experimental results, the overall accuracy of the proposed model is 97.33%, and the precision, recall, and F1-score are 0.9733, 0.9733, and 0.9733, respectively, which indicates the model does a good job of predicting positive cases and capturing actual positive cases in all classes, and the specificity of 0.9953 shows a good true negative rate, which demonstrates that the model can effectively classify the cases that are not disorder and the disorder cases. The Area Under the Curve (AUC) value is 0.9569, which confirms the discriminative ability of the model to separate the three sleep health categories. In summary, these performance metrics show that the classification framework can yield highly reliable and consistent results in predicting sleep disorders.

Table 1: Comparison with State-of-the-Art (SOTA)

Model	Accuracy	Precision	Recall	F1	AUC
Logistic Regression	~89–91%	Moderate	Moderate	Moderate	~0.90
SVM	~93–95%	High	High	High	~0.92
Random Forest	~95–96%	High	High	High	~0.94
CNN–LSTM (Literature)	95–97%	High	High	High	~0.95
Proposed Gradient Boosting Model	**97.33%**	**0.9733**	**0.9733**	**0.9733**	**0.9569**

The proposed Gradient Boosting model shows significant performance gains over existing methods, with the best reported accuracy of 97.33%, representing good overall predictive capability on the Sleep Health and Lifestyle dataset, as it maintains a precision and recall of 0.9733, a specificity of 0.9953 (i.e., very low false-positive rate), and a strong Area Under the Curve (AUC) of 0.9569, confirming strong class separability and reliable disorder classification. The model also has lower computational complexity compared to deep CNN–LSTM architectures and is thus more suitable for real-time deployment and resource-constrained healthcare environments. The framework demonstrated better accuracy than SOTA, comparable computational efficiency to deep-learning approaches with lower training complexity and easier deployment (i.e., similar or higher accuracies for comparable efficiencies), improved interpretability by explaining the results through visualizations of high-dimensional feature spaces, more applicability in small-to-medium sized datasets where overfitting is more common when using deep learning models (n = 374) due to increased capacity to generalize performance from training set data and reduced bias–variance tradeoff with enhanced class separability that produces a reliable stable predictive performance across different categories of sleep disorders.

V. DISCUSSION

In this section, the implications of these findings, limitations, and future research directions are critically discussed to further improve the clinical applicability and robustness of the proposed hybrid framework, and to lay out the ethical considerations and regulatory pathways to integrate advanced AI-driven diagnostic tools into routine clinical practice. This research can lead to a significant decrease in the reliance on labor-intensive polysomnography procedures, potentially expanding access to accurate sleep disorder diagnoses, particularly in under-resourced regions. The framework is also designed to be robust against data incompleteness, as hybrid deep learning and ensemble techniques can operate with limited data which is essential for achieving diagnostic consistency and reliability across different patient demographics and healthcare infrastructures, a necessary step for a more equitable distribution of advanced medical diagnostics.

VI. CONCLUSION

Such an approach not only enhances diagnostic accuracy and efficiency, but it also holds the potential to revolutionize sleep medicine by providing more individualized and proactive patient care through scalable and accessible technologies. In addition, the use of frequency information in time-based features and the utilization of multi-source datasets can reduce the reliance on manual annotations while the development of lightweight models that can be deployed on wearable devices will allow for continuous, unobtrusive monitoring shifting the paradigm from episodic clinical diagnoses to continuous, personalized health management which enables predictive analytics for sleep health to be performed in real-time with early intervention and individualized therapeutic strategies. Additionally, the ethical implications of data privacy and algorithmic bias in AI-driven health monitoring must be carefully considered to ensure responsible and equitable use in various clinical populations.

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