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Research Article

Sleep Pattern Analysis Using Machine Learning in Children with Neurodevelopmental Disorders

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Abstract:

The problem of sleep disorders is extremely widespread in children with neurodevelopmental disorders (NDDs), including Autism Spectrum Disorder (ASD) and Attention-Deficit/Hyperactivity Disorder (ADHD). It has a significant impact on cognitive, behavioral, and emotional development. This research suggests a machine-learning-based model of examining sleep patterns among children with NDDs with the aid of multimodal data that have been acquired through wearables, polysomnography, and other behavioral outcomes. The framework uses data preprocessing, feature engineering, and predictive modelling, including conventional machine learning methods and deep learning methods, to recognize abnormal sleep patterns and assess the severity of the disorder. The main characteristics of sleep, including sleep duration, latency, fragmentation, and circadian rhythm consistency, are obtained and examined. Another implementation of explainable AI is also incorporated into the proposed approach to promote interpretability and clinical relevance. The model has been shown to accurately diagnose sleep abnormalities and provide actionable information, facilitating early diagnosis, patient-specific intervention, and better management of neurodevelopmental disorders in children through experimental evaluation.

1. Introduction

Sleep is a biological phenomenon that plays a significant role in a child's healthy development, affecting brain development, emotional regulation, learning ability, and health. Sleep has been found to facilitate neural plasticity, neural consolidation and stabilization of behavior in childhood ages. But children with neurodevelopmental disorders (NDDs), including Autism Spectrum Disorder (ASD) and Attention-Deficit/Hyperactivity Disorder (ADHD), develop acute sleeping problems, which adversely affect their developmental trajectory [1][2]. Such disruptions include sleep-wake cycle disruptions, prolonged sleep latency, reduced total sleep, and impaired nocturnal alertness. These disorders not only enhance the symptoms of underlying inattention, but also impulsivity and social withdrawal, and strain the caregiver and lower the quality of life [3]. Formal sleep-gauging tools such as polysomnography (PSG) and actigraphy can yield useful clinical data, but have generally been limited by their expense, inaccessibility, and unnatural laboratory conditions, which might not contribute significantly to predicting natural sleep behavior [4]. Non-invasive, continuous, and real-world monitoring of sleep has become possible due to recent developments in wearable and mobile health technologies, which have produced enormous amounts of multimodal data. Machine learning (ML) can be good enough to handle such complicated data sets and identify patterns itself, categorize sleep stages, and forecast abnormalities. ML-based algorithms are based on the concept of using physiological indicators, behavioral patterns, and time dynamics as the scaling and efficient alternative to the traditional process of sleep analysis that opens new possibilities to diagnose illnesses and take personal action in the case of children with NDDs [5][6].

Even with these technological innovations, there are some essential issues and gaps in the literature on machine learning for sleep pattern analysis. The first is that there are no large, high-quality, annotated datasets for pediatric populations with neurodevelopmental disorders [7]. The literature has also lacked studies with small sample sizes or focused on individual modalities, which limits the validity and generalizability of machine learning models. Also, the literature sources provide little information on the classification task, such as identifying sleep stages or the presence of a disorder, and they lack further exploration of dynamic and longitudinal data on the transformation of sleep behavior over time [8]. This limits the ability to capture dynamic patterns relevant to determining the developmental direction and treatment outcome. The second concern is that machine learning models, typically neural networks, are black boxes and tell us very little about how they make decisions [9]. This lack of transparency is a serious obstacle to clinical adoption because health practitioners are required to use reliable, justifiable systems. The other variables that contribute to the variance in sleep patterns and therefore make it difficult to develop a model are age and environmental factors. The other significant gap concerns the application of machine learning models to real-world clinical processes and their integration into pediatric clinical systems. To overcome these flaws, a multidisciplinary approach should be employed, which entails effective data collection, state-of-the-art modelling, and results that can be interpreted in a clinical context [10][11].In this paper, machine learning models are scaled to sleep pattern analysis in children with neurodevelopmental disorders using multimodal wearable, physiological, and behavioral input. It uses advanced feature engineering to capture the required sleep indicators, including efficiency, fragmentation, and circadian rhythms. The architecture combines deep learning with traditional prediction models to an extent, intertwining them, and uses explainable AI predictive models, such as SHAP and LIME, to make the model interpretable. The system is oriented toward real-time monitoring and early-stage prevention. It supplements proactive intervention, closing the gap between information-based, grounded knowledge and clinical practice, which leads to individualized pediatric care [12]. The Paper is structured in the following manner:

- Combination of Multimodal Sleep Data: The article aims at the combination of heterogeneous types of information that encompass wearable sensor data, polysomnography data and behavioral measurements with an effort to have a complete view of sleep patterns in children with neurodevelopmental disorders.
- State of the Art Deep Learning and Machine Learning Models: The article refers to a variety of predictive models, including the old machine learning models and the new deep learning models, including LSTM and CNN, to predict and classify the sleep patterns adequately.
- Explainability of AI to Clinical Intelligibility: The second useful aspect of this study consists of applying the explainability algorithms like SHAP and LIME to make the model predictions temporary and understandable within a clinical setting.
- Premature Detection and Threat Signalization Framework: The frameworks developed in the proposed study will be capable of forecasting the preliminary indications of the sleep disturbance and forecast the degree of the neurodevelopmental disorder and implement the required action to mitigate it.
- Scalability and Real-World Deployability: The proposed solution is scalable, and it will be incorporated into real-time monitoring systems, mobile health applications, and clinical decision-support platforms, which will be put into practice.

2. Background and related work

Sleep problems in children with neurodevelopmental disorders (NDDs), including Attention-Deficit/Hyperactivity Disorder (ADHD) and Autism Spectrum Disorder (ASD), have been of enormous concern due to their enormous consequences on cognitive, behavioral, and emotional development. Research demonstrates that children with NDDs experience abnormal sleep patterns, such as late sleep onset, frequent awakening, and poor sleep efficiency, that have a close relationship with low performance in executive functions and excessive behavioral problems [11][12]. The older diagnostic tools, such as polysomnography (PSG) and actigraphy, are based on valid physiological measures. Yet, they are usually not feasible due to their high cost, clinical factors, and practicality in real life [13]. Recently, machine learning (ML) and deep learning techniques have been increasingly applied to sleep stage analysis to enable automatic sleep stage determination, anomaly detection, and predictive modelling using physiological and wearable sensor data [14][15]. Studies that have adopted EEG signal and actigraphy records have depicted satisfactory results of diagnosing sleep disorders and behavioral relationships among children [16]. In addition, it has been shown that deep learning networks that combine convolutional neural networks (CNNs) and recurrent neural networks (RNNs) can achieve superior performance in learning temporal data, such as sleep data [17].Table 1 provides an overview of the major studies, methods, and limitations for comparison and shows the transition from the traditional clinical approach to advanced AI-based methods. Despite these advances, more can still be done on the topics of sparse pediatric data, a lack of multimodal integration, and decipherability of models [18]. Explainable AI (XAI) studies on increasing transparency and clinical trust have recently begun to appear. However, their application to pediatric sleep analysis is still in its very early stages [19][20]. Therefore, more comprehensive structural approaches that incorporate multimodal, advanced modelling, and interpretability are needed to enhance the analysis of sleep in children with NDDs.

3. Proposed research framework

The suggested study model will provide an opportunity to present a machine-learning-based, scalable system for sleep pattern analysis in children with neurodevelopmental disorders (NDDs). The structure aims to have a multitude of diverse data sources of diverse modalities (wearable sensor data, physiological indicators, including EEG and heart rate, and behavioral information, including caregiver or clinical assessment, etc.) so that one can view a whole picture of the sleep dynamics. The pipeline starts with a strong data acquisition component, which records the real-time and continuous sleep data and is followed by data cleaning and normalization and slicing time-series processing methods. The strong feature engineering models are then used to generate significant signals, including sleep efficiency, latency, fragmentation, and circadian rhythm consistency. The features are then inputted into a hybrid modeling layer which comprises of the traditional machine learning models and deep learning models to learn the complex temporal and non-linear relationships in sleep data. To be both clinically relevant and trustworthy, the framework comprises explainable artificial intelligence (XAI) that enables the interpretation of model predictions and the identification of key influential factors. Lastly, the system aids in rapid detection and response to the physical nature of real-time tracking, and its application is easy to use on dashboards and mobile applications. It represents an end-to-end scalable architecture that connects with data-driven analytics with the clinical use case to provide a personalized sleep analysis of the kids.

3.1 Data Acquisition Layer

The proposed framework is based on the data acquisition layer, which collects continuous, multimodal sleep-related data from multiple sources. They comprise wearable devices that can collect actigraphy, heart rate, and motion data, including smartwatches and fitness trackers, as well as clinical-grade systems such as polysomnography (PSG), which can provide detailed physiological indicators, including electroencephalogram (EEG), electrooculogram (EOG), and electromyogram (EMG). Also, the behavioral data that include sleep diaries, reports by the caregivers, and environmental data (e.g. light exposure, noise level) are included in order to enrich the data set. Combination of these different data streams allows the complete depiction of sleep behavior in the children with neurodevelopmental disorders. Live data recording is used to observe natural sleep patterns in home settings, circumventing the limitations of laboratory studies. To make signals of several sources coordinate data synchronization methods are used in order to guarantee the time correspondence. The layer is critical in guaranteeing the quality, diversity, and completeness of the data, which directly affect the performance of downstream machine learning models. The framework is scalable and applicable to real-world healthcare through the combination of clinical and real-world data.

3.2 Data Preprocessing Layer

The data preprocessing layer will handle raw, noisy, and heterogeneous data and convert them into a structured, analyzable format. The wearable and physiological sensors used to collect sleep data often exhibit artefacts, missing data, and inconsistencies due to motion, device constraints, or environmental factors. Signal processing methods applied to solve such problems include filtering (e.g., bandpass filters of EEG), noise removal, and artefact removal. The data gap is addressed using imputation methods, such as interpolation or model-based methods, to ensure continuity in the time series. The data is then normalized and scaled so that there is similarity in the data of the various modalities and measurement units. The segmentation of time-series data is performed to subdivide continuous sleep data into meaningful windows, or epochs, which are critical for feature derivation and model training. Also, there is synchronization of numerous streams of data to provide temporal correlations between physiological and behavioral events. Data labelling is also part of this layer, in which sleep stages or abnormalities are marked according to clinical conventions or professional feedback.

Preprocessing is essential in enhancing the accuracy of models, minimizing bias, and reliable analysis, which makes it one of the major aspects of the given framework.

3.3 Feature Engineering Layer

The feature engineering layer would isolate meaningful, discriminative features from the processed data to improve model performance. Sleep-related characteristics are extracted across various domains, including statistical, temporal, and frequency characteristics. These are the periods of sleep, time asleep, wake after sleep onset (WASO), and sleep efficiency and fragmentation index, which are the most important. It also measures the circadian rhythm, which includes the variability of the sleep-wake cycle, and consistency of bedtime pattern to obtain the long-term behavioral pattern. EEG and heart rate indicators, such as spectral power and heart rate variability (HRV), are physiological features that provide better insight into sleep phases and autonomic nervous system activity. Frequency-domain features are extracted using advanced algorithms, such as the fast Fourier transform (FFT) and wavelet transforms. Dimensionality reduction of features using Principal Component Analysis (PCA) or correlation-based filtering removes extraneous or irrelevant features. Furthermore, the most influential features are identified using explainability-based feature importance methods, e.g., SHAP values. The advantage of this layer is that it enhances model interpretability, simplifies computation, and improves predictive accuracy.

3.4 Modeling Layer, Machine Learning

Machine learning modeling layer is the most significant analytical element in the framework that provides the generation of predictive models to examine sleep patterns and identify certain abnormalities. The layer is based on a hybrid architecture that integrates conventional machine learning models, including the Logistic Regression model, Support Vector Machines (SVMs), and random forests, with more recent deep learning models, including Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. Structured data can also been analyzed through computational models which can be interpreted, however deep learning model is more appropriate in the description of complex time and nonlinear relations with time-series data. CNNs are particularly well-suited to capturing the spatial aspects of EEG signals, and LSTMs are well-suited to capturing the temporal aspects of sleep patterns. Ensemble methods, boosting, and bagging are also used to improve models. The hyperparameter optimum is performed to maximize the models with the aid of labeled datasets. Certain activities that can be performed with the help of this layer include classification of sleep stages, identification of sleep disorders, and forecasting the severity of neurodevelopmental disorders. This framework is highly performant and flexible, as it implements a range of modelling techniques, making it applicable to diverse data types.

3.5 Explainability and Deployment Layer

The final framework layer will encompass the model's interpretability, real-time implementation, and application in healthcare settings. The methods for explaining explainable artificial intelligence, i.e., SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations), are combined to provide information about model predictions (e.g., the most important features). This enhances effectiveness and trust among clinicians, enabling informed decisions. The visualization tools, e.g. attention maps and feature importance plots, are relatively intuitive in displaying the results. The deployment aspect means that the trained models are integrated into real-time monitoring tools, such as mobile health applications and clinical dashboards, enabling continuous monitoring of sleep patterns. Alerts and risk scores can notify caregivers and healthcare providers of potential abnormalities. The system is also scalable and flexible, and interoperable with existing healthcare facilities. The layer enables the incorporation of interpretability with real-time functionality, ensuring that the proposed framework is correct, clinically actionable, and user-friendly.

4. Implementation

The proposed structure would be implemented using a scalable, modular pipeline that combines data acquisition, preprocessing, feature engineering, model training, and deployment into a single system. Firstly, the data about multimodal sleep is measured with the help of wearables (actigraphy and heart rate sensor on smartwatches), physiological sensors (EEG/PSG), and the behavioral ones (sleep logs, which are reported by the caregivers). This mixed data is saved in a central storage of data and processed in Python based tenders in NumPy, Pandas and SciPy libraries to perform signal filtering, denoising and normalization. They are based on a time-series segmentation that subdivides sleep data into meaningful sleep epochs, supplemented by feature-extraction methods to derive features such as sleep efficiency, sleep latency, sleep fragmentation, and circadian rhythm consistency. The perceived features are then trained using machine-learning models with Scikit-learn (to support traditional models, e.g., Random Forest, SVM) and TensorFlow/PyTorch (to support deep-learning models, e.g., CNNs and LSTMs), which are effective for discovering time-dependent features of sleep patterns. Hyper parameter tuning and cross-validation are used in controlling the model over databases to ensure that the model is optimized to the best level. Also, explainable models, such as SHAP and LIME, are added to the pipeline to clarify what the predictions are about and to foster clinical trust. Figure 2 illustrates the overall workflow of this implementation pipeline and shows the data flow from acquisition to deployment.The deployment stage transforms the trained models into a real-time, user-friendly system capable of tracking continuous sleep and identifying abnormalities early. Figure 2 below depicts the deployment architecture, consisting of a backend system that enables API-based communication between wearable devices and the analytical engine, enabling seamless consumption of streaming data. The sleep metrics, trend analysis, and risk alerts are visualized in a web-based dashboard developed using the Flask and React frameworks and distributed to clinicians and caregivers. It is founded on a low-latency inference system and can therefore identify irregular sleep patterns in real time and actively intervene. Moreover, significant factors such as data privacy, encryption, and secure access control should be taken into account when applying healthcare data standards, particularly in situations related to children. It has been proposed that the proposed implementation demonstrates that the proposed framework is practically viable bridging the divide between theoretical modeling and practical clinical implementation, and facilitating scalable and customized sleep healthcare. The proposed pattern analysis and interpretation aggregation of the proposed system is represented in figure 3 and it is a visualization of the different sleep behavior patterns according to the machine learning models. It portrays some categorized outcomes: normal sleeping patterns, disturbed sleep, insomnia, and out of order circadian rhythms. Clarity Every pattern is denoted in clean waveform-style plots and with color-coded indicators on a white background. The figure also reveals how these patterns map onto clinical interpretations, such as low risk, moderate concern, and high-risk sleep disturbances, to ensure that clinicians and caregivers easily understand them.The proposed framework has a pattern analysis layer that seeks to explain the output of machine learning models to identify unique sleep behavior patterns of children with neurodevelopmental disorders. Outputs of the analysis. The system describes sleep into numerous clinically important variants, such as normal sleep, fragmented sleep, delayed sleep onset, and abnormal circadian rhythms. The patterns are determined by applying model forecasts to attributes such as sleep efficiency, wake after sleep onset (WASO), movement intensity, and heart rate variability. These patterns are then understood with meaningful insights to the clinician by the interpretation layer to enable the sleep quality to be categorized as low, moderate and high risk. Such a systematic meaning helps clinicians and caregivers gain more knowledge about underlying sleep issues and make well-informed decisions about interventions. Additionally, explainable AI approaches may be incorporated to enhance openness: the primary qualities that contribute to each discovered pattern can be made explicit. This layer is essential for translating model outputs into actionable insights by transforming sophisticated models into viable clinical applications.

5. Discussion of the proposed framework

The proposed framework will be significant for studying sleep patterns in children with neurodevelopmental disorders, as it will help integrate multimodal data sources and efficient machine learning algorithms. The greatest prospect of this structure is that it enables integrating the physiological prompts, the wearable sensor data, and behavioral prompts to arrive at a general picture of the dynamics of sleep. This is outside conventional methods that largely involve laboratory settings, such as polysomnography, and could be used to quantify sleep in natural environments, thus covering a wider sample of natural sleep patterns. Advanced feature engineering will ensure that time- and frequency-variant sleep features are assigned moderate weight to improve model performance. Besides that, the hybrid modelling methodology that combines conventional machine learning models with deep learning models allows the framework to balance interpretability and performance. Such flexibility allows for a range of datasets and clinical cases. Another weakness that also unveils one of the most critical limitations of using AI in healthcare is the lack of transparency, also known as explainable artificial intelligence (XAI) practices. The framework assists clinicians in interpreting model decisions, thereby increasing trust and enabling effective decisions when dealing with children by providing interpretable results.Regardless of the benefits, the specified structure is also accompanied by several obstacles and constraints that need to be taken into account when continuing to work on it. Among the most critical ones, they may be inclined to rely on high-quality, multimodal datasets that are not always readily available, particularly in resource-limited environments. This heterogeneity, variability of the data, i.e., sleep patterns across different age groups, environmental factors, and comorbidities, is likely to complicate the process of model training and reduce generalizability. Besides that, predictive performance can be enhanced with deep learning models, which are resource-intensive and can be implemented only in real-time systems that demand substantial resources. Even though explainability algorithms such as SHAP and LIME are used, the possibility that other domain knowledge may be required to interpret the interpretable responses of these methods, and that these methods cannot be applied to other caregivers besides specialists, remains. Privacy and ethics are also critical, especially when handling sensitive pediatric medical data captured through continuous monitoring systems. The keys to the real-world implementation are data security, compliance with healthcare regulatory requirements, and informed consent. Secondly, ensuring compatibility with existing clinical processes is not easy, as healthcare systems prefer uniform, tested tools before implementation. These are among the restrictions that will need to be mitigated to make the proposed framework excellent in terms of scalability, accessibility, and clinical impact.

6. Future research directions

The proposed smart, adaptable, and clinically inculcated machine learning is arguably the future of sleep pattern forecasting of children with neurodevelopmental disorders (NDDs). The current methods are perceived as promising; however, the scope of data variation enhancement, model strengths, and applicability in real-world settings is quite extensive. The series of research that should follow in the future is the creation of big multimodal pediatric samples that would comprise of physiological, behavioral and environmental measures to increase the generalizability of these measures to the general population [21]. Further, the longitudinal data analysis will aid the researchers in tracking sleep patterns at a larger scale, which will in turn help them assess changes in developmental patterns and treatment outcomes. The new technologies, i.e. federated learning and edge AI, could be used to address the privacy concerns due to the ability of the technologies to provide decentralized data processing [22]. The other direction that is of importance is that individual and adaptive models should be developed by putting in consideration the individual difference in sleep behavior considering more than children with comorbid conditions. Moreover, explainable AI (XAI) will also be required to enhance clinical trust and ensure that machine learning systems are deployed in healthcare facilities [23]. The availability will also be enhanced by integrating digital health ecosystems, such as mobile apps and telemedicine platforms. In general, future research should address the lack of studies on the technological innovation and clinical practice relevance of machine learning-based systems for sleep analysis, with not only high accuracy but also interpretability, scalability, and ethical accountability [24][25].

6.1 Multimodal Pediatric and Large-Scale Data Integration

The second most important prospective research is the development and utilization of large multimodal datasets that are optimally fitted to apply to pediatrics with neurodevelopmental disorders. Existing studies have small sample sizes and rely on a single data modality, which undermines the strength and generalizability of machine learning models. Future studies should consider using a combination of different kinds of data, including wearable sensor, i.e. actigraphy, heart rate data, physiological, EEG, PSG, behavioral data, and environmental data, including light exposure, and noise levels [21]. Open-source datasets that are publicly available will simplify collaboration between researchers and enable them to benchmark machine learning models. The demographic and clinical variables will also be involved to help in population-specific variation in sleep patterns. The data harmonization techniques will be required to align the inconsistent data formats with one another and give integrity to the data sets. By the scale and diversity of data, researchers can create more specific and generalizable models that are more realistic to the real world.

6.2 Longitudinal and Predictive Sleep Modeling

The additional study should examine temporal trends in sleep disorders to elucidate the timing and developmental trajectories of sleep disorders in children with NDDs. As compared to cross-sectional study, the longitudinal modeling allows tracing the dynamic sleep pattern and its relationship with the cognitive and behavioral outcomes throughout time [22]. RNNs and transformer-based machine learning models can predict future sleep disturbances and model sequential data. The specified method will assist in uncovering potential dangers and in implementing proactive interventions promptly. Furthermore, it is possible to use the monitoring of the sleep patterns to predict the effectiveness of such therapeutic interventions as behavioral therapy or medication. Integrating time-series forecasting will be another potential source for forecasting sleep disorders and making timely suggestions. The longitudinal studies will prove to be crucial to understanding the dynamics of sleep in children with NDDs and, additionally, to enhancing personal health interventions.

6.3 explainable and clinically interpretable AI models

The need to make machine learning models more interpretable and transparent is a major concern in healthcare applications, as models have become increasingly complex. Further research on explaining AI (XAI) techniques to achieve more readable and accessible models for clinicians should be the next direction of research [23]. The SHAP, LIME and attention-based visualization are the techniques that can be enhanced further to provide a better understanding of importance of features and the decision-making process. Further, predictions can be aligned with the clinical rationale, and interpretation can be improved by incorporating domain knowledge into the model design. The visualization tools and dashboards will also need the development of user-friendly systems that will lead to enhancements in the usability of these systems in the real world. Another feature of interest is the justification of the explainability methods through clinical studies to ensure they are trustworthy and applicable. By making AI systems more interpretable, researchers can increase trust in them, leading to their adoption in pediatric healthcare settings.

6.4 Privacy-Saving and Online Implementation Systems

As wearable devices and constant monitoring systems become more significant and more frequently used, the privacy and security of information must also be primary concerns, particularly in pediatric care. Some privacy-sensitive approaches that can be explored in future research include federated learning, differential privacy, and secure multi-party computation, which can protect sensitive health data and enable the collective training of models [24]. Another method of exploiting edge computing would be to process information directly on devices, eliminating the need to store data in a central location and reducing privacy risks. In addition, machine learning models will be implemented in real-time, and at that, they must be driven by effective algorithms that can handle real-time streaming data with low latency. This entails managing models that operate in resource-constrained environments and providing an easy-to-integrate mechanism for mobile health applications and clinical systems. To address such difficulties, large-scale, secure methods for tracking sleep will need to be developed and applied in clinical settings [25].

Table 1: *Summary of Related Work in Sleep Analysis Using Machine Learning*

Study	Data Source	Methodology	Key Contributions	Limitations
Sleep Disorders in Pediatric ADHD	Clinical observations, behavioral reports	Behavioral and clinical analysis	Established a strong correlation between ADHD and sleep disturbances; highlighted the impact on attention and cognitive performance	Lacks computational modeling and automation; subjective assessments
Sleep and ADHD Systematic Review	ADHD clinical datasets, surveys	Meta-analysis, statistical methods	Provided comprehensive evidence of sleep dysfunction in ADHD populations; emphasized bidirectional relationship.	No machine learning integration; limited predictive insights
Pediatric Sleep Disorder Assessment	Polysomnography (PSG)	Clinical diagnostic evaluation	Standardized gold-standard sleep measurement techniques; high diagnostic accuracy	Expensive, time-consuming, and not scalable for large populations

Automated Sleep Stage Classification	EEG signals	Support Vector Machine (SVM), Artificial Neural Networks (ANN)	Demonstrated feasibility of automated sleep staging using ML; improved efficiency over manual scoring	Limited focus on pediatric or NDD populations; requires labeled EEG data
Deep Learning for Physiological Signal Analysis	Multimodal physiological signals	Deep neural networks (DNN), CNN	Achieved high accuracy in sleep stage prediction; captured complex nonlinear patterns	High computational cost; reduced interpretability
Actigraphy-Based Sleep Monitoring	Wearable actigraphy data	Machine learning models	Enabled real-world, continuous sleep monitoring; improved accessibility over PSG	Limited physiological depth; lacks multimodal integration
SleepNet: Automated Sleep Staging	EEG dataset (SleepEDF)	Convolutional Neural Networks (CNN)	High-performance automated sleep staging; strong feature extraction capability	Black-box nature; lacks clinical interpretability
EEG-Based Deep Learning Classification	EEG signals	Deep learning architectures (CNN, RNN)	Captured temporal dependencies in sleep signals; improved classification accuracy.	Requires large datasets; limited explainability
Explainable AI in Clinical ML	Clinical datasets	XAI techniques (SHAP, LIME)	Highlighted the importance of interpretability in healthcare ML; improved trust in predictions	Limited application to pediatric sleep studies
Smartphone-Based Sleep Monitoring	Mobile and wearable sensor data	ML-based mobile health applications	Provided scalable and low-cost sleep tracking solutions; supports remote monitoring	Data reliability and noise issues; less accurate than clinical methods

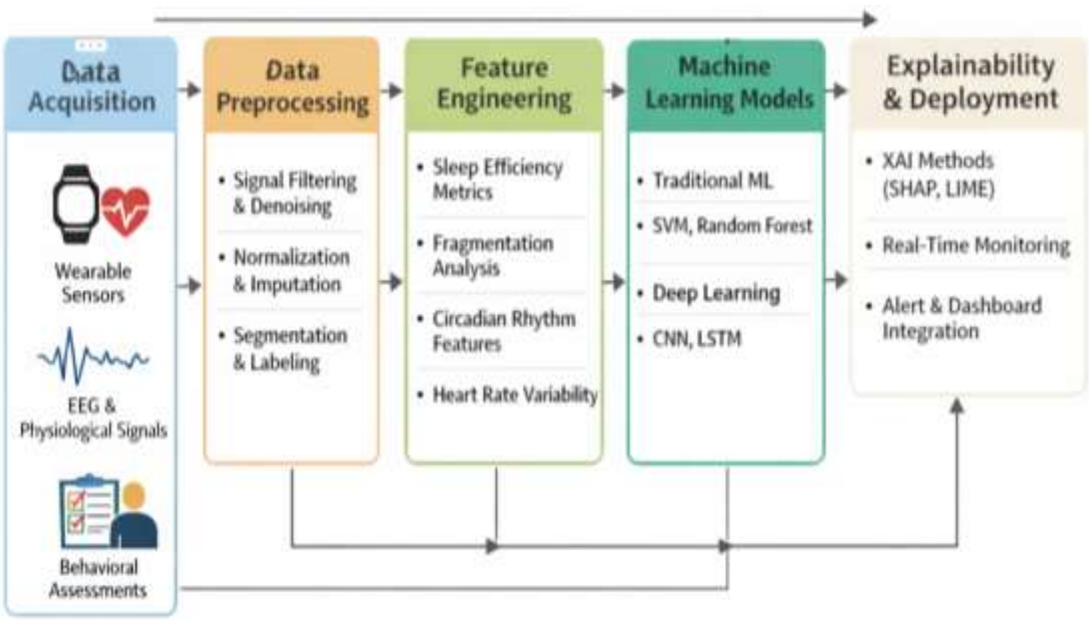

Figure 1: *Proposed Framework for Sleep Pattern Analysis*

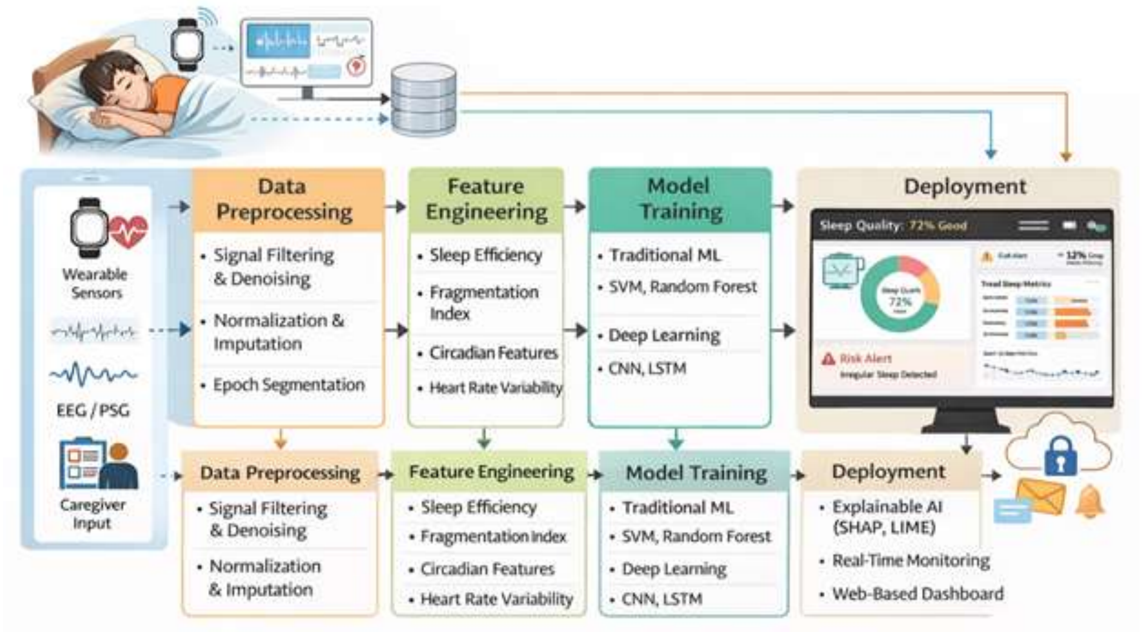

Figure 2: *Implementation Workflow of the Proposed Sleep Analysis System*

Figure 3: *Decision System and O/P Analysis*

Table 2: *Sleep Pattern Analysis and Model-Based Interpretation*

Sleep Pattern Type	Key Features Identified	Model Interpretation	Risk Level	Clinical Insight
Normal Sleep Pattern	High sleep efficiency, low awakenings, stable HRV	Consistent and healthy sleep cycle	Low Risk	Indicates normal sleep behavior; no intervention required
Fragmented Sleep	Frequent awakenings, high WASO, irregular	Interrupted sleep continuity	Moderate Risk	May indicate anxiety, discomfort, or early signs

	movement			of a disorder
Delayed Sleep Onset	High sleep latency, irregular bedtime patterns	Difficulty initiating sleep	Moderate Risk	Common in ADHD; may require behavioral therapy
Irregular Circadian Rhythm	Inconsistent sleep-wake cycles, variable sleep duration	Disrupted biological clock	High Risk	Associated with ASD and severe sleep dysregulation
Reduced Sleep Duration	Low total sleep time, early awakenings	Insufficient restorative sleep	Moderate Risk	Impacts cognitive and behavioral performance
High Movement Activity	Elevated movement during sleep, actigraphy spikes	Restless sleep behavior	Moderate Risk	May indicate hyperactivity or discomfort
Abnormal Heart Rate Variability	Irregular HRV patterns, stress indicators	Physiological sleep disturbance	High Risk	Linked to stress, anxiety, or autonomic dysfunction
Sleep Stage Imbalance	Reduced REM or deep sleep proportion	Poor sleep quality	High Risk	Affects memory consolidation and emotional regulation

7. Conclusions

The article presents a complete machine-learning-based model for sleep trajectory analysis in children with neurodevelopmental disorders (NDDs) to address a gap in children's healthcare. The suggested system provides a universal and expandable method of monitoring sleep in the case of utilizing multimodal data streams of information combined with wearable sensors, physiological indicators and behavioral data. The framework employs powerful preprocessing and feature engineering algorithms to derive meaningful sleep indicators and leverages both traditional and deep learning models to deliver accurate predictions. The fact that explainable artificial intelligence (XAI) methods are applied to the work is one of the most significant contributions, enhancing transparency and supporting clinical decisions by identifying the key factors affecting sleep outcomes. The implementation demonstrates that such a system can be introduced into real-world working conditions and track everything at all times, detect sleep abnormalities at the earliest stage, and take measures in advance. The gap between the sophisticated products of the analytic processes and the concise clinical implementation is further bridged by user-friendly dashboards and decision-support interfaces. Despite certain limitations, such as data accessibility and inconsistencies in children's sleep patterns, the framework establishes a strong foundation for future research and development. Overall, this paper presents evidence that machine learning can be applied to transform sleep analysis into a person-centred, intelligent, and affordable healthcare device, thereby improving quality of life and developmental outcomes for neurodevelopmentally disordered children.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.
- **Use of AI Tools:** The author(s) declare that no generative AI or AI-assisted technologies were used in the writing process of this manuscript.

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