International Journal of Engineering Science Invention Research & Development; Vol. 12, Issue 9, March 2026
www.ijesird.com, E-ISSN: 2349-6185

LEVERAGING ARTIFICIAL INTELLIGENCE FOR ACCURATE SLEEP DISORDER PREDICTION

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ABSTRACT:

AI is changing healthcare in a bunch of ways, especially with stuff like machine learning and deep learning to go through all that medical data. Natural language processing helps make sense of it too, I guess. In sleep medicine, there's just so much physiological information collected, way more than in other areas, which makes it perfect for trying out AI ideas. Good sleep matters a lot for staying healthy overall. But a ton of people have problems with it. Like, around one billion worldwide deal with obstructive sleep apnea, or at least that's what estimates say. Diagnosing everyone and getting them treated is tough though, because healthcare resources are limited everywhere. Sleep apnea leads to all sorts of health issues, and a lot of folks don't even know they have it. Even when they get diagnosed, treatment can be tricky for different reasons. AI might step in and fix some of that, it seems. It could make things easier for doctors. Beyond apnea, AI is useful for other sleep stuff too, like insomnia or hypersomnia, parasomnias, narcolepsy, that shift-work disorder, and periodic limb movements during sleep. All those get managed better with machine learning techniques. This paper looks at sleep health problems through AI and machine learning. It's kind of messy how these disorders overlap, but the tech helps analyse the data patterns. I think that's the main point here, though not everything is fully clear yet.

1. INTRODUCTION

Sleep is super important for keeping our bodies and minds in good shape, and when it's messed up with irregular patterns, it can throw off a lot of normal stuff we do every day. I think recent studies show that bad sleep really hits academic performance hard, like students who don't get enough might struggle more in school. The National Sleep Foundation has these surveys pointing out how sleep problems are getting more common, especially with about 40 percent of people who have medical issues also dealing with sleep disturbances or something like that. It makes me wonder why we don't pay more attention to tracking sleep better. Anyway, the American Academy of Sleep Medicine breaks sleep down into stages, like Wake, REM, and then NREM which splits into N1, N2, N3. Each one involves different brain waves and helps with restoring the body in various ways. Usually, to figure out these stages, experts look at EEG signals, which are these complex patterns analyzed in short chunks, say 30 seconds at a time. It's kind of fascinating how the brain shifts around during the night. Sleep studies help diagnose things like insomnia or obstructive sleep apnea, which is OSA, and even rarer ones such as REM sleep without atonia or idiopathic REM sleep behaviour disorder, iRBD. All these can lead to bigger health problems if not caught. In the last few years, AI has started playing a bigger role in making these diagnoses faster and more accurate, using machine learning on body signals and such. Deep learning techniques have given some really good results in sorting out sleep stages or spotting disorders. But a lot of the reviews out there just stick to classifying sleep stages or focus on one thing like apnea. It seems like there's not enough broad coverage on how AI is used across sleep research in general. So, this paper tries to fill that gap by looking at recent AI methods for both stage classification and disorder detection. It goes over the main models, what datasets people use, the physiological stuff they measure, and how they evaluate it all. Maybe from there, we can see some ideas for where to go next in this area, though I'm not totally sure what the biggest challenges are yet.

2. IMPORTANCE OF ARTIFICIAL INTELLIGENCE IN SLEEP STUDIES

Sleep studies take a whole night, you know, with technicians hooking people up to all these machines. They track brain waves through EEG, heart stuff with ECG, eye movements via EOG, muscles with EMG, and then breathing and oxygen too. It's a lot of data. After that, someone has to score the sleep stages by hand, and then a specialist looks it over for disorders. It works okay, but man, it takes forever, costs a bunch, and people mess up sometimes. Plus, different technicians might score things differently, so diagnoses aren't always the same. I think AI is starting to change that. Lately, machine learning and those neural networks are getting used more for figuring out sleep stages automatically and spotting disorders. They just look at the raw data from the monitors, no need for all that manual checking. Things get done quicker this way, and it seems more accurate, without the inconsistencies. Computing power is better now, and algorithms keep improving, so AI handles sleep staging pretty well, detects narcolepsy, even predicts sleep apnea. with AI taking over the boring repetitive parts, doctors can spend more time actually helping patients. It makes clinics run smoother, cuts down on expenses, gets results to people faster. That part feels important, though I'm not totally sure how widespread it is yet.

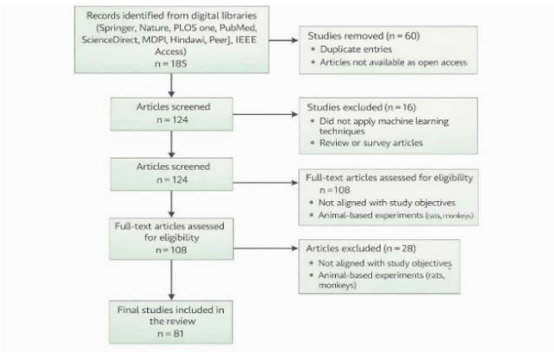

Fig.1 A PRISMA flow diagram was used present the article selection procedure.

3. METHODOLOGY

This study performed a systematic literature review to explore the role of artificial intelligence in sleep research, focusing mainly on sleep stage classification and sleep disorder detection. The review had three main phases: identifying relevant studies, extracting data, and analysing the findings. Researchers gathered articles from multiple databases using specific keywords. They excluded those that did not meet the inclusion criteria. In the end, 81 studies were chosen for in-depth analysis. The review looked at key aspects such as AI models, their performance, data sources, dataset sizes, physiological signals used, and the types of sleep disorders addressed. The research questions directed the analysis, starting with identifying the most common physiological parameters in AI-based sleep studies. These included EEG, EOG, EMG, ECG, respiratory airflow, and pulse oximetry, along with how they affected model performance. EEG appeared to be the most significant signal, and the review examined its impact carefully. Another research question investigated the size and distribution of datasets in AI sleep research. It looked at whether larger datasets led to better model performance. Some studies used small datasets, while others relied on large collections, making dataset size a crucial factor affecting the results. The review also evaluated which AI algorithms worked best for sleep stage classification and disorder detection. It compared commonly used models and their reported performance. Additionally, it analysed the evaluation methods in these studies, including validation techniques and performance metrics such as accuracy, F1-score, Cohen’s kappa, sensitivity, and specificity. A structured search strategy was put in place, covering several databases and using four main keyword groups: artificial intelligence in sleep studies, machine learning in sleep studies, sleep stage classification, and sleep disorder detection. The initial search resulted in 185 publications. After removing duplicates and excluding studies that were inaccessible, off-topic, or outside the selected time frame, 81 articles remained for final analysis. Among these, 52 focused on sleep stage classification and 29 on sleep disorder detection. This shows a stronger research emphasis on sleep staging. Overall, the review process effectively sifted through the literature and laid a clear foundation for analysis.

4. ARTIFICIAL INTELLIGENCE MODELS

The review identified 32 different AI models, with five being the most widely used. These five models are discussed below regarding their working principles, strengths, and limitations.

4.1. Convolutional Neural Network (CNN)

Convolutional Neural Networks are commonly used in image and signal classification tasks. They apply convolution and pooling layers to extract important features, followed by fully connected layers for classification. CNNs are very effective at learning complex patterns from data. However, they need large amounts of labelled data, significant computational resources, and standardized input sizes.

4.2. Recurrent Neural Network (RNN)

Recurrent Neural Networks are built for sequential data, such as time series and text.

Their feedback connections let them hold onto information from previous inputs, making them suitable for tasks that rely on temporal context. Despite this advantage, RNNs are challenging to train due to issues like vanishing and exploding gradients. They also require a lot of computational power.

4.3. Support Vector Machine (SVM)

Support Vector Machines are used for both classification and regression, especially in high-dimensional spaces or with limited data. By using kernel functions, SVMs create effective decision boundaries between classes. However, their performance drops with very large or noisy datasets, and training can become computationally expensive.

4.4. Long Short-Term Memory (LSTM)

Long Short-Term Memory networks are a type of RNN designed to capture long-term dependencies in sequential data. They use gated mechanisms to control information flow, which allows for better memory over extended sequences. Although LSTMs often perform better, they require significant computational resources and careful adjustment of parameters.

4.5. Random Forest (RF)

Random Forest is an ensemble learning method that combines several decision trees to improve prediction accuracy and reduce overfitting. It works well with incomplete data and is generally robust. However, the resulting models can be complex and hard to interpret, and using many trees increases computational costs.

5. RESULTS AND DISCUSSION

In this section, the extracted results are organized into five subsections. These focus on dataset size, physiological parameters, performance metrics, AI models used for sleep stage classification and disorder detection, and an overall summary. The research questions are addressed by looking at commonly used data sources and dataset scales, identifying key physiological signals for sleep analysis, highlighting popular AI models, and reviewing the evaluation metrics that measure model performance.

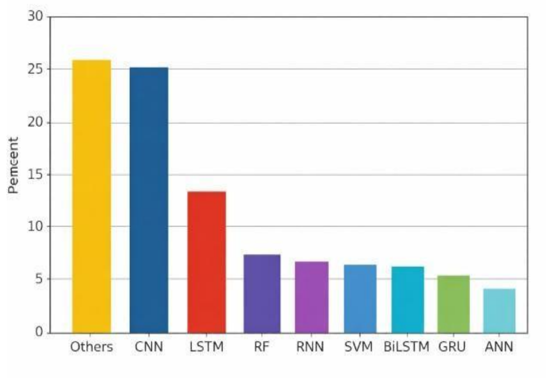

Fig.2 Top ten AI models.

6. FUTURE RESEARCH DIRECTIONS

Future studies should focus on more than just classifying sleep stages. They need to prioritize predicting and diagnosing sleep disorders like sleep apnea, insomnia, and restless leg syndrome. It's essential to improve how models work across different datasets for real-world clinical use. Using multimodal physiological data, such as EEG, heart rate, respiratory signals, and eye movements, can boost accuracy and reliability. Additionally, combining these systems with explainable AI methods will enhance transparency and trust, helping clinicians make better-informed decisions.

7. CONCLUSIONS

This review looks at the progress in artificial intelligence-based sleep research from 2016 to 2023. It focuses on sleep stage classification and sleep disorder detection. It examines physiological signals, training datasets, AI models, and methods for evaluating performance in this field. Most studies relied heavily on brain signals, specifically EEG. These were often paired with heart rate and respiratory data. The most commonly used sources included publicly available datasets from PhysioNet and data from universities and research institutions. Models based on neural networks, particularly CNN, RNN, and LSTM, were widely used and showed strong performance. Traditional methods like SVM and ensemble techniques were also frequently applied. Model evaluation primarily looked at metrics such as accuracy, precision, F1-score, sensitivity, and specificity. A key limitation of this review is the limited access to paid research articles due to financial constraints. This may have excluded some relevant studies. Despite this drawback, the review provides a clear overview of current trends, methods, and developments in AI-driven sleep research based on freely available literature.

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