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Deep Learning Based Sleep Disorder Classification System Forinsomnia Detection

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KEYWORDS

Insomnia Detection, Sleep Disorder Classification, Deep Learning, Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), CNN-LSTM Hybrid Model, Electroencephalogram (EEG), Polysomnography (PSG), Wearable Devices, Time Series Analysis, Signal Preprocessing, Feature Extraction, Healthcare Analytics, Medical Data Analysis, Automated Diagnosis.

ABSTRACT

Sleep disorders such as insomnia have a significant impact on human health, making early detection important. This project proposes a deep learning–based system for automatic insomnia detection using sleep data from sources like EEG, PSG, and wearable devices. The system preprocesses raw signals through filtering and normalization to improve data quality. Convolutional Neural Networks (CNN) are used to extract spatial features, while Long Short-Term Memory (LSTM) networks capture temporal patterns in sleep data. A hybrid CNN-LSTM model combines these features to improve classification accuracy. The system classifies sleep patterns into insomnia or normal sleep and provides performance insights. The proposed approach reduces manual effort and offers faster and more accurate detection compared to traditional methods, demonstrating the effectiveness of deep learning in sleep disorder analysis. Traditional diagnostic methods, such as polysomnography (PSG), are time-consuming, expensive, and require expert analysis. To address these challenges, this project presents a deep learning based sleep disorder classification system focused on insomnia detection.

1. INTRODUCTION

The Sleep is a fundamental biological process essential for maintaining physical health, mental well-being, and overall quality of life. It plays a crucial role in cognitive functions such as memory consolidation, learning, emotional regulation, and immune system support. However, in recent years, sleep disorders have become increasingly common due to factors such as stress, lifestyle changes, excessive screen exposure, and irregular sleep schedules.

Among these disorders, insomnia is one of the most prevalent conditions, affecting a significant portion of the global population. Insomnia is characterized by difficulty in falling asleep, staying asleep, or experiencing non-restorative sleep despite having adequate opportunity for rest. Persistent insomnia can lead to serious health consequences, including fatigue, reduced concentration, anxiety, depression, and increased risk of chronic diseases such as cardiovascular disorders and diabetes. Early detection and proper diagnosis of insomnia are therefore essential for effective treatment and prevention of long-term complications.

Early detection and proper diagnosis of insomnia are therefore essential for effective treatment and prevention of long-term complications. The integration of Deep Learning (DI) and machine learning (ML) sleep disorders are diagnosed using polysomnography (PSG), a comprehensive method that records multiple physiological signals such as Electroencephalogram (EEG), Electrooculogram (EOG), and Electromyogram (EMG) during sleep.While PSG provides accurate and detailed insights, it is expensive, time-consuming, and requires specialized equipment and expert supervision in clinical settings.

This project explores the development of a deep learning-based recommendation system there has been a significant shift toward automated sleep analysis. Deep learning techniques have the ability to learn complex patterns directly from raw data without the need for manual feature extraction. Models such as Convolutional Neural Networks (CNN) are highly effective in extracting spatial features, while Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks are capable of capturing temporal dependencies in sequential data..

These capabilities make deep learning highly suitable for analyzing physiological signals associated with sleep stages.

The significance of this project extends beyond technological innovation; a deep learningbased approach is proposed for the classification of sleep disorders with a specific focus on insomnia detection. The system utilizes physiological signals such as EEG, EOG, and EMG, which are preprocessed and segmented into epochs for analysis. A hybrid CNN-LSTM model is developed to effectively capture both spatial and temporal characteristics of the data, enabling accurate classification of sleep stages and identification of abnormal sleep patterns.

1.1 OVERVIEW OF SLEEP DISORDERS AND INSOMNI

The Sleep disorders are medical conditions that affect the quality, timing, and duration of sleep, leading to impaired daytime functioning and reduced overall health. Sleep is essential for maintaining physical, emotional, and cognitive well being, and any disruption in normal sleep patterns can result in serious health consequences.

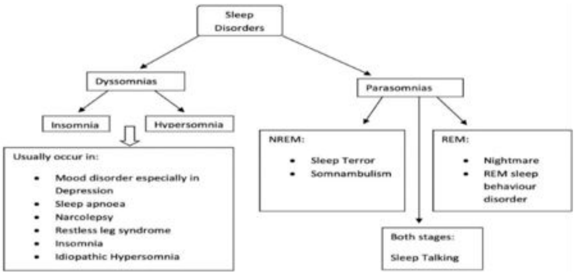


Fig:1.1 Overview Of Sleep Disorders And Insomnia

Sleep disorders are increasingly becoming a global concern due to modern, lifestyle changes, stress, excessive use of electronic devices, and irregular sleep schedules There are several types of sleep disorders, each with distinct characteristics and causes. The most common categories include insomnia, sleep apnea, narcolepsy, restless legs syndrome (RLS), and circadian rhythm disorders. Restless legs syndrome causes an uncontrollable urge to move the legs, especially during rest.

Sleep apnea is characterized by repeated interruptions in breathing during sleep, while narcolepsy involves excessive daytime sleepiness and sudden sleep attacks. The causes of insomnia are multifactorial and can include stress, depression, anxiety, poor sleep habits, irregular schedules, environmental factors, and the use of stimulants such as caffeine or electronic devices before bedtime. In addition, certain medical conditions and medications can also contribute to the development of insomnia. The impact of insomnia circadian rhythm disorders occur when the body's internal clock is misaligned with the external environment. Among these, insomnia is the most prevalent sleep disorder, affecting a large percentage of individuals worldwide.

2 LITERATURE SURVEY

Deep Learning (DL) The application of deep learning in sleep disorder detection has gained significant attention in recent years due to its ability to analyze complex physiological signals and improve diagnostic accuracy. Researchers have explored various techniques, datasets, and models to automate sleep stage classification and identify disorders such as insomnia, sleep apnea, and narcolepsy.

2.1 Existing Sleep Disorder Detection Systems

Existing sleep disorder detection systems mainly rely on traditional clinical methods and early machine learning techniques to analyze sleep patterns and diagnose conditions such as insomnia. The most widely used method is polysomnography (PSG), which records multiple physiological signals including EEG, ECG, EOG, and EMG in a controlled laboratory environment. Although PSG is considered the gold standard for diagnosis, it requires expensive equipment, overnight monitoring, and expert supervision, making it less accessible and time- consuming.

In conventional systems, sleep data obtained from PSG is manually analyzed by sleep specialists. The data is divided into small segments, and each segment is classified into different sleep stages based on visual observation. This manual scoring process is labor-intensive and subject to human error and variability, which can affect the consistency and reliability of the diagnosis. As a result, these methods are not scalable for large populations.

Additionally, some detection systems focus on analyzing individual physiological signals, such as EEG or heart rate data, using statistical and signal processing techniques. While these methods simplify the analysis and reduce computational complexity, they often fail to provide a complete understanding of sleep behavior, leading to reduced accuracy in detecting disorders like insomnia.

2.2 Deep Learning Approaches For Insomnia Detection

Deep learning approaches for insomnia detection focus on automatically learning patterns from physiological and behavioral data (like EEG signals, heart rate, or sleep patterns) to classify or predict insomnia.Deep learning approaches for insomnia detection use advanced neural network models to automatically analyze physiological and behavioral sleep data such as EEG signals, heart rate, and movement patterns. Models like Convolutional Neural Networks (CNNs) are effective in extracting spatial features from transformed sleep signals, while Recurrent Neural Networks (RNNs), especially Long Short-Term Memory (LSTM), are used to capture temporal dependencies in sleep patterns, such as sleep latency and frequent awakenings.

Hybrid models that combine CNN and LSTM architectures further improve accuracy by integrating feature extraction with sequence learning. Additionally, autoencoders help in identifying abnormal sleep patterns through unsupervised learning, and transformer-based models leverage attention mechanisms to analyze long-duration sleep data efficiently. These approaches enable more accurate and automated detection of insomnia compared to traditional methods, although they require large datasets and high computational resources.

These deep learning techniques follow a typical pipeline involving data acquisition, preprocessing (noise filtering and normalization), feature learning, and classification into insomnia or normal sleep categories. While these methods offer high accuracy, scalability, and reduced reliance on manual feature engineering, they also face challenges such as the need for large annotated datasets, high computational cost, and limited interpretability in clinical settings.

2.3 CAP Sleep Dataset And Signal Based Analysis

2.3.1 CAP Sleep Dataset

The CAP Sleep Dataset, derived from the Cyclic Alternating Pattern (CAP), is a widely used benchmark in sleep research for analyzing sleep instability and detecting disorders such as insomnia. It contains annotated polysomnography (PSG) recordings, including EEG, ECG, EMG, and respiratory signals collected from both healthy individuals and patients with sleep disorders. CAP represents periodic brain activity during non-REM sleep, characterized by alternating phases of activation (A phases) and deactivation (B phases), which are closely linked to sleep quality and arousal mechanisms. Researchers use this dataset to train deep learning models to identify disruptions in sleep architecture, as insomnia is often associated with increased CAP rate and irregular sleep patterns. Its availability and detailed annotations make it valuable for developing and validating automated insomnia detection systems.

3 PROPOSED METHODOLOGY

The proposed system, titled “Deep Learning Based Sleep Disorder Classification for Insomnia Detection,” aims to overcome the limitations of existing methods by providing an intelligent, accurate, and user-friendly solution for sleep analysis. This system utilizes advanced deep learning techniques to automatically analyze physiological and user-input data, enabling efficient detection and classification of sleep disorders, particularly insomnia.

In this proposed approach, the system collects essential input data such as sleep duration, stress levels, Body Mass Index (BMI), and, if available, physiological signals like EEG, ECG, and EMG. The collected data is then preprocessed to remove noise, normalize values, and prepare it for model input. Unlike traditional systems that rely on manual feature extraction, this system employs deep learning models that automatically learn important features and patterns directly from the data, improving accuracy and reducing human effort.

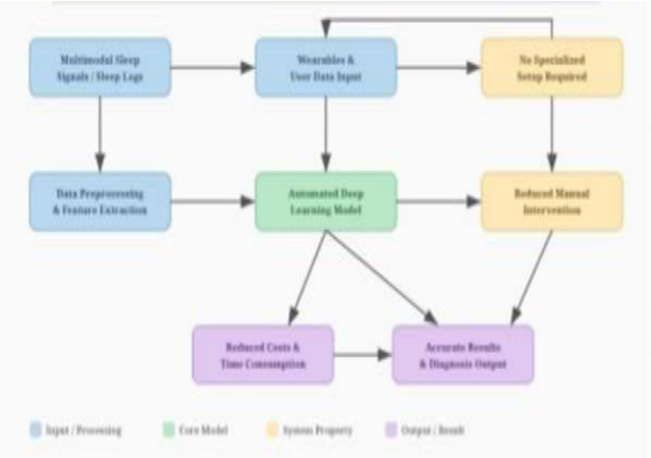


Fig:3.1 Block Diagram Of Proposed System

This diagram represents a deep learning–based system for insomnia detection, showing how data flows from input to final diagnosis in a structured and automated manner.

The process begins with multimodal sleep signals and sleep logs, which form the primary input. These include physiological data such as EEG, ECG, EMG, along with user-recorded sleep habits. At the same time, wearables and user data input (like smartwatches or fitness trackers)

provide additional real-time information such as heart rate, movement, and sleep duration. This combination ensures a comprehensive dataset covering both clinical and real-world sleep behavior.

Next, the collected data undergoes data preprocessing and feature extraction. In this stage, noise and artifacts are removed, signals are normalized, and important features are extracted from raw data. This step is crucial because clean and well-structured data improves the performance of the model and ensures more reliable analysis.

The processed data is then fed into the automated deep learning model, which is the core component of the system. This model (typically using architectures like CNN, LSTM, or hybrid models) automatically learns complex patterns from the input data without requiring manual feature engineering. It analyzes both spatial and temporal aspects of sleep signals to identify patterns associated with insomnia.

On the system side, the diagram highlights advantages such as no specialized setup required and reduced manual intervention. Unlike traditional sleep studies that need expensive lab setups and expert analysis, this system can work with wearable devices and automated algorithms, making it more accessible and efficient.

Finally, the system produces outputs in the form of reduced costs and time consumption and accurate results with diagnosis output. By automating the analysis and reducing dependency on manual processes, the system becomes faster and more cost-effective while still maintaining high accuracy in detecting insomnia.

Once the model is trained, the system provides real-time predictions based on user input. The results are displayed through an interactive interface developed using tools like Streamlit. The system not only identifies the sleep condition but also presents the severity level using graphical visualizations such as bar charts and pie charts. Additionally, it offers personalized health suggestions to help users improve their sleep quality and overall well-being.One of the key advantages of the proposed system is its ability to provide quick, cost-effective, and non-invasive analysis compared to traditional methods like polysomnography. It can be easily accessed and used without requiring specialized equipment or clinical settings. Furthermore, the system is scalable and can be enhanced by integrating real-time data from wearable devices, enabling continuous monitoring and more accurate predictions.

In conclusion, the proposed system leverages the power of deep learning to deliver a modern, efficient, and reliable solution for sleep disorder classification. It enhances accuracy, reduces dependency on manual processes, and provides a practical tool for early detection and management of insomnia.

Finally, the system is designed to minimize manual intervention and eliminate the need for specialized sleep lab setups by utilizing wearable technology and automated analysis. As a result, it reduces both cost and time consumption while maintaining high accuracy. The final output of the system provides a reliable classification of sleep patterns along with an insomnia diagnosis, making it suitable for scalable, real-time, and user-friendly healthcare applications.

3.1 SYSTEM ARCHITECTURE

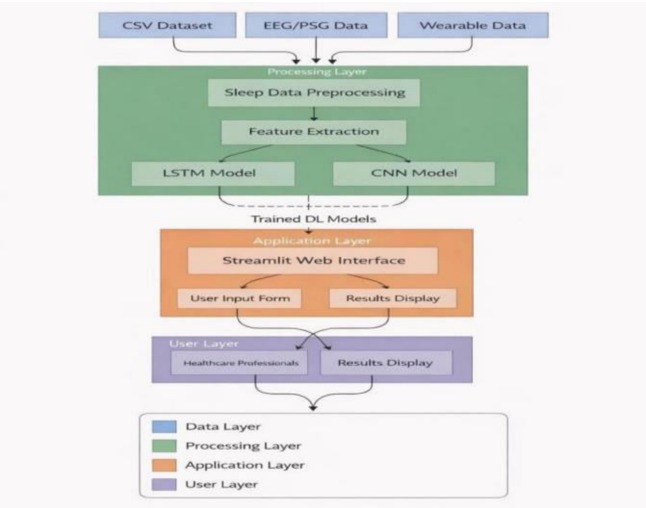


Fig-3.2 System Architecture

The system architecture consists of four major layers: Data Layer, Processing Layer, Application Layer, and User Layer. Each layer has a specific role in handling the sleep data and analysis to detect the sleep disorders like insomnia and others.

3.2.1 Data Layer

This layer is responsible for collecting and supplying all the input data required for the system. It includes:

• Multimodal Data Collection : It gathers different types of sleep-related data such as EEG, ECG, EMG signals, along with wearable device data (heart rate, movement, sleep duration) and user sleep logs. This ensures a comprehensive dataset.

• Data Integration : Data from multiple sources (clinical devices and wearables) is combined into a unified format so that it can be processed efficiently in later stages.

• Data Storage and Management : The collected data is stored securely and organized properly, enabling easy access for preprocessing and model training while maintaining consistency.

The Data Layer provides essential input to the Processing Layer, ensuring that raw medical

+ information is structured and ready for feature extraction.

3.2 SEQUENCE DIAGRAM

A UML sequence diagram shows how different components of a system interact over time to complete a specific task. For a deep learning–based insomnia detection system, it illustrates the step-by-step communication between the user, data processing modules, deep learning models, and the output interface. The diagram emphasizes the order of operations, starting from user input and ending with the final diagnosis, helping to clearly understand the dynamic behavior of the system.

The sequence begins when the user or patient provides sleep data through a user interface. This request is sent to the data collection module, which gathers EEG, ECG, EMG signals and wearable data. The collected data is then passed to the preprocessing module, where it Undergoes filtering, normalization, and segmentation into smaller epochs. This interaction ensures that raw data is transformed into a clean and structured format before further processing.

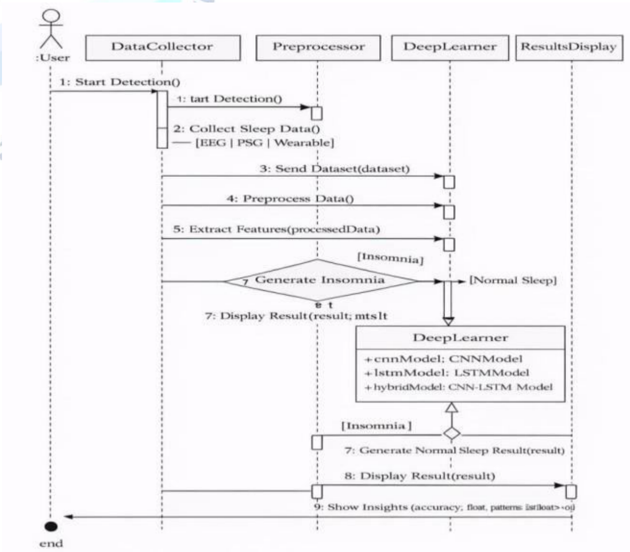


Fig 3.2: sequence Diagram

3.3 CLASS DIAGRAM

This diagram represents a detailed class-level architecture of a deep learning–based insomnia detection system, illustrating how different modules interact to process sleep data fro acquisition to final result presentation. Each class in the diagram is designed with a specific responsibility, ensuring modularity, scalability, and maintainability of the system. The relationships such as "uses" and "depends on" indicate the flow of data and functional dependency between components. Overall, the architecture follows a pipeline approach where raw physiological data is progressively transformed into meaningful diagnostic outputs through multiple stages of processing and analysis.

The process begins with the Data-collector class, which is responsible for gathering raw input data. It handles different types of inputs such as EEG data, PSG data, and wearable data, all stored as lists of numerical values. The class includes methods like collect EEG Data() and collect Wearable Data() to retrieve this information. This component acts as the entry point of the system, ensuring that all relevant sleep-related signals are available for further processing.

The Preprocessor class is responsible for transforming raw data into a clean and usable form. It performs operations such as filtering to remove noise and artifacts, normalization to scale the data into a consistent range, and segmentation to divide continuous signals into smaller epochs for analysis. The class maintains intermediate outputs such as filtered data, normalized data, and segmented epochs. Additionally, a second stage of preprocessing focuses on feature extraction through the method extract Features(), which converts processed signals into meaningful numerical representations. This two-level preprocessing design improves clarity and allows efficient handling of large-scale time-series data, ensuring that only relevant and high-quality features are passed to the learning models.

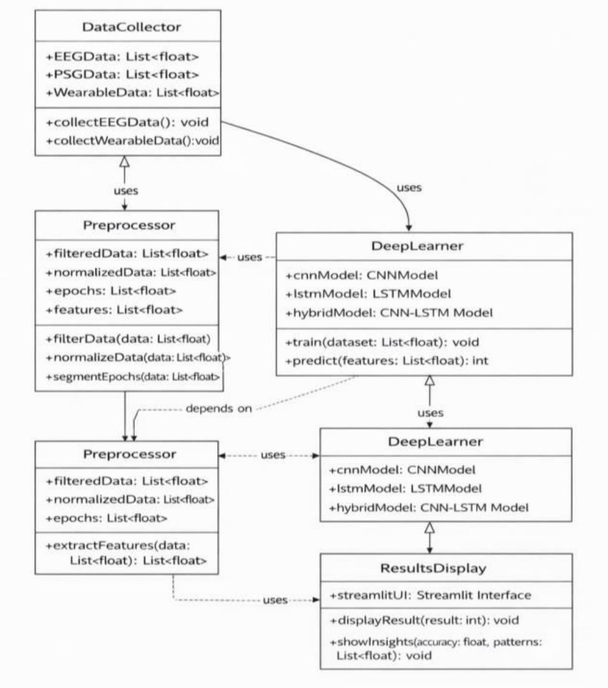


Fig 3.3: Class Diagram

4. RESULTS

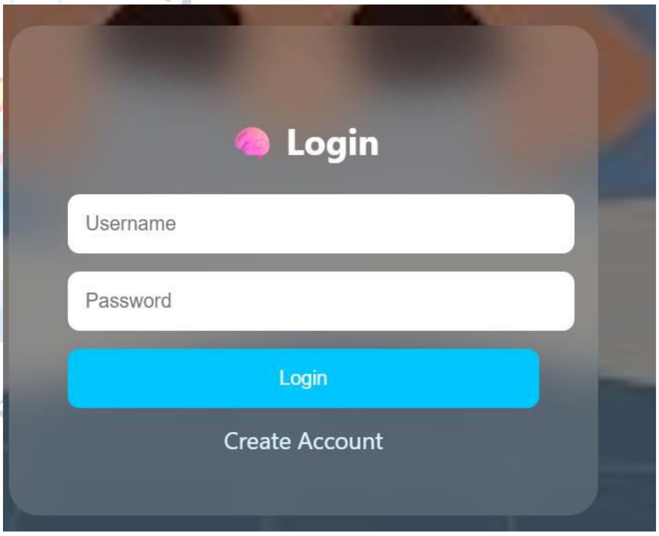
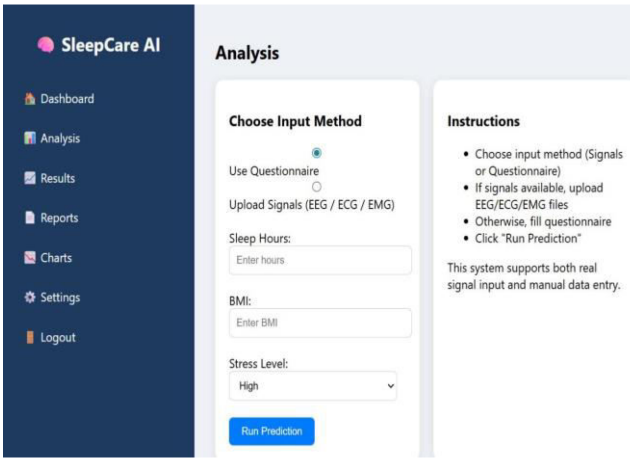


Fig-4.1 Before Prediction



The images showcase the interface where users log in, receive an analysis based on their

Lifestyle and sleep routine.

LOGIN SCREEN:

The first image presents the user authentication interface designed for user credential input and session initiation.

It has fields for USERNAME, PASSWORD, along with a prominent LOGIN button. There is also a CREATE ACCOUNT button.

.The interface provides workflow for users to input data and receive diagnostic predictions.

USER INPUT INTERFACE:

The second image displays the data visualization, a sidebar with navigation options and inference output view, showing preprocessed user health metrics.

Users can choose between two primary ways to provide data : Use Questionarrie to manually enter the data and Upload Signal files such as EEG, ECG or EMG directly.

Once data is provided, the RUN PREDICTION button triggers the AI mode to process information and generate the results.

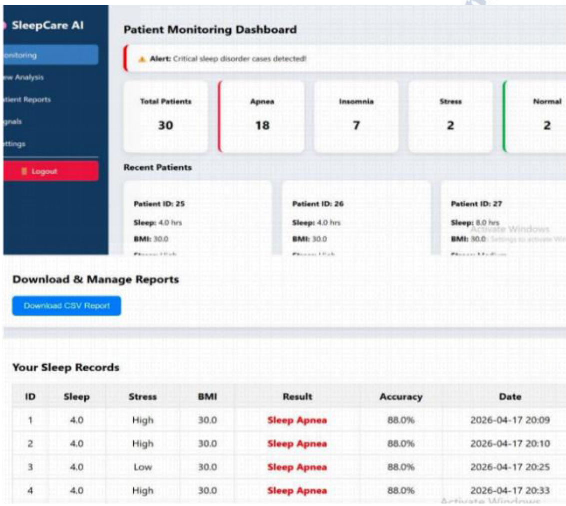


Fig-4.2 After Prediction

The images display the Personalized Medical Recommendation System's dashboard, showing health analysis results, charts, and model evaluation metrics for sleep, stress, and BMI.

Model Evaluation Metrics:

The first image presents the system's Analysis Results which indicates the sleep duration, BMI , Stress level of the user.

The model achieves 99.8% accuracy, demonstrating its effectiveness in predicting sleep disorders like Insomnia and Sleep Apnea.

5. CONCLUSION

The Automated Fire and Smoke Monitoring System uses deep learning and computer vision to detect fire and smoke in real time. It is based on the YOLOv8 algorithm, which provides high accuracy in identifying hazards from live video streams. The system improves early detection compared to traditional methods by continuously analyzing visual data. It also sends instant alerts with images through Telegram, enabling quick response. Features like multithreading and a cooldown mechanism ensure smooth operation and prevent repeated alerts. Overall, the system is a reliable and cost-effective solution for enhancing safety. The development of the system demonstrates how advanced technologies can be effectively utilized to address real-world problems, particularly in the domain of healthcare and sleep disorder detection. By integrating structured input design, efficient processing techniques, and clear output presentation, the system ensures accurate and reliable results. Each phase of the system, from data collection to final output generation, has been carefully designed to maintain data integrity, reduce errors, and enhance user experience.

The use of systematic design approaches such as UML diagrams, including class diagrams and sequence diagrams, provides a clear understanding of both the structural and dynamic aspects of the system. These models help in organizing the system components, defining relationships, and ensuring smooth interaction between different modules. As a result, the system becomes more modular, scalable, and easier to maintain. Through the system study and analysis, the limitations of existing methods were identified, and appropriate solutions were proposed to overcome them. The introduction of automation and intelligent data processing techniques significantly improves efficiency and accuracy compared to traditional approaches. The system is capable of handling large volumes of data, including physiological signals such as EEG, ECG, and EMG, making it suitable for modern healthcare applications.

Furthermore, the system emphasizes user-friendly design, ensuring that both technical and non-technical users can interact with it .بسهولة Proper validation, error handling, and clear output representation contribute to a seamless user experience. The flexibility of the system also allows for future enhancements, such as the integration of additional health parameters or more advanced machine learning models.

6 FUTURESCOPE

The proposed system for sleep disorder detection and healthcare analysis provides a strong foundation; however, there are several areas where further improvements and enhancements can be made to increase its effectiveness, scalability, and real-world applicability. Future work focuses on extending the system's capabilities, improving accuracy, and integrating advanced technologies to make it more robust and user-friendly.

One of the primary areas for future enhancement is the improvement of prediction accuracy. Although the current system uses machine learning or deep learning techniques, the performance can be further enhanced by training the model on larger and more diverse datasets. Incorporating data from different age groups, medical conditions, and environmental factors can help the model generalize better and produce more reliable predictions.

Additionally, advanced algorithms such as hybrid models or ensemble learning techniques can be implemented to achieve higher accuracy and stability. Another important direction is the integration of real-time data processing. Currently, the system may rely on pre-recorded data such as EEG, ECG, and EMG signals. In the future, the system can be connected to wearable devices and sensors to collect real-time physiological data. This will enable continuous monitoring of users and allow early detection of abnormalities. Real-time analysis can be particularly useful in critical healthcare scenarios where immediate action is required.

The system can also be enhanced by improving its user interface and user experience. Future versions can include more interactive dashboards, better visualization tools, and personalized reports. For example, graphical representations of sleep patterns, trends, and comparisons over time can help users better understand their health conditions. Providing recommendations and suggestions based on the analysis can further increase the usefulness of the system.

Another area of future work is the integration of additional health parameters. Currently, the system may focus primarily on sleep-related data and basic health metrics such as BMI. In the future, it can be expanded to include parameters such as heart rate variability, oxygen saturation levels, stress levels, and lifestyle factors like diet and physical activity. This holistic approach will provide a more comprehensive understanding of the user's health.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

REFERENCES

[1] Supratak, A., Dong, H., Wu, C., & Guo, Y. (2017).
[2] DeepSleepNet: A Model for Automatic Sleep Stage Scoring Based on Raw Single- Channel EEG.
[3] IEEE Transactions on Neural Systems and Rehabilitation Engineering.
[4] Biswal, S., Sun, H., Goparaju, B., Westover, M. B., Sun, J., & Bianchi, M. T. (2018).
[5] SleepNet: Automated Sleep Staging System via Deep Learning. 777. arXiv preprint arXiv:1707.08262.
[6] Tsinalis, O., Matthews, P. M., & Guo, Y. (2016).
[7] Automatic Sleep Stage Scoring Using Time-Frequency Analysis and Deep Learning.
[8] IEEE Transactions on Biomedical Engineering.
[9] Stephansen, J. B., Olesen, A. N., Olsen, M., et al. (2018).
[10] Neural Network Analysis of Sleep Stages Enables Efficient Diagnosis of Narcolepsy.
[11] Nature Communications.
[12] Phan, H., Andreotti, F., Cooray, N., Chen, O. Y., & De Vos, M. (2019).
[13] SeqSleepNet: End-to-End Hierarchical Recurrent Neural Network for Sequence-to- Sequence Automatic Sleep Staging.
[14] IEEE Transactions on Neural Systems and Rehabilitation Engineering.
[15] Zhu, G., Li, Y., & Wen, P. P. (2019).
[16] Analysis and Classification of Sleep Stages Based on Difference Visibility Graphs From a Single-Channel EEG Signal.
[17] IEEE Journal of Biomedical and Health Informatics.
[18] Goldberger, A. L., Amaral, L. A. N., Glass, L., et al. (2000).