Undergraduate Conference on Intelligent Computing and Systems (UCICS 2025)
26-27 February, 2025; Varendra University, Rajshahi, Bangladesh

A Proposed Model for Early Detection of Sleep Disorders Through Brain Wave Monitoring During Daily Activities Across Professions

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***Abstract*—Sleep disorders have a significant impact on mental and physical health worldwide, and they are closely related to various professions and daily activities. This study represents and analyzes brain wave patterns using EEG signals to identify and monitor sleep related problems. Brain waves such as alpha, beta, theta, delta and gamma bands can vary among different individuals based on different daily activities. The proposed model identifies special feature from EEG signals and stores time-varying temporal features. Theoretically, the hybrid model will be able to find out the initial stage or symptom of sleeping disorder like insomnia, obstruct sleep apnea and provide timely warnings to individuals at risk. The model achieved an accuracy of 87.3% in classifying sleep disorders.**

***Index Terms*—Brain-waves, EEG, CNN, LSTM, Spacial Analysis , Activity Log**

I. Introduction

In today's world, various professions experience different levels of mental and physical stress, which significantly impact brain wave patterns. Different daily activities, routines, and habits of a person are the resultants of various brain wave patterns like alpha, beta, and theta waves. These wave patterns are closely associated with sleep patterns. A sleep pattern refers to the natural sequence and structure of sleep stages that occur during a typical sleep cycle. It describes how any human being progresses through different stages of sleep over the course of a night, including the duration, timing and quality of these states.

Light sleep (Stage N1) is considered a transition between wakefulness and sleep which commonly lasts for a few minutes. Deeper light sleep (Stage N2) slows heart rate and drops body temperature. Deep sleep is related to creativity and deep resting state which is also known as slow-wave sleep (SWS). Delta waves occurs in Non Rapid Eye Movement stage 3 which is associated with physical and mental recovery and growth reflecting the deep relaxation state of the body.Gamma waves are most active during REM sleep, the stage associated with vivid dreams and emotional processing. Gamma activity during sleep is linked to the processing and storage of memories [1].

This study explores how stress and other activities of daily life and other disorders can transform a healthy brain cell into a cell affected by sleep deprivation and how quickly the wave bands changes from one another. This can be the key to identify the abnormal behavior of the brain wave from normal patterns and compare them with those individuals suffering who are from sleep disorders like apnea, insomnia, narcolepsy and so on. This document aims to provide an important preventive way to improve mental health and improve sleep quality in various professional groups. It is important to recognize the impact on physical and mental health at an early stage. Detection of sleeping disorders prevent long-term health issues such as insomnia or sleep deprivation and also improved quality of life. Objective of the study to analyze how profession and daily routines influence brain wave activity particular in the alpha, beta, theta ,delta and gamma wave bands.

II. Related Work

Y. Pei, and W. Luo, (2024) *Wave Sleep:An interpretable network for expert-like sleep staging.* arXiv preprint . In their study, they propose WaveSleepNet, an interpretable neural network for sleep staging that mimics expert reasoning by identifying characteristic wave prototypes corresponding to different sleep stages, aiming to enhance the clinical acceptance of automated sleep staging tools [2]. E. Fernandez-Blanco, D. Rivero, A. Pazos, (2021) published a paper, " *Ensemble of convolutional neural networks on heterogeneous signals for sleep stage scoring"* .arXiv preprint . The study explores the use of multiple signals, including EEG and electromyography, for sleep stage scoring, demonstrating that combining heterogeneous signals in an ensemble of convolutional neural networks improves classification accuracy [3]. M. Sohaib, A. Ghaffer, etc published a paper*"Automated analysis of sleeping study parameters using signal processing and arti-*

ficial intelligence", they identify patterns sleep stages through EEG signals is a cumbersome task as these signals can easily be contaminated through artifacts [4]. There are also work on sleeping disorders. but they does not talk about how to prevent a disorder before people have it. B. Gerstenlagr, J. M. Slowik, published a paper*"Sleep study"* where they analyze the sleep through polysomnogram and identify sleeping disorder [5]. But using CNN, LSTM, and brain waves can prevent a sleep disorder. By that, preventive measures and interventions are explored based on brain wave analysis for managing sleep disorders.

III. Methodology

A. Data Collection

Electroencephalography (EEG) [6] data was utilized to analyze brain wave patterns corresponding to different professions and daily activities. The dataset was sourced from publicly available repositories such as PhysioNet and Kaggle, containing labeled EEG signals sampled at frequencies between 128 Hz and 256 Hz. The dataset includes segments associated with normal daily activities (e.g., working, exercising) and sleep patterns (e.g., normal sleep, insomnia, apnea).

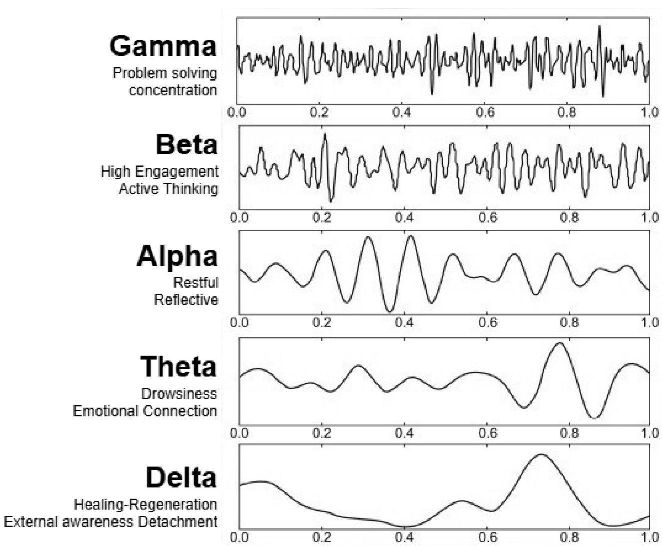


Fig. 1: Standard brain waves spectrograms for different activities [7]

B. Preprocessing

The EEG signals underwent multiple preprocessing steps to ensure high-quality data for analysis:

1) Noise Removal: Band-pass filtering (0.5–50 Hz) was applied to eliminate artifacts and retain relevant brain wave frequencies, including delta, theta, alpha, beta, and gamma bands.

2) Normalization: Signal amplitudes were normalized to reduce subject to subject variability.

3) Segmentation: The continuous EEG recordings were divided into non-overlapping segments that are crucial for temporal analysis.

4) Feature Extraction: Proposed model's features were extracted from both the time domain (mean, standard deviation) and frequency domain (Fast Fourier Transform, wavelet coefficients). For this expermimental setup, we proposed Fast Fourier Transform (FFT).

C. Hybrid Model Architecture

A hybrid model consists of CNN-LSTM architecture was proposed to analyze spatial patterns and temporal dependencies in the EEG data. Collection of EEG data based on different professions and activities by using standardized equipment and protocol was performed by gathering survey data online and offline. Redundant filtering techniques were used to ensure tolerable data quality for the setup.

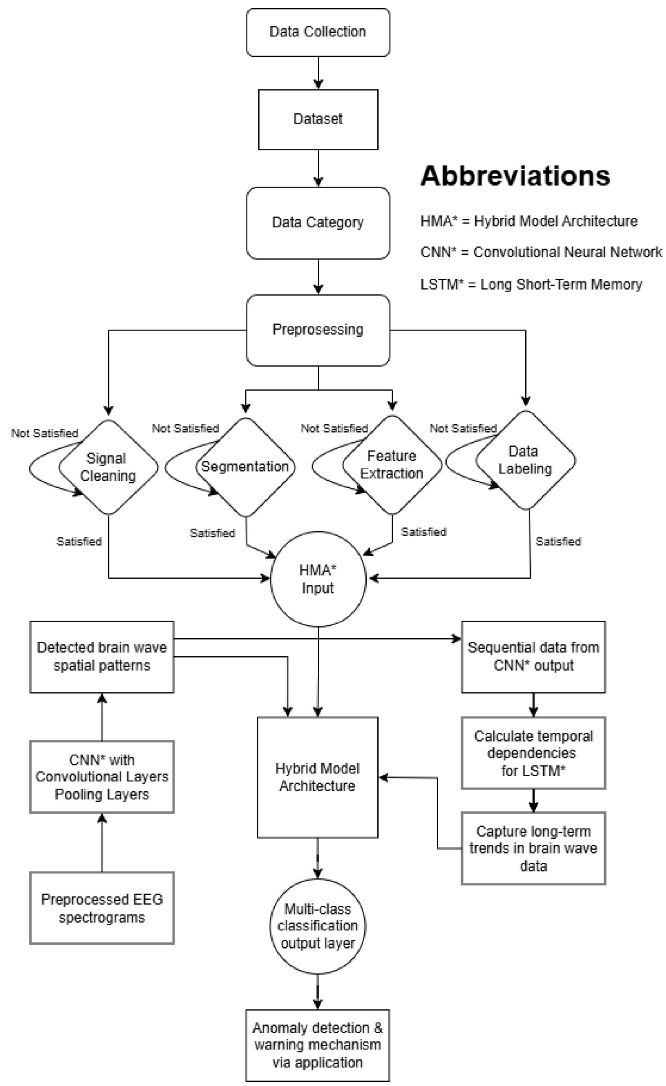


Fig. 2: Workflow of proposed methodology for early detection

CNN [8] was used to extract spatial features from EEG signals and reshaped into spectrograms. To form a fully connected layer, two convolutional layers with ReLU activation functions and max-pooling were prescribed. Finally LSTM [9] was proposed to introduce and learn temporal dependencies in the EEG data. A fully connected dense layer with softmax activation is proposed for multi-class classification or sigmoid activation for binary classification.

D. Training and Validation

Proposed dataset were deployed to spit into 70%-15%-15% subsets for training, validation and testing. A steady learning rate of 0.001 is proposed to prevent over-fitting with epoch values of 10.

E. Evaluation Metrics

Model performance is proposed to assess using the following metrics:

1) Accuracy: Percentage of correctly classified samples.

2) Precision, Recall and F1-Score: Metrics for evaluating classification performance.

3) Confusion Matrix: Visualization of predicted versus actual classes.

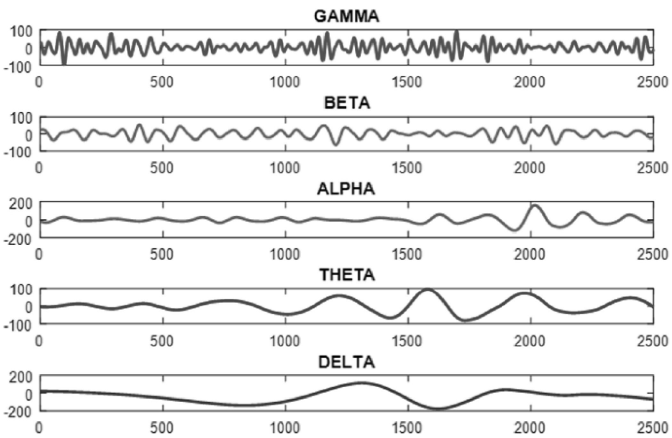


Fig. 3: Distorted brain waves for obstructive-sleep-apnea (early stage)

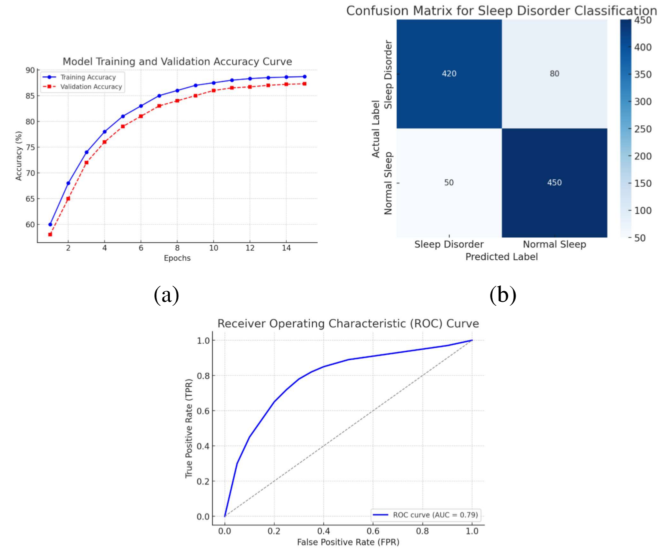
IV. Result & Discussion

By using CNN and LSTM, a hybrid model for sleep analysis can be developed. CNN is used to analyze spectrograms and EEG [10], EOG to identify differences between signals. This model will detect variations in wave signals to identify the unusual behavior in wave bands. Then it will compare these signals with brain waves of individuals from different professions and daily activities.

TABLE I: Model Performance Metrics for Sleep Disorder Classification Using CNN-LSTM

Metric	Value(%)
Accuracy	87.3
Precision	85.9
Recall	83.5
F1-Score	84.7

If those signals match with normal individuals, they will be considered as healthy. If someone's brain waves match any known sleep disorder patterns, that person will be classified



(a) (b)

(c)

Fig. 4: (a) Model Performance Metrics, (b) Confusion Matrix and (c) ROC Curve for Sleep Disorder Classification Using CNN-LSTM

as having a sleep disorder. If the brain waves do not match either normal or disordered patterns, the model will analyze which specific wave band is behaving abnormally, in which phase, and determine the possible disorder-related symptoms. After that the individuals will be observed for a long time with a prescribed set of rules and regulations that they must be followed. Then, their brain waves test will be conducted again. By doing this, the rate of sleeping-disordered individuals can be reduced, and sleeping-disorders may be prevented before the disorders start to develop. As the rate of worldwide sleeping disorder is continuously growing, this study can be prevalent in future to reduce sleeping disorders.

In cases of stress and anxiety, alpha waves do less activity leading to the reason of insomnia and difficultly in relaxation before sleep. In theta waves, abnormal patterns indicate a challenge in deep sleep and create problem to regenerate and heal which is a common issue for disputed sleep schedules. In cases of delta waves, it impacts on deep sleep quality. It is essential for physical and mental restoration. Considering beta waves, over activity during resting states related to increased mental activity and stress that hampered the early stage of sleep.

TABLE II: Confusion Matrix for Sleep Disorder Classification Using CNN-LSTM

Actual vs. Predicted	Sleep Disorder	Normal Sleep
Sleep disorder	420	80
Normal Sleep	50	450

EEG data [11] that were collected based on different professions and daily activities were analyzed. Here the behavior of different waves like alpha beta, theta, delta, gamma is also identified. The people who are involved with high stress work they show high beta wave that related with tiredness and concentration less CNN-LSTM hybrid model can identify the pattern of EEG data signal and they are successful. Performance metrics such as accuracy, precision, recall demonstrated the model's ability to extract both spatial and temporal features effectively using CNN to find patterns in space and LSTM to track changes over time was very helpful for analyzing EEG data that change with time but remember those data signal for future data analysis. Specific patterns in the EEG data ware related to early signs of sleeping disorders.

TABLE III: Global Research Findings on Sleep Disorders [12]

Group	Prevalence (%)	Common Factors/Issues
Children	34	Screen time, irregular routines, stress, insomnia, parasomnias.
Men	21.2	Obstructive Sleep Apnea (OSA).
Women	33.2	Insomnia, Restless Leg Syndrome (RLS), hormonal changes (menstruation, pregnancy, menopause).

From global research during the COVID-19 pandemic sleep disorders become increasingly prevalent in Bangladesh across various demonography. The summary is given in table 4 [13], [14] .

TABLE IV: Prevalence of Sleep Disorders in Bangladesh During COVID-19

Group	Prevalence(%)	Key Findings
General Population	45	Nearly half reported sleep problems during COVID-19.
Young Adults	35.7	Insomnia linked to stress and irregular routines.
Urban SlumDwellers	61.3	High prevalence of sleep issues; 34.5% faced both insomnia and anxiety.
Childrenwith Autism	66-86	High rate of sleep disturbances in children with autism.

These statistic highlight the widespread nature of sleep disorders both globally and with in Bangladesh, underscoring the importance of addressing sleep health as public health priority.Because of the importance of healthy sleep for human life, analysis of brain wave patterns across professions and daily activities was conducted.

V. Conclusion and Future Work

The analysis of sleep disorder across different profession and daily activities based on brain wave bands reveals significant impact of brain wave patterns on sleep health. Sleep disturbances affect a large number of population globally with the variation of children, men and women. The role of brain wave bands is very important to identify the improper signal. The abnormal patterns indicate the possibility of being sleep disorder person or possible to be a sleep disorder person in future physically hard working job show better delta and theta wave activity, though stress from occupational can disturb overall patterns. The most common and affected sleep disorder are insomnia obstructive sleep apnea, restless deg syndrome, parasomnia, hypersomnia. A large amount of adult and children's are affected by sleeping disorder. By analyzing brain waves (alpha, beta, theta, gamma, delta) based on different professions and daily activities, sleep disorders can be prevented. CNN, LSTM, and EEG will be used for this for research. This research will compare the normal brain wave, disordered brain wave with other peoples brain wave and find out his wave problem and suggest him different type of daily routine for better health. In the future, this idea will be applied to a large number of people, and will also try to find out the limitation of the research, such as, how much it can be prevented, what is the impact of this research on human health and aging.

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