International Research Journal of Education and Technology
Peer Reviewed Journal
ISSN 2581-7795

A HOLISTIC METHODOLOGY FOR CLASSIFICATION OF SLEEP STAGES WITH EEG SIGNALS

[1]Hariprasath P, [2]Pushparaj G,[3]Dr Harikumar R

[1,2] *Student, Department of Electronics and Communication Engineering*

[3]*Professor, Department of Electronics and Communication Engineering*

[1,2,3] *Bannari Amman Institute of Technology*

---***---

Abstract - *Sleep is a fundamental aspect of human physiology, with a profound impact on overall health and well-being. Sleep disorders, affecting a significant portion of the global population, present a pressing health challenge. To address this issue, our project aspires to develop a holistic methodology for sleep stage classification using EEG signals. This methodology holds the potential to revolutionize sleep science by enhancing our understanding of sleep physiology, improving sleep disorder diagnosis, and enabling personalized sleep therapy. Furthermore, it aims to contribute to sustainable and environmentally conscious sleep monitoring and therapy practices by optimizing energy consumption and resource utilization in sleep monitoring devices. The primary objective of this project is to advance the field of sleep medicine by accurately classifying sleep stages from EEG signals. Sleep is conventionally categorized into two main stages: Non-Rapid Eye Movement (NREM) and Rapid Eye Movement (REM). Accurate classification of these stages is essential for understanding sleep patterns and diagnosing sleep disorders. Leveraging sophisticated machine learning techniques, including Gaussian Mixture Models, K-Nearest Neighbors, Softmax Discriminant classifiers, and Logistic Regression, we aim to precisely delineate these sleep stages. Our project unfolds in several phases. We begin by collecting raw EEG data, a crucial prerequisite for accurate analysis. Data preprocessing techniques are then employed, involving noise reduction, filtering, and artifact removal, to enhance data quality.*

Keywords: *REM, NREM, artifact removal, noise reduction, holistic methodology.*

1.INTRODUCTION

Sleep is a fundamental aspect of human life, essential for maintaining physical health, cognitive function, and emotional well-being. However, for many individuals, the quality of sleep remains elusive due to sleep disorders and inadequate monitoring. In light of these challenges, this project is driven by a multifaceted aim: to enhance our understanding of sleep physiology, improve sleep disorder diagnosis, enable personalized sleep therapy, and promote sustainable and eco- conscious sleep monitoring practices.

1.1 Evolution of Sleep Study

The study of sleep and its various stages has evolved significantly over the years. Early research into sleep primarily relied on subjective observations and basic physiological measurements, but advances in technology and research methodologies have revolutionized our understanding of this essential aspect of human life. Historically, the understanding of sleep was limited to its basic dichotomy: wakefulness and sleep. This binary classification gradually evolved into a more nuanced categorization of sleep stages, particularly the recognition of two main stages - Non-Rapid Eye Movement (NREM) and Rapid Eye Movement (REM) sleep. NREM sleep is further divided into four stages, each characterized by distinct physiological and electrical patterns.

1.2 Advantages of Studying Sleep Physiology

Understanding sleep physiology and classifying sleep stages using advanced techniques, such as EEG signals, offers several key advantages:

1.2.1 Improved Sleep Disorder Diagnosis: One of the primary benefits is the enhancement of sleep disorder diagnosis. By accurately classifying sleep stages, healthcare professionals can gain deeper insights into patients' sleep patterns, leading to more precise and personalized treatment plans. This, in turn, results in improved overall health and quality of life for individuals suffering from sleep disorders.

1.2.2 Reduced Energy Consumption: The project emphasizes the use of raw EEG data or time-frequency representations instead of handcrafted features in sleep monitoring devices. This approach has the potential to significantly reduce the computational complexity of these devices. Lower energy consumption not only makes portable sleep monitoring devices more sustainable but also extends their battery life, increasing their usability.

1.2.3 Personalized Sleep Therapy: A better understanding of sleep stages through the holistic methodology allows for the design of personalized sleep therapy based on individual sleep patterns. Tailoring treatment plans in this manner optimizes their effectiveness, leading to improved sleep quality and overall health outcomes.

1.2.4 Public Health Impact: Sleep plays a crucial role in overall health and quality of life. Accurate sleep analysis, timely diagnosis of sleep disorders, and promotion of healthier sleep practices can have a significant impact on public health. This project aims to foster a deeper understanding of sleep-related health issues and alleviate the burden of sleep-related health problems.

1.2.5 Closed-Loop Systems: Accurate sleep stage classification can contribute to the development of closed-loop sleep modulation systems. These systems automatically adjust environmental factors, such as room temperature, lighting, and sound, to optimize sleep quality. They also promote energy-efficient and environmentally conscious practices.

1.3 Applications of Sleep Physiology Understanding

The holistic methodology for sleep stage classification based on EEG signals has broad applications across various domains:

1.3.1 Healthcare: In the healthcare sector, the project's outcomes are particularly valuable. Accurate sleep disorder diagnosis and personalized therapy can significantly improve the quality of patient care. Healthcare providers can use this methodology to develop precise treatment plans for individuals, ultimately leading to better health outcomes.

1.3.2 Consumer Electronics: Consumer-oriented sleep monitoring devices are becoming increasingly popular. By optimizing energy consumption and resource utilization in these devices, manufacturers can create more sustainable products that appeal to environmentally conscious consumers.

1.3.3 Research and Development: The project's advanced methodologies and algorithms can contribute to the broader field of sleep science. Researchers can use these tools to conduct in-depth studies, leading to new discoveries about sleep patterns and their impact on human health.

1.3.4 Public Health Initiatives: The project's emphasis on promoting better sleep practices aligns with public health initiatives aimed at improving the well-being of communities. By raising awareness about the importance of sleep and providing tools for accurate sleep monitoring, this project contributes to the larger goal of healthier societies.

1.3.5 Environmental Conservation: Sustainable sleep monitoring practices reduce energy consumption, contributing to environmental conservation efforts. As society becomes increasingly aware of the need for eco-conscious practices, such innovations are essential in minimizing our ecological footprint.

2. OBJECTIVES AND METHODOLOGY

2.1 Proposed Work Plan

Our holistic methodology for the classification of sleep stages from EEG signals is designed to provide a systematic and effective approach to achieving accurate automated sleep stage classification.

2.1.1 Sleep disorder is one of the common disorders which affect many of the people around the world.

2.1.2 Based on sleep macro structure, sleep can be classified into 2 main stages:

2.1.3 Non-Rapid Eye Movement (NREM) and Rapid Eye Movement (REM) sleep.

2.1.4 To classify sleep stages from EEG Signals.

2.1.5 To analyze the classifier performance in sleep stage detection.

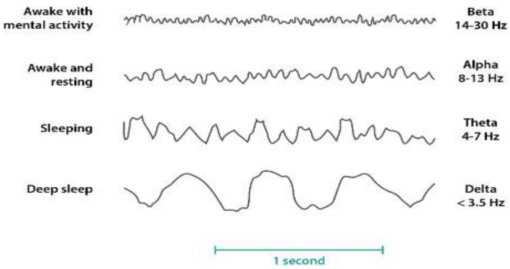

Figure 1: Various Frequency For Awake And Rem

2.2 Enhanced Prediction Of Proposed Work

2.2.1 Integrating multiple physiological signals offers a more comprehensive understanding of sleep patterns. Sleep is a complex process that involves various physiological systems, and combining data from multiple sources allows for a more complete characterization. Different sleep stages are associated with distinct physiological changes. By incorporating ECG, EMG, and respiratory signals, the classification model can leverage this rich information to enhance predictive accuracy. For example, EMG signals can help identify muscle tone changes associated with REM sleep.

2.2.2 Multi-modal data fusion can increase the robustness of the classification model. If one modality is affected by artifacts or noise, the model can rely on information from other modalities for more reliable predictions. Healthcare professionals often use a combination of physiological signals to diagnose sleep disorders. Multi-modal integration aligns with clinical practice, making the methodology more clinically relevant and inter-predictable. Different individuals may exhibit unique patterns in their physiological signals during sleep. Multi-modal data fusion allows for the development of personalized models that adapt to an individual's specific physiology. Some sleep disorders, such as sleep apnea, are closely related to both EEG and respiratory patterns. Multi-modal integration can aid in the identification of co-occurring disorders, leading to more accurate diagnoses.

2.3 Synthetic Procedure/Flow Diagram Of The Proposed Work

Our holistic methodology for the classification of sleep stages from EEG signals is designed to provide a systematic and effective approach to achieving accurate automated sleep stage classification. This methodology consists of several key stages, each contributing to the overall process.

2.3.1. Data Acquisition

Data Collection: Acquire a dataset of EEG recordings, ideally from a diverse group of subjects, encompassing different sleep stages, such as wakefulness, REM sleep, and various non-REM stages.

2.3.2 Feature Extraction

Hilbert Transform: The Hilbert transform is a mathematical operation that, when applied to a signal, generates a complex-valued signal from a real-valued one. It is often used in signal processing to calculate the analytic representation of a signal, which includes amplitude and phase information. In EEG analysis, the Hilbert transform can help capture the time-frequency characteristics of EEG signals.

The *Hilbert transform* of a Fourier transformable signal $g(t)$ is defined by

$$\hat{g}(t) = \frac{1}{\pi}\int_{-\infty}^{\infty} \frac{g(\tau)}{t-\tau}\, d\tau$$

Correspondingly, the *inverse Hilbert transform* is defined by

$$g(t) = -\frac{1}{\pi}\int_{-\infty}^{\infty} \frac{\hat{g}(\tau)}{t-\tau}\, d\tau$$

Discrete Cosine Transform (DCT): DCT is a mathematical transformation commonly used for signal processing and image compression. In EEG feature extraction, DCT can be employed to transform EEG data into a frequency domain, allowing for the extraction of spectral features that may be relevant for sleep stage classification.

$$DCT: \quad F(k) = \sum_{n=0}^{N-1} 2x(n)\cos\left(\frac{\pi}{2N}k(2n+1)\right), \qquad 0 \le k < N$$

$$Inverse\ DCT: \quad x(n) = \frac{1}{N}\sum_{k=0}^{N-1} w(k)F(k)\cos\left(\frac{\pi}{2N}k(2n+1)\right), \qquad 0 \le k < N$$

$$w(k) = \begin{cases} \frac{1}{2}, & k = 0 \\ 1, & 1 \le k < N \end{cases}$$

Non-Linear Regression: Non-linear regression is a modeling technique used to fit data to a non-linear equation. In EEG feature extraction, non-linear regression methods can be applied to model the complex relationships between EEG signal characteristics and sleep stages. This allows for the extraction of features that capture non-linear patterns in the data.

2.4 FEATURE SELECTION AND DIMENSIONALITY REDUCTION

2.4.1 Particle Swarm Optimization (PSO): PSO is a computational technique inspired by the social behavior of birds and fish. In the context of feature selection, PSO is used to find the most relevant subset of features from a larger set. It does this by iteratively adjusting a population of potential feature subsets to maximize a specified objective function, often related to classification accuracy. In the project, PSO can help identify the most informative features from EEG signals for sleep stage classification.

2.4.2 Harmonic Search: Harmonic search is a nature-inspired optimization algorithm based on the concept of harmonic oscillation. It is used to find the global optimum of a function by iteratively updating the search space. In the context of feature selection, harmonic search can be employed to select the most relevant features for sleep stage classification by exploring the feature space efficiently

$$H(x_1, x_2, \ldots x_n) = \frac{1}{A(\frac{1}{x_1}, \frac{1}{x_2}, \ldots \frac{1}{x_n})},$$

$$A(x_1, x_2, \ldots x_n) = \frac{1}{H(\frac{1}{x_1}, \frac{1}{x_2}, \ldots \frac{1}{x_n})},$$

2.5 CLASSFICATION

2.5.1 Gaussian Mixture Model (GMM): GMM is a probabilistic model that represents a mixture of multiple Gaussian distributions. It's commonly used in clustering and classification tasks. In sleep stage classification, GMM can be utilized to model the probability distribution of EEG features for each stage, enabling the categorization of new data points into different stages.

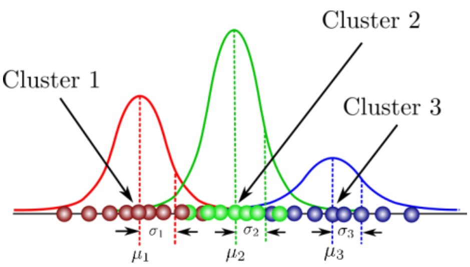

Figure 2: Classification Model For Gaussian Mixture Model (Gmm)

2.5.1 K-Nearest Neighbor (KNN): KNN is a simple and effective classification algorithm. It classifies data points by examining the majority class among their k- nearest neighbors in the feature space. In sleep stage classification, KNN can be applied to EEG features to determine the sleep stage based on the similarity to neighboring data points.

2.5.2 Softmax Discriminant Classifier: The softmax discriminant classifier is a multi-class classification algorithm commonly used in machine learning. It calculates the probability distribution over multiple classes and assigns the class with the highest probability to a data point. In sleep stage classification, the softmax classifier can assign EEG data to different sleep stages based on their features, likelihood in each class.

2.5.3 Logistic Regression: Logistic regression is a widely used statistical method for binary and multi-class classification. It models the probability of a data point belonging to a particular class using a logistic (S - shaped) function. In sleep stage classification, logistic regression can predict the likelihood of EEG features corresponding to each sleep stage and classify data accordingly.

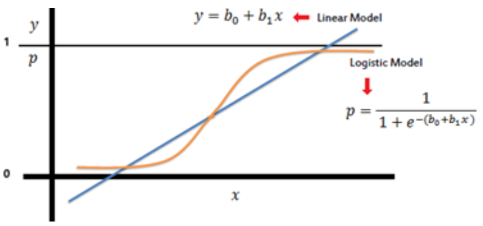

Figure 3: Classification Model For Logistic Regression

2.6 EVALUATION

The following performance metrics are commonly used to evaluate the performance of sleep stage classification algorithms:
2.6.1 Accuracy: This is the percentage of sleep stages are correctly classified.
ACCURACY RATE = TP+TN/TP+TN+FN+FP
2.6.2 Error rate: This is the percentage of sleep stages that are incorrectly classified.
ERROR RATE = FP+FN/TP+TN+FP+FN
2.6.3 F1 score: This is a measure of the accuracy and precision of the classifier. F1 SCORE = (2 * PRECISION * RECALL)/(PRECISION+RECALL)

2.6.4 MCC: This is a measure of the correlation between the predicted and actual sleep stages.

$$MCC= \frac{TP*TN-FP*FN}{\sqrt{((TP+FP)(TP+FN)(TN+FP)(TN+FN))}}$$

2.6.5 Kappa: This is a measure of the agreement between the predicted and actual sleep stages, adjusted for chance.

$$K= \rho - \rho e / 1- \rho e$$

2.6.6 G Mean: This is a measure of the accuracy of the classifier that takes into account the imbalance in the number of sleep stages.

$$GMean = \sqrt{(TPR*TNR\ (\%))}$$

3 SOFTWARE USED

MATLAB is a powerful tool for simulating and analyzing EEG(Electroencephalogram) signals. Simulating EEG signals in MATLAB can be useful for various purposes, including testing algorithms, developing and validating signal processing techniques, and conducting research in neuroscience.

It has a high-level programming language and environment specifically designed for numerical and scientific computing. It provides a wide range of built-in functions and toolboxes for signal processing, machine learning, and data analysis.

3.1 MATLAB Signal Processing: This toolbox provides functions and tools for the analysis, processing, and visualization of signals, which is essential for EEG signal preprocessing and feature extraction.
3.2 MATLAB Machine Learning: You'll need this toolbox to implement and train machine learning models for sleep stage classification. It offers various classifiers and tools for model evaluation.
3.3 MATLAB Statistics and Machine Learning: This toolbox contains additional functions and algorithms for statistical analysis and machine learning, which can be helpful for feature selection, model evaluation, and optimization.
3.4 EEG Data: You'll need access to EEG datasets, such as the PhysioNet Sleep-EDF dataset, to train and test your models. Make sure to preprocess the data properly to remove noise and artifacts.
3.5 Data Visualization Tools: Software for visualizing your EEG data and the results of your analysis, which can include MATLAB's built-in plotting functions or external tools like Tableau or Python's Matplotlib for more advanced visualization.

4 PROCEDURES

4.1 Data Preprocessing: Load the EEG data from your source (e.g., PhysioNet Sleep Database). Filter the EEG signal to remove noise and artifacts. Common filters include high- pass and low-pass filters. Segment the EEG data into smaller time windows or epochs, typically 30 seconds to 2 minutes in length, to analyze specific periods of sleep. Apply techniques for artifact removal, such as Independent Component Analysis (ICA) or Principal Component Analysis (PCA), to further clean the data.
4.2 Feature Extraction: Extract relevant features from the preprocessed EEG data. These features capture important information about the EEG signal that can be used for classification. Common EEG features include spectral features (e.g., power in different frequency bands), statistical features (e.g., mean, variance), and time-domain features. Features can be computed for each epoch of EEG data.
4.3 Data Labeling: Annotate each epoch of EEG data with the corresponding sleep stage label (e.g., Wake, NREM, REM) using a polysomnography (PSG) dataset. Ensure that you have a labeled dataset for training and testing your sleep stage classifier.
4.4 Classifier Selection and Training: Choose a machine learning classifier for sleep stage classification. Common classifiers include Support Vector Machines (SVM), Random Forests, and Neural Networks. Split your dataset into a training set and a testing set (e.g., 70% for training, 30% for testing). Train the selected classifier on the training dataset using the extracted features and their corresponding sleep stage labels.
4.5 Model Evaluation: Evaluate the performance of your sleep stage classifier using the testing dataset. Common evaluation metrics include accuracy, sensitivity, specificity, F1-score, and confusion matrix.

Adjust hyperparameters or select different features if needed to improve classifier performance.
4.6 Visualization: Visualize the results by plotting the EEG signals, true sleep stages, and predicted sleep stages to assess the classifier's performance visually.
4.7 Application and Analysis: Apply the trained classifier to unseen EEG data to predict sleep stages in real-world scenarios. Analyze the results and consider fine-tuning the classifier based on the performance in practical applications.

5 FLOW CHART OF PROPOSED WORK

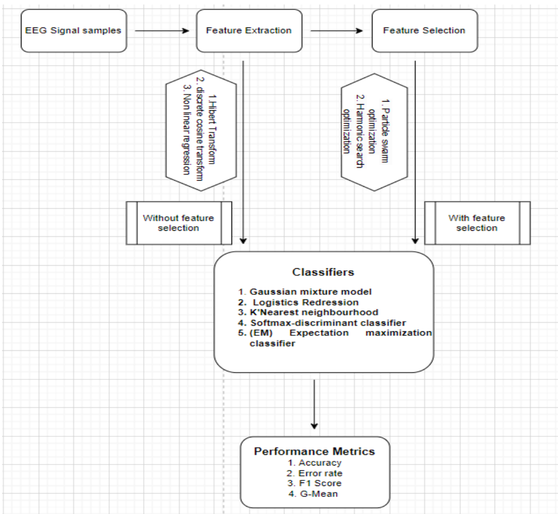

Figure 3: Flow Chart Diagram On Prepration Of Model

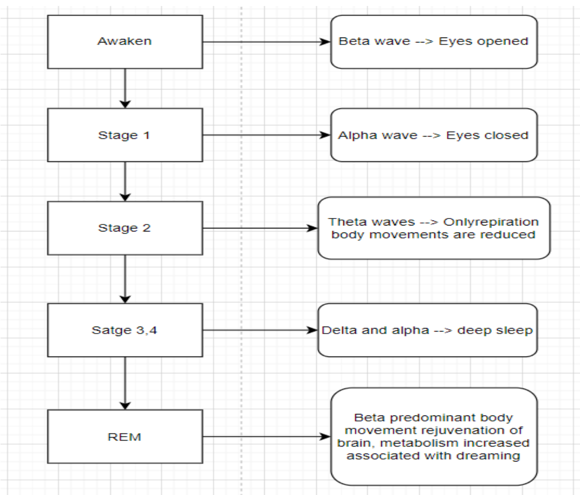

Figure 4: Stages Involved In Sleep Cycles

6 PROPOSED WORK MODULES

6.1 PICKING THE RIGHT MODEL(CLASSIFIER)

6.1.1 Gaussian Mixture Model (GMM): GMM is a probabilistic model that can be used for both clustering and classification tasks. Typical Results for GMM can perform well in tasks with complex data distributions, but it may require careful initialization and hyperparameter tuning. The main advantage, Probabilistic model suitable for capturing complex data distributions. It can work well with multi-modal data.
6.1.2 K-Nearest Neighbors (KNN): KNN is a simple yet effective algorithm that classifies data points based on the majority class among their k-nearest neighbors. Typical Results for KNN can work well when the data has clear local structures. Its performance may degrade when dealing with high-dimensional data. The Pros are, Simple to understand and implement. Effective when local structures in the data are important.
6.1.3 Logistic Regression: Logistic Regression models the probability that a given input belongs to a particular class. It's commonly used for binary classification but can be extended to multi-class problems. Typical Results, Logistic Regression can provide interpretable results and works well when the relationship between features and the target variable is approximately linear. The main use of this classifier is to Simple and interpretable, Works well when the relationship between features and target is approximately linear.
6.1.4 Softmax Discriminant Classifier: The Softmax classifier is often used for multi-class classification tasks. It computes the probabilities of each class and assigns the class with the highest probability. Typical Results for Softmax classifiers are widely used in deep learning and can perform well in multi-class problems when paired with neural networks. It also used for Suitable for multi-class classification. Often used in deep learning neural networks.
6.1.5 Expectation-Maximization (EM): EM is used for clustering and density estimation tasks. In classification, it can be used indirectly through Gaussian Mixture Models (GMMs). Typical Results, EM can capture complex data distributions but may require careful initialization and can be sensitive to local optima. The main use of EM to Effective for modeling complex data distributions. Works well when data clusters are not well-separated. The primary problem being addressed is the need for accurate sleep stage classification using EEG signals for better diagnosis and therapy of sleep disorders.

6.2 METHODOLOGY OF PROPOSED WORK

6.2.1 Data Collection: Raw EEG data is collected from sources like the SLEEP EDF DATASET, which includes EEG signals recorded at 256 samples per second for 10 seconds. This raw data is essential for subsequent analysis.
6.2.2 Data Preprocessing: The raw EEG data goes through preprocessing steps, including noise reduction, filtering, and artifact removal. This ensures that the data is clean and ready for analysis.
6.2.3 Feature Extraction: Feature extraction techniques such as Hilbert Transform, Discrete Cosine Transform, and non-linear regression are applied to the preprocessed EEG data. These techniques help extract relevant features that capture sleep stage characteristics.
6.2.4 Feature Selection: To improve the accuracy of sleep stage classification, feature selection techniques like Particle Swarm Optimization and Harmonic Search are used to select the most relevant features.

6.2.5 Classification: Various classifiers are employed, including Gaussian Mixture Models (GMM), K-Nearest Neighbors (KNN) Algorithm, Softmax Discriminant Classifier, and Logistic Regression. These classifiers are trained on the selected features to classify sleep stages accurately.
6.2.6 Model Optimization: Model optimization techniques like Particle Swarm Optimization (PSO) and Harmonic Search are applied for feature selection and hyperparameter tuning. This step ensures that the classifiers perform optimally.

Table- I: Performance Analysis of Classifiers for awaken signal

Sl.no	Classifiers	TN	FP	MC	Sensitivity	Specificity	Accuracy
1	Non Linear Regression	81.04	19.16	0	81.04	100	90.51
2	Linear Regression	91.61	8.78	0	91.61	100	94.57
3	Logistic Regression	73.53	26.54	0	73.53	100	86.76
4	EM	84.19	0	15.3	100	84.3	92.13
5	Compensatory EM	83.55	0	17.53	100	83.55	91.21
6	EM with Logistic Regression	59.94	0	39.03	100	59.94	80.47
7	compensatory EM with Logistic Regression	81.28	0	18.75	100	81.28	90.68

6.2.7 Model Validation: The trained models are validated using k-fold cross-validation to prevent overfitting and ensure their reliability and generalizability.
6.2.8 Performance Evaluation: The performance of the classifiers is assessed using various metrics such as accuracy, error rate, F1 score, GDR, MCC, Kappa, and g Mean. These metrics help in comparing and selecting the most suitable classifier for sleep stage classification.
6.2.9 Feasibility Analysis: Different aspects of feasibility, including technical feasibility, economic feasibility, performance feasibility, and scalability feasibility, are evaluated to determine the viability of the proposed system.

7 RESULTS AND DUSCUSSION

Our project has made significant strides in advancing the understanding of sleep physiology, improving sleep disorder diagnosis, and promoting sustainable and eco- conscious sleep monitoring practices. Finally, The performance examination of classifiers for the NREM sleep and awaken stages of the EEG signal was the main emphasis of this paper. The linear regression model for awaken signal achieves the highest accuracy of 94.57%. As a result, the Non Linear Regression model holds well for the wakeup signal whereas the linear regression model holds well for the sleep signal. For classification of sleep stages, next study will focus on machine learning and deep learning techniques. The advantage for the LR to be more accurate is it has limited data or want a straightforward model for initial exploration, logistic regression can be a good starting point.

Table- II: Performance Analysis of Classifiers for awaken signal

Sl.no	Classifiers	TP	FN	MC	Sensitivity	Specificity	Accuracy
1	Non Linear Regression	84.38	16.23	0	84.38	100	92.39
2	Linear Regression	78.67	20.31	0	79.71	100	89.57
3	Logistic Regression	57.09	42.85	0	57.09	100	78.92
4	EM	71.68	27.78	0	71.68	100	84.83
5	Compensatory EM	60.23	39.58	0	60.23	100	80.61
6	EM with Logistic Regression	66.21	34.79	0	66.21	100	83.10
7	Compensatory EM with Logistic Regression	64.8	36.19	0	64.8	100	82.19

8 SIGNIFICANCE OF PROPOSED WORK

The proposed work holds significant implications and contributions across multiple domains, ranging from healthcare and sustainability to technological advancement. Here, we outline the key areas where the project's significance is most pronounced:
8.1 Enhanced Sleep Disorder Diagnosis: To improve the diagnosis of sleep disorders by developing a holistic methodology for sleep stage classification using EEG signals. The significance lies in the potential to significantly enhance the accuracy and reliability of sleep disorder diagnosis. This advancement will empower healthcare professionals to better understand patients' unique sleep patterns and provide personalized treatment plans. The direct result is improved overall health and quality of life for individuals suffering from sleep disorders. It not only reduces misdiagnoses but also helps in more targeted and effective interventions, reducing the long-term healthcare burden.
8.2 Personalized Sleep Therapy: The project introduces the concept of personalized sleep therapy based on individual sleep patterns. This aspect signifies a paradigm shift in healthcare, where treatments are tailored to an individual's specific needs. The significance lies in optimizing treatment effectiveness, resulting in improved sleep quality and overall health outcomes for individuals. Personalized sleep therapy has the potential to revolutionize the approach to sleep-related health issues, offering a higher level of care that caters to individual variability.
8.3 Public Health Impact: The significance of the proposed work extends to public health at large. Sleep plays a fundamental role in overall health and quality of life. By promoting healthier sleep practices, encouraging timely diagnosis of sleep disorders, and fostering a deeper understanding of sleep-related health issues, this project can have a substantial positive impact on public health. The reduction in the burden of sleep-related health problems can lead to better well-being for society as a whole, reducing healthcare costs and improving the quality of life.
8.4 Technological Advancement: Beyond healthcare, the project contributes to the broader field of technological advancement. It involves the development of advanced machine learning algorithms, signal processing techniques,

and software architectures. These innovations can have applications beyond sleep science, potentially leading to novel breakthroughs in machine learning and signal processing.

9 CONCLUSION

A comprehensive and ambitious approach to advancing our understanding of sleep physiology, improving sleep disorder diagnosis, and enabling personalized sleep therapy. By harnessing the power of EEG signals and cutting- edge machine learning techniques, we aim to enhance the accuracy and reliability of sleep stage classification. To sleep stage classification using EEG signals presents promising avenues for enhancing sleep disorder diagnosis, personalized therapy, and sustainable monitoring practices. The utilization of diverse classifiers and advanced feature extraction techniques holds the potential to revolutionize sleep science by providing accurate insights into sleep patterns. The project's ultimate success lies in its ability to bridge the gap between accurate sleep analysis and improved overall health and well-being, making a positive impact on public health and ecological consciousness.

10 REFERENCE

[1]. Harikumar Rajaguru, Sanjai Khan N, Vinitha Krishnamoorthy, "Performance Analysis of Classifiers in Identifying NREM Sleep and Awaken Stages from EEG Signals", "International Journal of Recent Technology and Engineering (IJRTE) ISSN: 2277-3878, Volume-X, Issue-X, July 2019"

[2]. C Ganesh Babu, M Gowri Shankar & Harikumar Rajaguru, "Performance Exploration of Multiple Classifiers with Grid Search Hyperparameter Tuning for Detecting Epileptic Seizures from EEG Signals","Journal of Scientific & Industrial Research :Vol. 81, July 2022, pp. 754-766"

[3]. M. Manjusha; R. Harikumar, "Performance analysis of KNN classifier and K-means clustering for robust classification of epilepsy from EEG signals"," 2016 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET) ISSN: 16304212, September 2019"

[4]. Sunil Kumar Prabhakar , Harikumar Rajaguru , Semin Ryu
, In cheol Jeong and Dong-Ok Won, "A Holistic Strategy for Classification of Sleep Stages with EEG", Sensors 2022, 22(9), 3557; May 2022"

[5]. R.Harikumar, B.Sabarish Narayanan ,"Fuzzy Techniques for Classification of Epilepsy Risk Level from EEG Signals", ISSN: 7993255; IEEE on October 2003.

[6]. Wessam Al-Salman, Asam Almohamed, Sadiq Altamimi , "Sleep Waveforms Detection in Sleep Stage 2 Using EEG Signals: Applying Different Set of Features and Classification Algorithm", "3rd Information Technology to Enhance e-learning and Other Application (IT-ELA2022), Baghdad College of Economic University, Baghdad-Iraq; December 2022".

[7]. A. R. Hassan, S. Siuly, and Y. Zhang, "Epileptic seizure detection in EEG signals using tunable-Q factor wavelet transform and bootstrap aggregating," Computer methods and programs in biomedicine, vol. 137, pp. 247-259, 2016.

[8]. Khald Ali I. Aboalayon, Miad Faezipour, ORCID, Wafaa S. Almuhammadi and Saeid Moslehpour," Sleep Stage Classification Using EEG Signal Analysis: A Comprehensive Survey and New Investigation" vol.18, Issue 9, 2016.

[9]. Khatwani, P ; Tiwari, A," A survey on different noise removal techniques of EEG signals", Int. J. Adv. Res. Computer science Eng. 2013, 2, 1091–1095.

[10]. Li, Y Yingle, F. Gu, L; Qinye, T. "Sleep stage classification based on EEG Hilbert–Huang transform", In Proceedings of the 4th IEEE Conference on Industrial Electronics and Applications (ICIEA), Xi'an, China, 25–27 May 2009.

[11]. E. Estrada; H. Nazeran; P. Nava; K. Behbehani; J. Burk; E. Lucas , "EEG feature extraction for classification of sleep stages", Published in ,The 26th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, San Francisco, USA, 01-05 September 2004.

[12]. Reza Boostani, Foroozan Karimzadeh, Mohammad Nami,"A comparative review on sleep stage classification methods in patients and healthy individuals", Computer Methods and Programs in Bio medicine, Volume 140, March 2017, Pages 77-91.

[13]. P. J. Durka and K. J. Blinowska, A unified time-frequency parametrization of EEGs. IEEE Eng. Med. Biol. Mag. 2001; 20:47–53.

[14].Katarzyna Blinowska , Piotr Durka, "Electroencephalography (EEG)" Warsaw University Warszawa, Poland, Wiley Encyclopedia of Biomedical Engineering,14 April 2006.

[15]. B. Kemp, P. Jaspers, A. J. M. W. Janssen, "An optimal monitor of the electroencephalographic sigma sleep state", Computer Science Biological Cybernetics, 51, 263–270 (1985).