Sleep Apnea and Rapid Eye Movement Detection using ResNet-50 and Gradient Boost

Ganti Venkata Varshini[1], Sakthivel V[2], Prakash P[3], Mansoor Hussain D[4], Jae Woo Lee[5]
School of Computer Science of Engineering, Vellore Institute of Technology, Chennai, India[1, 2, 3, 4]
Konkuk Aerospace Design-Airworthiness Institute (KADA), Konkuk University, Seoul, South Korea[5]

***Abstract*—Sleep apnea is a prevalent sleep problem marked by interruptions in breathing or superficial breaths while asleep. This frequently results in disrupted sleep patterns and can pose significant health risks such as cardiovascular issues and daytime exhaustion Rapid Eye Movement (REM) sleep stage is easily identifiable due to rapid eye movements, intense dreaming, and muscle immobility. This stage is vital for cognitive processes, the strengthening of memories, and the regulation of emotions. Detection of REM sleep is essential for understanding sleep architecture and diagnosing various sleep disorders. This paper proposes two machine learning models to detect these disorders from physiological signals. The study employs the Apnea-ECG dataset from PhysioNet for sleep apnea detection and the Sleep-EDF dataset for REM detection. For sleep apnea, a ResNet-50 deep learning model is adapted to process ECG signals, treating them as image-like representations. ResNet-50 is trained on the Apnea-ECG dataset, which provides annotated electrocardiogram recordings for supervised learning. For REM detection, Gradient Boosting, an ensemble machine learning technique, is applied to EEG signals from the Sleep-EDF dataset. Relevant features associated with REM sleep phases are extracted from EEG signals and used to train the model. This paper contributes to automated sleep disorder diagnosis by presenting tailored machine learning models for detecting sleep apnea and REM from physiological signals.**

Keywords—Sleep Apnea; Rapid Eye movement; ResNet-50; Gradient boost; sleep stage; sleep disorders

I. Introduction

Sleep disorders, can alternatively be referred to as sleep-wake disorders, encompass a range of issues related to sleep's timing, quality, and duration resulting in daytime impaired functioning and distress. Disorders like these often coincide with medical conditions or various mental health or medical conditions issues like anxiety, depression or cognitive disorders. They encompass various types, with insomnia being the most frequent, along with parasomnias, obstructive sleep apnea, restless leg syndrome, and narcolepsy.

Challenges with sleep impact both physical and emotional well-being, exacerbating existing mental health conditions and potentially indicating other mental health disorders. Insomnia is prevalent, affecting about a third of adults, with 6-10 percent crossing the scale for insomnia disorder. Sleep is essential for overall health, occurring in cycles throughout the night with REM sleep, related with dreaming, and Non-REM sleep, including deeper stages. The sleep timing is regulated by a 24-hour circadian rhythm.

Sleep needs vary by age and individual, with recommendations suggesting seven to nine hours of sleep per night for most adults. However, a significant portion of the population falls short of these guidelines, with many adults sleeping lower than six hours per night and only a minority of high school students achieving adequate sleep. Many Americans rate their sleep quality as poor, and millions struggle with chronic sleep disorders.

Sleep apnea is a problem which creates interruptions in breathing during sleep, categorized into Central Sleep Apnea (CSA) and Obstructive Sleep apnea (OSA). Symptoms include loud snoring, abrupt awakenings, and daytime sleepiness, potentially leading to serious health issues if untreated. Diagnosis involves sleep studies, and treatments range from lifestyle adjustments to surgical interventions for severe cases.

REM sleep is a distinct phase marked by increased brain activity, vivid dreaming, and rapid eye movement. It is essential for emotional regulation, learning, and memory consolidation, with disruptions affecting cognitive function and emotional well-being. Monitoring REM patterns is crucial for understanding sleep disorders and overall sleep health.

While sleep apnea and REM sleep are interconnected aspects of sleep physiology, they represent distinct phenomena. Sleep apnea involves breathing interruptions during sleep, disrupting the sleep cycle, while REM sleep is a specific stage crucial for cognitive and emotional processes.

With respect to REM sleep, individuals with sleep apnea often experience disruptions in this specific sleep stage. During REM sleep, the muscles become temporarily paralyzed (atonia) to prevent the acting out of dreams. In individuals with sleep apnea, the relaxation of throat muscles and partial or complete airway obstruction can lead to brief awakenings to resume normal breathing. These interruptions can fragment REM sleep, affecting the overall sleep architecture and potentially contributing to daytime sleepiness and other symptoms associated with sleep apnea. Monitoring REM patterns in sleep studies is essential for understanding the impact of sleep apnea on different sleep stages.

II. Background

Sleep apnea is a common sleep condition which entails constant interruptions in breathing throughout sleep, varying from partial to full obstructions of the airway. Central sleep apnea (brain signaling issue), obstructive sleep apnea (muscle-related), and complex sleep apnea syndrome are main types in sleep apnea. Factors that increase the likelihood of risk encompass age, sex, obesity, and familial medical background. Symptoms encompass snoring, daytime sleepiness, and concentration difficulties. Left untreated, sleep apnea poses risks like cardiovascular disease. Treatment options range from lifestyle changes to medical interventions, emphasizing the importance of professional diagnosis and intervention. Sleep apnea and rapid eye movement (REM) are critical aspects of sleep monitoring, impacting over-all health and well-being. Sleep apnea is identified by interruptions in breathing or superficial breaths while asleep, resulting in disturbances to typical sleep rhythms. REM sleep is a phase where vivid dreaming occurs and is crucial for cognitive function and emotional wellbeing.

Conventional approaches to identifying sleep disorders typically depend on physiological indicators like electromyogram (EMG), electroencephalogram (EEG) and electrooculogram (EOG). These signals provide valuable information, but the complex interactions between different physiological factors can be challenging to capture effectively.

Sleep Apnea and Rapid Eye Movement (REM) are linked because episodes of sleep apnea can happen both during REM sleep and other sleep phases. In the course of REM sleep phase, the body enters a phase where muscles experience a natural state of paralysis or atonia, believed to prevent individuals from physically acting out their dreams. This muscle relaxation during REM sleep can contribute to the occurrence of sleep apnea episodes. The muscles in the throat may become overly relaxed, leading to an increased likelihood of airway obstruction.

III. Literature Review

In their study, Soler A. et al. [1] aimed to automatically Identify when rapid eye movements (REM) commence within REM sleep from EEG data by utilizing EEG signals, electrooculogram (EOG), and sub-mental electromyograms (EMG) collected from eight participants. The researchers introduced an algorithm focused on three key EOG parameters associated with REM: amplitude, duration, and slope. They utilized a process of resampling the data to 80Hz, followed by employing a double derivative method to detect peaks within the data. In their research, Seongju Lee et al. [2] introduced a sleep scoring approach utilizing EEG signals. Their model endeavors to categorize successive single-channel EEG segments into different sleep stages, paying special attention to classifying the EEG segment marked as the target, denoted as the L-th input EEG segment. Díaz, C. H et al. [3] in their paper proposed a system which detects Rapid Eye Movement using Support Vector Machine using EOG signals which were recorded by placing electrodes placed at the right and left canthus. The recorded signals were first marked by an expert who marked which candidate corresponds to REM (Rapid eye movement) and then using SVM the signals were classified whether they correspond to REM or not. The results obtained from SVM were later compared to results marked by the expert. In their study, Bahrami, M et al. [4] conduct a thorough examination of neural network-based learning and computational learning algorithms applied to the PhysioNet ECG Sleep Apnea dataset. They begin by preprocessing and segmenting electrocardiogram (ECG) signals. Then, they employ a variety of conventional machine learning as well as deep learning architectures for detecting sleep apnea. The dataset is divided into training, validation, and testing subsets to refine model parameters, hyperparameters, and evaluate model effectiveness. Through 5-fold cross-validation, the research reveals that hybrid deep learning models exhibit the most effective detection performance, achieving notable accuracy, sensitivity, and specificity. In their paper, Bernardini, A et al. [5] examine the significance of polysomnography (PSG) in diagnosing Obstructive Sleep Apnea Syndrome (OSAS), especially in individuals who have experienced a stroke. Traditionally, physicians manually identify OSAS episodes in PSG recordings, which is crucial due to the link between OSAS and increased mortality and neurological deficits in stroke patients. However, the limited availability of polysomnographs and healthcare professionals creates challenges in diagnosing OSAS, particularly in stroke patients. This research concentrates on data collected from 30 stroke patients treated at Udine University Hospital in Italy, with few exclusion criteria applied. The dataset comprises overnight vital signs from ECG, photoplethysmography, and PSG, along with expert annotations for OSAS. Despite the presence of noise and concurrent medical conditions within the data, the study endeavors to aid the creation of automated techniques for detecting Obstructive Sleep Apnea Syndrome (OSAS) using regularly monitored vital signs, applicable for practical use in real-world scenarios. Yoo, Y. et al. [6] in their paper presented an unsupervised method utilizing 61 GHz FMCW radar to detect three sleep stages which are wake sleep stage, REM sleep stage, and non-REM sleep stage by extracting characteristic breathing and movement information. Experimental results using clinical data show a 68% average similarity to polysomnography (PSG)-observed sleep stages, indicating the potential of Frequency Modulated Continuous Wave (FMCW) radar as a substitute for polysomnography (PSG) for sleep-stage detection. In their research. Gulyani, Majumdar, et al. [7] offer a comprehensive review concentrating on rapid eye movement (REM) sleep and the importance of investigating its deprivation. They delve into the historical context of REM sleep research along with its physiological attributes. The review underscores the importance of studies involving REM sleep deprivation in comprehending its functional importance and emphasizes the necessity for additional research in this domain. Yetton et al. [8] introduce a novel machine-learning strategy aimed at automatically identifying rapid eye movements (REMs). Their method, designed to enhance REM detection in sleep research, presents promising prospects for refining REM identification processes using advanced computational techniques. Hong et al. [9] investigate the importance of quick and vivid eye movements during sleep as a distinct marker of consciousness. They posit that REM sleep presents a special avenue for scrutinizing consciousness, providing valuable insights into its neural mechanisms and operations. The study elaborates on how delving into REM sleep can enhance comprehension of consciousness and associated phenomena. Vallat et al. [10] present a publicly available tool for automated sleep staging, created to effectively analyze sleep EEG data. The tool is intended to deliver superior performance and precision in categorizing sleep stages, thereby aiding both research and clinical endeavors. It serves as a beneficial asset for individuals in the scientific and medical communities who require dependable approaches for automated sleep staging. Abbasi et al. (2021) [11] present a comprehensive review of obstructive sleep apnea (OSA), covering its epidemiology, pathophysiology, clinical manifestations, diagnosis, and treatment options. The paper provides an overview of the current under-standing of OSA, highlighting its prevalence, risk factors, and associated health consequences. It serves as a valuable resource for healthcare professionals and researchers interested in OSA management and advancements in the field. Osman et al. [12] provide contemporary viewpoints on obstructive sleep apnea (OSA), covering its prevalence, underlying mechanisms, symptoms, diagnostic approaches, and treatment options. The article offers perspectives on recent progress in OSA research and therapeutic interventions, acknowledging the complex nature of the condition. It stands as a valuable asset for healthcare practitioners and researchers aiming to gain a thorough grasp of OSA. Hirani et al. (2023) [13] conduct a scoping review to assess the current status of knowledge regarding sleep apnea. They explore various aspects of the disorder, including its prevalence, risk factors, diagnostic methods, treatment options, and associated comorbidities. The review provides an overview of the existing literature on sleep apnea, highlighting areas of consensus, gaps in knowledge, and avenues for future research. Levy et al. [14] introduce a study utilizing deep learning methods to diagnose obstructive sleep apnea (OSA) by analyzing single-channel oximetry data. Their investigation centers on harnessing sophisticated computational techniques to create a precise and effective diagnostic solution for OSA. The study showcases the promise of employing deep learning methodologies to enhance the detection and treatment of disorders in sleep, notably OSA, using oximetry data. Djonlagic et al. [15] examine how OSA specifically associated to REM sleep influences motor memory consolidation and emotional well-being. Their investigation seeks to determine if REM-related OSA impacts the consolidation of motor memories differently compared to emotional health. By delving into these areas, they aim to clarify the importance of REM-related OSA in both behavioral and mental functioning when you sleep. Chen et al. [16] presented a model with the help of single-lead ECG signals, on spatio-temporal learning for identifying sleep apnea. Their study concentrates on employing sophisticated computational methods to devise a reliable technique for recognizing sleep apnea occurrences. The research adds to the field by presenting an innovative method that utilizes spatio-temporal patterns in ECG signals to achieve precise sleep apnea detection, potentially enhancing diagnostic accuracy. Mukherjee et al. [17] carry out an experimental investigation centered on employing various deep learning models to identify and detect the apneas. Their study evaluates the efficacy of integrating various deep learning techniques to enhance the precision of sleep apnea detection. The research adds value to the field by showcasing the capability of ensemble methods in boosting the effectiveness of automated sleep apnea detection systems, offering significant insights for both future research endeavors and clinical implementations. Chang et al. [18] design a detection system for sleep apnea employing a single-lead ECG with a one-dimensional deep neural network model (CNN) architecture. Their study endeavors to devise an efficient technique for recognizing sleep apnea occurrences utilizing ECG data. The research adds to the field by offering a fresh approach that harnesses automation of apnea detection using deep learning techniques, utilizing readily available ECG signals. Gabryelska et al. [19] investigated the relationship between REM phenotype, excessive daytime sleepiness (EDS), and the severity of obstructive sleep apnea (OSA). Their investigation investigates whether there exists a link be-tween the severity of OSA and the occurrence of EDS, with a particular focus on analyzing the REM phenotype as a potential influencing factor. The study aims to clarify the interaction among these variables, offering understanding into the clinical consequences of REM-related sleep disruptions in OSA patients.

IV. Proposed System

The proposed system aims to detect sleep apnea and REM (Rapid Eye Movement) sleep using machine learning models trained on physiological signals. Two separate models will be developed: one for detecting sleep apnea from ECG signals and another for detecting REM from EEG signals.

For detecting Sleep Apnea ResNet-50 algorithm is used which is a deep learning model. The dataset used is Apnea-ECG dataset from physionet. The dataset comprising of ECG recordings collected for 7-10 hours. The R-R interval from ECG recordings is extracted and saved as images. From this R-R interval heart rate is calculated and the plots are saved as images. To this image data ResNet-50 algorithm is employed and the data is classified into two categories: sleep apnea, non-sleep apnea and the result is displayed in terms of accuracy.

For detecting REM (Rapid Eye Movement) Gradient Boost is used which is a ma-chine learning algorithm. The dataset used is Sleep-EDF dataset from physionet. The dataset comprises of polysomnographic data which includes EMG, EEG and EOG signals. EEG (electroencephalogram) Fpz-Cz is extracted from the data and stored in npz file format. These recordings are 8 to 10 hours long which are later divided into 30 seconds interval. The data is stored in array format in npz file from which da-ta(frequency) and label (sleep stage) is given as input for Gradient boost algorithm. Data is split into 70 percent training data and 30 percent testing data. The data is classified into two categories: REM and Non-REM sleep stage. The metrics used is displayed in terms of accuracy. Fig. 1 shows different phases and modules of the proposed system explained above.

A. Modules

1) Data acquisition and pre-processing: To change the default, adjust the template as follows.

a) Sleep apnea: The Apnea-ECG dataset, sourced from PhysioNet, is utilized for sleep apnea detec-tion, focusing on ECG signals. It includes 70 entries divided into a training set of 35 records namely (a01 to a20, b01to b05, and c01 to c10) and a test set of 35 records (x01 to x35). Each record includes continuous digitized ECG signals, human-expert-generated apnea annotations based on simultaneous respiration signals, and QRS annotations generated by machine. Eight recordings (file of a01 to a04, b01, and c01 to c03) also feature additional signals such as respiratory effort (Resp C and Resp A), oral-nasal airflow (Resp N), and oxygen level (SpO2). Multiple files are associ-ated with each recording, with specific data formats detailed in corresponding .hea text header files. Binary annotation files (.apn) indicate the occurrence or ab-sence of apnea per minute in the training set recordings., while machine-generated QRS annotation files (.qrs) offer convenience for those not using their own QRS detectors. The dataset encompasses three subjects (a, b, c) and includes ECG signals classified into severe sleep apnea (Class A), moderate sleep apnea (Class B), and normal sleep (Class C). The model initially plots ECG signals and stores results in pkl file format, subsequently extracting heart rates from the recordings. Fig. 2, 3, and 4 depict plots of ECG signals from patients in Class A, B, and C, respectively.

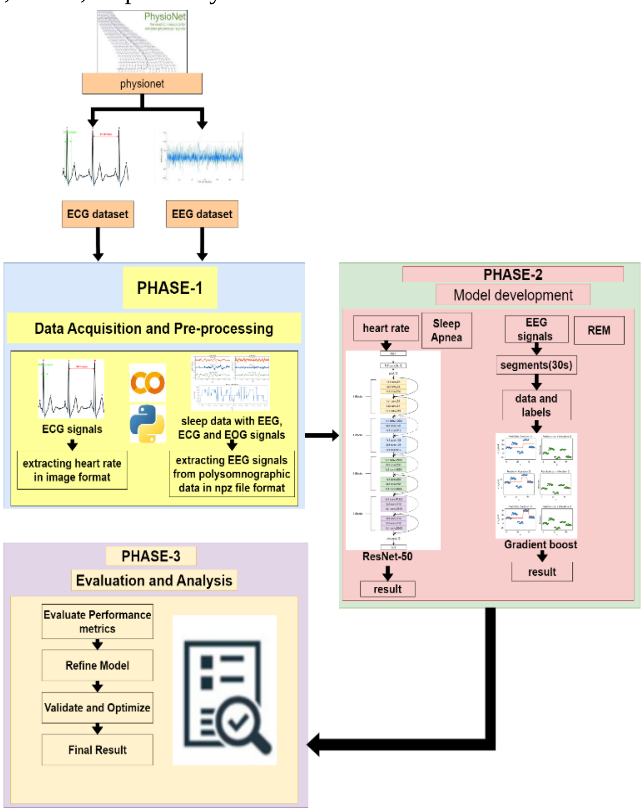

Fig. 1. System diagram.

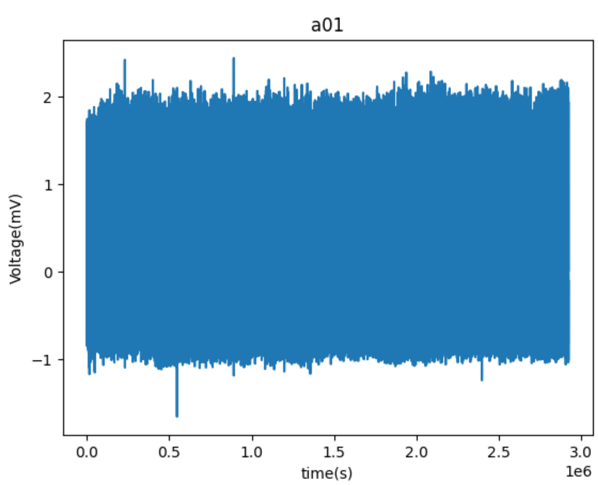

Fig. 2. Class A patient ECG signal plot.

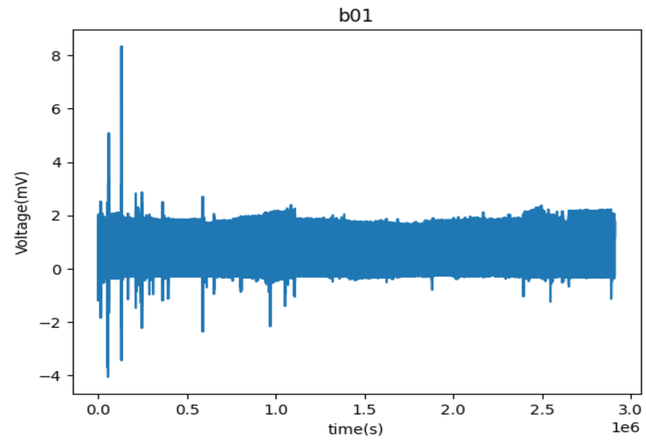

Fig. 3. Class B patient ECG signal plot.

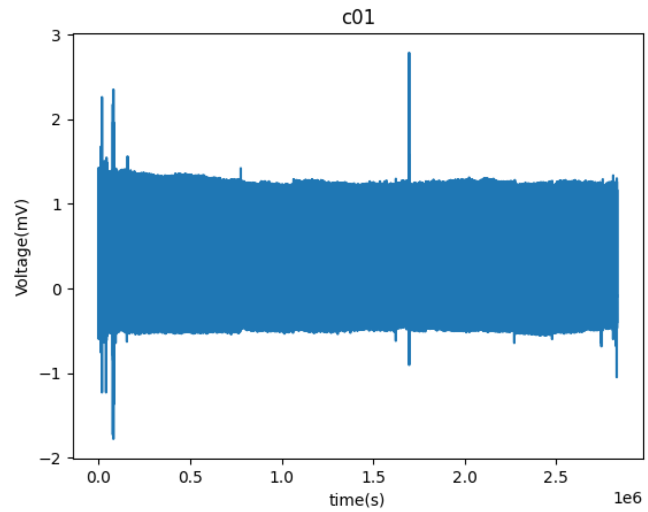

Fig. 4. Class C patient ECG signal plot.

ECG signals will have three waveforms which is P, QRS complex and T waves. The P waveform is depolarization of atria which is contraction of myocardial muscle. The QRS complex is depolarization of ventricles. The Q wave succeeds the P wave and begins with a slight downward deviation. The R wave follows Q wave and it is a sharp peak in the wave which is then followed by S wave which is small deflection downwards. If the QRS complex is 80-120ms then the heart is functioning properly. The t wave is repolarization of ventricles. The model will calculate heart rate from R-R interval. R-R interval is time lapse between two R waves. By dividing R-R interval from 60 it will get heart rate.

From the pkl files which were created the model will be extracting r-r interval and calculate the heart rate from it. It will extract the heart rate signal images and store them in a folder. Biosppy library in python is used to extract R-R inter-vals from ECG signal recordings. The biosppy library is a toolbox used for bio signal processing in python. The model will calculate heart rate by dividing r-r interval from 60. The heart rate is stored in mage format. Fig. 5, 6 and 7 shows heart rate plots of different patients belonging to A, B and C classes respectively where heart rate is in beats per second (BPS) and time is in seconds.

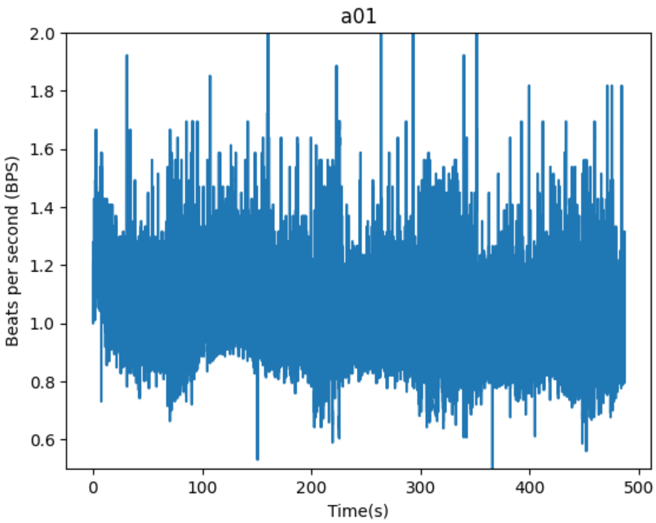

Fig. 5. Class A patient heart rate plot.

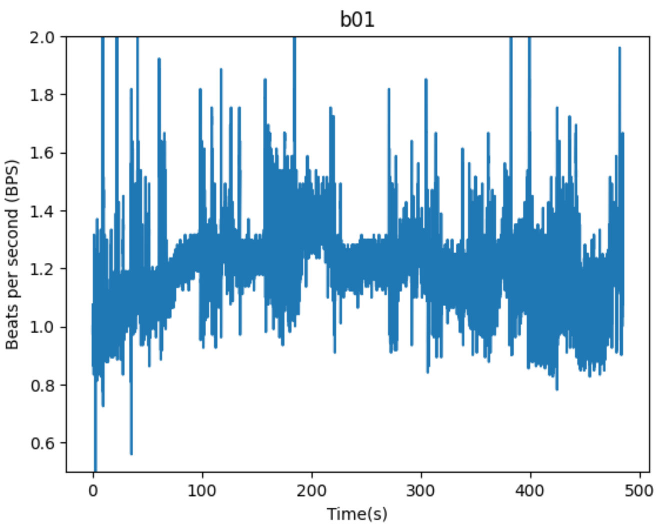

Fig. 6. Class B patient heart rate plot.

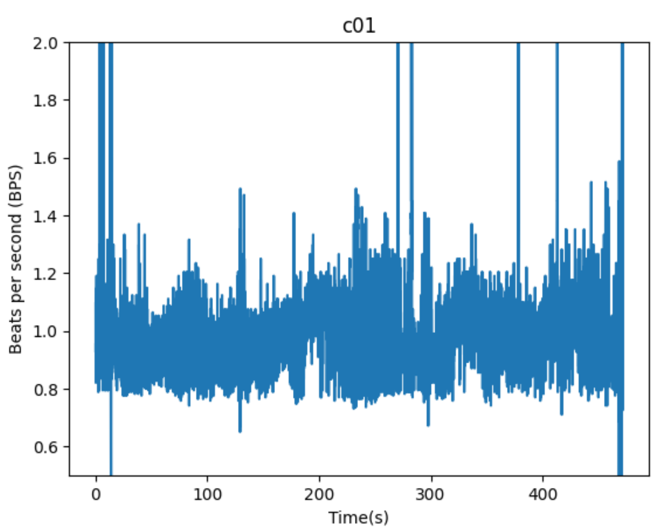

Fig. 7. Class C patient heart rate plot.

b) Rapid eye movement: The Sleep-EDF dataset sourced from PhysioNet includes 197 full-night polysomnographic sleep recordings, including event markers, EEG, chin EMG, and EOG. Data on body temperature and respiration are also included in certain record-ings. Trained technicians manually scored hypnograms corresponding to these re-cordings, detailing sleep patterns based on the Rechtschaffen and Kales manual. These annotated hypnograms are available within the database. From the Sleep-EDF data, the model extracts EEG Fpz-Cz signals and stores them in array format in npz files. A total of 39 recordings, each lasting 8 to 10 hours, are extracted. This data is then segmented into 30-second intervals, and the frequency and labels, stored in array format, are extracted and utilized as input data. This input data is divided into testing and training sets in a 30:70 ratio. Fig. 8 shows plots of EOG, EMG, and EEG signals from the data of Sleep-EDF procured from PhysioNet.

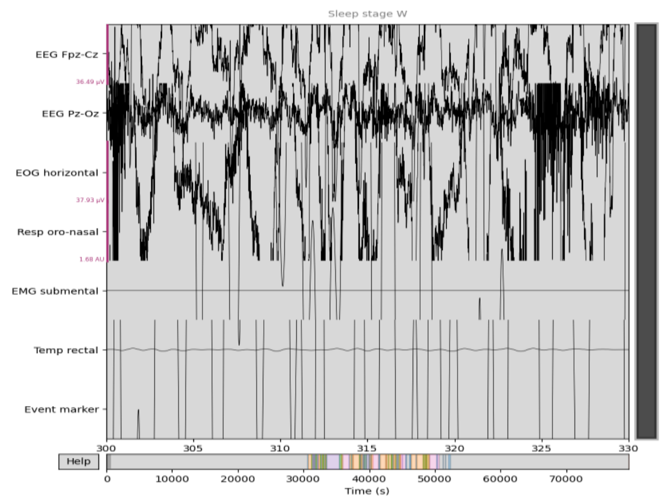

Fig. 8. EEG, EOG and EMG signals.

2) Implementation:

a) ResNet-50 for sleep apnea detection: The model will utilize the ResNet-50 architecture for sleep apnea detection, employing transfer learning. Transfer learning involves repurposing a model trained on one task (the source task) for another related task (the target task). Usually, this involves adjusting the pre-existing model using a smaller set of data tailored to the particular task at hand. This approach leverages the insights acquired from the original task to improve performance on the new task, particularly in situations where there is limited labeled data available for training. The model will be using pre-trained ResNet-50 model. ResNet-50 algorithm is employed to detect sleep apnea from heart rate images. ResNet-50 operates by incorporating residual connections into the architecture, which serves to maintain continuous information flow and mitigate gradient vanishing issues. The residual connection, functioning as a shortcut, allows information to bypass one or more layers, reaching the output directly. By learning residual functions, the network can efficiently make incremental parameter updates, facilitating faster convergence and enhanced performance. This approach is grounded in the concept that learning the residual function, which maps inputs to desired outputs, is more straightforward than mastering the intricate mapping between inputs and outputs. ResNet-50 is organized as a series of residual blocks, each comprising layers of convolution, activation using ReLU, batch normalization, and incorporating skip connections. ResNet-50 model is built on following layers to detect Sleep Apnea. Let x_i be the input to the model where i indexes the elements in the input vector (features). The ResNet-50 model generates an output labeled as x, which undergoes processing through a Global Average Pooling layer, denoted as $GAP(x)$. The result of this pooling layer is a fixed-length vector, termed as g. The subsequent layers consist of fully connected (dense) layers followed by dropout layers:

$$h\_i = \sigma(w\_i.g + b\_i) \quad (1)$$

where, w_i represents the weight matrix, denotes the bias vector, σ stands for the activation function which is ReLu for ResNet-50 and g is output of previous layer.

First fully connected layer: $h\_1 = \sigma(w\_1.g + b\_1)$

First Dropout layer: $h\_2 = Dropout(h\_1)$ where h_2 is the output after applying dropout to h_1

Second fully connected layer: $h\_3 = \sigma(w\_2.h\_2 + b\_2)$

Second Dropout layer: $h\_4 = Dropout(h\_3)$

Third fully connected layer: $h\_5 = \sigma(w\_3.h\_4 + b\_3)$

Third Dropout layer: $h\_6 = Dropout(h\_5)$

Fourth fully connected layer: $h\_7 = \sigma(w\_4.h\_6 + b\_4)$

Fourth Dropout layer: $h\_8 = Dropout(h\_7)$

Output layer (softmax): $\hat{y} = softmax(w\_5.h\_8 + b\_5)$, where $\hat{y}$ is the predicted output vector.

The softmax function calculates the probability distribution across the output classes. The ReLU activation function brings non-linearity to neural networks, enabling them to capture intricate patterns within the data. It is a commonly employed component in deep learning models because of its straightforwardness and efficacy in mitigating the vanishing gradient issue during training.

$$f(x) = (0, x) \quad (2)$$

The sparse categorical cross entropy loss function is used to compute loss. Rather than using one-hot encoded vectors, this function is frequently employed in classification problems when the target labels are integers. It is suitable when the classes are mutually exclusive (each sample belongs to exactly one class).

b) Gradient boost for REM detection: For REM detection, Gradient Boosting is utilized to identify the sleep stage. Gradi-ent Boosting functions through iterative steps: it starts with a simple base model, typically a decision tree or a constant prediction, and sequentially fits fresh models to the prior models' residuals. A fresh weak learner is taught to reduce the mistakes produced by the collection of models that have already been built in each epoch. Residuals, indicating the differences between the actual and predicted values, are computed and utilized as the target for subsequent models. The predic-tions of each new model are integrated with those of the previous ones, gradually refining the ensemble's predictions. Techniques like regularization, includ-ing shrinkage and tree constraints, are applied to prevent overfitting and improve generalization. Through this iterative process, Gradient Boosting maximizes a given loss function, such cross-entropy in classification or mean squared error in regres-sion., ultimately generating a robust predictive model capable of accurately capturing intricate patterns in the data.

3) Model evaluation and final result: After the models are built and they are trained with the training data created in the data pre-processing module. The performance of the models is checked using accuracy as the performance metrics. The hyperparameters of models are refined based on the accuracy achieved. The best accuracy is considered as the final result.

Accuracy is a commonly used measure in machine learning to evaluate how well a classification machine learning or deep learning model performs. It quantifies the ratio of accurately classified instances to the total instances.

Mathematically, it is calculated as:

$$accuracy = \frac{no\ of\ correct\ predictions}{total\ no\ of\ predictions} * 100 \quad (3)$$

The count of correct predictions refers to instances where the model's prediction aligns with the actual target label. The total number of predictions denotes the overall count of instances present in the dataset.

V. Experimental Setup

The proposed system is deployed on a DELL laptop of Inspiron 5490 model equipped with an Intel(R) Core (TM) i5-10210U processor. The CPU boasts a base clock speed of 1.60GHz, indicating its capability to execute tasks at a consistent rate. Furthermore, it features a maximum clock speed of 2.11GHz, which suggests enhanced performance potential, particularly during more demanding computational tasks. The device is efficient enough and has the ability to handle more intensive workloads, making it suitable for running the computational models for sleep apnea and REM detection effectively.

The proposed system was developed and executed using Google Colaboratory, a no-cost, cloud-based platform created by Google. It offers a collaborative environment based on Jupyter notebooks for coding in Python. Google Colaboratory pro-vides access to GPUs and TPUs for performing high-performance computing tasks and train machine learning models efficiently. Integrated with Google Drive, Colab allows seamless saving and sharing of notebooks and for storage of extracted data. Google Colaboratory is pre-installed with popular libraries like TensorFlow and NumPy. It supports data analysis and machine learning workflows. Further-more, Colab offers access to various Google services such as Cloud Storage and BigQuery, enhancing its versatility and integration capabilities for a wide range of projects and applications.

A. Dataset Size

For sleep apnea the heart rate images are extracted from ECG signals. The R-R intervals of ECG signals which are recorded for 7 to 10 hours have been divided in 60 seconds intervals to calculate heart rate. These heart rate images are stored as training, validation and testing data. Fig. 9, 10 and 11 shows the training data, validation data and testing data sizes respectively which are used to train and test the model developed.

20099 images from both classes belong to training data.

```
[ ] train_generator = datagen.flow_from_directory(
        directory="/content/gdrive/MyDrive/capstone/cnn/Apnea_train/train",
        classes = class_names,
        target_size=(224, 224),
        batch_size=32,
        class_mode="binary",
    )

    Found 20099 images belonging to 2 classes.
```

Fig. 9. Training data size for sleep apnea.

The validation data consists of 6741 images in both classes.

```
[ ] # validation data
    valid_generator = datagen.flow_from_directory(
        directory="/content/gdrive/MyDrive/capstone/cnn/Apnea_train/val",
        classes = class_names,
        target_size=(224, 224),
        batch_size=32,
        class_mode="binary",
    )

    Found 6741 images belonging to 2 classes.
```

Fig. 10. Validation data for sleep apnea.

Testing data consists of 6291 images in both classes.

```
[ ] # test data
    test_generator1 = datagen.flow_from_directory(
        directory="/content/gdrive/MyDrive/capstone/cnn/testing_final1",
        classes = class_names,
        target_size=(224, 224),
        batch_size=32,
        class_mode="binary",
    )

    Found 6291 images belonging to 2 classes.
```

Fig. 11. Testing data for sleep apnea.

For REM the dataset size consists of X and Y. X consists of data and Y consists of labels which is shown in Fig. 12.

```
[3] # Load npz files

    # Change variable 'path' with own path

    path = '/content/gdrive/MyDrive/rem/data' #the path where the npz files were saved in the first notebook.

    files = os.listdir(path)
    filespath = []
    for i in files:
      filespath.append(os.path.join(path,i))

    X, Y = _load_npz_list_files(filespath)

    X = X.reshape((X.shape[0], X.shape[1]))
    print(X.shape, Y.shape)

    (42308, 3000) (42308,)
```

Fig. 12. Dataset size for REM detection.

VI. RESULT AND DISCUSSION

ResNet-50 and Gradient boost algorithms were used to detect sleep apnea and REM (Rapid eye Movement) respectively. Accuracy is the metric employed to assess and contrast the outcomes of the proposed model with those of other models. ResNet-50 model classified heart rate images and detected the presence of sleep apnea. The model demonstrated validation accuracy of 90.21 and test accuracy of 90.001.

To visualize the performance of the model, few graphs were plotted.

Fig. 13 shows loss curve which depicts the change in the loss function's value over time (epochs or iterations) during the training of a machine learning model. The loss function evaluates the difference in variability between the predicted values and the actual target values, acting as an indicator of the model's effectiveness. Training loss and validation loss of each epoch is plotted using line graph.

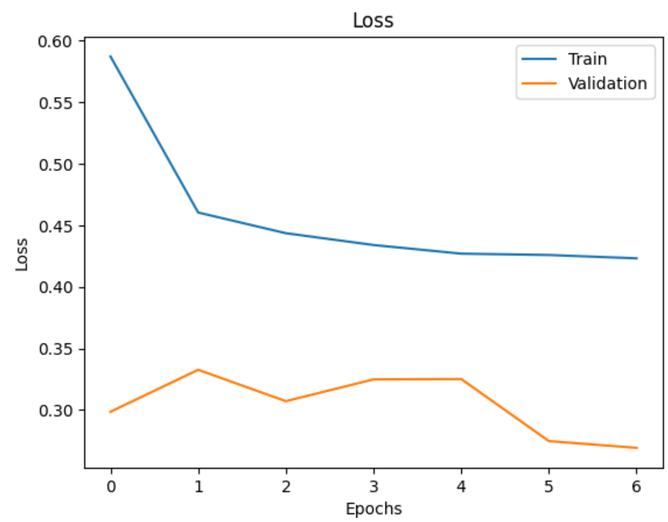

Fig. 13. Loss curve.

Fig. 14 shows accuracy curve. The testing and validation accuracy of each epoch is plotted using a line graph.

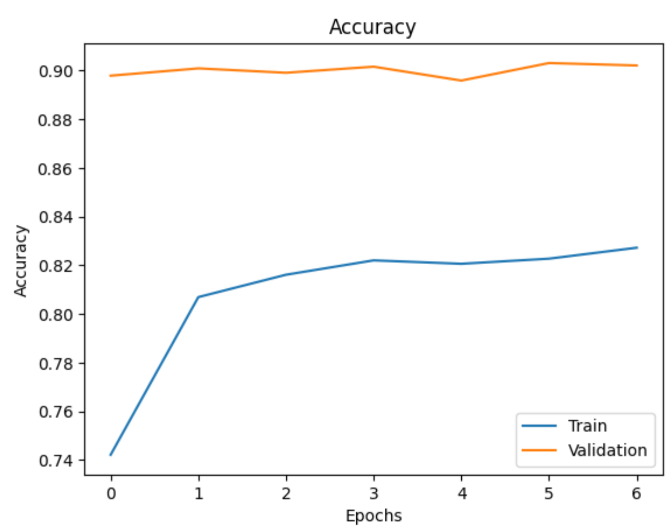

Fig. 14. Accuracy curve.

Fig. 15 and Fig. 16 shows the bar graph plot of duration in minutes where each patient doesn't experience Sleep Apnea and duration in minutes where each patient experiences Sleep Apnea.

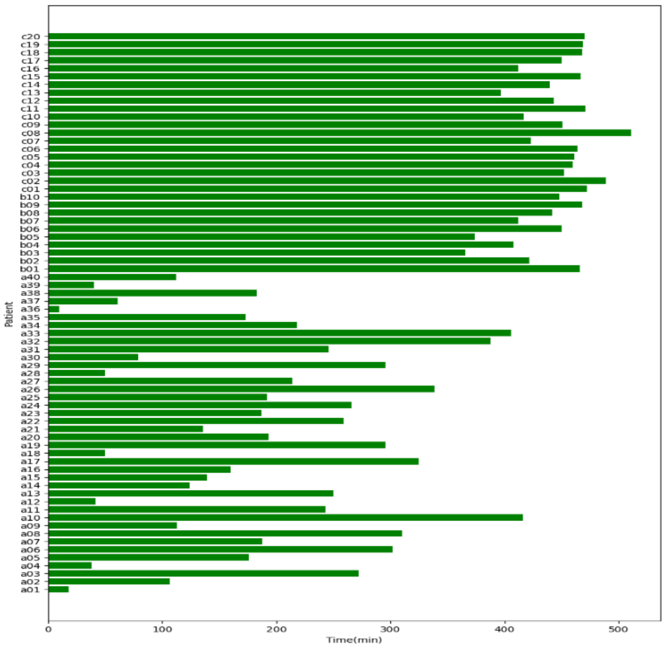

Fig. 15. Non-Apnea duration for each patient.

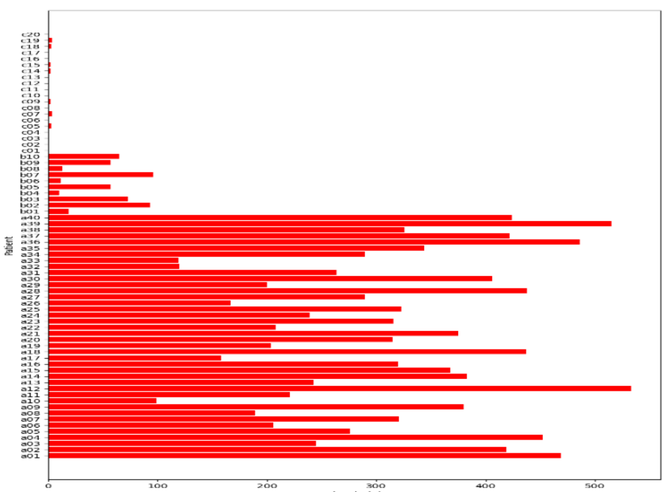

Fig. 16. Apnea duration for each patient.

Fig. 17 shows overall duration in minutes from all the recording of patients where sleep apnea was detected and duration in minutes when sleep apnea is not present in the recordings. This plot shows the sum of duration in minutes of sleep apnea and duration when patients didn't experience sleep apnea from each ECG signal recording.

Feature correlation for each feature in the dataset has been calculated to find out which features are more important. Fig. 18 shows a bar graph where each feature of the data along with its importance according to the feature correlation calculated is plotted.

Table I gives an insight into other machine learning and deep learning models and the accuracies of each model compared with the ResNet-50 model. The accuracies have been referred from Bahrami, M et al. [4].

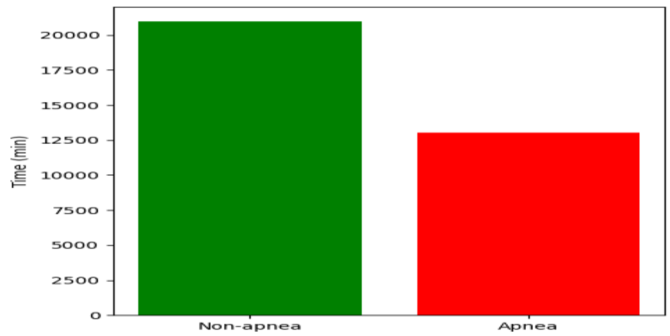

Fig. 17. Total Apnea and non-Apnea duration.

TABLE I. COMPARING THE ACCURACY PERFORMANCE OF THE RESNET-50 MODEL WITH THAT OF OTHER MODELS. THE MODEL ACCURACIES HAVE BEEN REFERRED FROM [4]

Model	Accuracy (%)
ResNet-50	**90.001**
LSTM (Long Short-term memory)	82.52
BiLSTM	82.45
GRU (Gated Recurrent Unit)	82.93
ZFNet	87.36
AlexNet	87.09
VGG16	87.26
VGG19	86.75
VGG16-LSTM	88.02
VGG16- GRU	87.78
VGG16- BiLSTM	88.01
VGG19- LSTM	87.06
VGG19- GRU	86.62
VGG19- BiLSTM	86.92
AlexNet- LSTM	87.32
AlexNet- GRU	87.11
AlexNet- BiLSTM	87.43
ZFNet- LSTM	87.84
ZFNet- GRU	87.43
ZFNet- BiLSTM	88.13
LDA (Linear Discriminant Analysis)	76.77
QDA (Quantitative Descriptive Analysis)	75.54
LR (Logistic Regression)	76.91
GNB (Gaussian Naïve Bayes)	75.96
GP (Gaussian Process)	77.26
SVM (Support Vector Machine)	78.44
KNN (K-nearest neighbours)	77.85
DT (Decision Tree)	74.47
RF (Random Forest)	77.79
ET (Extra Tree)	78.33
AB (AdaBoost)	77.09
GB (Gradient Boosting)	77.52
MLP (Multi-Layer perceptron)	78.52
MV (Majority Vote)	79.39

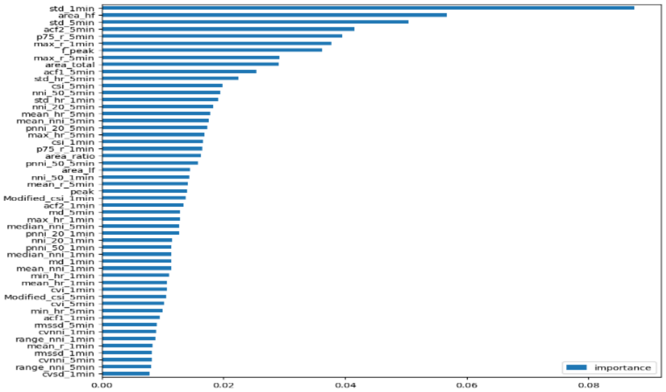

Fig. 18. Feature importance plot (max_r_5min, max_hr_1min, min_hr_5min etc.).

For REM the model used Gradient Boosting algorithm. The gradient boost algorithm has classified the sleep dataset into two stages: Non-REM and REM. The metrics used to validate the model is accuracy. The model has demonstrated an accuracy of 81.65% and precision of 50.77%, area under ROC curve is 54.39% recall score is 1.0.

The Receiver Operating Characteristic (ROC) curve visually represents the diagnostic effectiveness of a binary classifier system as it adjusts its discrimination threshold.

To visualize the model performance, ROC curve has been shown in Fig. 19.

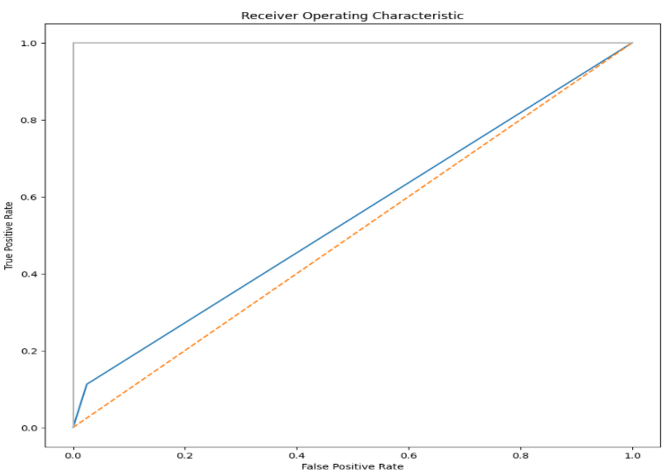

Fig. 19. ROC curve for REM detection using Gradient Boost.

The SHAP (SHapley Additive exPlanations) plot is a visual tool utilized for interpreting the results of machine learning models, particularly those with intricate decision making mechanisms such as tree-based models or deep neural networks. SHAP plots aid in comprehending the significance and impact of various features in the prediction process. SHAP values were plotted for all instances of the dataset. Fig. 20 shows shap plot where each feature of the data is plotted against its calculated SHAP value.

To visualize precision and recall scores, precision-recall curve was plotted. Fig. 21 shows precision score on y-axis and recalls core on x-axis.

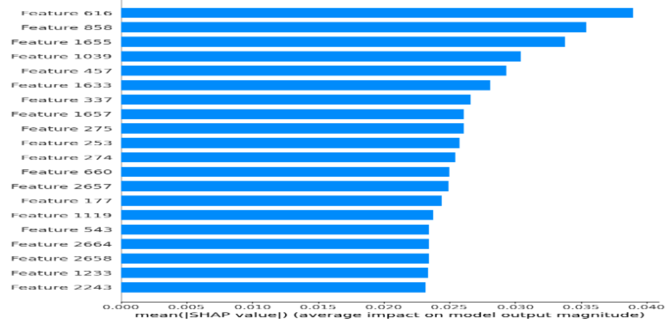

Fig. 20. SHAP plot for REM.

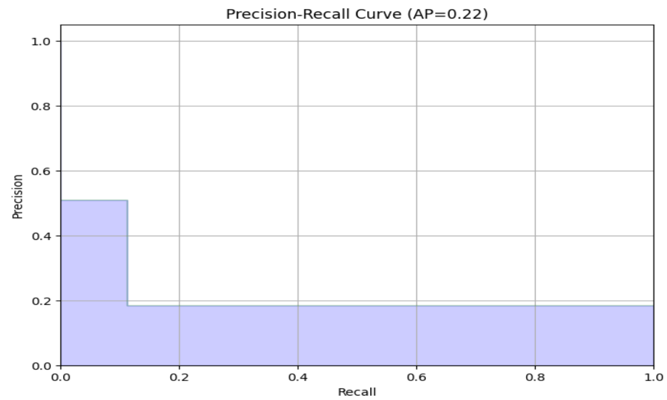

Fig. 21. Precision-recall curve REM.

VII. CONCLUSION AND FUTURE WORK

In conclusion, this paper aimed at developing a comprehensive system to detect Sleep Apnea and Rapid Eye Movement (REM) using a multi model approach using ECG signals dataset from Apnea-ECG dataset from physionet and EEG signals data from Sleep-EDF data from physionet.

This provides a complete sleep analysis as the system is detecting sleep stage which is REM and sleep disorder Sleep apnea. For sleep apnea detection heart rate was extracted from ECG signals and ResNet-50 model was employed to detect Sleep apnea. Loss and accuracy curve was plotted to visualize the model performance. For REM EEG signals have been extracted from polysomnographic data which is Sleep-EDF data and Gradient Boost model was employed to detect the REM sleep stage. ROC curve, SHAP plot and precision-recall curves have been plotted to visually assess the model's effectiveness. Both the models have been validated using accuracy as the main performance metric.

Sleep apnea, both obstructive and central, can occur during REM sleep. During REM sleep, the muscles of the upper airway, including those in the throat, tend to relax more, which can exacerbate breathing difficulties in individuals with sleep apnea disorder. With reference to REM sleep, individuals suffering with sleep apnea often experience disruptions in this specific sleep stage. During REM sleep stage, the muscles become temporarily paralyzed (atonia) to prevent the acting out of dreams. In individuals with sleep apnea, the relaxation of throat muscles and partial or complete airway obstruction can lead to brief awakenings to resume normal breathing. These interruptions can fragment REM sleep, affecting the overall sleep architecture and potentially contributing to daytime sleepiness and other symptoms associated with sleep apnea.

Future work could involve further investigation and validation to improve the system, facilitating its integration into clinical practice and enhancing the detection and treatment of sleep apnea and REM disorders, ultimately improving patient care. One promising direction is to develop a real-time implementation of the model that can run on edge devices, enabling the detection of sleep apnea and REM in home environments. This can be complemented by creating a mobile application that utilizes the trained models to provide immediate feedback and alerts to users, making sleep health monitoring more convenient. To ensure accessibility and user satisfaction, it is essential to design an intuitive, user-friendly interface suitable for non-technical users. Additionally, incorporating educational materials into the app can help users better understand their sleep patterns.

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