Analyzing and Predicting Sleep Apnea using CNN

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Abstract- The word Sleep apnea (SA) in the term of Obstructive sleep apnea (OSA) is becoming the most ordinary respiratory disorder during sleep, which is distinguish by stopping of airflow to the lungs. These interrupt in breathing must last for more than 10 seconds to be considered an apnea event. Apnea occurrence may occur 5 to 30 times an hour and may occur up to four hundred times per night in those with severe Sleep Apnea. The most frequent night symptoms of SA can mainly include the activities like snoring, nocturnal arousals, sweating, restless sleep and many more. Moreover, sleeping disorders, symptoms of sleep apnea do not occur just during the night. Daytime symptoms also can range from morning headaches, depression, impaired concentration and excessive sleepiness which cause mortality from traffic and industrial accidents. In this paper an attempt is made to develop a system to detect sleep apnea in an individual using National Sleep Research Resource dataset. The system builds a prediction model by using Convolution Neural Network (CNN) technique.

Keywords: *Sleep Apnea,* **Obstructive** *sleep Apnea (OSA), Convolution Neural Network (CNN)*

I. INTRODUCTION

Sleep apnea is a potentially serious sleep disorder that occurs when a person's breathing is interrupted during sleep. Actually, Sleep Apnea is not a issue to be taken gently, since it is related with a major risk factor of health implications and expand cardiovascular disease and sudden death.

Sleep Apnea Syndrome→Medical Definition

Sleep Apnea Syndrome: SAS is a sleep disorder characterized by breathing stops during sleep. Breathing stops for more than 10 seconds is said to be apnea. It is diagnosed as SAS by a professional physician using data from specialized instruments.

The severity of symptoms is as follows: if the apnea is happened

• 5 to 14 times per hour is mild;
• 15 to 29 times per hour is moderate;
• more than 30 times per hour is severe.

OVERVIEW OF SLEEP STAGES AND THE CLASSIFICATION STRUCTURE

There are five stages of sleep that has been proved: stage 1, stage 2, stage 3, stage 4, rapid eye movement (REM) [8]. To facilitate the assessment of sleep apnea, only two categories are essential: deep sleep (DS) and light sleep (LS). The average DS and LS distribution of normal people and sleep apnea patients is represented in following figure;

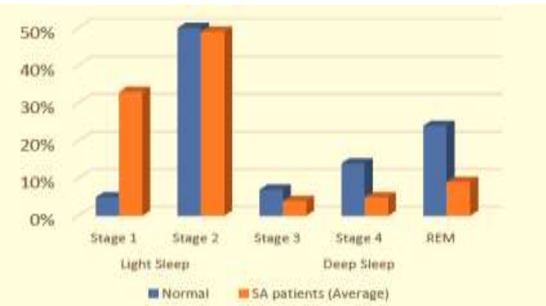


Figure: - Average distribution of sleep stages for normal people and sleep apnea patients.

LS is responsible for body relaxation normally before DS. However, sleep apnea patients suffer from long term LS renders inefficient sleep quality. Moreover, lack of DS also renders insufficient sleep. Therefore, in this paper, LS and DS are newly defined based on the conventional sleep stages:

- **LS: Sleep stage 1:** typically soon after "sleep action"; body is not inhibited yet; breath slow down; blood pressure and brain temperature decreases.
- **Sleep stage 2:** slower heart rate than sleep stage 1; brain starts to emit large waves; more metabolic functions slow down.

- **DS: Sleep stage 3 & 4:** brain waves become slow down and larger than sleep stage 2; most potential sleep disturbances can be ignored.
- **REM:** eyes move rapidly; dreams usually happen; increase of heart rate.

II. COMPUTER AIDED SLEEP APNEA DETECTION

Over the past few years most of the related research has focused on presenting methods for the automatic processing of different statistical features of different signals such as thorax and abdomen effort signals, nasal air flow, oxygen saturation, electrical activity of the heart (ECG), and electrical activity of the brain (EEG) for the detection of SA. The validated database used to assess the detection algorithms in the related research studies is supplied online from the PhysioNet web site. All apneas in the recordings are either obstructive or mixed.

What is Polysomnography?

Polysomnography is a comprehensive recording of physiological changes that occur during sleep, which includes brain activity, heart rhythm, eye-movement, and skeletal muscle activation [10]. Despite its extensive capabilities, polysomnography is very troublesome to be implemented because many sensor modules need to be placed on the body surface of the patient. Following are more detail parameter that is recorded by polysomnograph.

The full overnight polysomnogram recordings were divided into a set of one-minute segments. Each segment was annotated based on visual scoring of disordered breathing during sleep and if at any time during that minute there was evidence of sleep apnea the segment was classified as "apnea"; otherwise it was classified as "normal". Segments containing hypopneas were also classed as apnea.

III. EXISTING SYSTEM

Existing system has used SVM, for classification and they used heart rate variability & Oxygen Saturation was considered in detecting OSA which is providing 82% of accuracy. The combination of K-Means and K-NN algorithm using the term Re-weighting achieves the accuracy of least 88%.

DISADVANTAGE

- Takes more time for computation of the results.
- SVM classification accuracy is very low
- Considering the ECG signals as they are not as accurate as ECG wave interpretation.

IV. LITERATURE REVIEW

METHOD: - OSA severity classification using a Deep Learning (DL) approach

DESCRITION:-A heap of one-dimensional Convolutional Neural Networks (1-D CNNs) with 256, 128 and 64 units, separately, for programmed highlight parceled them into 10 equivalent measured subsamples to such an extent that there were 10 subsamples with 100 examples in each. For each subsample, it at that point stays 900 examples from the aggregate. Extraction [6]. Each CNN layer is trailed by group standardization; the amended straight unit initiation work just as the maximum pooling process with pool size equivalent to 2 so as to separate just significant highlights from the yield of its past layer. After model improvement, we assessed our primary classifier utilizing exactness, particularity, affectability and F-score.

METHOD: - SaO2

DESCRITION:-The study assessed analysis of a comprehensive feature set based on blood oxygen saturation (SaO2) from nocturnal oximetry in order to evaluate sleep quality. The three features of SaO2 signal which are delta index, central tendency measure and oxygen desaturation index are evaluated. Central tendency measure accuracy was higher than those provided by delta index and oxygen desaturation index.

ADVANTAGES: - central tendency measure the sensitivity was 90.1% and the specificity was 82.9%.

METHOD: - HEART RATE VARIABILITY (HRV)

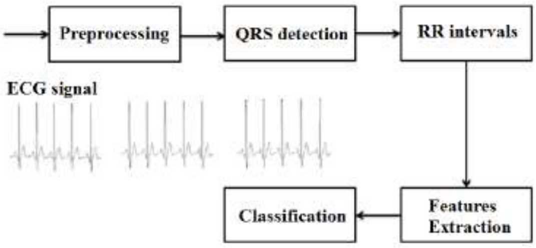
DESCRITION:-Based on spectral components of heart rate variability (HRV), frequency analysis was performed in [9] to detect sleep apnea. Using Fourier and Wavelet Transformation with appropriate application of the Hilbert Transform, the sensitivity was 90.8%. In addition, in [10] a bivariate autoregressive model was used to evaluate beat-by-beat power spectral density of HRV and R peak area.

ACCURACY: - where the sleep apnea classification results showed accuracy higher than 85%.

METHOD: - Electrocardiogram (ECG) signal

DESCRITION:-Many studies show that detection of OSA can be performed through the Electrocardiogram (ECG) signal due to cyclic variations in the duration of a heartbeat. This consists of bradycardia during apnea followed by tachycardia upon its cessation [9, 11]. In our previous published research, we developed a model based on a linear kernel Support Vector Machines (SVMs)using a selective set of RR-interval features from short duration epochs of the ECG signal. The results show that our automated classification system can recognize epochs of SA with a high degree of accuracy.

PROCESS:-



ACCURACY: - accuracy, approximately 96.5%

METHOD: - Electroencephalographic (EEG)

DESCRITION: - Electroencephalographic (EEG) arousals are seen in EEG recordings as an awakening response of the human brain. EEG arousals were defined according to the American Sleep disorders Association (ASDA) report [4]. Principal features of EEG arousals in the time series were: appearance of arousal response longer than 3 s; and existence of sleep period lasting at least 10 s immediately before arousal responses. In recorded EEG time series for patients with OSAS, EEG arousals occur by the resumption of ventilation immediately after the apnea interval, and have crucial meanings in the clinical diagnosis of OSAS. Obstructive apnea is defined as total cessation of airflow at the nose and mouth, lasting at least 10 s and associated with ongoing thoracic and abdominal efforts to inspire. Waveforms of airflow pressure and airflow temperature are almost flat during the apnea interval.

PROCESS:-

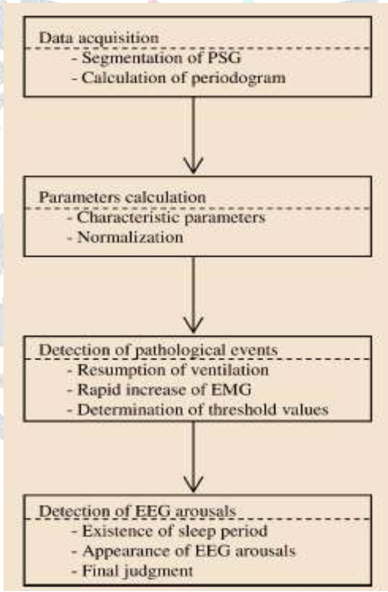


Figure: - Flowchart for automatic detection of EEG arousals. The method consists of four procedures: data acquisition; parameter calculation; detection of pathological events; and detection of EEG arousals.

V. PROPOSED METHODOLOGY

1. Data Uploading and feature understanding

The data downloaded from National Sleep Research Resource is pre-processed first so that we can extract important features that are quite essential to detect sleep Apnea. This Sleep Apnea data from National Sleep Research Resource is used as input to the system to find features that are responsible for sleep Apnea, and learn to predict the probability of sleep Apnea in the individual. The main features used to Apnea prediction are as follows:

Features	Description
cent_obs_ratio	Ratio of central apneas to obstructive apneas from eligibility scoring pass

n_cent_apneas	Number of central apneas from eligibility scoring pass
aphypi	Overall Apnea-Hypopnea Index (AHI) from Embletta Sleep Report
nhypa	Apnea/Hypopnea: Hypopnea Apneas or Hypopneas per hour
apnea90s	Apnea-Desaturation Relation: Greater than 90% Apnea
nca	Apnea/Hypopnea: Central Number
avgdesat	SpO2: Average Desaturation
ndesat	Oxygen Desaturation Events
napnea	Apnea/Hypopnea: Apnea Number
aphypins	Non-Supine Apnea-Hypopnea Index (AHI)
desati	Oxygen Desaturation Events
Decision (aphypi)	From the overall Apnea-Hypopnea Index (AHI) sleep report we can predict the sleep apnea/hypopnea is absence and/or Presence in the respective individual.

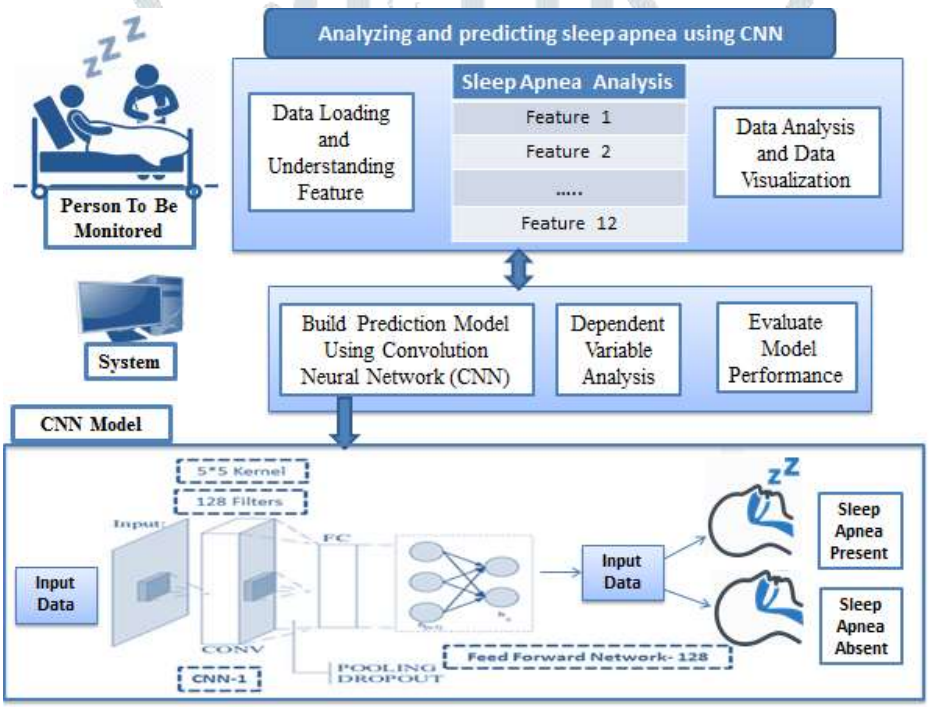


Figure: - System Architecture

2. Dependent Variable Analysis

Dependent variables or Predicted variable are the one that helps to get the factors that mostly dependent on key variables that mainly includes Apnea-Hypopnea Index (AHI), Central apnea, Oxygen Desaturation and Hypopnea. For example the employee ID or employee count has nothing to do with the attrition rate. So here by using the dataset we achieve the terms or the factor that are mostly affect the employee attrition rate.

The analyzed data is visualized for word to vector formation and on this fine-tuned data we can apply algorithm to get the final result.

3. Analytics :

Exploratory Data Analysis is an initial process of apnea and hypopnea, in which you can summarize characteristics of data from which we can predict the probability of the sleep apnea in an individual.

4. Built Prediction Model using Convolution Neural Network (CNN)

The system builds a prediction model by using Convolution Neural Network (CNN) technique.

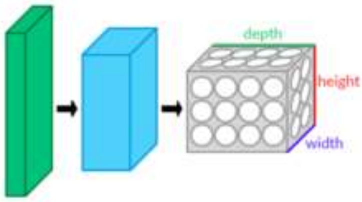
Input for CNN is taken from National Sleep Research Resource website

https://sleepdata.org/datasets/shhs/files

Output:-Prediction for an individual has apnea or not, according to the following scale:

0 – Sleep Apnea is Absent
1 – Sleep Apnea is Present

A CNN consists of an input and an output layer, as well as multiple hidden layers. The hidden layers of a CNN typically consist of Convolutional layers, pooling layers, fully connected layers and normalization layers. CNN will be used to train the images analytics engine for recognizing important data from images.



A. Algorithm Used

Algorithm 1:- Convolution Neural Network (CNN)

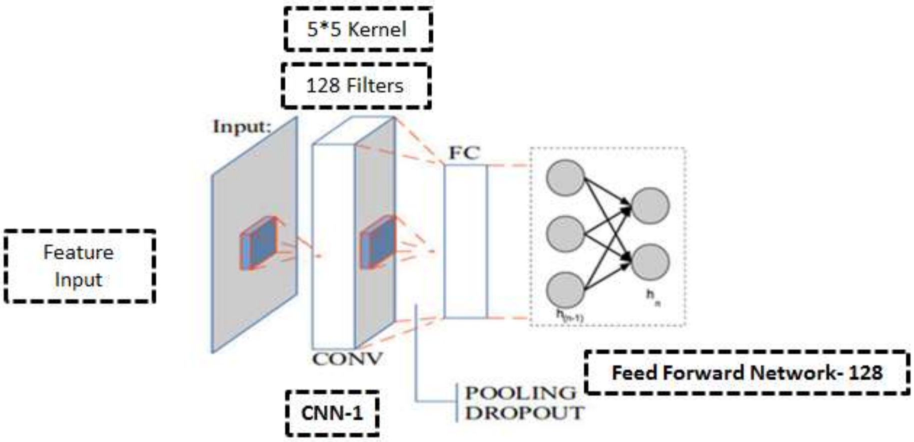
CNN algorithm was applied on 2 features that are rating and its class to people to predict the movie review which are directly proportional and affects the result of prediction.

We have described an interesting framework called Word2vec + CNN on the available public dataset of movie reviews. The experimental results suggest that convolutional neural networks that are properly trained can outperform the shallow classification algorithms.

Input→ The data downloaded from National Sleep Research Resource. The data set contain the data of apnea and hypopnea

Output→ Prediction for an individual has apnea or not, according to the following scale:

0 – Sleep Apnea is absent
1 – Sleep Apnea is Present



Step 1:- Initially the features data are the inputs to the Convolutional Neural Network.

Step2:- Conv that is 1-D Convolutional Neural Network layer often followed by Pool layers. In Pooling layer the receptive field of filters (F*F) is included here we are using 5*5 kernel matrix along with 128 filters. The output of this layer acts as the input to the next layer.

Step 3:- The output of the pooling layer is forwarded to the "Fully Connected Layer." Fully connected layer that takes the end result of the pooling process as input and reaches a classification decision (result).

Step 4:- The output of the CNN is the Prediction for an individual has apnea or not, according to the following scale:

0 – Sleep Apnea is Absent
1 – Sleep Apnea is Present

VI. RESULT AND DISCUSSIONS

A) Dataset Used

1) Large data set of Sleep Apnea.

Input for CNN is taken from National Sleep Research Resource website https://sleepdata.org/datasets/shhs/files

B) Results →Screenshots

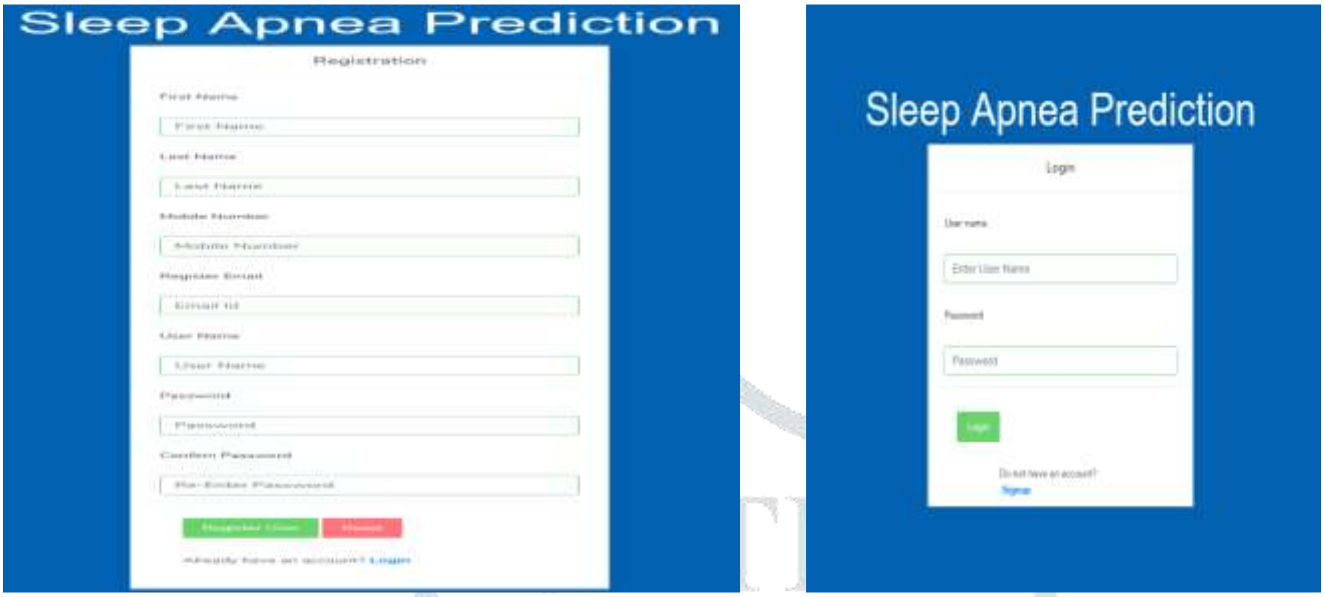


Figure: - Login and Registration Page

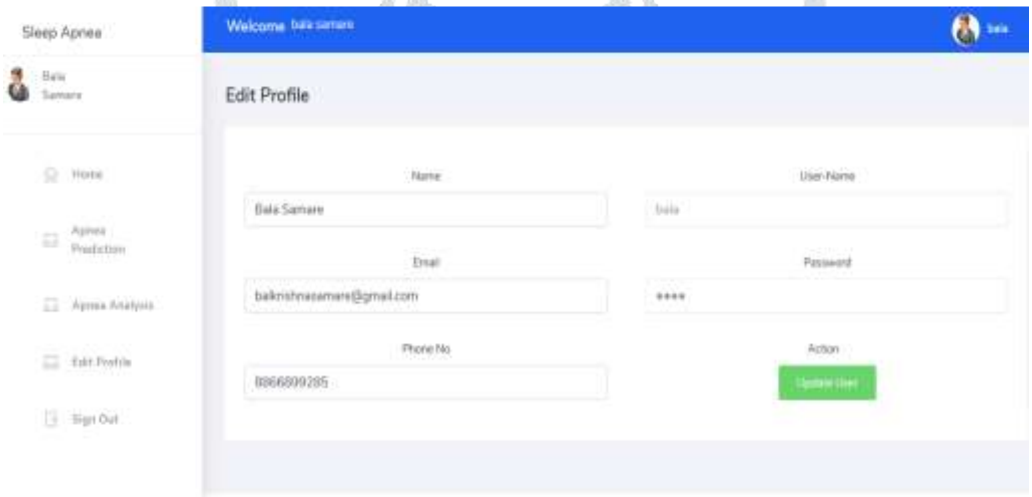


Figure: - Update Users

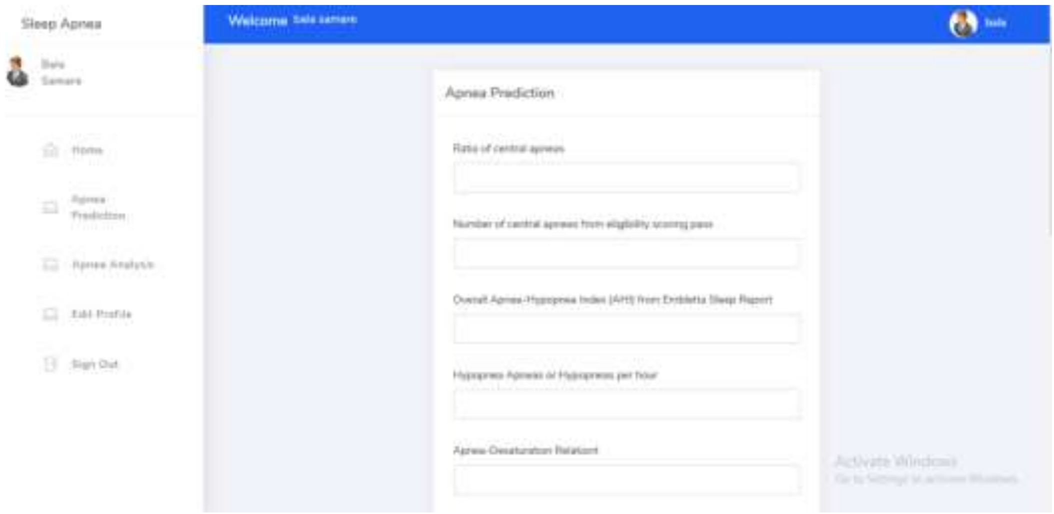


Figure: - Sleep Apnea Features

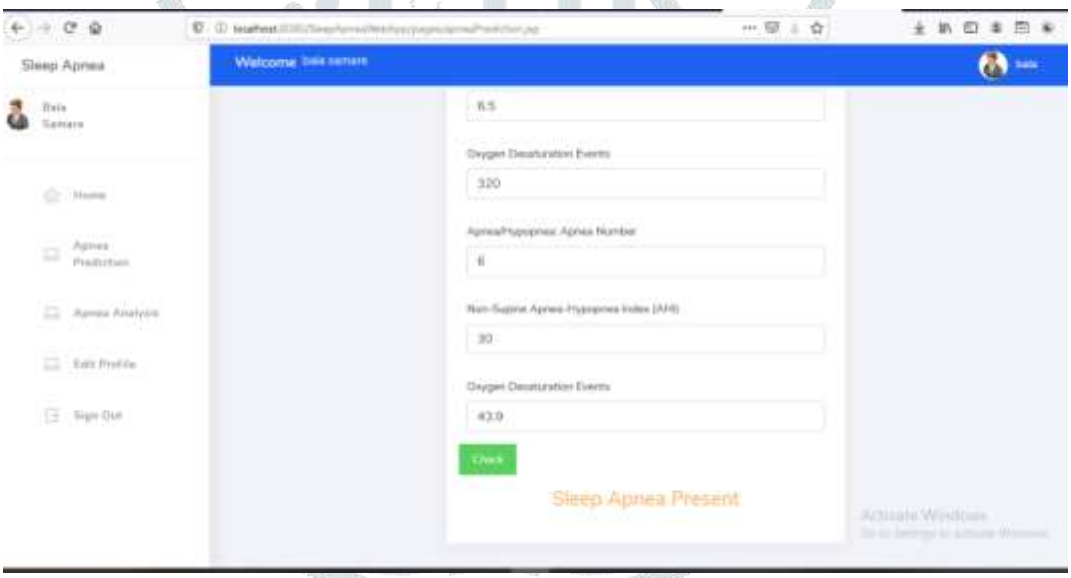


Figure:- according to the Sleep Apnea features system predicts the sleep apnea.

VII. CONCLUSION

Sleep quality is one of main factor to determine human health and well-being. Sleep quality monitoring is one the solution to maintain the quality of sleep and prevents chronic diseases, mental problem, or accidents caused by sleep disorder. This study proposed a new method for detecting Sleep Apnea. The key feature of the method was selected by studying the data set of National Sleep Research Resource dataset. The system builds a prediction model by using Convolution Neural Network (CNN) technique. The proposed method can identify useful information for the interpretation AHI for patients with sleep apnea (SA). This method will thus provide us a useful system for diagnosis of the sleep apnea by inspecting the individual.

REFERENCES:

[1] T. Sugi, F. Kawana, M. Nakamura “Automatic EEG arousal detection for sleep apnea syndrome 2009 Elsevier Ltd. All rights reserved.

[2] Ali Jezzini, Mohammad Ayache, Lina Elkhansa,Zein al abidin Ibrahim, "ECG Classification for Sleep Apnea Detection," 2015 International Conference on Advances in Biomedical Engineering (ICABME), pp. (pp. 2476-2486). IEEE., 2015.

[3] Yuan, Y., Jia, K., Ma, F., Xun, G., Wang, Y., Su, L., & Zhang, A. (2018). variable Sleep Stage Classification Mistreatment Hybrid Self-Attentive Deep Learning Networks. 2018 IEEE International Conference on Bioinformatics and Biomedicine (BIBM).

[4] Li, X., Cui, L., Tao, S., Chen, J., Zhang, X., & Zhang, G.- Q. (2018). HyCLASSS: A Hybrid Classifier for Automatic Sleep Stage grading. IEEE Journal of medical specialty and Health science, 22(2), 375–385.

[5] Li, Y., Pan, W., Li, K., Jiang, Q., & Liu, G.-Z. (2018). slippy Trend Fuzzy Approximate Entropy as a completely unique Descriptor of vital sign Variability in impeding apnea. IEEE Journal of medical specialty and Health science, 1–1.

[6] Phan, H., Andreotti, F., Cooray, N., Chen, O. Y., & De Vos, M. (2018). Joint Classification and Prediction CNN Framework for Automatic Sleep Stage Classification. IEEE Transactions on medical specialty Engineering, 1–1.

[7] Alvarez D, Hornero R, Marcos JV, del Campo F. 2010. Multivariate analysis of blood oxygen saturation recordings in obstructive sleep apnea diagnosis. IEEE Transactions on Biomedical Engineering 57:2816-2824

[8] Azarbarzin A, Moussavi Z. 2013. Snoring sounds variability as a signature of obstructive sleep apnea. Medical Engineering & Physics 35:479-485

[9] DeChazal P, Heneghan C, Sheridan E, Reilly R, Nolan P, O'Malley M. 2000. Automatic classification of sleep apnea epochs using the electrocardiogram. Vol 27 (Cat 00CH37163): IEEE. In: Computers in cardiology 2000. 745-748

[10] Young T, Peppard P, Palta M, Hla KM, Finn L, Morgan B, Skatrud J. 1997. Population-based study of sleep-disordered breathing as a risk factor for hypertension. Archives of Internal Medicine 157:1746-1752

[11] Khandoker AH, Palaniswami M, Karmakar CK. 2009. Support vector machines for automated recognition of obstructive sleep apnea syndrome from ECG recordings. IEEE Transactions on Information Technology in Biomedicine 13:37-48