Analysing and Predicting Sleep Apnea using CNN

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Abstract- ***Sleep apnea is a sleep related or breathing disorder in which breathing stops at the time of sleeping. It causes breathing to repeatedly stop and start during sleep which over years increases the risk of hypertension, heart disease, stroke, Alzheimer's, and cancer. Detecting such disorder can significantly saves peoples life to a great extent.***

This paper presents a system that can effectively detects the presence of the apnea and hypopnea in the individual using CNN. The experimentation is carried out on the National Sleep Research Resource dataset. The system builds a prediction model by using Convolution Neural Network (CNN) technique. System can identifies 12 important features that mainly includes Apnea-Hypopnea Index (AHI), Central apnea, Oxygen Desaturation and Hypopnea for the prediction of sleep apnea.

Keywords: Prediction of sleep apnea, Convolution Neural Network (CNN), Apnea-Hypopnea Index (AHI), Dependent Variable Analysis, Feature extraction.

I. INTRODUCTION

Sleep-disordered is characterized by repetitive episodes of partial or complete blockage of the upper airway during sleep. This leads to partial reductions (hypopneas) and complete pauses (apneas) in breathing that last at least 10 seconds or may lies between 10 and 30 seconds, up to one minute or longer [1]. Such obstruction can lead to abrupt reductions in blood oxygen saturation, results in more severe cases.

Undiagnosed and untreated obstructive sleep apnea (OSA) is a major health concern significantly widespread with a global estimation of 200 million people [2]. Among the apnea patients, 93% of middle-aged women and 82% of middle-aged men with moderate to severe sleep apnea were undiagnosed [2] that associated with several severe health consequences, such as cardiac arrhythmia, heart attacks, stroke [3], and even sudden death.

Polysomnography (PSG)[1][3] is the procedure for the accurate diagnosis of sleep disorders. It is performed at a specialized sleep center or laboratory. Polysomnography records six Multiple physiological signals affecting electroencephalogram (EEG), electrooculograms (EOG), electromyogram (EMG), electrocardiogram (ECG), respiration, and pulse oxygen saturation (SpO2)[2][4] as shown in figure 1 during the overnight. These recordings are manually analyzed by sleep specialists along with multi-sensor equipment, which is time-consuming, labor-intensive, and error-prone, making it a complex and expensive process, which markedly affects the availability and accessibility of OSA diagnostic resources.

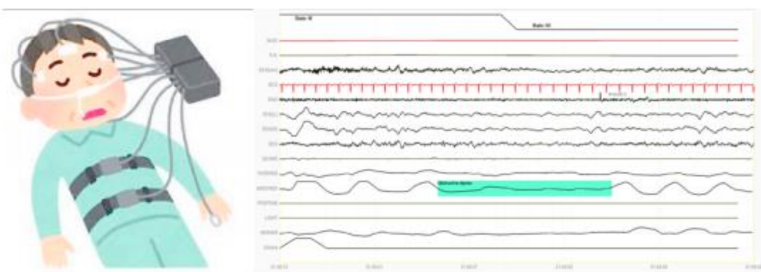


Figure 1: Polysomnography to Detect Obstructive Sleep Apnea

Many efforts have been taken already testing for routine screening of OSA, but the accuracy of most analysis software has been shown to be relatively poor, underestimating the condition. Therefore, there is a need for an intelligent OSA diagnostic system that uses fewer signals, analyzes more patients more rapidly, and eliminates the high intra- and inter-scorer variability.

Deep learning is gaining higher interest due to database availability, newly developed techniques, the possibility of producing machine-created features, and higher computing power that allows the algorithms to achieve better performance than the shallow classifier.

AHI is one of the important features that mostly used for detecting apnea. The AHI level/index decides, the presence and the intensity of the sleep apnea for the patients, like

- AHI index < 5 Then, the patient condition is normal and not prone to sleep apnea
- AHI index in between 5-14 / hour → Classified as mild sleep apnea prone.
- AHI index in between 15-19 / hour → Classified as moderate sleep apnea conditions.
- AHI index in between 30 or more / hour → Classified as severe category of sleep apnea.

The paper presents an alternate system that helps to analyze and detect the Presence of apnea and hypopnea in the individual using CNN. A convolutional neural network (CNN) is a kind of deep neural network that can automatically learn effective feature representation from training data and has been successfully applied in many fields. In this system, we have considered 12 features that are mainly responsible for sleep apnea.

II. LITERATURE SURVEY

Taehoon Kim, et al.[6] aimed to identify acoustic biomarkers indicative of the severity of sleep-disordered breathing (SDB) by analyzing the breathing sounds collected during sleep, without conducting attended full-night PSG using a deep neural network. Several standard audio features are extracted from the breathing sound data from full-night PSG. The statistical analysis is done to identify acoustic biomarkers and verified their effectiveness using a train-test classification framework based on the SDB severity.

DeChazal P et al.[8] considers spectral components of heart rate variability (HRV), frequency analysis to detect sleep apnea. Using Fourier and Wavelet Transformation with appropriate application of the Hilbert Transform, the sensitivity was 90.8%. In addition, in [9] a bivariate autoregressive model was used to evaluate beat-by-beat power spectral density of HRV and R peak area. The sleep apnea classification results showed accuracy higher than 85%.

Tom Van Steenkiste et al.[10] presented a technique Long Short-Term Memory Neural Networks for automatically extracting features and detecting sleep apnea events in respiratory signals. The Sleep-Heart-Health-Study-1 dataset is used for experimentation that gives per-epoch sensitivity and specificity scores comparable to the state of the art. a considerable improvement in the hypopnea index is gained compared to conventional methods.

Ahnaf Rashik Hassan et al.[11] has been implemented LogitBoost method for automated sleep apnea detection. Results suggest that the detection accuracy of the apnea screening scheme is higher as compared to other methods.

Anju Prabha et al.[12] show the detection of obstructive sleep apnea (OSA) can be automated using a support vector machine (SVM). The features like heart rate variability (HRV) and respiratory rate variability (RRV) parameters derived from electrocardiogram (ECG) and respiratory effort signals (RES) are used for detection. The signals in the rapid eye movement (REM) stage of sleep are used as a major feature for detection.

III. PROPOSED DESIGN

A. System Architecture

The main aim of the proposed system is to analyze the breathing data of the patient and detect the apnea in the patient. Figure 2 shows the system design followed with detailed working of the system.

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.

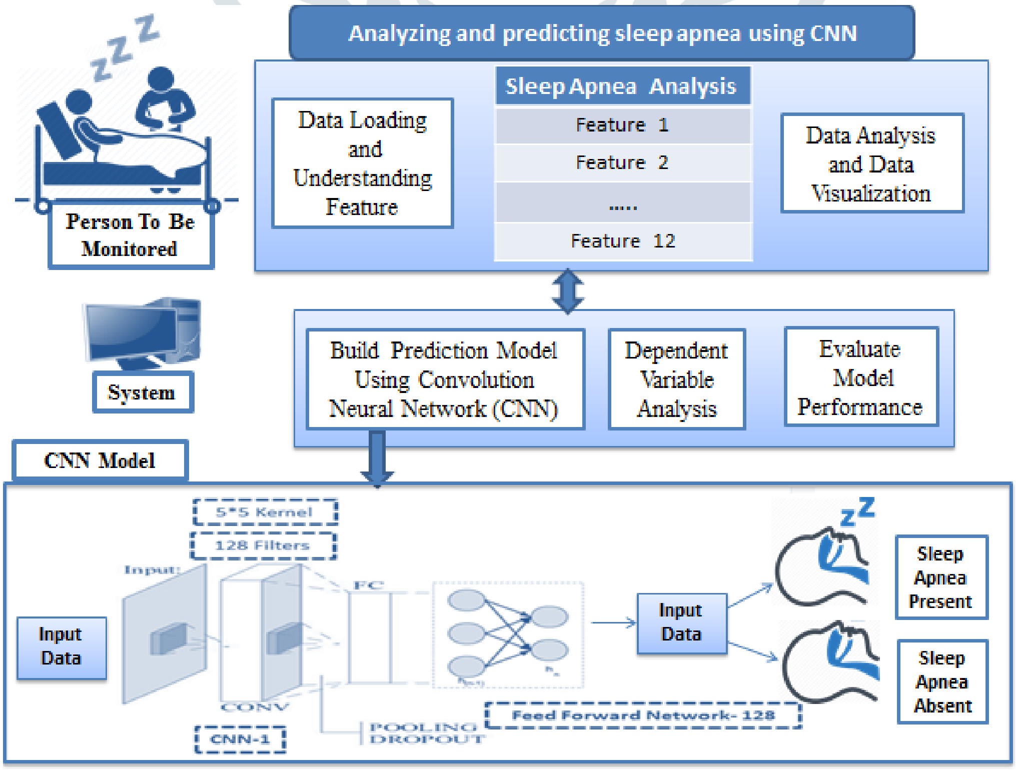


Figure 2: - System Architecture

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)

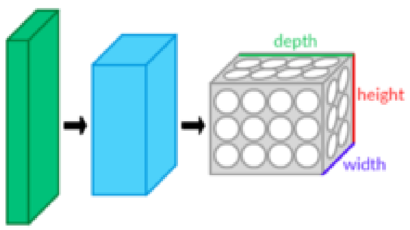
The system builds a prediction model by using Convolution Neural Network (CNN) technique.
Input for CNN is taken from National Sleep Research Resource website

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.



B. Software/ Hardware Requirement for project Development

➢ **Software Requirement:**

- **IDE:** Eclipse Luna or above
- **Backend:** MySQL Database
- **Programming language:** Java JDK 1.8

➢ **Hardware Requirement:**

- **Processor:** 1 gigahertz (GHz) or faster processor or SoC.
- **RAM:** 1 gigabyte (GB) for 32-bit or 2 GB for 64-bit.
- **Hard disk space**: 16 GB for 32-bit OS 20 GB for 64-bit OS

III. TECHNIQUE USED

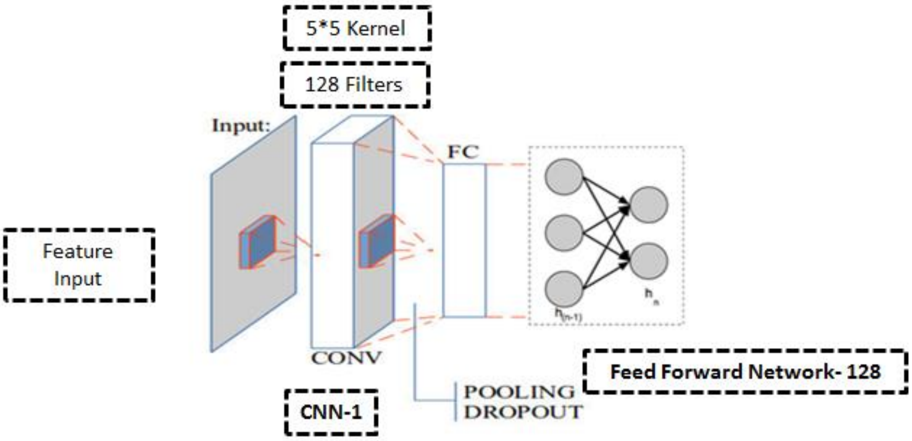
A. Convolution Neural Network (CNN)

- 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

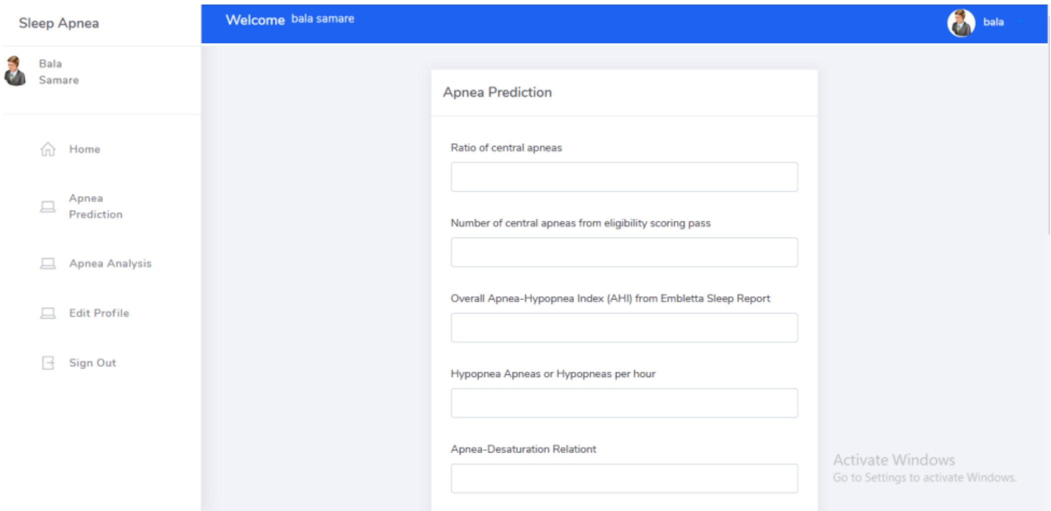
A) Dataset Used

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



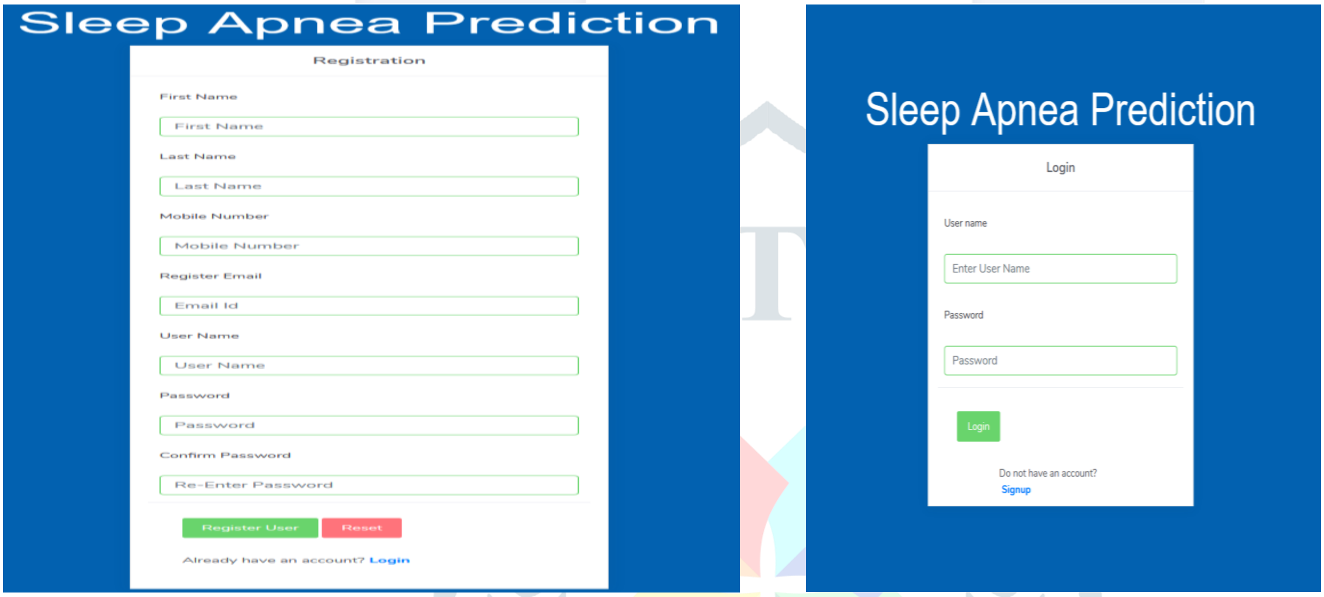


Figure: - Login and Registration Page

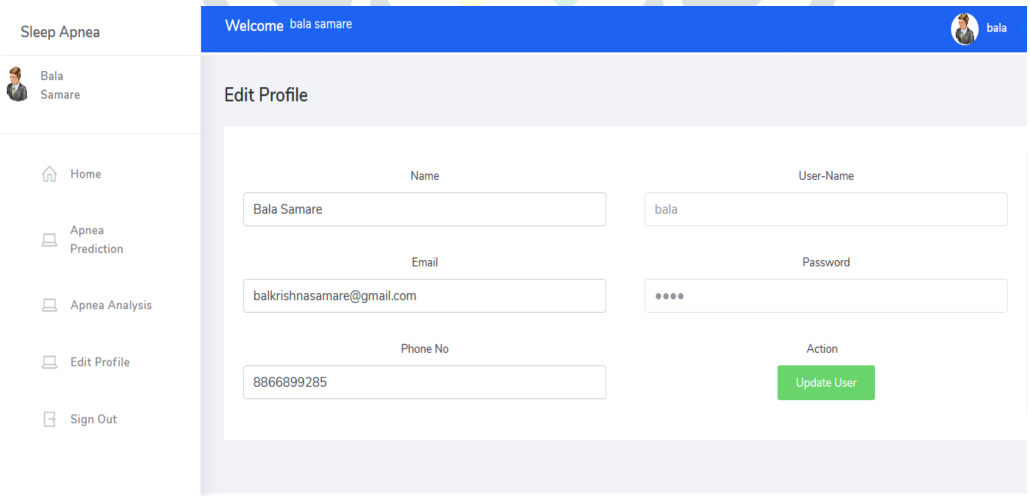


Figure: - Update Users

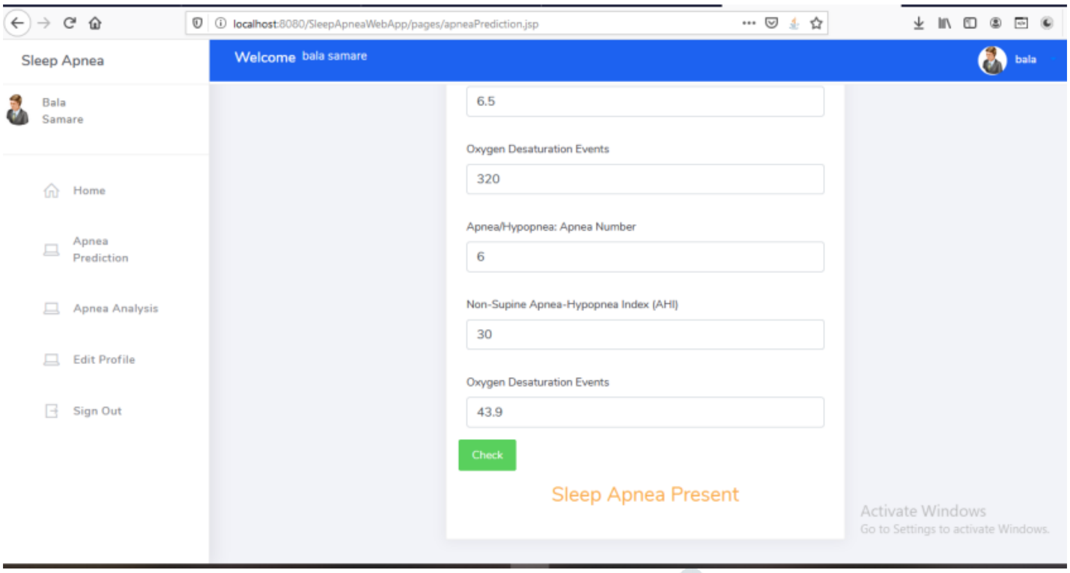


Figure: - Sleep Apnea Features

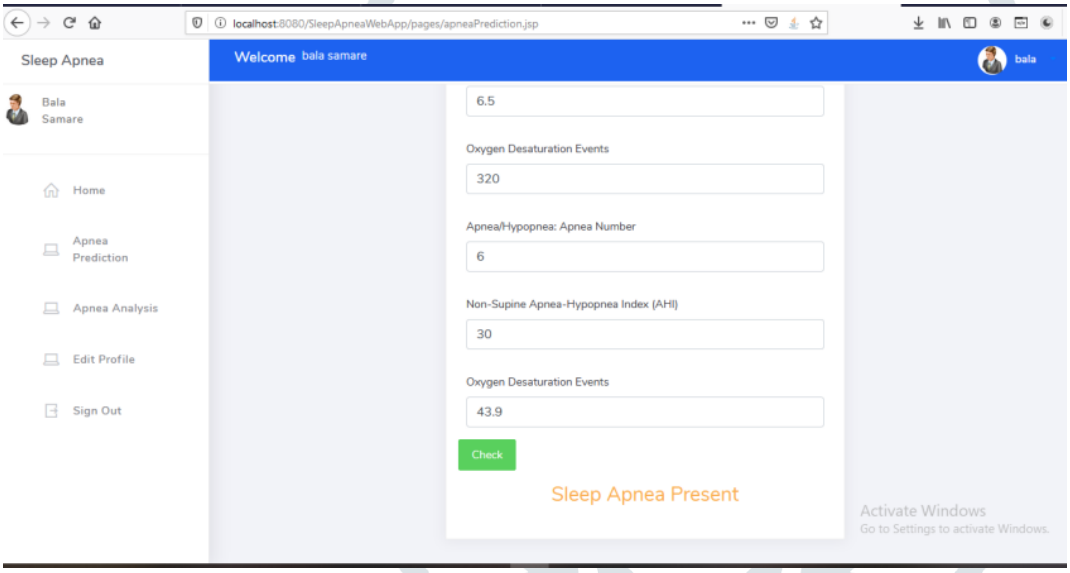


Figure:- According to the Sleep Apnea features system predicts the sleep apnea

VII. CONCLUSION

The system builds a prediction model by using the Convolution Neural Network (CNN) technique. The proposed method can identify useful information for the interpretation of AHI for patients with sleep apnea (SA). This method will thus provide us a useful system for diagnosis of sleep apnea by inspecting the individual. The key feature of the method was selected by studying the data set of the National Sleep Research Resource dataset.

REFERENCES:

[1] T. Sugi, F. 1. Sondre Hamnvik,, Pierre Bernabe and Sagar Sen,"Yolo4Apnea: Real-time Detection of Obstructive Sleep Apnea",Proceedings of the Twenty-Ninth International Joint Conference on Artificial Intelligence (IJCAI-20) Demonstrations Track.

[2] Sheikh Shanawaz Mostafa,1,2,* Fábio Mendonça,1,2 Antonio G. Ravelo- García,3 and Fernando Morgado-Dias,"A Systematic Review of Detecting Sleep Apnea Using Deep Learning",Published online 2019 Nov 12. doi: 10.3390/s19224934.

[3] Taehoon Kim1 , Jeong-Whun Kim2* and Kyogu Lee,"Detection of sleep disordered breathing severity using acoustic biomarker and machine learning techniques",Kim et al. BioMed Eng OnLine (2018) 17:16 https://doi.org/10.1186/s12938-018-0448.

[4] Debangshu Dey, Sayanti Chaudhuri,corresponding author and Sugata Munshi,"Obstructive sleep apnoea detection using convolutional neural network based deep learning framework",Springer, 2018.

[5] M.V.Vijaya Saradhi, Kalli Srinivasa Nageswara Prasad,"Predictive Analytics for Obstructive Sleep Apnea Detection",International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-8, Issue- 9S2, July 20.

[6] Taehoon Kim, Jeong-Whun Kim, Kyogu Lee,"Detection of sleep disordered breathing severity using acoustic biomarker and machine learning techniques",BioMedical Engineering OnLine,2018.

[7] 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.

[8] 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.

[9] 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.

[10] Tom Van Steenkiste; Willemijn Groenendaal; Dirk Deschrijver; Tom Dhaene,"Automated Sleep Apnea Detection in Raw Respiratory Signals Using Long Short-Term Memory Neural Networks", IEEE Journal of Biomedical and Health Informatics (Volume: 23, Issue: 6, Nov. 2019).

[11] Ahnaf Rashik Hassan; Syed Khairul Bashar; Mohammed Imamul Hassan Bhuiyan,"Computerized obstructive sleep apnea diagnosis from single-lead ECG signals using dual-tree complex wavelet transform",2017 IEEE Region 10 Humanitarian Technology Conference (R10-HTC).

[12] Anju Prabha; Akta Trivedi; A. Anand Kumar; C Santhosh Kumar,"Automated system for obstructive sleep apnea detection using heart rate variability and respiratory rate variability",2017 International Conference on Advances in Computing, Communications and Informatics (ICACCI).