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An Efficient Method to Detect Sleep Apnea

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ABSTRACT: Sleep apnea is defined as sleep disorder that is typified by repeated pauses in breathing during sleep, leading to fragmented sleep patterns and decreased blood's oxygen saturation values. This study seeks to deploy an artificial neural network model to diagnose sleep apnea utilizing a dataset comprising various physiological and demographic factors. These factors include BQ, ESS, BMI, weight, height, head circumference, neck circumference, waist circumference, buttock circumference, age, gender, and marital status. The dataset will undergo preprocessing to handle ignored data and outliers before training, validation, and testing of the ANN model. Performance evaluation will include parameters like specificity, also sensitivity, and Receiver Operating Characteristic curve's area under the curve. The outcomes might have significant effects on improving the identification and management of sleep apnea, thereby enhancing the well-being of affected individuals and alleviating healthcare system burdens.

KEYWORDS: ANN - Artificial Neural Network, Sleep apnea, Epworth Sleepiness Scale.

I. INTRODUCTION

Sleep apnea is a typical sleep ailment that impacts millions of people worldwide. It is characterized by the repeated interruption of breathing while person is asleep, which could lead to in daytime fatigue, irritability, and other health problems. Deep learning methods are gaining prominence recently as a means of identifying and dealing with sleep apnea.. Algorithms using deep learning can examine large datasets, such as those containing patient information and sleep study results, to identify find trends and forecast outcomes about sleep apnea risk and severity. Using deep learning to determine and manage sleep apnea, a large and diverse dataset is essential. The dataset should include various factors that contribute to sleep apnea include body mass index (BMI), weight, height, neck circumference, and other anthropometric measurements. Other relevant information such as age, gender, and marital can be incorporated into the dataset. These elements are appropriate for supervised learning strategies. training to accurately predict the amount of sleep apnea and its presence in individuals. In this context, dataset for in-depth analysis should be comprehensive and well-curated to ensure accurate predictions. For instance, the dataset should include objective measurements such as polysomnography, It serves as the benchmark for sleep apnea diagnosis. Additionally, subjective measures such as Epworth Sleepiness Scale (ESS) and the Berlin Questionnaire (BQ) can also be included to evaluate the individual's subjective perception of sleepiness and the likelihood of sleep apnea. By incorporating such data into deep learning process, The estimation of sleep apnea will be predictable accurately and enhance the quality of patient care. Among the main benefits of applying deep learning methods to sleep apnea diagnosis is their ability to extract complex features from high-dimensional data. Convolutional neural networks (CNNs) and also recurrent neural networks (RNNs) are two examples models of advanced computing that may automatically learn and extract significant characteristics from sleep study data, without the requirement for a manual feature engineering. For example, CNNs can find structures throughout the raw polysomnography signals, such as apneas, hypopneas, and snoring events, and use them foreseeing the severity of sleep apnea. Similarly, RNNs can capture the temporal dependencies between sleep stages and respiratory events, enabling accurate diagnosis of sleep apnea. Another key advantage deep learning's capacity to handle ignored information and noisy signals.

Sleep apnea diagnosis often relies on multiple sources of data, including patient self-reports, polysomnography, and other physiological measurements. Machine learning algorithms offer a chance to be trained, using approaches as imputation and data augmentation, to improve performance and reduce errors.

Furthermore, systems in neural networks can handle large and complex datasets, allowing for the integration of multiple data sources and the identification of novel biomarkers for sleep apnea.

II. PROBLEM STATEMENT

To create a model built upon clinical and personal data of the five individuals that can determine if they have sleep apnea or not. The model needs to look at the traits associated with sleep apnea. The occurrence of sleep apnea can effectively be predicted by an artificial neural network type of sequential model, taking into account the medical and epidemiological data of study participants. The objective is to use this dataset to train a sequential artificial neural network (ANN) algorithm that can predict, based on these features, whether a person has sleep apnea or not.

III. RELATED WORK

The study conducted in [1] discusses the exploration of the blood oxygen saturation characteristics for employing an ANN classifier to identify sleep apnea. Here, writers seek to pinpoint an ideal subset of features for detecting accurately, leveraging genetic algorithms (GA) for selection. This study utilizes a database of 8 subjects and achieves a high percentage of 97.7% accuracy with only seven selected features. Significantly, blood oxygen saturation features, particularly in the time-frequency domain, are found to function well in classification. The combination of ANN with GA proves successful in optimizing sleep apnea detection, outperforming previous methods.

The study conducted in [2] discusses several electrophysiological signals, including the Electromyogram (EMG), Electrocardiogram (ECG), Electroencephalogram (EEG), and ECG Derived Respiration (EDR) signals, were utilized to explore and diagnose OSA. Various research papers have utilized ECG, EEG, and SpO₂ signals for identifying this illness, with instances of using multiple signals for identification. Additionally, thoracic and abdominal signals were examined for diagnosis but didn't yield optimal results. These signals were primarily detected during polysomnography (PSG). Statistics are implemented for kurtosis, variance, mean, median, and standard deviation while creating models for artificial intelligence to identify sleep apnea.

Research [3] presents an effective approach for minute-based identifying sleep apnea through the processing of Electrocardiogram (ECG) signals. By utilizing the PhysioNet apnea-ECG dataset, Heart Rate Variability (HRV) and ECG-derived respiration (EDR) were extracted utilizing a median filter. The features that were retrieved were utilized for training, testing, and validation of an Artificial Neural Network (ANN). Instruct and evaluate sets were obtained by randomly dividing the data until it reaches a good performance using a k-fold cross validation (k=10). The ANN demonstrated a promising accuracy of 82.120% in identifying sleep apnea.

This study [4] evaluates a novel noncontact sensing system employing Sonar technology for screening Sleep Disordered Breathing (SDB). By utilizing a smartphone with a personalized app placed on a bedside table, the system monitors breathing and motions during sleep. Proprietary algorithms within the app identify SDB patterns and identify sleep stages. Trained on 94 overnight recordings alongside polysomnography (PSG) monitoring, the system demonstrated excellent performance on an 68 recordings in a separate set, with high sensitivity (94%) and specificity (97%) for SDB detection.

[5] Introduces an automated deep-learning approach to identify obstructive sleep apnea (OSA). By analyzing single lead electrocardiography signals, the system identifies OSA without a requirement for separate feature extraction or classification algorithms. It outperforms existing methods significantly, achieving maximum accuracy also demonstrating robustness against signal noise. The approach integrates feature extraction and classification within a deep learning format, streamlining OSA detection. Its findings demonstrate that the performance improved than existing methods, achieving a significant average accuracy improvement of over 9%.

IV. METHODOLOGY

In this project, we will use an informational dataset about patients suffering from sleep apnea. The dataset includes the following variables:

BQ: Berlin Questionnaire score is an assessment of the risk about sleep apnea

ESS: Epworth Sleepiness Scale score, an estimate about daytime sleepiness

BMI: Body Mass Index, an evaluation in body fat based on height and weight

Weight: Weight in pounds

Height: Height in inches
Head: Head circumference in inches
Neck: Neck circumference in inches
Waist: Waist circumference in inches
Buttock: Buttock circumference in inches

Age: Age in years
M: Gender (1 for male, 0 for female)

Status: Sleep apnea status (1 for positive, 0 for negative). It initially involves Data Preparation, where the dataset is imported from a CSV file into the program. Later on, data preprocessing is conducted, encompassing work includes handling missing values, addressing outliers, and normalizing the data.

In addition, Feature Selection is performed, wherein analyzing the dataset features and their relevance to Sleep apnea study has been performed. Removing any characteristics that aren't likely to contribute significantly to the detection task. The next step is data split, here split the dataset into instruct and evaluate sets, 80 percent of data for instructing the model and 20 percent of data for testing the model. Then Feature Scaling, scale the numerical features to a standard range, such as normalizing them from 0 to 1 or using z-score normalization. This step helps to improve the teaching of the ANN. The Designing of the ANN Architecture involves creating an input layer with sixty-four neurons, implemented using 'keras.layers'.Dense with the 'input_dim' parameter according to quantity of input features. There is one hidden layer on neural network on thirty two neurons and activating function is set to 'ReLU'. The 'ReLU' activation function stands for the Rectified Linear Unit, popular activation function in neural networks.

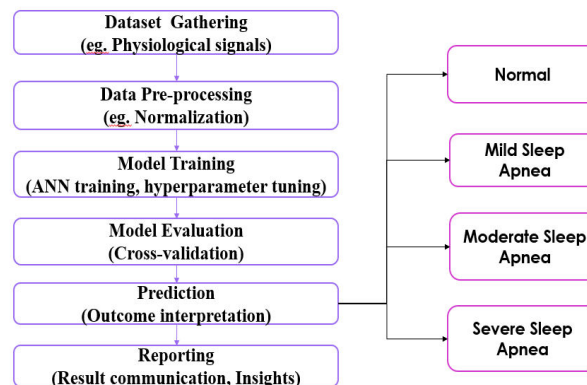


Fig. 1. Work Flow Diagram

The four neurons in the result layer additionally, activation mechanism set to 'softmax'. The 'softmax' activation function is commonly followed for multi-class classification problems as it produces a probability distribution over the classes. Subsequently, ANN model is trained. Preceding to training the model is compiled by using the 'compile()' function. The model is compiled with the parameters, used 'adam' optimizer, 'sparse_categorical_crossentropy' as loss function used for multi-class classification problems. The model will be assessed using the accuracy metric during training.

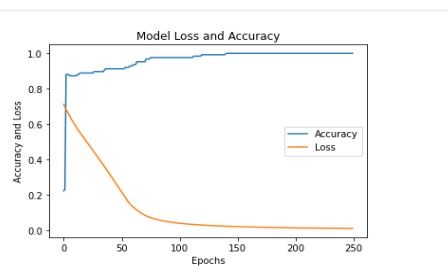


Fig.2. Loss and accuracy loss graph

$$y = \sigma \left(\sum_{i=1}^n w_i x_i + b \right)$$

eq (1). Perceptron Model

$$\sigma(x) = \frac{1}{1 + e^{-x}}$$

eq(2). Sigmoid

$$\frac{\partial w}{\partial L} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial z}{\partial w}$$

eq(3). Backpropagation

Loss Functions:

$$L = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

eq (4) Mean Squared Error (MSE)

$$L = -\frac{1}{n} \sum_{i=1}^n [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)]$$

eq (5) Cross-Entropy Loss

The model is trained using 'fit()' function. And this function is utilized with 'X_train' and 'Y_train' representing the instruction set and corresponding labels, respectively. Epochs specified is hundred, epochs specifies how frequently the model will go through the entire training dataset.

The batch_size is thirty two, which determines the amount of samples there are processed before model's internal parameters are updated. Validation_split is 0.1 means 10 percent within training information is used as validation data for monitoring the model's performance during training. After training is completed, the trained model is saved to an H5 file. Subsequently Model evaluation, during Model Evaluation, the model's performance is assessed using validation data. This assessment occurs subsequent to the training phase, utilizing the validation data specified during training. Model evaluation is executed by invoking the evaluate() function on the trained model object. The evaluate() function returns the loss value and metric's value computed on the test data.

IV. EXPERIMENTAL RESULTS

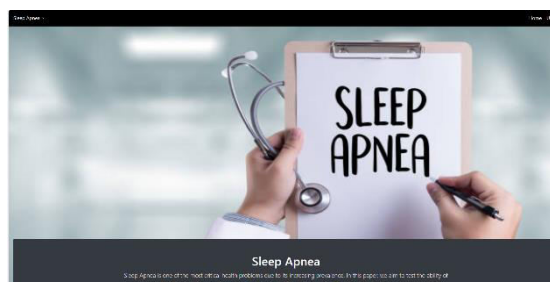


Fig.3. Welcome Page

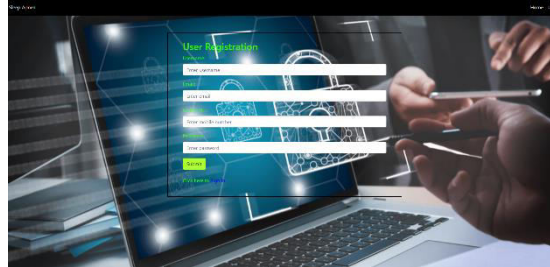


Fig.4. User Registration Page

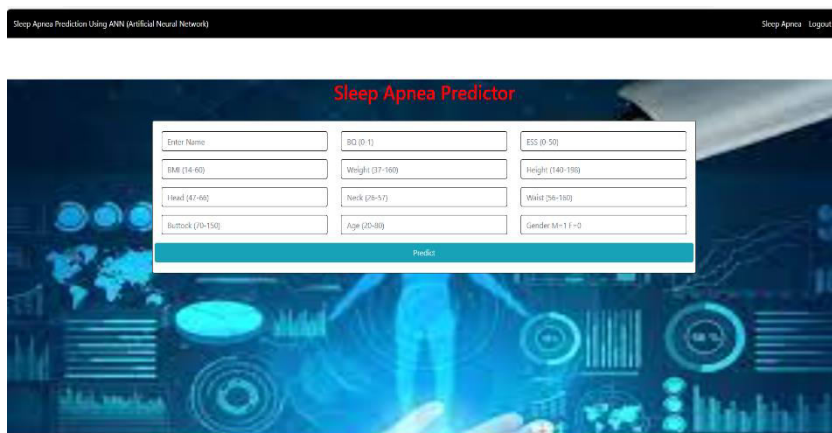


Fig.5. Data intake page

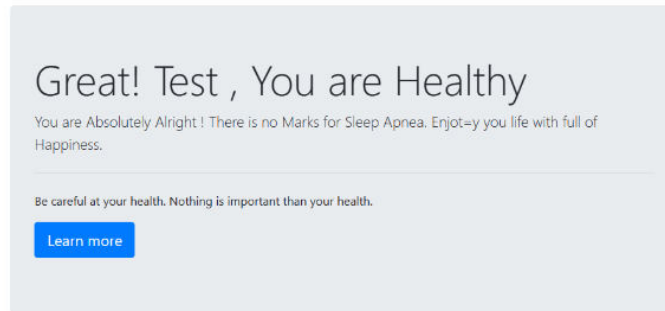


Fig.6. Result Page for no apnea

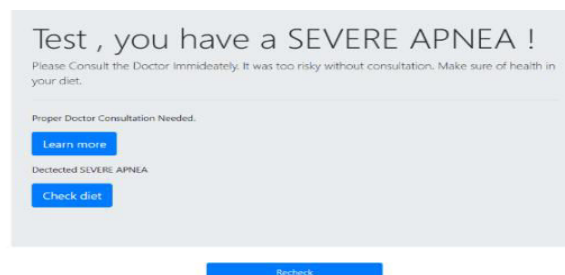


Fig.7. Result Page for having severe apnea

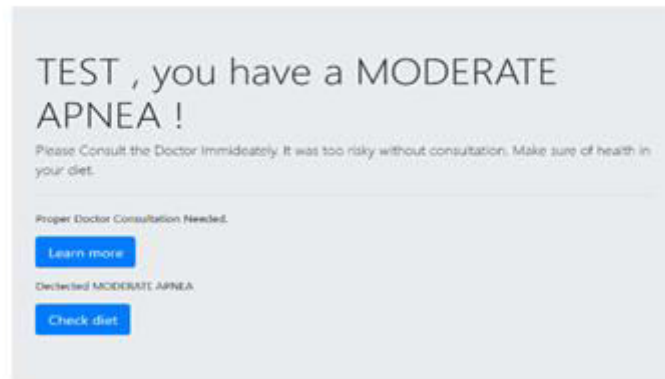


Fig.8. ResultPage for having moderate apnea

The software appears as systematic tool for managing and predicting sleep apnea. It begins with an initial welcome screen [Fig.3], offering options such as 'Home' and 'User', providing a user-friendly interface for navigation. Upon selecting the 'User' option, individuals are directed to a page on which they may choose to log in with existing credentials or registration page [Fig.4] as new users by providing necessary details like username and password mail id. Once logged in, users access a dedicated section where user can enter input details [Fig.5] relevant data for the system to estimate the possibility of developing sleep apnea. This likely involves entering information includes medical history, symptoms, and possibly biological metrics. The system then processes, and generate a prediction [Fig.6], [Fig.7], [Fig.8] regarding the whether sleep apnea is present or not, which is displayed to the user. Additionally, the software seems to offer support beyond minimal prediction, as evidenced by the provision of dietary recommendations tailored specifically for individuals diagnosed with sleep apnea. These suggestions likely aim to optimize sleep quality and overall health while managing the condition. In general, the system appears to offer a holistic approach to sleep apnea management, integrating prediction, user-friendly interface, and personalized support for individual's dealing with this sleep disorder.

V. CONCLUSION

A deep learning part which utilize artificial neural networks (ANNs) has been proposed to address sleep apnea, encompassing both muscle relaxation and neural issues. This model utilizes rectified linear unit (ReLU) activation for hidden layers, known for its effectiveness in ANNs, and SoftMax activation for many classification at the output layer. Demonstrating robustness and speed, the model created an impressive 92% accuracy on the TMUH-5241 dataset, making it a potent tool which employs patient data to pinpoint sleep apnea. Artificial Neural Networks (ANNs) have shown great potential in various healthcare applications, including the detection and sleep apnea diagnosis. A category of insomnia called sleep apnea can occur by repeated interruptions in breathing while being asleep, this may include major health implications if left untreated. ANNs can be leveraged to analyze sleep related data and identify patterns indicative of sleep apnea, aiding in early detection and intervention. Here are some future scopes for utilizing to identify sleep apnea ANNs: Experimenting with different network structures, like recurrent neural networks (RNNs) and also convolutional neural networks (CNNs), tailored for analyzing sleep data could improve accuracy by better capturing relevant patterns and features. Optimizing activation functions like ReLU or sigmoid can enhance the network's ability to detect complex patterns in sleep data, potentially leading to improved accuracy in sleep apnea detection. Advanced optimization techniques like Adam or RMSProp can speed up model training and convergence, ultimately improving the overall the effectiveness and precision of the sleep apnea detection model.

Techniques like dropout, L1/L2 regularization, or batch normalization helps to avoid the model in overfitting to the instruction set, ensuring that it generalizes well to unseen sleep data and enhances accuracy. Leveraging ensemble methods of type bagging, boosting, or stacking allows integrating forecasts from several models, which often leads to improved accuracy by capturing diverse aspects in sleep data and reducing model variance. Exploring these avenues

can aid in the advancement of more precise and reliable sleep apnea finding models using ANNs, thereby advancing the area of sleep medicine.

REFERENCES

- [1] "Optimization of sleep apnea detection using SpO2 and ANN", Sheikh Shanawaz Mostafa; Joao Paulo Carvalho; Fernando Morgado-Dias; Antonio Ravelo-García, 2017.
- [2] "An Efficient Method to Detect Sleep Hypopnea- Apnea Events Based on EEG Signals", Yao Wang, Siyu Ji, Tianshun Yang, Xiaohong Wang, Huiquan Wang, Xiaoyun Zhao, 2020.
- [3] "Sleep Apnea Detection Using a Feed-Forward Neural Network on ECG Signal", Andre Miguel da Silva Pinho, Nuno Pombo, Nuno M. Garcia, 2021.
- [4] "Detection of Sleep Apnea Using Sonar Smartphone Technology", Graeme Lyon, Roxana Tiron, Alberto Zaffaroni, Ahmed Osman, Hannah Kilroy, Katharina Lederer, Ingo Fietze, Thomas Penzel, 2022.
- [5] "Obstructive sleep apnea detection using convolutional neural network based deep learning framework", Debangshu Dey, Sayanti Chaudhuri, and Sugata Munshi, 2022.
- [6] "Different neural networks approaches for identification of obstructive sleep apnea", Sarah Qasim Ali; Abdulnasir Hossen, 2018.
- [7] "A Real-Time Auto-Adjustable Smart Pillow System for Sleep apnea Detection and Treatment", J. Zhang, Q. Zhang, Y. Wang and C. Qiu, 2013.
- [8] "Sleep apnea detection with EEG, ECG and respiratory signals", Mehmet Feyzi Akşahin; Aykut Erdamar; Atakan İşik; Asena Karaduman, 2017.
- [9] "Detection of Sleep Apnea from ECG Signals Using Artificial Neural Networks", P. G. Arias-Mendoza, L. R. Tarazona-Meza, H. A. Villegas-Pulgarin, 2017.
- [10] "An Artificial Neural Network for the Detection of Obstructive Sleep Apnea through Electrocardiogram Analysis", K. R. Jeyabharathi, S. K. Bhatia, 2018
- [11] L. R. Kline. "Clinical Presentation and Diagnosis of Obstructive Sleep Apnea in Adults", 2022.
- [12] Ruehland WR, Rochford PD, O'Donoghue FJ, Pierce RJ, Singh P, Thornton AT. The new AASM criteria for scoring hypopneas: impact on the apnea hypopnea index. *Sleep*. 2009 Feb;32(2):150-7. doi: 10.1093/sleep/32.2.150. PMID: 19238801; PMCID: PMC2635578.
- [13] Jirakittayakorn N, Wongsawat Y, Mitirattanakul S. ZleepAnlystNet: a novel deep learning model for automatic sleep stage scoring based on single-channel raw EEG data using separating training. *Sci Rep*. 2024 Apr 29;14(1):9859. doi: 10.1038/s41598-024-60796-y. PMID: 38684765; PMCID: PMC11058251.
- [14] ElMoaqet H, Eid M, Ryalat M, Penzel T. A Deep Transfer Learning Framework for Sleep Stage Classification with Single-Channel EEG Signals. *Sensors (Basel)*. 2022 Nov 15;22(22):8826. doi: 10.3390/s2222882 .PMID: 36433422; PMCID: PMC9693852.
- [15] Redline S, Kapur V K, Sanders M H, Quan S F, Gottlieb DJ, Rapoport DM, Bonekat WH, Smith PL, Kiley JP, Iber C. Effects of varying approaches for identifying respiratory disturbances on sleep apnea assessment. *Am J Respir Crit Care Med*.;161(2 Pt 1):369-74. doi: 10.1164/ajrccm.161.2.9904031. PMID: 10673173.



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