Analysis of ECG Data to Detect Sleep Apnea using Deep Learning

Mamtha Mohan[1], Veena G N[2], Pavitha U S[3], Vinod H C[4]

[1,2,3] Department of Electronics and Communication Engineering, Ramaiah Institute of Technology, Bengaluru, India
[4]Department of Computer Science,Christ (Deemed to be University),Bengaluru,India

Abstract
Sleep plays a significant role in preserving daily productivity and the health of the body and brain. The disaster of chronic disease can be increased by the absence of sleep eminence, depression, strain, and due to lack of attentiveness as of sleeplessness. So, maintaining a person's physical and mental health depends on getting enough sleep. With the invent of Artificial Intelligence and Machine Learning a trustworthy sleep superiority monitoring system is made possible. The greatest significant features of Machine Learning is the aptitude to forecast the consequences. This presented the Analysis of ECG Data to Detect Sleep Apnea using Deep Learning.

Keywords-Obstructive sleep apnea Introduction, Polysomnography, Artificial intelligence and machine learning

I INTRODUCTION

The sleep disorder obstructive sleep apnea (OSA) causes breathing pauses or shortness of breath. It is categorized by recurrent pharyngeal collapse total upper respiratory tract blockage, and it disrupts ventilation during sleep. It leads to a drop in blood oxygen levels and insufficient air getting to the lungs. Patients are more prone to wake up because of the lack of oxygen in their brains, which frequently causes their sleep to be interrupted. In those with cardiovascular illness. OSA is linked to the occurrence and morbidity of hypertension, coronary heart disease, arrhythmia, heart failure, and stroke. For diagnosing OSA, polysomnography is the gold standard (PSG). Physiological sleep signs such as electroencephalography (EEG), electrooculography (EOG), electrocardiography (ECG), electromyography (EMG), SaO2 saturation, thoracic abdominal effort, and nasal-oral airflow are frequently used to identify OSA in patients. Several sensors are needed to measure blood pressure, heart rate, and leg movement during these tests, which are conducted overnight at a sleep laboratory or sleep centre. The total number of apneas and hypopneas per hour of sleep, as determined by the apnea-hypopnea index, can be used to classify the severity of OSA (AHI).as none (AHI 5), light (AHI 5 to 15), medium (15 to 30), or severe (AHI 30). The creation of a practical Many studies have been conducted in recent years with the goal of developing an affordable OSA screening system that uses fewer physiological markers, such as blood oxygen levels, ECG, the abdominal and chest respiratory signals, breathing noises, and the composite signals. The PSG is a difficult, drawn-out, and specialised examination method. 5, intermediate (15 AHI 30), severe (AHI 30), or light (5 AHI 5). The PSG is a difficult, drawn-out, and unique examination technique

Techniques for single-lead ECG-based detection have evidence to support them that focus on the maximum level of global categorization by figuring out how many people use the algorithms developed for a single source sensor. Techniques for identifying sleep-disordered breathing frequently utilised include examination of heart rates, ECG waveforms, and events associated to apnea and hypopnea that are recorded on the ECG. A specific feature extraction technique is required to separate out ECG characteristics in the bulk of earlier efforts, from RR intervals, fluctuations in heart rate (HRV), ECG waveforms, and respiration signals derived from the electrocardiogram (EDR), which were primarily focused on feature engineering. Many educational settings have used neural networks that can recognise features automatically. Singh and Majumder proposed KNN, SVM, LDA, and Ensemble classifiers are combined in a decision fusion strategy to increase the sensitivity for recognising apnea occurrences. They also presented a pre-trained two-dimensional (2D) AlexNet model based on a convolutional neural network to extract attributes from 2D time-frequency images of ECG data (CNN). In order to identify and extract characteristics from both normal and apnea events, [2] Wang et al. presented a modified LeNet-5 CNN model employing 1D ECG data with RR intervals. Li et al. created RR interval properties can be extracted using a deep neural network to do unsupervised education, for which simply unlabeled ECG data are necessary. They also intended to use two Apnea occurrences are recognized using a variety of classifiers, including as artificial neural networks (ANN) and SVM. The aforementioned techniques have proven to be the best in identifying apnea incidents. As a result, the complexity of the signal preprocessing necessary to create the CNN model is significantly reduced. A method for identifying sleep that uses a 1D deep CNN model and single-lead 1D ECG measurements [1]. New types of research may result from looking into this aspect of healthcare. The MIT Physio Net Apnea-ECG collection is made up of a public dataset of 35 footages and a concealed dataset of 35 footages, both digitalized with a sampling rate of 100 Hz and 12-bit resolution. The recording lasts anywhere between 401 and 587 minutes. It is made out of an annotated single-lead ECG signal. The letters N or A, which stand for normal and apnea events, respectively, are labelled on each 1-min ECG signal. Either mixed or obstructive apnea episodes occur in every case. The episodes of Cheyne-Stoke respiration or pure central apnea are not included in the database. A 1-min ECG signal is also defined as apneic if it contains hypopneas that alternately have respiratory flow reductions of less than 50% and drops in oxygen [7], [12] saturation of at least 4% and are accompanied by compensatory hyperventilation. The Class A (Apnea), Class B (Borderline), and Class C ECG footages are divided into (Control). A minimum of one hour of recordings from classes A and B must have an apnea index of 10 or higher and 5 or higher, respectively. A minimum of 100 minutes' worth of apnea or hypopnea, between five and ninety minutes, or less than five minutes, respectively, are present in recordings in classes A, B, and C. Each dataset—released and withheld—contains 20 recordings from Class A, five from Class B, and ten from Class C. The suggested 1D deep CNN model was trained using the publicly available data, and its effectiveness was verified using the privately held data. The public and withheld datasets were used to extract 34,213 1-min ECG signals for this investigation. Among the 16,979 minutes in the publicly available dataset, 10,322 and 6657 minutes are designated as normal events and apnea events, respectively. Of the 17,234 minutes in the 10,717 and 6517 minutes in the withheld dataset are categorized as normal and apnea events, respectively.

II RELATED WORK

When both Cheyne-Stokes breathing and obstructive sleep apneas are present at the same time, the use of prolonged electrocardiography (ECG) for the identification of sleep disordered breathing (SDB) is investigated. Each form of SDB is identified by a multi-tier algorithm that employs quantitative changes in the morphology of the QRS complex of Lead 1 and V4 caused by SDB events and blends those changes with differences in heart rate. EKG impulses are split into 15-minute epochs for this reason. Then, baseline wander reduction and R peak recognition are applied to these epochs. To determine R wave attenuation, a calculated envelope of R peaks is used (RWA). The heart rate variability (HRV) is also calculated concurrently. [14]

Deep learning is a machine learning method that instructs computers to learn by doing what comes easily to people. Driverless vehicles use deep learning as a crucial technology to identify stop signs and tell a pedestrian from a lamppost apart.[11].

Investigation of alternative methods of finding sleep disordered breathing is appealing due to the high expense of diagnostic studies to detect it and the absence of accredited sleep labs in all populated areas. This research sought to determine whether nighttime electrocardiography could distinguish between Cheyne-Stokes respiration (CSR) and obstructive sleep apnea (OSA) electrocardiography (ECG). [15]

Sleep apnea has been successfully classified using feature extraction from heart rate variability signals obtained from electrocardiograms (ECG). In previous studies, classifiers like logistic regression and support vector machines have been used with time-domain features, frequency-domain features, and a mix of the two. Deep learning techniques, however, have lately outperformed these traditional feature engineering and categorization methods in a number of uses. The use of convolutional neural networks (CNN) for sleep apnea section detection is investigated in this study. The image classification method CNN has demonstrated reliable success in a variety of signal classification uses. [16]

III. METHODOLOGY

Noise is eliminated by processing the signal and normalized. The signal preprocessing comprises of high pass filtering and adjustment. To decrease noise and baseline drift, the ECG signals of each patient were with a fourth-order Butterworth high pass filter and a 0.5 Hz cutoff frequency. The butter function and the filtfilt function for the Scipy library are used to create the Butterworth high pass filter at a sampling rate of 100 Hz. The filtered ECG signals were standardized using the z-score function, which was defined as follows:

z = (x-mean) Standard Deviation

where, x = value of each sample and z = value of sample after normalization

The z score displays the deviation of the input signal from the mean. The suggested 1D deep CNN model was fed the preprocessed 1D ECG signals in order to distinguish between normal and apneic occurrences. TensorFlow and Keras are used in its implementation. Many deep learning techniques can be handled by TensorFlow. With the aid of Keras, Building, training, and testing Deep learning neural network models is possible because to a high-level application programming interface (API) that runs on top of TensorFlow. Ten identical feature extraction layers are used in the feature extraction and classification stages of the proposed [10] 1D deep CNN model to extract features from each ECG signal. A batch normalisation layer, an activation layer, and a 1D CNN layer (Conv-45) with 45 feature mappings and a kernel length of 32 make up each feature extraction layer. [3]Using 4 identical classification layers built using a 1D feature vector, the classification stages categorise both normal and apnea occurrences. 512 neurons in the fully connected (FC) layer, a batch normalisation layer, and a ReLU-based a dump layer with a failure rates, and an activation layer of 0.5 make up each classification layer. The likelihood of the outputs from the two FC-2 layers are calculated using a softmax activation function after four classification layers. The two outputs are regular events and apnea events. The group that has a higher probability of matching the output is the classification's outcome. The weights are initialised using the normal initialization approach in the CNN and FC layers. The initialization of the weights considers the size of the previous After the CNN and FC layers in the feature layers for extraction and categorization, batch normalisation layers were added to enhance the efficiency, reliability, and consistency of neural networks.Before the data enters the ReLU activation layer, these layers normalise it. The risk for overfitting by selecting the maximum assistance helps to reduce the network's complexity[4][13]. The feature extraction layers' maximum pooling layers activation on a feature map that is adjacent to a neuron. When the pooling size is 2, each feature map's size is When the dropout layers' dropout rate is 0.5, overfitting is reduced by a factor of two and minimised. By randomly eliminating half of the nodes while the suggested network is being trained as shown in the figure1.

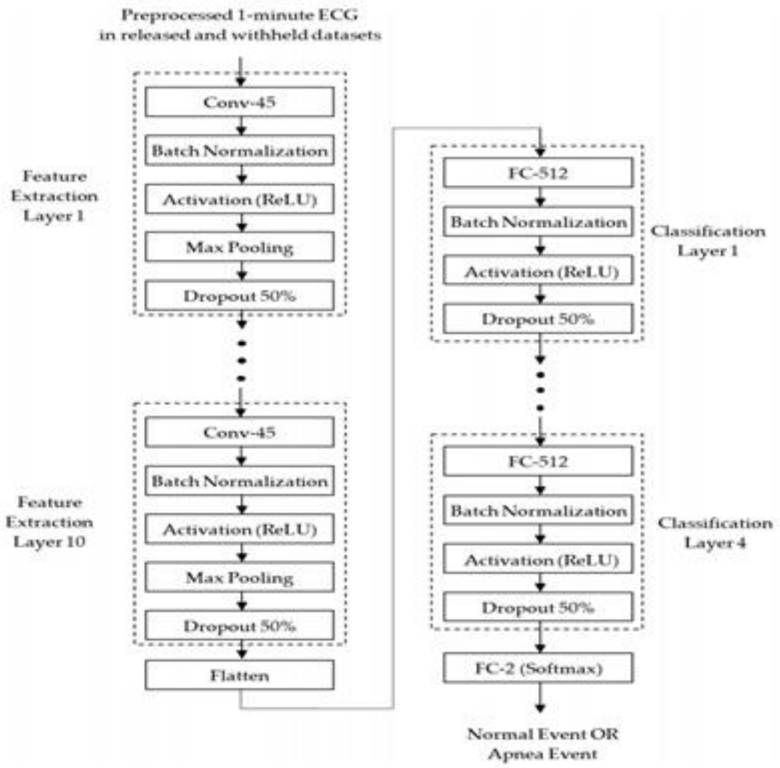

Figure1: Block diagram of the proposed 1D deep CNN model for identifying normal and apena events

IV. RESULTS

Despite using the padding option "same," which ensures the size of each feature map is equal to the input size, the Conv-45 layer with 45 feature maps does not guarantee this. The input's form is not altered by the layers of residual blocks and activation. The maximum pooling layer's output form is condensed to (None, 3000, 45). The maximum pooling layer shrinks each feature map by half when pooling length is two and strides are two. The dropout layer does not alter the input's form; it just ignores 50% of the nodes. A feature 1D vector containing 225 features is recovered after the Flattening of data has occurred. We developed and verified the suggested 1D deep CNN model for 50 epochs using the disclosed and concealed datasets, which each contained 1-min ECG signals. In addition to 4 identical classification layers, the CNN model has 10 consistent layering for feature extraction, a flattening layer, a softmax FC layer, and a layer for flattening. The 1-min ECG signal's features [5] were extracted using 10 1D- in total. CNN layers, and the normal and apnea episodes were classified using totaling five FC layers based on the extracted features. There were 10 in the batch. For per-minute apnea detection. The suggested approach has the best accuracy (87.9%), specificity (92.0%), sensitivity (81.1%), and AUC (0.94) values. The per-recording classification performance has an accuracy, sensitivity, and specificity that can approach 97.1% accuracy, 95.7% sensitivity, and 100% specificity.

V. CONCLUSION

In this study, a 1D deep CNN model for the detection of apnea events is proposed. This model can only interpret 1D ECG signals. CNN's suggested model consists of ten feature extraction and classification layers based on CNN. Just Butterworth high pass filtering and z-score normalization are necessary signal preparation stages for the identification of QRS complexes, the study of RR intervals, or additional signal alterations. The MIT PhysioNet Apnea-ECG database's public and concealed datasets were used to train and evaluate the proposed CNN model. Comparing the proposed method to other earlier studies, it has the greatest per-minute apnea AUC of 0.94, sensitivity of 81.1%, specificity of 92.0%, and detection accuracy of 87.9%. It is possible to attain an accuracy of 97.1%, a specificity of 100%, and a sensitivity of 95.7%. For a given recording's classification performance. The suggested method is both practical and complex, and it can diagnose OSA with only 1D ECG measurements. A PSG [9] test is advised to assess the severity of OSA if the predicted AHI crosses over or comparable to five.

The rise of Internet of Things technology has given us the chance to take advantage of the quick advancements in sensor and mobile technology to develop a trustworthy sleep quality monitoring system. One of the key characteristics of the Internet of things is its capacity to provide Machine-to-Machine (M2M) communication without necessitating human-to-human contact. Another area where IoT and AI may be used to their full potential is in remote monitoring systems for the healthcare industry. So, we will examine several metrics such as the[8] ECG, blood oxygen level, and heart rate while collaborating with IoT-based systems. This analysis has the potential to inspire fresh approaches to study in this area of medicine. Hardware and a website are the two components of the IoT project. Real-time functionality will be a feature of both the website and the hardware sensors. After recording the patient's ECG and SP02 for an entire night of sleep, [6] the Convolution Neural Network Model to Identify Sleep Apnea, trained using the MIT PhysioNet Apnea-ECG database, will be implemented to run in the backend to identify Sleep Apnea in a specific patient.

REFERENCES

[1] Chang HY, Yeh CY, Lee CT, Lin CC. A Sleep Apnea Detection System Based on a One-Dimensional Deep Convolution Neural Network Model Using Single-Lead Electrocardiogram. Sensors (Basel). 2020 July.

[2] Wang, Tao et al. “Sleep apnea detection from a single-lead ECG signal with automatic feature-extraction through a modified LeNet-5 convolutional neural network.” PeerJ vol. 7 e7731. 20 Sep. 2019.

[3] Khincha, Rishab & Krishnan, Soundarya & Parveen, Rizwan & Goveas, Neena. (2020). “ECG Signal Analysis on an Embedded Device for Sleep Apnea Detection”. I. S. Jacobs and C. P. Bean, “Fine particles, thin films and exchange anisotropy,” in Magnetism, vol. III, G. T. Rado and H. Suhl, Eds. New York: Academic, 1963, pp. 271–350.

[4] Banluesombatkul, Nannapas & Rakthanmanon, Thanawin & Wilaiprasitporn, Theerawit. (2018). Single Channel ECG for Obstructive Sleep Apnea Severity Detection Using a Deep Learning Approach. 2011-2016

[5] R. Rodríguez, A. Mexicano, J. Bila, S. Cervantes, R. Ponce, “Feature Extraction of Electrocardiogram Signals by Applying Adaptive Threshold and Principal Component Analysis”, Journal of Applied Research and Technology, Volume 13, Issue 2, 2015,Pages 261-269

[6] Chaw, Hnin & Kamolphiwong, Sinchai & Wongsritrang, Krongthong. “Sleep apnea detection using deep learning”. Tehnički glasnik. 13. 261-266. (2019)M. Young, The Technical Writer’s Handbook. Mill Valley, CA: University Science, 1989.

[7] Tsuiki, Satoru & Nagaoka, Takuya & Fukuda, Tatsuya & Sakamoto, Yuki & Almeida, Fernanda & Nakayama, Hideaki & Inoue, Yuichi & Enno, Hiroki. “Machine learning for image-based detection of patients with obstructive sleep apnea: an exploratory study. Sleep and Breathing”,(2021).

[8] Nader Salari,Amin Hosseinian et al,”Detection of sleep apnea using Machine learning algorithms based on ECG Signals: A comprehensive systematic review”Expert Systems With Applications 187 (2022) 115950.

[9] P. Janbakhshi ∗, M.B. Shamsollahi," Sleep Apnea Detection from Single-Lead ECG Using Features Based on ECG-Derived Respiration (EDR) Signals. https://doi.org/10.1016/j.irbm.2018.03.002

[10] K. R. Swetha, N. M, A. M. P and M. Y. M, "Prediction of Pneumonia Using Big Data, Deep Learning and Machine Learning Techniques," 2021 6th International Conference on Communication and Electronics Systems (ICCES), Coimbatre, India, 2021, pp. 1697-1700, doi: 10.1109/ICCES51350.2021.9489188.

[11] S. K. Sunori et al., "Unsupervised and Supervised Learning based Classification Models for Air Pollution Data," 2021 2nd Global Conference for Advancement in Technology (GCAT), Bangalore, India, 2021, pp. 1-5, doi: 10.1109/GCAT52182.2021.9587793.

[12] R. Dutta, B. K. Nirupama and et.al., "Intrusion Detection System(IDS) Analysis Using ML," 2022 IEEE 2nd Mysore Sub Section International Conference (MysuruCon), Mysuru, India, 2022, pp. 1-4, doi: 10.1109/MysuruCon55714.2022.9972442.

[13] V. K. Reshma, Ihtiram Raza Khan, M. Niranjanamurthy, Puneet Kumar Aggarwal, S. Hemalatha, Khalid K. Almuzaini, Enoch Tetteh Amoatey, "Hybrid Block-Based Lightweight Machine Learning-Based Predictive Models for Quality Preserving in the Internet of Things- (IoT-) Based Medical Images with Diagnostic Applications", Computational Intelligence and Neuroscience, vol. 2022, Article ID 8173372, 14 pages, 2022. https://doi.org/10.1155/2022/8173372

[14] S. R. Suhas, K. Behbehani, S. Vijendra, J. R. Burk and E. A. Lucas, "ECG Biomarkers for Simultaneous Detection of Obstructive Sleep Apnea and Cheyne-Stokes Breathing," 2007 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Lyon, France, 2007, pp. 1047-1050, doi: 10.1109/IEMBS.2007.4352474.

[15] S. R. Suhas, S. Vijendra, J. R. Burk, E. A. Lucas and K. Behbehani, "Classification of Cheyne Stokes Breathing and Obstructive Sleep Apnea Using ECG," 2006 International Conference of the IEEE Engineering in Medicine and Biology Society, New York, NY, USA, 2006, pp. 3561-3564, doi: 10.1109/IEMBS.2006.259983.

[16] R. V. Sharan, S. Berkovsky, H. Xiong and E. Coiera, "ECG-Derived Heart Rate Variability Interpolation and 1-D Convolutional Neural Networks for Detecting Sleep Apnea," 2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), Montreal, QC, Canada, 2020, pp. 637-640, doi: 10.1109/EMBC44109.2020.9175998.