

Sleep Apnea Classification and Prediction Using Improved Graph Neural Network

Dr.R. Rooba¹, Dr. D. Kavitha², Dr.P. Yoganandhini³, Dr.V. Priya⁴, Dr.A.R. Karthekeyan⁵

¹Associate Professor, Department of Computer Technology and Information Technology, Kongu Arts and Science College (Autonomous), Erode 638107,

Email ID: roobar@kasc.ac.in.

²Associate Professor and Head, Department of Information Technology, Nandha Arts and Science College (Autonomous), Erode-638052,

Email ID: kavitha.d@nandhaarts.org.

³M.C.A., M. Phil, Ph.D., Assistant Professor, Department of Computer Science
Vellalar College for Women, Erode -12.

Email ID: p.yoganandhini@vcw.ac.in

⁴M.Sc.,M.Phil.,B.Ed.,Ph.D., Associate Professor Department of Computer Technology
Vellalar College for Women, Erode -12.

Email ID: priya@vcw.ac.in

⁵Assistant Professor, Department of Computer Science, Kongu Arts and Science College (Autonomous), Erode – 638107,
Email ID: karthikmca.srkv@gmail.com

Cite this paper as: Dr.R. Rooba, Dr. D. Kavitha, Dr.P. Yoganandhini, Dr.V. Priya, Dr.A.R. Karthekeyan, (2025) Sleep Apnea Classification and Prediction Using Improved Graph Neural Network. *Journal of Neonatal Surgery*, 14 (14s), 690-704.

ABSTRACT

Sleep apnea is a common yet serious sleep disorder that affects millions of individuals worldwide. Timely and accurate detection of sleep apnea can significantly improve patient outcomes and quality of life. In this study, we propose an advanced approach for sleep apnea classification and prediction using the Improved Graph Neural Network (GNN) algorithm. Our methodology includes preprocessing steps such as Z-score normalization to standardize the data and improve algorithm performance. Additionally, we employ an improved Pan-Tompkins algorithm for feature selection, which helps in identifying relevant features from physiological signals such as electrocardiogram (ECG) and oxygen saturation (SpO2) data. The Improved GNN algorithm, known for its deep learning capabilities, is utilized for the classification and prediction tasks. This algorithm uses the power of deep Convolutional Neural Networks (CNNs) to automatically learn discriminative features from the input data and make accurate predictions. By integrating Z-score normalization, improved feature selection, and the Improved GNN algorithm, our proposed system aims to achieve high accuracy in detecting and predicting sleep apnea episodes. We evaluate the performance of our approach using a comprehensive dataset containing a diverse range of sleep apnea cases. Our results demonstrate the effectiveness of Z-score normalization in improving data quality and the role of the improved Pan-Tompkins algorithm in selecting informative features.

Keywords: Improved GNN, classification, deep learning, prediction, Sleep apnea

1. INTRODUCTION

Disruptions to the sleep cycle have a significant impact on people's well-being and health. One of the most common sleep disorders is obstructive sleep apnea (OSA), which happens repeatedly while sleep [1]. The blockage of the upper airway causes a ten-second pause in breathing in patients with OSA. The person gets up and keeps breathing since their oxygen saturation drops when they stop breathing [2]. The severity of sleep apnea syndrome can be evaluated using many metrics, one of which is the Apnea and Hypopnea Index (AHI) [3]. A high number of episodes each hour is used to calculate the AHI. An hourly episode frequency for a moderate OSA patient range from five to fifteen times [4]. Patients with mild symptoms had 15 or less episodes per hour, whereas those with severe symptoms have 30 or more episodes per hour [5-6]. Fatigue, sadness, and memory difficulties are all consequences of this issue, which has a profound impact on people's daily lives [7-8]. Stroke, arrhythmia, and myocardial interaction are all increased risks in moderate to severe OSA patients when they sleep. Consequently, a critical concern in this situation is the detection or prediction of OSA episodes [9-10]. All forms of sleep apnea can be reliably diagnosed using polysomnography. Electroencephalogram (EEG), electrocardiogram (ECG),

respiration (Resp) signal, blood oxygen level, and eye movement data make up the polysomnogram (PSG) signal [11, 12]. Under the guidance of a sleep expert, this signal is captured throughout the night from individuals who are suspected of having a sleep disturbance. The expert has the option of using online monitoring or offline observation to identify sleep episodes. However, the professional finds this technique challenging. As say, it's a tedious process that demands your undivided attention [13–14].

Adults can have sleep apnea syndrome (SAS) when their airways momentarily constrict while they sleep, preventing air from reaching their lungs [15]. If this happens, cannot be able to breathe for almost ten seconds. One typical adverse effect is a drop in blood oxygen saturation, which might cause to wake up from your sleep just to breathe [16]. It is believed that intermittent hypoxia generated by repeated obstructive events that happen during sleep triggers an oxidative stress response and activates oxygen free radicals [17]. The most common pattern of sleep-associated hypoxia (SAS) events, based on whether the patient shows signs of respiratory effort, is known as Obstructive Sleep Apnea (OSA) and occurs when the air flow completely stops during a patient's sleep [18]. When these two symptoms occur simultaneously, it's called mixed sleep apnea (MSA). In this condition, the patient has a central respiratory arrest followed by an obstructive ventilator effort very quickly thereafter. Hypopnea, which occurs when part of the airway is partly obstructed, also lowers oxygen supply to the lungs and produces shallow, slow breathing [19–20].

The main contribution of the paper is:

- Dataset preprocessing using Zscore Normalization
- Classification and Prediction using improved GNN Algorithm

1.1 Motivation of the paper

The motivation behind this paper is to address the critical need for timely and accurate detection of sleep apnea, a widespread and serious sleep disorder impacting millions globally. By proposing an advanced approach that integrates cutting-edge techniques like Z-score normalization for data standardization, improved feature selection using the Pan-Tompkins algorithm, and the deep learning capabilities of Improved GNN, we aim to significantly enhance the accuracy and efficacy of sleep apnea classification and prediction. This work is driven by the potential to improve patient outcomes and quality of life through more precise and efficient diagnosis and management of sleep apnea episodes.

2. BACKGROUND STUDY

Ahmed, S. et al. [1] The author found that by combining the most relevant questions, diagnostic accuracy for pediatric OSA can be increased, as part of these authors effort to study the predictive validity of affordable and simple test protocols like questionnaires. By using feature selection approaches, the authors were able to construct a new survey that outperformed the old ones in terms of accuracy. Dong, Q. et al. [4] these authors research introduces a technique for identifying OSA using a convolutional neural network. A variety of augmentation techniques were investigated for the validating dataset, in addition to the conventional data augmentation for the training dataset. Improving identification accuracy was possible with the help of representation learning. Increasing the size of the neural network and the quantity of labelled datasets can further enhance the accuracy. Learning, M. U. S. M. [8] the findings show that self-reported symptoms and readily accessible characteristics for modeling provide excellent results when using a machine learning technique to predict OSA. As a quick and inexpensive supplementary tool, it might be used by doctors or medical personnel to assess individuals at high risk of OSA. Manoochehri, Z. et al. [10] while comparing the two models that were examined, the C5.0 algorithm outperformed LRM, which had an accuracy of 0.737 and a specificity of 0.78, compared to another model. So, instead of using PSG, C5.0 decision trees can be utilized to diagnose OSA patients. Mencar, C. et al. [12] Early screening and diagnosis of OSAS was essential for the use of an efficient treatment for treating the illness. This can be achieved by addressing a current important research topic on how to categorize individuals with a probable diagnosis of OSAS based on the severity of their illness. Onargan, A. et al. [14] The goal of this study was to create a signal processing method that could use multi-channel EEG data to distinguish between individuals with apnea and healthy controls. The "EMD" method, a multivariate extension of the popular signal separation technique, was used for the EEG signal analysis. Phan, H. et al. [16] the author provide a multi-task convolutional neural network (CNN) architecture for automated sleep staging, which combines categorization and prediction. The goal of the framework, which was driven by the interdependence of sleep epochs, was to classify an input epoch and forecast its neighbors' labels in the context output all at once.

Table 1: Comparison table for sleep apnea prediction methods

Author	Year	Methodology	Advantage	Limitation
Alimardani, M., & de Moor, G.	2021	SVM	The advantage of this study lies in its use of EEG signals to not only detect	One limitation of this study is the relatively small sample size of 25

			apnea episodes but also classify their severity and types accurately.	apnea patients from whom EEG signals were collected.
Johnson et al.	2020	Sleep apnea prediction model developed for African Americans	Develops a tailored prediction model for sleep apnea in a specific demographic group, improving accuracy and relevance of diagnostic tools.	Can lack generalizability to other populations or ethnicities, requires validation in diverse cohorts.
Mazzotti et al.	2019	Symptom subtypes of obstructive sleep apnea predict incidence of cardiovascular outcomes	Identifies specific symptom subtypes of sleep apnea that correlate with cardiovascular outcomes, aiding in targeted intervention strategies.	Focuses on symptom subtypes and cardiovascular outcomes, cannot cover all aspects of sleep apnea diagnosis and management.
Taghizadegan et al.	2021	Obstructive sleep apnea event prediction using recurrence plots and CNNs	Utilizes recurrence plots and CNNs for predicting obstructive sleep apnea events, providing a data-driven approach for event detection.	Relies on specific signal processing and machine learning techniques, can require expertise for implementation and interpretation.
Alimardani & de Moor	2021	Automatic Classification of Sleep Apnea Type and Severity using EEG Signals	Provides an automated approach for classifying sleep apnea types and severity using EEG signals, aiding in accurate diagnosis and management.	Limited to EEG-based classification, cannot capture all aspects of sleep apnea diagnosis such as respiratory events.

2.1 Problem definition

The problem addressed in this study is the need for improved methods of detecting and predicting sleep apnea. Despite being a common and serious sleep disorder with significant impact on patient outcomes and quality of life, accurate detection remains a challenge. The study aims to develop an advanced approach using the Improved GNN algorithm, combined with Z-score normalization and an improved Pan-Tompkins algorithm for feature selection, to enhance the accuracy of sleep apnea classification and prediction.

3. PROPOSED METHODOLOGY

The proposed methodology has divided into dataset collection, pre-processing, feature selection and classification. The proposed workflow has presented at figure 1.

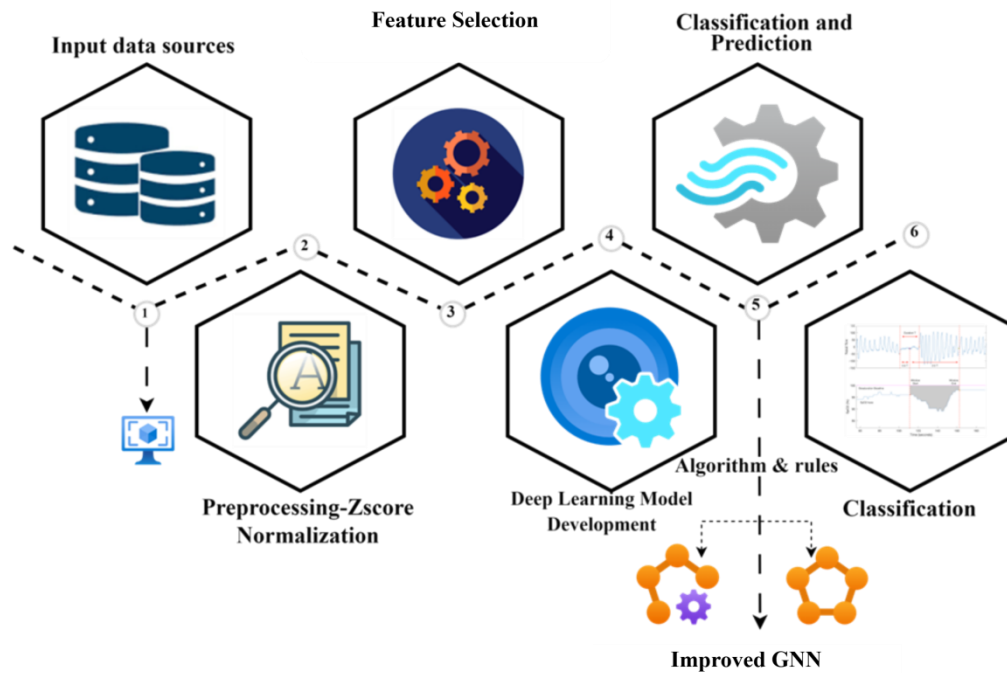


Figure 1: Overall architecture

3.1 Dataset collection

The dataset was collected from Kaggle website

<https://www.kaggle.com/competitions/sleepapneadetection>

3.2 Preprocessing-Z score Normalization

Data pre-processing is cleaning up the raw data before using it. Simply said, data obtained from various input characteristics is often obtained in an unusable raw format, making analysis a challenging task. Therefore, certain procedures are followed to transform the data into an accurate dataset. Data pre-processing is the name given to this procedure. Data that is inconsistent, noisy, or missing values is common in real-world datasets, making it difficult to analyze them further.

Using the Z-score Normalized Data Pre-processing model, we conduct missing value analysis to improve the outcomes of this work. To fill in the blanks in the database, our study makes use of Z-Score Normalized Data Pre-processing. Using the formula score deviation/standard deviation in a database, it is also used to standardize scores on the same scale. Here we can get the number of standard deviations for the provided data point from the mean. A schematic of the Z-score normalized data preparation model is shown in Fig. 2.

It is composed of thirteen characteristics, denoted as 'n', where 'n'= 13', and each component belongs to one of three distinct categories, 'T= T1, T2, T3', which are objective, examination, and subjective, respectively. The next step is to arrange the patient data into a "PXM" patient vector matrix with "u" rows and "n" columns, where "n" stands for the number of characteristics and "m" for the number of patients.

$$PVM = \begin{bmatrix} P_{11} & P_{12} & P_{13} & P_{1n} \\ P_{21} & P_{22} & P_{23} & P_{2n} \\ \dots & \dots & \dots & \dots \\ P_{m1} & P_{m2} & P_{m3} & P_{mn} \end{bmatrix} \text{----- (1)}$$

For instance, according to Eq. (1), the first row of the data set for patient number "1" is represented by the values of features "i" for the feature "i" associated with patient number "1," and the subsequent rows are labeled "P11, P12, P13, and P1n."

Standard deviation of features

$$(\sigma) = \sqrt{\frac{\sum_{i=1}^n (F_i - \mu_i)^2}{n}} \text{----- (2)}$$

Each feature's value 'F_i' and the mean of features μ_i relative to the total number of features n' are used to estimate the standard deviation of the overall patient vector matrix, as shown in Eq. (3). After that, we can estimate each feature's log-

transformed Z-score function using the formula below.

$$Z - score(LT) = \frac{1n(F_{ij}) - 1n(\mu_i)}{\sigma[1n(F_i)]} \text{-----} (3)$$

As a general rule, if the length is smaller than the maximum limit, then the Z-score is at least one standard deviation higher than the mean. After normalizing the data, log transformed Z-scores are shown below in pseudo code form.

The goal of pre-processing the raw information for sleep apnea disease with enhanced accuracy and speed to predict SA disease stays the same as in the previous method. Here, the missing values are filled in using Z-score log-transformation as part of the pre-processing. First, for each characteristic, we look at the mean and standard deviation of the relevant patient data. After that, we assess the lower and higher limits using the initialized lower and upper thresholds, and we normalize the log-transformed Z-score function. Lastly, this is used to standardize the various patient characteristics and convert them to the same magnitude. Using this method helps improve the accuracy and speed of SA disease prediction by ensuring that the findings are independent on the data's size; this is because the algorithm's sole function is to reject the quantity.

3.3 Feature Selection

The feature selection process for Sleep Apnea data involves identifying the most relevant physiological and signal-based attributes that significantly contribute to accurate classification. Initially, raw data such as ECG, SpO₂, airflow, and respiratory effort signals are collected. Pre-processing techniques like median filtering are applied to remove noise. Then, statistical features (mean, variance, skewness), frequency-domain features (e.g., spectral power), and time-domain features (e.g., RR intervals, apnea duration) are extracted. Dimensionality reduction methods like Principal Component Analysis (PCA) or feature importance ranking (using correlation, mutual information, or tree-based models) are used to select key features. This reduces computational load, avoids overfitting, and improves the performance of models like Graph Neural Networks (GNNs) for effective Sleep Apnea classification.

3.4 Sleep Apnea Classification and Prediction using improved GNN Algorithm

In the classification and prediction of Sleep Apnea using Graph Neural Networks (GNNs), models are created that organize physiological (EEG, ECG, SpO₂, etc.) signals as graph data, where each sensor or component of a signal is a node, and the relationships between the different components and sensors form the edges. The ability of GNNs to capture complex dependencies over time between the different physiological signals facilitates a better understanding of patterns associated with apnea events. GNNs are able to learn spatial features, as well as temporal features and can therefore improve the classification of different sleep stages and help detect episodes of apnea. In contrast to other approaches, GNNs are also robust when faced with irregularities in data, including noise and gaps. This modeling facilitates the development of early detection tools and personalized monitoring for Sleep Apnea, ultimately leading to improved patient outcomes.

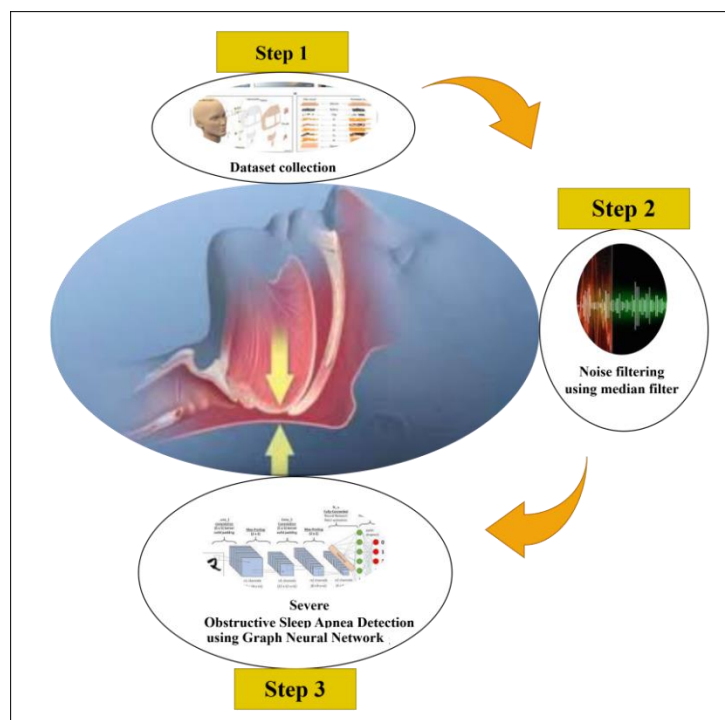


Figure 2: Sleep Apnea Detection

Figure 2 illustrates a three-step process for Sleep Apnea detection using Graph Neural Networks (GNN). **Step 1** involves collecting physiological data such as EEG, ECG, or oxygen saturation levels. **Step 2** applies a median filter to remove noise from the data, enhancing signal quality. **Step 3** uses a GNN model to analyze the preprocessed data, effectively detecting severe Obstructive Sleep Apnea by learning relationships among signal features.

The Improved GNN algorithm is a deep learning model designed for ECG signal classification and prediction tasks, particularly in the context of cancer detection and diagnosis from medical data like ECG. It uses ResNet architecture with cascading layers to effectively capture intricate patterns and features within the ECG signals. Classification involves categorizing signals into different classes, while prediction tasks can include estimating disease progression or treatment response based on ECG signal data.

It uses a label encoder to standardize the input, in particular. We substitute the labels without numbers with their numerical equivalents. Word counts, textual frequency, or TF-IDF can be transformed into an integer sequence or vector with a binary coefficient using the Tokenize tool.

The total number of times a certain token occurs in a particular content record is known as Tf , or token frequency. The proportion of token occurrences in the content record as a percentage of all tokens, as calculated in equation 5.

$$tf_{ij} = \frac{n_{ij}}{\sum_k n_{ik}} \text{----- (5)}$$

Researchers in the field of statistics use the Inverse Data Frequency (idf) statistic to find the frequency with which unexpected tokens appear in historical data. Tokens that appear infrequently in the record document are more likely to be (6)

$$df(w) = \log\left(\frac{N}{df_i}\right) \text{----- (6)}$$

By combining a word's TF score (3) with its IDF score (w) (4), we can get its TF-IDF score (w). To be more precise, I am referring to equation 7.

$$W_{i,j} = tf_{i,j} \times \log\left(\frac{N}{df_i}\right) \text{----- (7)}$$

$tf_{i,j}$ = counting the occurrences of I in j

df_i = records where I is the id value

N = the whole count of files

To begin training the model, the text to sequence tool is used to convert tokens into word sequences.

$$\text{argmin}_U \|D(N, X, T) - D(N, X, T \cdot U)\| + \lambda \Omega(U) \text{----- (8)}$$

In line with what has been said so far, this structural optimization belongs to the class of problems called NP-hard due to its computational complexity of $O(2n)$. It is well recognized that GAs garnered the most attention when applied to NP-hard problems. Thus, GA might be used to enhance the aforementioned design. One way to improve the architecture of a ResNet network is shown in Algorithm 1.

Consider the gene $vk(wij)$ as a switch that, when turned on, indicates whether the edges connecting nodes I and j are indeed linked. The only way for neurons I and j to be linked in ResNet is for $vk(Tij)$ to be set to 1. If it's not, the connection is destroyed.

In order to find an optimal network design, we evaluate each representation in equation 7 using the following evolution function.

$$\text{fitness} = \alpha \|D(N, X, T) - D(N, X, T \cdot U)\| + \lambda \Omega(U) \text{----- (9)}$$

$$\Omega(U) = 1 - \frac{\sum_{k=1}^N u_k}{N} \text{----- (9)}$$

Where α and λ are weight-changing adaptive parameters that provide a search pressure between the loss function and the network's architecture in equation 10.

$$z1 = |D(N, X, T) - D(N, X, T \cdot U)| \text{----- (10)}$$

$$z2 = \Omega(U) \text{----- (11)}$$

$$a = \frac{r}{\sum_1^{\max} - z_1^{\min}} \text{----- (12)}$$

$$r = \frac{1-r}{z_2^{\max} - z_2^{\min}} \text{----- (13)}$$

Since the gene is either 1 or 0, when mutated it will become the latter (or 1).

From a methodology standpoint, GA operates as follows: in the present generation t , $P(t)$ represents the parents and $C(t)$ represents the offspring; the detailed implementation of GA is explained in Algorithm 1.

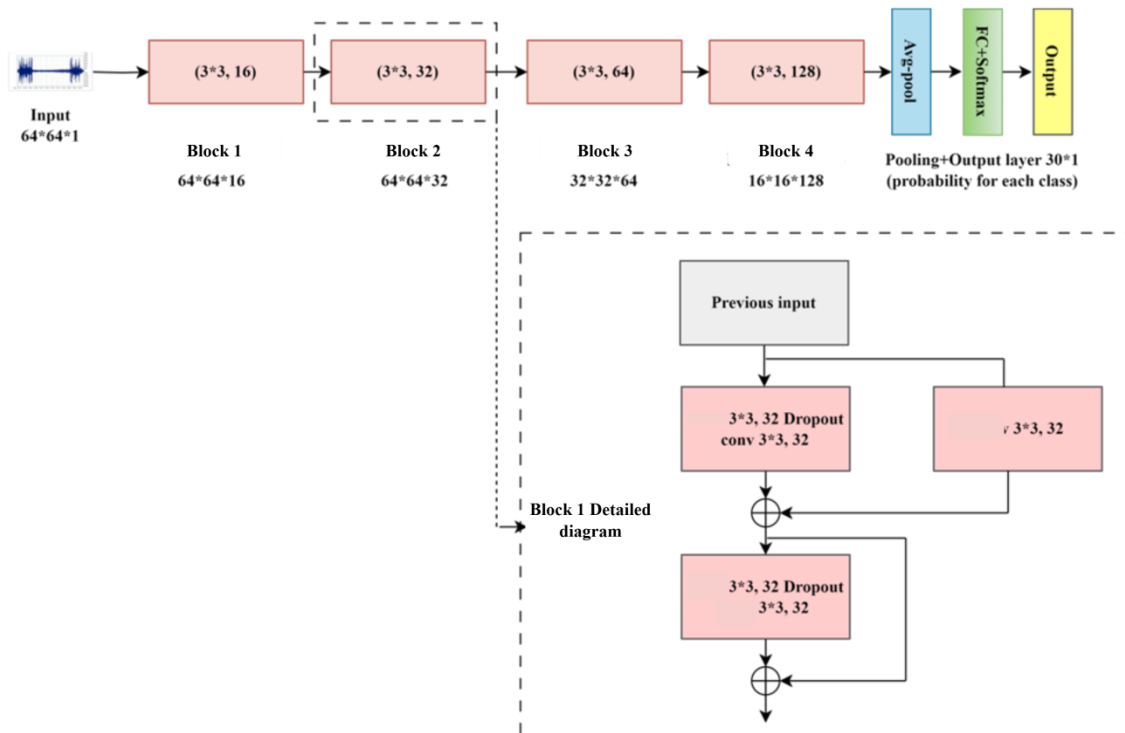


Figure 3: Improved GNN architecture for Classification

Figure 2 represents an **Improved GNN** for audio classification. The input is a waveform or spectrogram, processed through a series of convolutional layers with increasing filter sizes: $(3 \times 3, 16)$ to $(3 \times 3, 128)$. It uses a **Residual Block** with skip connections and dropout for regularization. After feature extraction, **average pooling** is applied, followed by a fully connected layer with **softmax** activation to produce the final output class probabilities.

A Deep Convolutional Neural Network (CNN) is highly effective for accurate prediction in Sleep Apnea detection due to its ability to automatically learn spatial and temporal patterns from physiological signals or image-based data. CNNs use layers of convolutional filters to extract key features such as waveform shapes or frequency components related to apnea events. Pooling layers reduce dimensionality, improving computational efficiency and minimizing overfitting. The extracted features are passed through dense (fully connected) layers for final classification. This architecture allows CNNs to deliver high accuracy and generalization, making them ideal for medical signal analysis and automated diagnosis.

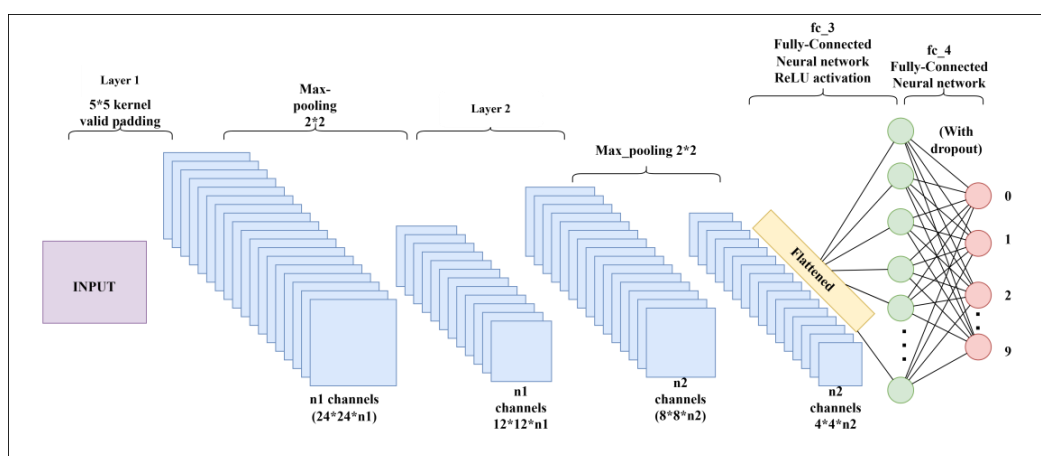


Figure 4: CNN Model for Accurate Prediction

Figure 4 represents the deep learning mode flow sample. The **input layer** receives raw data (e.g., physiological signals or images), which is passed through multiple **convolutional and pooling layers** to extract relevant spatial features. These feature maps are then **flattened** into a single vector, which feeds into **fully connected (dense) layers**. Finally, the **output layer** performs classification—e.g., identifying the severity level of Sleep Apnea. The structure enables automatic learning of hierarchical features crucial for accurate detection.

Algorithm 1: Improved GNN

Input:

- Preprocessed ECG signals from sleep apnea patients
- Label encoder for normalization
- Tokenizer for word-to-sequence conversion
- Transition matrix U for network structure optimization

Steps:

Algorithm:

1. Initialize the Improved GNN model with a modified ResNet architecture suitable for sleep apnea classification.

$$\Omega(U) = 1 - \frac{\sum_{k=1}^N u_k}{N}$$

2. Preprocess the input ECG signals using the label encoder and tokenizer.
3. Apply TF-IDF transformation to the tokenized data to obtain word scores.

$$a = \frac{r}{\sum_1^{\max} - z_1^{\min}}$$

4. Train the Improved GNN model using the preprocessed ECG data and the fitness function (equation 9) tailored for sleep apnea classification.

Optimize the network architecture using a genetic algorithm (GA) with the following steps:

- Generate an initial population of network structures (U) based on mutation rate and population size.

$$r = \frac{1-r}{z_2^{\max} - z_2^{\min}}$$

- Evaluate the fitness of each network structure using the fitness function (equation 9) specific to sleep apnea classification.
- Select parent structures ($P(t)$) based on fitness scores and apply crossover and mutation to create child structures ($C(t)$).

Output:

- Trained Improved GNN model parameters
- Optimized network architecture (U)

Algorithm 2: Deep CNN for Sleep Apnea Prediction

Input: Preprocessed physiological signal (e.g., ECG, SpO₂, or spectrogram)

Step 1: Data Preprocessing

Normalize signal values (e.g., Z-score normalization)

Segment signals into fixed-size windows (e.g., 30s epochs)

Convert to spectrograms if using CNN on image-like data

Step 2: Model Initialization

Define input shape (e.g., 1D vector or 2D spectrogram)

Initialize a Deep CNN architecture with the following layers:

- Conv Layer 1: 16 filters, 3×3 kernel, ReLU, BatchNorm
- Conv Layer 2: 32 filters, 3×3 kernel, ReLU, BatchNorm, MaxPooling
- Conv Layer 3: 64 filters, 3×3 kernel, ReLU, Dropout
- Conv Layer 4: 128 filters, 3×3 kernel, ReLU, MaxPooling
- Global Average Pooling
- Fully Connected Layer (Dense): 128 units, ReLU, Dropout
- Output Layer: Softmax or Sigmoid (for binary classification)

Step 3: Training

Compile the model with:

- Loss Function: Binary Crossentropy (for apnea classification)
- Optimizer: Adam
- Metrics: Accuracy, Precision, Recall, F1

Train on labeled dataset for multiple epochs (e.g., 50–100)

Validate performance using validation set

Step 4: Evaluation

Evaluate the model on the test dataset

Compute metrics: Accuracy, Precision, Recall, F-measure

Plot confusion matrix for error analysis

Step 5: Prediction

Feed new physiological signal into trained model

Output prediction: Apnea or Non-Apnea

Output: Predicted label (Apnea / Non-Apnea)

4. RESULTS AND DISCUSSION

This section presents and analyzes the outcomes of the experiment. The experimental has implemented by using MATLAB Software.

4.1 Performance evaluation

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \text{ ----- (14)}$$

$$Precision = \frac{TP}{TP + FP} \text{ ----- (15)}$$

$$Recall = \frac{TP}{TP + FN} \text{ ----- (16)}$$

$$F1 \text{ score} = 2 * Precision * Recall / (Precision + Recall) \text{ ----- (17)}$$

Table 2: Classification performance metrics comparison

	Algorithm	Accuracy	Precision	Recall	F-measure
Existing methods	Densenet	96.21	92.65	94.01	94.23
	VGG-16	97.35	93.87	95.10	95.07

	Resnet	98.11	95.32	96.75	97.14
Proposed methods	improved GNN	99.62	97.11	97.84	98.21

The table 2 presents performance metrics for existing methods (Densenet, VGG-16, Resnet) and a proposed method (improved GNN) across various evaluation criteria. Firstly, in terms of accuracy, improved GNN outperforms all existing methods with an accuracy of 99.62%, showcasing its superior classification capability. When considering precision, which measures the ratio of correctly predicted positive instances, improved GNN also exhibits the highest precision at 97.11%. Furthermore, in terms of recall (also known as sensitivity), which indicates the proportion of actual positive instances correctly identified, improved GNN maintains a high value of 97.84%, highlighting its ability to capture most positive instances. Finally, the F-measure, which harmonizes precision and recall, demonstrates improved GNN's robust performance with an F-measure of 98.21%, further underscoring its effectiveness in classification tasks compared to the existing methods.

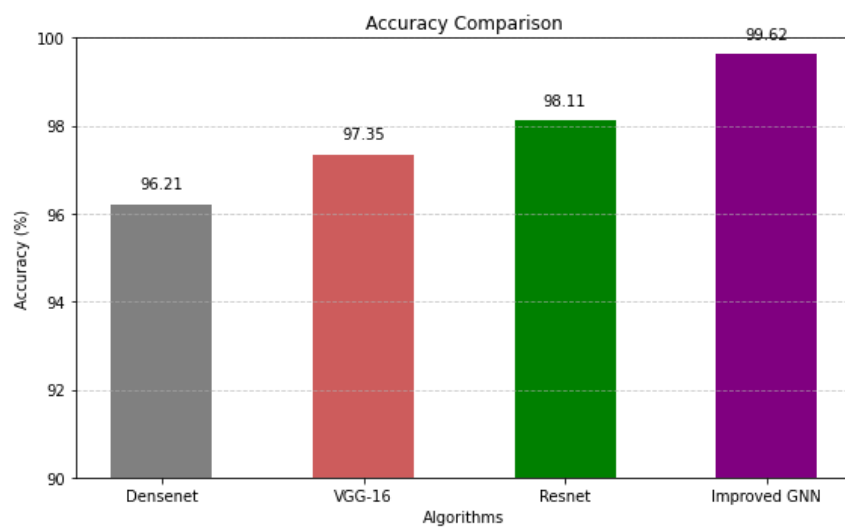


Figure 5: Accuracy comparison chart for Classification

A chart comparing accuracy is shown in figure 5. On one side, can see algorithms, and on the other, can see scores for accuracy in percentage.

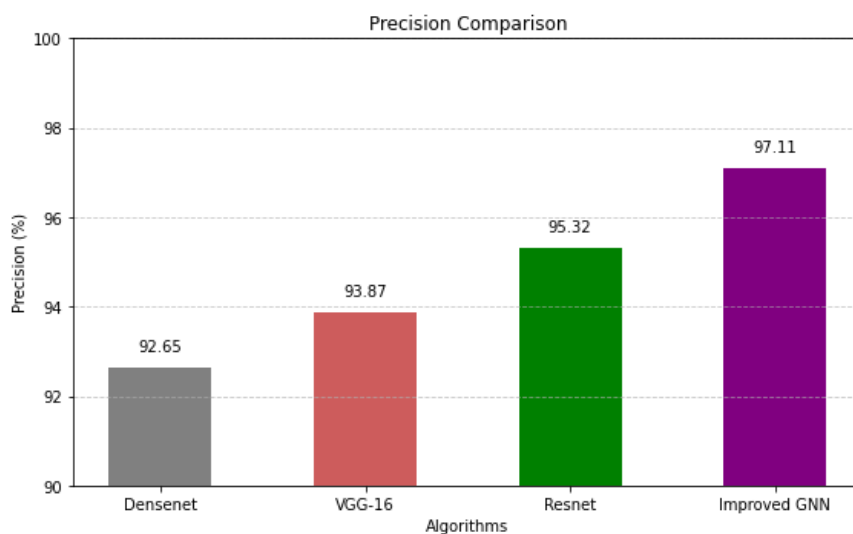


Figure 6: Precision values comparison chart for Classification

Figure 6 displays a chart comparing accuracy values. Algorithms are shown on the x-axis, while accuracy values are shown on the y-axis.

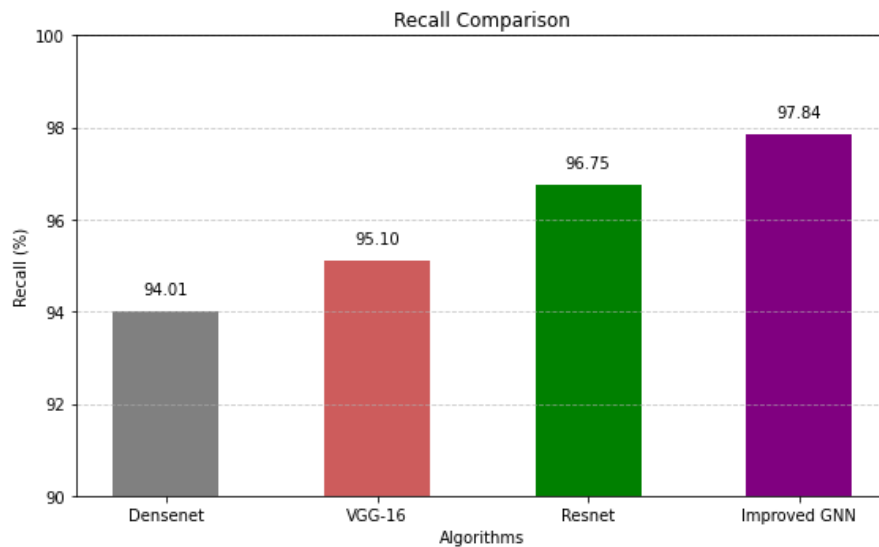


Figure 7: Recall comparison chart for Classification

Recall comparison table is shown in picture 7. Recall values are shown on the y-axis and algorithms are shown on the x-axis.

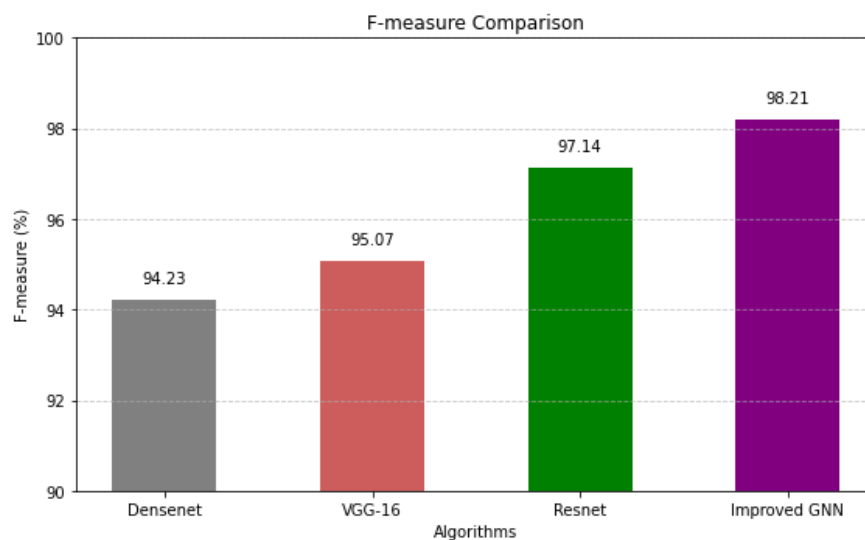


Figure 8: F-measure value comparison chart for Classification

Figure 8 displays a chart comparing F-measure values. On one side, we have algorithms, and on the other, we have the F-measure value.

Table 3: Prediction performance metrics comparison

	Algorithm	Accuracy	Precision	Recall	F-measure
Existing methods	SVM	96.27	92.29	94.20	94.30
	RF	97.43	93.10	95.43	95.45
	LSTM	98.53	95.28	96.92	97.43

Proposed methods	Deep CNN	99.70	97.84	97.99	98.29
-------------------------	----------	-------	-------	-------	-------

Table 3 compares existing and proposed methods for sleep apnea prediction based on key performance metrics. Traditional models like SVM and RF show strong performance, with RF achieving 97.43% accuracy. LSTM, a deep learning model, performs better with 98.53% accuracy. The proposed **Deep CNN** outperforms all, achieving **99.70% accuracy**, with high precision, recall, and F-measure, indicating superior ability to accurately detect apnea events with minimal false positives or negatives.

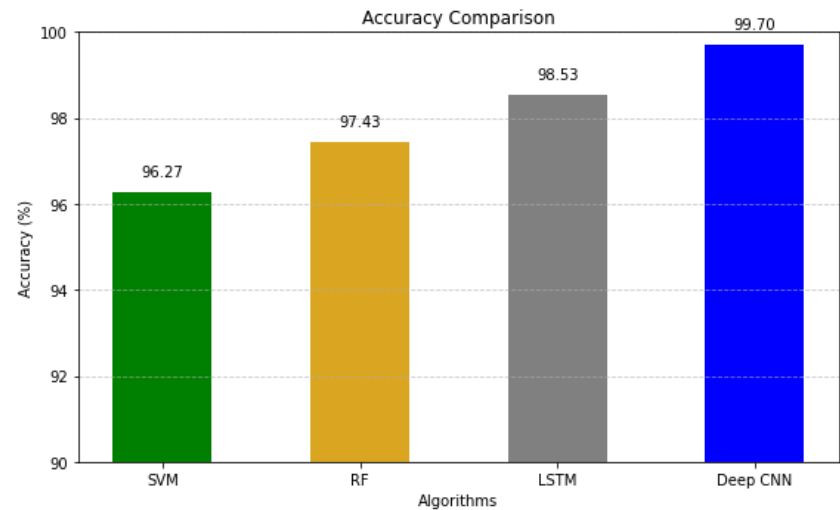


Figure 9: Accuracy value comparison chart for prediction

Figure 9 displays a chart comparing accuracy values for prediction. Algorithms are shown on the x-axis, while accuracy values are shown on the y-axis.

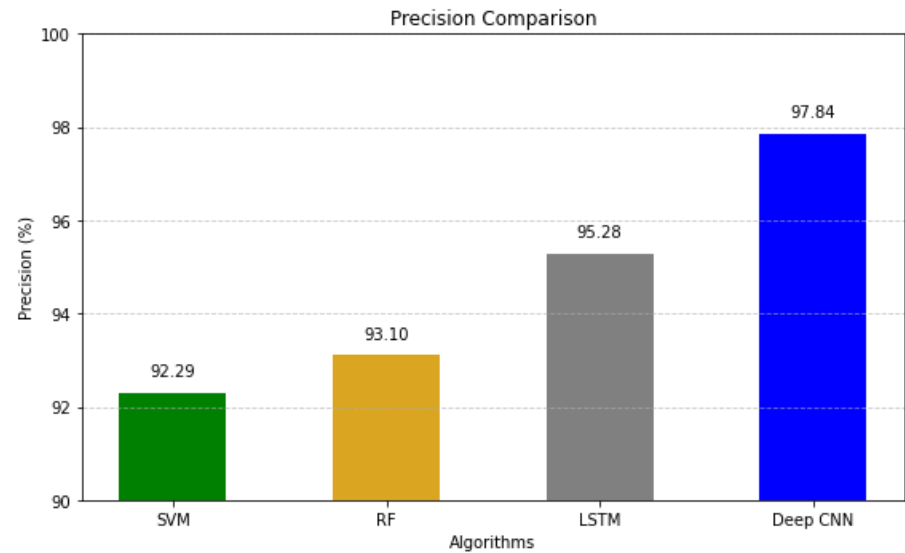


Figure 10: Precision value comparison chart for prediction

Figure 10 displays a chart comparing precision values for prediction. Algorithms are shown on the x-axis, while accuracy values are shown on the y-axis.

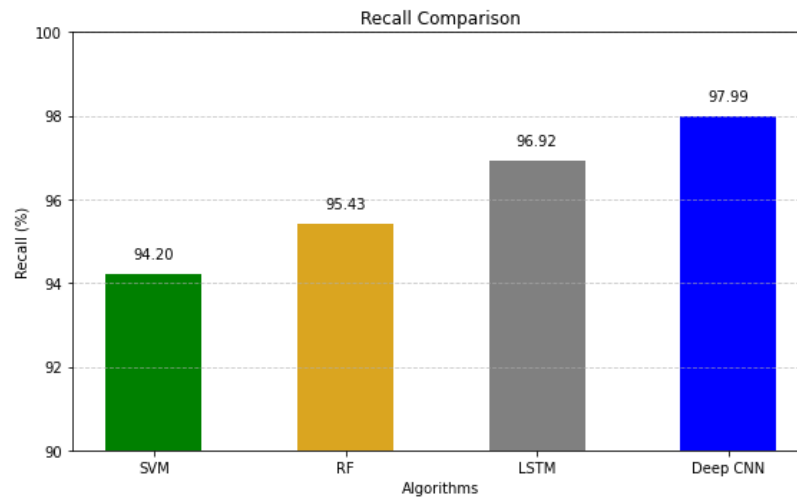


Figure 11: Recall value comparison chart for prediction

Figure 11 displays a chart comparing recall values for prediction. Algorithms are shown on the x-axis, while accuracy values are shown on the y-axis.

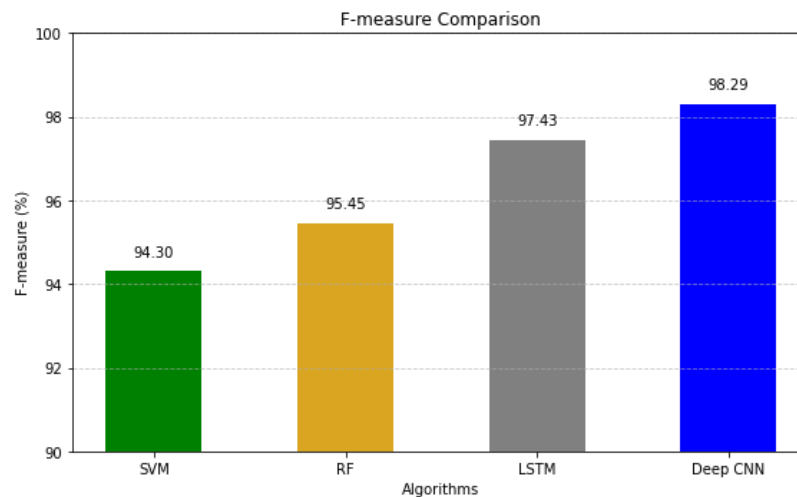


Figure 12: F-measure value comparison chart for prediction

Figure 12 displays a chart comparing f-measure values for prediction. Algorithms are shown on the x-axis, while accuracy values are shown on the y-axis.

5. CONCLUSION

In conclusion, our study presents a novel and effective approach for sleep apnea classification and prediction using the Improved GNN algorithm. Through the integration of Z-score normalization for data standardization, improved Pan-Tompkins algorithm for feature selection, and the deep learning capabilities of Improved GNN, we aimed to enhance the accuracy and reliability of sleep apnea detection and prediction. Our results on a diverse dataset affirm the effectiveness of these methodologies, showcasing improved data quality with Z-score normalization and the identification of relevant features crucial for accurate classification and prediction. Firstly, in terms of accuracy, improved GNN outperforms all existing methods with an accuracy of 99.62%, showcasing its superior classification capability and 99.70% accuracy in prediction. This study contributes to advancing the field of sleep disorder diagnosis and highlights the potential of advanced algorithms in improving patient outcomes and quality of life through timely and accurate sleep apnea detection. Future research can further explore optimization strategies and real-time implementation of these algorithms in clinical settings to translate these findings into practical healthcare solutions.

REFERENCES

- [1] Ahmed, S., Hasani, S., Koone, M., Thirumuruganathan, S., Diaz-Abad, M., Mitchell, R., ... Das, G. (2018). An Empirical Study of Questionnaires for the Diagnosis of Pediatric Obstructive Sleep Apnea. 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). doi:10.1109/embc.2018.8513389
- [2] Alimardani, M., & de Moor, G. (2021). Automatic Classification of Sleep Apnea Type and Severity using EEG Signals. In *BIODEVICES* (pp. 121-128).
- [3] Chyad, M. H., Gharghan, S. K., & Hamood, H. Q. (2020, March). A survey on detection and prediction methods for sleep apnea. In *IOP Conference Series: Materials Science and Engineering* (Vol. 745, No. 1, p. 012102). IOP Publishing.
- [4] Dong, Q., Jirarakopakun, Y., & Bhatranand, A. (2021). Convolutional Neural Network-Based Obstructive Sleep Apnea Identification. 2021 IEEE 6th International Conference on Computer and Communication Systems (ICCCS). doi:10.1109/icccs52626.2021.9449255
- [5] Islam, S. M., Mahmood, H., Al-Jumaily, A. A., & Claxton, S. (2018, December). Deep learning of facial depth maps for obstructive sleep apnea prediction. In 2018 international conference on machine learning and data engineering (iCMLDE) (pp. 154-157). IEEE.
- [6] Javeed, A., Berglund, J. S., Dallora, A. L., Saleem, M. A., & Anderberg, P. (2023). Predictive power of XGBoost_BiLSTM model: a machine-learning approach for accurate sleep apnea detection using electronic health data. *International Journal of Computational Intelligence Systems*, 16(1), 188.
- [7] Johnson, D. A., Sofer, T., Guo, N., Wilson, J., & Redline, S. (2020). A sleep apnea prediction model developed for African Americans: the Jackson Heart Sleep Study. *Journal of Clinical Sleep Medicine*, 16(7), 1171-1178.
- [8] Learning, M. U. S. M. (2020). Obstructive sleep apnea: a prediction model using supervised machine learning method. *The Importance of Health Informatics in Public Health during a Pandemic*, 272, 387.
- [9] Mahismita, P., Chandra, O. U., Dipti, G., Anshul, J., Shrabani, P., Baboo, S. R., & Sameer, V. (2019). Utility of combination of sleep questionnaires in predicting obstructive sleep apnea and its correlation with polysomnography. *Indian J Sleep Med*, 14, 61-6.
- [10] Manoochehri, Z., Rezaei, M., Salari, N., Khazaie, H., & Manoochehri, S. (2018). The prediction of obstructive sleep apnea using data mining approaches. *Archives of Iranian medicine*, 21(10), 460-465.
- [11] Mazzotti, D. R., Keenan, B. T., Lim, D. C., Gottlieb, D. J., Kim, J., & Pack, A. I. (2019). Symptom subtypes of obstructive sleep apnea predict incidence of cardiovascular outcomes. *American journal of respiratory and critical care medicine*, 200(4), 493-506.
- [12] Mencar, C., Gallo, C., Mantero, M., Tarsia, P., Carpagnano, G. E., Foschino Barbaro, M. P., & Lacedonia, D. (2020). Application of machine learning to predict obstructive sleep apnea syndrome severity. *Health informatics journal*, 26(1), 298-317.
- [13] Mubeen, N., Basha, S. F., & Women, J. N. T. U. A. (2022). Deep learning of facial depth maps for obstructive sleep apnea Prediction. *Journal of Engineering Sciences*, 13(12).
- [14] Onargan, A., Gavcar, B., Çalışkan, G., & Akan, A. (2021, November). Prediction of Sleep Apnea using EEG signals and machine learning algorithms. In 2021 Medical Technologies Congress (TIPTEKNO) (pp. 1-4). IEEE.
- [15] Parekh, A., Tolbert, T. M., Mooney, A. M., Ramos-Cejudo, J., Osorio, R. S., Treml, M., ... & Rapoport, D. M. (2021). Endotyping sleep apnea one breath at a time: an automated approach for separating obstructive from central sleep-disordered breathing. *American Journal of Respiratory and Critical Care Medicine*, 204(12), 1452-1462.
- [16] Phan, H., Andreotti, F., Cooray, N., Chén, O. Y., & De Vos, M. (2018). Joint classification and prediction CNN framework for automatic sleep stage classification. *IEEE Transactions on Biomedical Engineering*, 66(5), 1285-1296.
- [17] Pombo, N., Garcia, N., & Bousson, K. (2017). Classification techniques on computerized systems to predict and/or to detect Apnea: A systematic review. *Computer Methods and Programs in Biomedicine*, 140, 265–274. doi:10.1016/j.cmpb.2017.01.001
- [18] Singh, H., Tripathy, R. K., & Pachori, R. B. (2020). Detection of sleep apnea from heart beat interval and ECG derived respiration signals using sliding mode singular spectrum analysis. *Digital Signal Processing*, 104, 102796. doi:10.1016/j.dsp.2020.102796

- [19] Taghizadegan, Y., Dabanloo, N. J., Maghooli, K., & Sheikhan, A. (2021). Obstructive sleep apnea event prediction using recurrence plots and convolutional neural networks (RP-CNNs) from polysomnographic signals. *Biomedical Signal Processing and Control*, 69, 102928.
- [20] Zhao, X., Wang, X., Yang, T., Ji, S., Wang, H., Wang, J., ... & Wu, Q. (2021). Classification of sleep apnea based on EEG sub-band signal characteristics. *Scientific Reports*, 11(1), 5824.
-