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Sleep Stage Aware ECG-EEG Combined Apnea Type Classification and Severity Grading Using STG-Saru And FNFRL

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ABSTRACT

Sleep apnea is a common sleep disorder that involves periodic interruption of airflow during sleep, resulting in numerous health consequences like cardiovascular diseases and cognitive decline. Current detection techniques are mostly based on polysomnography, which is expensive and impractical for large-scale applications. This paper suggests a new sleep stage-aware apnea type classification and severity grading system that incorporates Electroencephalogram (EEG) and Electrocardiogram (ECG) signals. The approach suggested uses Spatio-Temporal Gated Self-Attention Recurrent Unit (STG-SARU) for classification of sleep stages and detection of apnea and Frobenius Norm Fuzzy Regularized Logic (FNFRL) for grading severity. Minimum Probability Gaussian Mixture Model (MinPro-GMM), Multi-Scale Entropy (MSE) analysis, and Canonical Kernelized Cross-Correlation Approximation (CKCCA) are employed together to extract and fuse discriminatory features from EEG and ECG signals. In addition, noise and artifact removal is maximized through Zero-Crossing Discrete Boundary Smoothing Wavelet Transform (ZDBSWT) and Quasi-Random Independent Sequential Component Analysis (QRISCA). Experimental verification on the PhysioNet Sleep Apnea dataset proves enhanced classification performance, outperforming traditional approaches in accuracy, precision, and robustness. The new framework provides a valid, non-invasive solution for early and accurate sleep apnea diagnosis, facilitating personalized treatment planning.

Keywords: ECG, EEG, STG, FNFRL

I. INTRODUCTION AND RELATED WORKS

Sleep apnea is one of the most common disorders characterized by decreasing or stopping the air stream during sleep. This decrease or stop of the air stream during sleeping is known as apnea, which can range in frequency and duration. Sleep apnea is divided into three types: obstructive, central, and mixed. Obstructive Sleep Apnea (OSA) is the most common disorder [1], which is characterized by partial or complete obstruction and recurrent collapse of the upper airway, affecting ventilation during sleep. On the other hand, Central Apnea (CSA) is distinguished by the failure of brain signals to activate muscles of respiration in the sleep process. The combination of these two apnea types is called Mixed Apnea (MIX), and it consists of a reduction of respiratory effort that leads to an upper airway obstruction. Currently, sleep-related breathing disorders are diagnosed using polysomnography, which is a sleep test performed in a hospital or at home under the supervision of a clinician are essential [2]. Even though polysomnography is the most important diagnostic tool in sleep medicine, its high costs and low comfort significantly reduce its diagnostic power. Therefore, various physiological signals, such as Electroencephalogram (EEG), Electrocardiogram (ECG), Electromyogram (EMG), Electrooculogram (EOG), breathing, Pulseplethysmograph (PPG), and various desired or necessary signals of patients are used for the diagnosis of Sleep apnea [3]. By using these signals, valuable information can be obtained to determine the patient's condition during nighttime sleep, which leads to proper diagnosis and treatment. Amongst the physiological signals, EEG signals are used frequently as they represent brain activities [4]. The EEG rhythms or waves—delta, theta, alpha, sigma, beta, and gamma—demonstrate the distinct characteristics of various sleep stages. Although sleep apnea is primarily a respiratory event, it significantly impacts multiple body systems, particularly the cardiovascular system[5]. Consequently, ECG signals provide valuable insights into apneic events [6]. Various research studies have utilized ECG and EEG signals independently to classify sleep apnea using Machine Learning (ML) and Deep Learning (DL) techniques [7]. However, by using either of the signals alone, the subtle changes in brain activity and cardiovascular signals for detecting apneic events were missed, which deviates from the detection results. Therefore, in this proposal, both the EEG and ECG signals are combinedly used to classify different types and severity grading of sleep apnea based on different sleep stages using STG-SARU and FNFRL.

Numerous studies have explored sleep apnea detection using various physiological signals and machine learning techniques. This section reviews significant contributions in this domain, highlighting their methodologies, results, advantages, and limitations. A self-training method using Maximum Classifier Discrepancy (MCD) for EEG-based emotion recognition, improving classification performance by leveraging unlabeled data to enhance model generalization and robustness in real-world scenarios [8]. Convolutional neural network (CNN) model to enhance oximetry-based diagnosis of pediatric obstructive sleep apnea, improving accuracy and automation by effectively analyzing oxygen saturation signals from children [9]. Hu et al. [10] proposed a single-lead ECG-based approach for Obstructive Sleep Apnea (OSA) detection using a Convolutional Neural Network (CNN)-based Autoencoder (AE). Their model achieved an accuracy of 86.3%, effectively identifying abnormal OSA-related features and assigning pseudo-labels to unknown data. However, the study did not focus on OSA severity grading, limiting its applicability in clinical assessment.

Taran et al. [11] developed a sleep apnea detection model based on Lampel-Ziv complexity of EEG signals, utilizing Tunable-Q Wavelet Transform (TQWT), Kruskal–Wallis (KW), and K-Nearest Neighbor (KNN) classifiers. Their method achieved 96% accuracy, proving to be computationally efficient. However, the TQWT parameters were not optimally tuned, which might have affected the performance. Bozkurt et al. (2021) Bozkurt et al. [12] explored single-channel ECG-based sleep-wake detection using Decision Tree, Support Vector Machine (SVM), and KNN classifiers. The approach reached an accuracy of 87.12%, benefiting from a diverse set of extracted features. Nonetheless, the relationships between these features were not analyzed, potentially affecting the classification performance.

Mahmud et al. [13] proposed a model for detecting sleep apnea frames from EEG signals, leveraging Variational Mode Decomposition (VMD), Fully Convolutional Neural Network (FCNN), and Bi-directional Long Short-Term Memory (Bi-LSTM). Their framework achieved an average accuracy of 93.22% and effectively captured apnea-induced spectral variations. However, the study was limited to binary classification (sleep apnea vs. normal EEG frames) without differentiating apnea types. Aswath et al. [14] introduced an Adaptive Sleep Apnea Detection Model incorporating Autoencoder (AE), Artificial Hummingbird Pity Beetle Algorithm (AHPBA), and Multi Cascaded Atrous-based Deep Learning Schemes (MCA-DLS). Their model attained an accuracy of 94.51%, successfully addressing dimensionality complexity issues. Nevertheless, the computational time for this cascaded approach was relatively high, which may impact real-time applications.

Existing studies have significantly contributed to sleep apnea detection, employing various signal modalities and machine learning techniques. However, key limitations persist, including lack of apnea type classification, suboptimal feature relationships, and absence of severity grading mechanisms. Addressing these gaps, this study proposes a sleep stage-aware apnea classification and severity grading framework using EEG-ECG fusion, STG-SARU, and FNFRL, enhancing detection accuracy and clinical relevance.

The reviewed studies on sleep apnea detection reveal several research gaps and challenges that need to be addressed. Different sleep stages pose unique challenges in apnea detection, and accurately distinguishing these stages can enhance classification performance and improve severity grading. However, no prior work has analyzed the relationship between sleep stages and apnea. Mahmud et al. (2021) focused only on binary classification between sleep apnea frames and normal EEG frames without identifying different apnea types. Similarly, Hu et al. (2023) did not concentrate on OSA severity grading, which is crucial as severe OSA increases the risk of hypertension, arrhythmias, heart attacks, and strokes, with a higher likelihood of sudden cardiac death during sleep. Moreover, most existing studies, such as Bozkurt et al. (2021), extract features from raw data but fail to analyze their interdependencies, leading to suboptimal model performance. Another major challenge is the contamination of ECG signals by motion artifacts, baseline wander, and powerline interference, while EEG signals are susceptible to noise from muscle activity (EMG), eye movements (EOG), and environmental factors, making it difficult to detect subtle variations indicative of sleep apnea. Additionally, apnea-induced changes in EEG (brain activity patterns) and ECG (heart rate variability and arrhythmias) are subtle, making their detection even more complex. Addressing these gaps requires a more comprehensive approach that integrates multi-modal signals, advanced noise reduction techniques, and robust feature extraction and fusion strategies to improve classification accuracy and severity grading in sleep apnea detection.

II. PROPOSED FRAMEWORK

The proposed sleep stage aware combined ECG-EEG based apnea type classification and severity grading using STG-SARU and FNFRL has the following steps: Load dataset, Signal splitting, Preprocessing, QRS detection, Sub-band separation, Apnea event separation, Multi-Scale Entropy (MSE) analysis, Feature extraction, Feature fusion, Data balancing, Sleep stage detection, Apnea type classification, AHI extraction, and Severity grading.

1. Dataset and Preprocessing

In the proposed work, for detecting apnea and classifying its types and severity with sleep stages, ECG and EEG signals are primarily taken as input from the physionet database. The combined ECG and EEG signals in the database are first splitted for the efficient processing of both signals separately. After separation, noise and artifacts present in both the ECG and EEG signals are removed using ZDBSWT and QRISCA, respectively. Discrete Wavelet Transform (DWT) decomposes the ECG signal into multiple frequency bands, allowing for analysis of the signal at different resolutions. By analyzing the signal at multiple scales, DWT can adaptively identify and suppress non-stationary noise (such as power line interference) and other artifacts that vary over time, making it superior to traditional methods. Nevertheless, the edge effects during wavelet decomposition can distort the signal at the boundaries. Thus, zero-crossing detection is adapted to identify significant points in the signal, where the ECG waveform changes direction. Boundary smoothing is applied at the zero-crossing points to reduce abrupt changes at the edges, thus helping to preserve the ECG signal's continuity while removing noise. Independent Component Analysis (ICA) performs blind source separation, meaning it does not require any prior knowledge of the sources (e.g., eye movement, muscle activity). It can automatically separate the EEG signal from mixed sources, making it ideal for real-world applications where the exact nature of noise is not known in advance. On the other hand, the inappropriate initialization of initial weights, nonlinearity function, and learning rate may converge to a local minimum instead of a global solution. This can result in inaccurate separation of the signals. As a result, a Quasi-Random Sequence that generates deterministic distributed points across a defined range is proposed. In ICA, the parameters are initialized using these sequences to ensure uniform coverage of the parameter space, improving the chances of finding globally optimal solutions. Next, from the ECG signals, QRS waves are detected using the PTA technique. Pan-Tompkins Algorithm (PTA) effectively detects QRS complexes with high sensitivity and specificity. It uses bandpass filtering, derivative operations, and squaring functions to suppress noise and artifacts, such as baseline wander and muscle noise while preserving the QRS complex. In the meantime, alpha, beta, gamma, and delta sub-bands of EEG signals are extracted.

2. Apnea event separation and Multi-Scale Entropy analysis

From both the ECG and EEG preprocessed signals, apnea events are distinguished based on the time frame present in the dataset using MinPro-GMM. Gaussian Mixture Model (GMM) models the data as a combination of multiple Gaussian distributions, each representing a cluster. Each point is assigned a probability that belongs to a cluster, providing a soft clustering approach that handles overlaps between apnea and non-apnea events effectively. It can model clusters of various shapes and orientations by adjusting covariance matrices. This is particularly useful for physiological signals like ECG and EEG, which often have overlapping and irregular patterns in the feature space. But, the performance of GMM heavily depends on selecting the correct number of Gaussian components.

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Overestimating the number of components can lead to overfitting, while underestimating can result in the loss of important patterns. Therefore, the number of Gaussian components is selected by means of Minimum Probability Flow (MPF). The process of probability flow minimization balances the bias-variance trade-off automatically by preventing the model from becoming too complex (which would lead to high variance and overfitting) or too simple (which would result in high bias and underfitting) by selecting the number of components dynamically. After that, Multi-Scale Entropy (MSE) analysis is carried out for both signals to extract the subtle changes in apnea events.

3. Feature Extraction and data balancing

Next, from the MSE output, extracted bands of EEG and detected waves of ECG features are extracted. The MSE features, such as Entropy Values at Different Scales, Slope of Entropy Curve, Variance of Entropy Values, Standard Deviation, Skewness, Kurtosis, Extremum Features, Complexity Index, RatioBased Features, and Transition Features are extracted. From the EEG bands, features, such as Mean, Variance, Standard deviation, Kurtosis, Zero-crossing, Skewness, Energy, Power spectral density, Relative power, Peak frequency, Spectral entropy, Hurst Exponent, Sample Entropy (SampEn), Median Absolute Deviation (MAD), and coherence are extracted. Similarly, from the detected waves of ECG signals, the features, such as Heart rate, RR-interval, Heart Rate variability, Morphological features, Amplitude mean and standard deviation, PSD, LF/HF ratio, Band power, Approximate Entropy (ApEn), Fractal dimension, kurtosis, Skewness, Coefficient of variation, and respiratory rate are extracted. Then, CKCCA is used to fuse both ECG and EEG features based on their interrelationships. Canonical Cross Correlation (3C) identifies and fuses features that maximize the correlation between ECG and EEG signals, enhancing the extraction of shared physiological insights. It captures meaningful relationships between the two modalities, improving the quality of fused features for subsequent analysis. However, calculating covariance matrices and solving generalized eigenvalue problems in 3C can be computationally expensive, thus making the process very slow. Thus, to mitigate this issue, Kernelized Approximation is utilized instead of covariance matrix computation. Kernelized 3C works in the feature space defined by a kernel function (typically a Radial Basis Function (RBF) kernel) to implicitly map data to a higher-dimensional space where correlations might be more easily captured. Afterward, to increase the number of data samples for increasing classification outcome, data balancing in terms of the Synthetic Minority Oversampling Technique (SMOTE) is utilized.

4. Sleep stage detection and apnea classification

Followed by data balancing, sleep stages are classified via STG-SARU. Gated Recurrent Unit (GRU) excels at capturing long-term dependencies in sequential data, enabling accurate recognition of sleep stages and detecting apnea events. GRUs maintain information over long-time sequences and remember historical data for pattern recognition, which is especially important for tasks like sleep stage classification and apnea detection. On the contrary, GRU may not effectively capture spatial-temporal dependencies between these different signals. This means that the relationships between the signals from different channels might not be fully captured by GRUs, leading to reduced accuracy in complex sleep or apnea classifications. To solve this issue, the Spatio-Temporal Self-Attention mechanism is developed. It applies both the spatial and temporal dimensions simultaneously to capture the relationships between different time steps and different spatial locations in the data. Based on the sleep stages and the balanced data, types of apnea are further categorized using STG-SARU.

5. Apnea severity grading

Finally, to grade the severity of each apnea type, the Apnea-Hypopnea Index (AHI) is extracted. Along with AHI, sleep stages and types of apnea are considered for grading the severity by means of FNFRL. The Fuzzy Rule (FR) can combine multiple features without defining strict thresholds. This makes the system more adaptive to varying signal patterns and less prone to overfitting. Moreover, FL can gradually change the classification based on the changing levels of signals. Nevertheless, defining an optimal set of fuzzy rules that generalize well across various apnea conditions and severity levels requires significant effort. Furthermore, as the rule base expands, it can become difficult to manage and maintain. Thus, Frobenius Norm regularization-based fuzzy rule optimization is done. The Frobenius norm can be applied to the weights of the rules, encouraging smoothness between adjacent rules and avoiding drastic changes in rule activation. This helps maintain a smooth and coherent decision boundary that generalizes well across different apnea conditions and severity levels. The block diagram of the proposed framework is shown below in figure 1.

The proposed sleep stage-aware combined ECG-EEG-based apnea type classification and severity grading framework using STG-SARU and FNFRL aims to enhance the accuracy and reliability of sleep apnea detection. Different sleep stages are classified using the Spatio-Temporal Gated Self-Attention Recurrent Unit (STG-SARU) to improve severity grading. To effectively differentiate multiple sleep apnea stages, STG-SARU is designed to separate apnea events from both EEG and ECG signals using the Minimum Probability Gaussian Mixture Model (MinPro-GMM). Addressing the risks associated with inadequate severity grading, the Frobenius Norm Fuzzy Regularized Logic (FNFRL) is developed based on the Apnea-Hypopnea Index (AHI), incorporating sleep stages and apnea types for more precise assessment. Furthermore, the potential relationships and interdependencies between extracted features are analyzed through Canonical Kernelized Cross-Correlation Approximation (CKCCA) to capture the full complexity of physiological data, improving overall model performance. To enhance signal quality, noise and artifacts in ECG and EEG signals are removed using Zero-Crossing Discrete Boundary Smoothing Wavelet Transform (ZDBSWT) and Quasi-Random Independent Sequential Component Analysis (QRISCA). Lastly, subtle changes in EEG and ECG signals indicative of apnea events are detected using Multi-Scale Entropy (MSE) analysis, ensuring a more effective classification of apnea types.

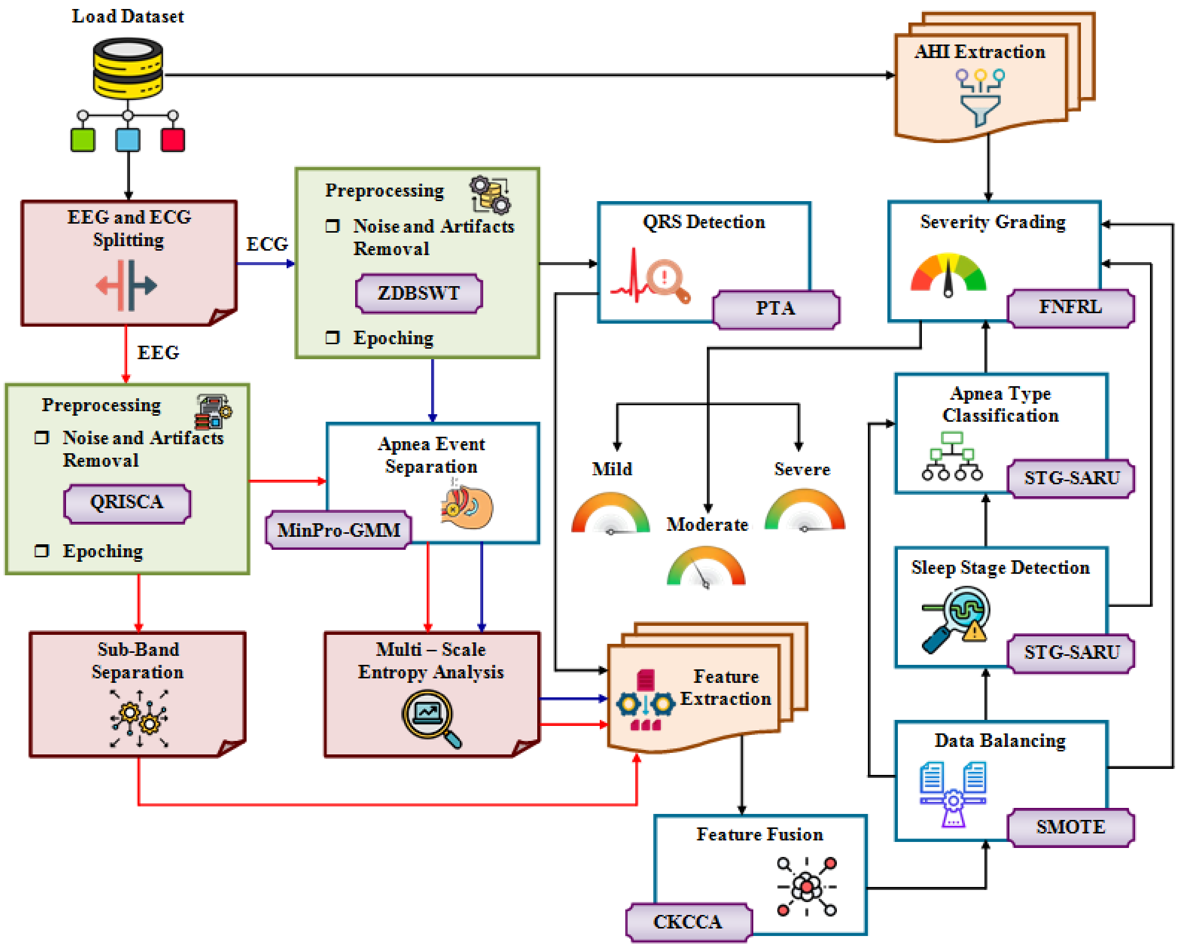

Figure 1: Block diagram of the proposed model

III. PERFORMANCE METRICS

1. Accuracy

Accuracy measures the proportion of correctly classified instances out of the total instances.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

2. Precision

Precision Measures how many of the predicted positive instances are actually positive.

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

3. Recall

Recall measures how many actual positive instances were correctly classified.

$$Recall = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{3}$$

4. F-measure

It is the measure is the harmonic mean of precision and recall, balancing both metrics.

$$F_{Measure} = \frac{2 * Re\,c\,all * Pr\,e\,cision}{Re\,c\,all + Pr\,e\,cision} \tag{4}$$

5. Specificity

Specificity measures how many actual negative instances were correctly classified.

$$Specificity = \frac{TN}{TN + FP} \tag{5}$$

6. False Positive Rate (FPR)

Measures the proportion of falsely predicted positive instances out of actual negative instances.

$$FPR = \frac{FP}{TN + FP} \tag{6}$$

7. False Negative Rate (FNR)

Measures the proportion of falsely predicted negative instances out of actual positive instances.

$$FNR = \frac{FN}{TN + FN} \tag{7}$$

8. Processing Time

Measures the computational time required for the model to make predictions.

$$\textit{Processing Time=Start time – end time} \tag{8}$$

9. Mean Squared Error (MSE)

Measures the average squared difference between actual and predicted values.

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$$MSE = \frac{1}{n}\sum_{j=1}^{n}\left|X_j - X_j'\right|^2 \tag{9}$$

10. Root Mean Squared Error (RMSE)

Square root of MSE, providing error in the same unit as the target variable.

$$RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n}\left|X_j - X_j'\right|^2} \tag{10}$$

11. Silhouette Score

Silhouette Score measures how well clusters are separated, with higher values indicating better clustering.

$$Silhouette\ Score = b - a/max(a, b) \tag{11}$$

a = Average intra-cluster distance (distance between a point and other points in the same cluster).

b = Average nearest-cluster distance (distance between a point and points in the nearest neighbouring cluster).

IV. RESULTS AND DISCUSSIONS

The performance analysis of the suggested STG-SARU architecture for apnea event prediction clearly shows its performance superiority over other available deep learning architectures such as Bi-GRU, GRU, LSTM, and DNN. The obtained results, as can be seen in the comparative graph, prove that the suggested model has the highest ranking in all major evaluation metrics such as accuracy, precision, recall, F1-score, and specificity. This proves that STG-SARU efficiently identifies useful apnea-related patterns with a strong focus on reducing false positives and false negatives. Among the baseline models, Bi-GRU and LSTM also have similar competitive performance with slightly poorer accuracy and recall than STG-SARU. This suggests that although these models are able to identify apnea events fairly well, they might not be able to capture the complete temporal dependencies of the physiological signals as effectively as the proposed model. In contrast, however, GRU and DNN perform comparatively lower on all parameters, highlighting their shortcomings in processing the intricate temporal and contextual patterns that can ensure proper apnea detection. One of the primary reasons why STG-SARU performs better is that it can model sequential dependencies efficiently while effectively overcoming vanishing gradient problems, which tend to plague other RNN-based models. The high specificity score also attests to the fact that the introduced architecture can consistently differentiate between apnea and non-apnea occurrences with a minimal chance of misclassifications. This makes it a solid candidate for real-world applications where precise and timely apnea detection is essential. Figure 2 shows the performance comparison of sleep stage detection apnea event detection. The proposed model has achieved 98.34 accuracy, 98.35 precision, 98.76 recall, 98.55 F-score and 97.8 specificity.

The plot in figure 3 provides a comparative analysis of the False Positive Rate (FPR) and False Negative Rate (FNR) for different models used in sleep prediction. These two metrics play a crucial role in determining the reliability of a model in distinguishing sleep events from non-sleep events. A lower FPR indicates fewer incorrect sleep event detections, while a lower FNR signifies better recall in identifying actual sleep events. Among all the models, the Proposed STG-SARU model outperforms the rest by achieving the lowest FPR and FNR, demonstrating its ability to accurately detect sleep events while minimizing misclassifications. Bi-GRU and GRU models also show promising results, but their performance is slightly inferior to STG-SARU. This suggests that while they can effectively learn temporal dependencies, they do not generalize as well as the proposed model. In contrast, LSTM and DNN models

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perform the worst, with higher FPR and FNR values, indicating that they struggle to distinguish between sleep and non-sleep events accurately. This suggests that these models might not be the optimal choice for sleep event detection. The results validate that STG-SARU is highly efficient in reducing misclassification errors, making it a reliable model for accurate sleep monitoring and diagnosis.

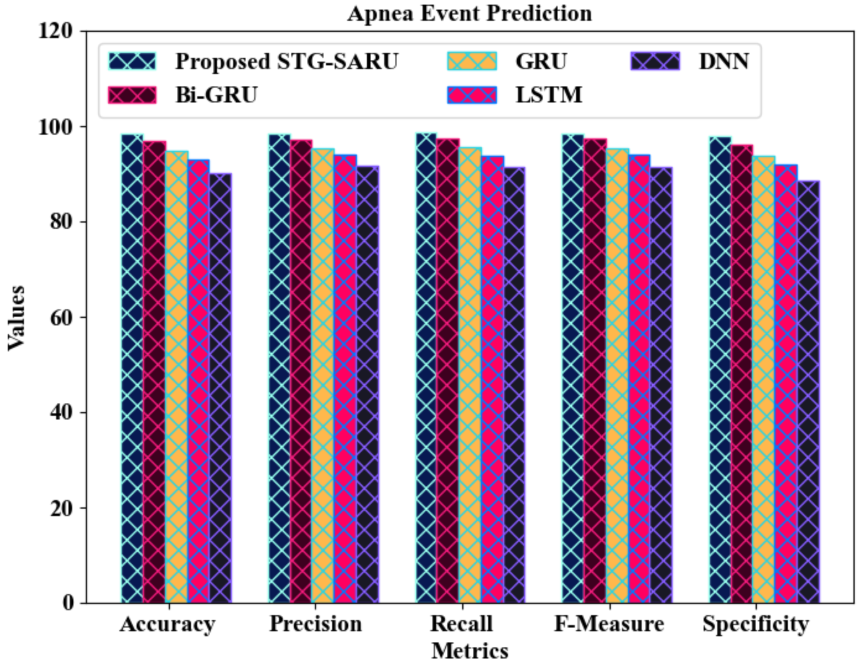

Figure 2: Comparison of apnea event prediction models

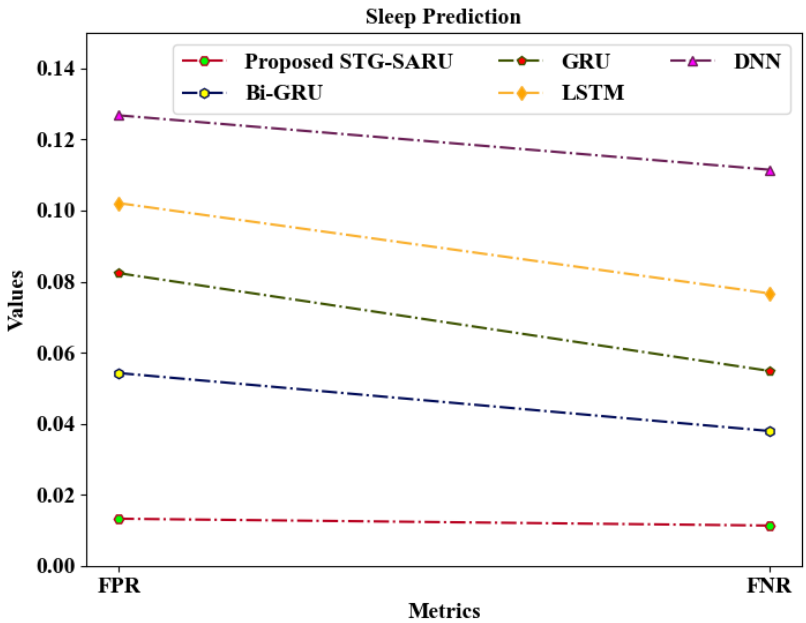

Figure 3: FPR and FNR of sleep prediction

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The plot in figure 4 describes the comparison of False Positive Rate (FPR) and False Negative Rate (FNR) of different models for sleep prediction. These two quantities are of most significance in the evaluation of accuracy of a model in detecting sleep events and non-sleep events. The STG-SARU model proposed is the best among all the other models with the least false negative and false positive rates, therefore the best model for sleep prediction. Bi-GRU and GRU show good performance but are less effective compared to STG-SARU. LSTM and DNN show the worst performance, suggesting that they may not be the best choice for sleep event detection. This explanation supports the fact that STG-SARU is highly effective at reducing misclassification errors, and this is thoroughly necessary for accurate sleep tracking and diagnosis.

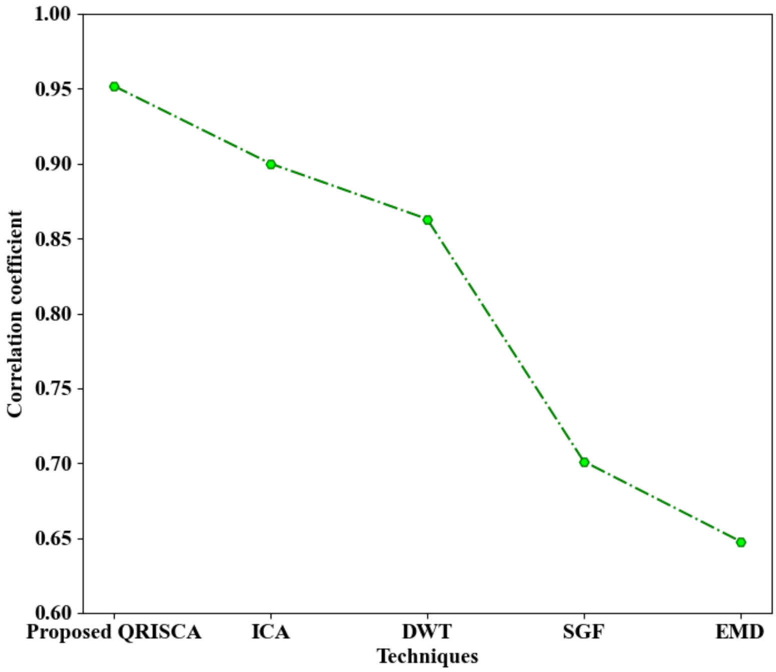

Figure 4: Correlation coefficient comparison of different models

Table 1: Comparison of fuzzy based models

Method	Prediction Rate	Fuzzification Time	Defuzzification Time	Rule Generation Time
Proposed FNFRL	99.84	558.697	523.013	448.998
Fuzzy	98.48	684.0825	615.013	520.99
Gaussian Fuzzy	96.128	758.406	689.01	570.99
Sigmoid Fuzzy	93.56	808.168	746.01	607.013
Trapezoidal Fuzzy	88.58	912.31	856.0064	658.013

Frobenius Norm Fuzzy Regularized Logic (FNFRL) is developed here to reduce the risks of other diseases due to inadequate severity grading of sleep apnea. This ensures a seamless and consistent decision boundary that effectively adapts to various apnea conditions and severity levels. The table 1 presents a severity comparative analysis of different fuzzy-based models, including the Proposed FNFRL (Fuzzy Neural Fuzzy Rule Learning), in terms of Prediction Rate, Fuzzification Time, Defuzzification Time, and Rule Generation Time.

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The silhouette score quantifies the goodness of clustering, with larger values representing more well-defined clusters. The plot in figure 5 compares the silhouette scores of different clustering techniques used for sleep apnea detection. The MinPro-GMM model proposed here has the highest silhouette score, which indicates its best clustering performance among all the methods. Among the other methods, Gaussian Mixture Model (GMM) and Hidden Markov Model with GMM (HMM_GMM) are relatively good but are still behind the proposed MinPro-GMM. Bayesian Gaussian Mixture Model (BGMM) and Gaussian Process Classifier (GPC) have the lowest silhouette scores, which means poorer cluster formation and lower reliability in detecting clear apnea and non-apnea events. The greater silhouette value of MinPro-GMM indicates that it has well-separated and cohesive clusters, enhancing the classification accuracy of sleep apnea. The downward trend in scores from MinPro-GMM to GPC indicates the growing challenge in correctly separating apnea-related events in less accurate models. The analysis supports the efficiency of the MinPro-GMM model in clustering physiological signals for sleep apnea monitoring, rendering it a more trustworthy option for accurate monitoring and diagnosis.

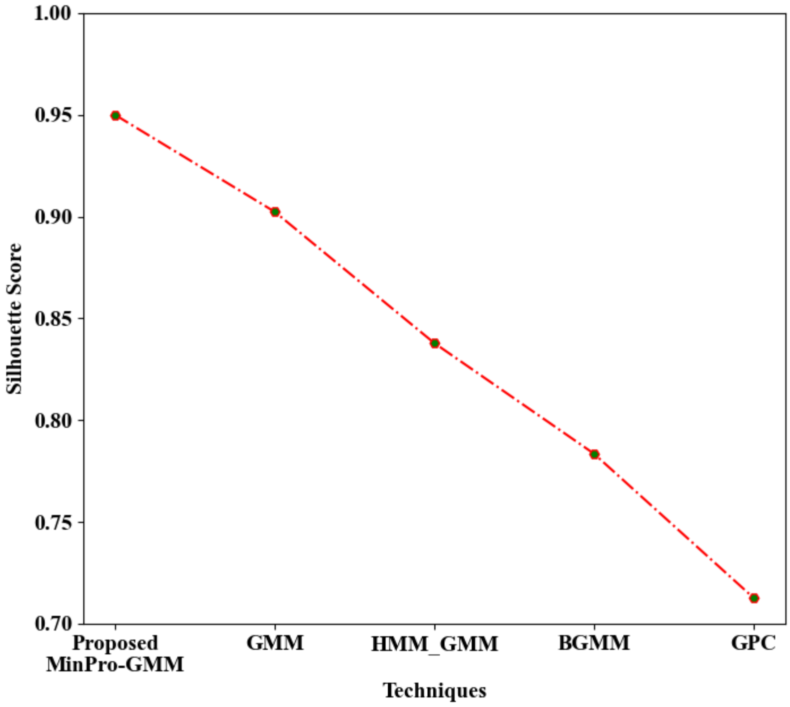

Figure 5: Silhouette score comparison

The chart in figure 6 compares the prediction rates of different Fuzzy Inference System (FIS) techniques, including the proposed FNFRL modelThe Proposed FNFRL model has the best prediction rate, with a value close to 99.84%, reflecting its high classification performance. Standard FIS also has good performance, but its prediction rate is lower compared to FNFRL. From the remaining models, Gaussian FIS, Sigmoid FIS, and Trapezoidal FIS have declining prediction rates in a decreasing manner, with the lowest performance coming from Trapezoidal FIS. This trend demonstrates the effectiveness of the FNFRL model, which combines fuzzy logic with an improved rule-learning mechanism, resulting in better prediction accuracy. The declining prediction rate from FNFRL to Trapezoidal FIS indicates that conventional fuzzy models are not as effective in managing complex and dynamic patterns in apnea-related signals. Thus, the FNFRL model emerges as a superior method for enhancing classification accuracy in sleep apnea detection.

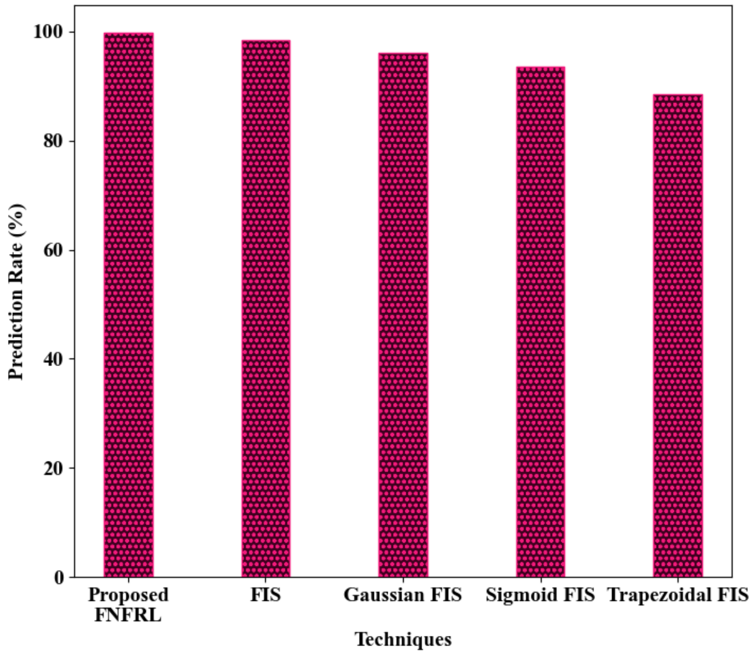

Figure 6: Prediction rates of different Fuzzy Inference System

V. CONCLUSION

The proposed framework for sleep apnea detection integrates advanced signal processing and machine learning techniques to enhance classification accuracy. It begins with preprocessing EEG and ECG signals, removing noise using QRISCA and ZDBSWT to ensure high-quality input. Apnea events are effectively separated using MinPro-GMM, followed by feature extraction through multi-scale entropy analysis and fusion using CKCCA. Severity grading is performed with FNFRL, while STG-SARU aids in apnea type classification and sleep stage detection. To improve model robustness, SMOTE is used for data balancing. This comprehensive approach ensures a reliable and efficient system for real-time sleep apnea diagnosis in clinical applications. In the future, this model can be extended by incorporating additional physiological signals such as SpO2 and respiratory effort to improve detection accuracy further. Moreover, deep learning-based feature extraction and real-time deployment on wearable devices could enhance its practicality for home-based monitoring and early diagnosis.

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