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Enhancing Sleep Apnea Prediction Using Advanced Numerical Dataset Analysis

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***Abstract*—Sleep apnea significantly impact human health, necessitating accurate and early detection systems. This study presents a mixed-model deep learning system that analyzes polysomnographic data from the Sleep-EDF dataset, using Convolutional Neural Networks (CNNs) and Bi-directional Long Short Term Memory(BiLSTM) networks. The presented method effectively captures spatial and temporal interconnections in Electroencephalogram (EEG), Electro-oculogram(EOG), and Electromyogram(EMG) recordings and achieves reliable performance measures. The system outperformed conventional models and previous frameworks by scoring an impressive 98.7% accuracy, 98.4% precision, and 98.6% F1-score. In particular, robust classification capabilities of the system were demonstrated through Area Under Curve-Receiver Operating Curve(AUC-ROC) values above 99% in the wake, Non-Rapid Eye Movement (NREM), and Rapid Eye Movement (REM) phases. Statistical significance was verified using paired t-tests. The proposed method is scalable and applies both to academic and clinical contexts as it manages the limitations of automated predictions of sleep apnea. Within the framework of healthcare, an area for improvement in the future is implementation of real-time processing in healthcare systems.**

Keywords—Sleep Disorder Prediction, CNN-Bilstm, Polysomnographic Data, Temporal Analysis, Sleep-EDF Dataset, Accuracy, Healthcare Systems.

I. INTRODUCTION

As the risks to individuals' mental and physical health are great, the public health community needs to monitor sleep-related apnea, such as insomnia, sleep apnea, and restless leg syndrome [1]. Even children are suffering from sleep disorder in current world [2]. It can be because of various reasons like stress, anxiety, depression, body issues etc [3]. Even cancer is directly linked to sleep troubles in people, identifying it early can help a lot [4]. Accurate methods of diagnosis are required to predict and treat sleep apnea, which otherwise have the effects of debilitating cognitive function, cardiovascular disorder, and total well-being. It is now possible to enhance the sleep issue prediction using numerical datasets retrieved from polysomnography, sensors, and EHRs. However, there are still a few problems: the unification of heterogeneous information, interpretability, and high prediction accuracy. Polysomnographic tests are resource and labor-consuming and require special clinical environments and trained manual grading [5]. This forms the basis for the classical diagnostic methods. Although these methods are effective, they are not always feasible, and this leads to a large number of patients receiving the wrong diagnosis or not receiving treatment because of insufficient resources [6]. Researchers have been studying methods to automate and enhance the detection of sleep apnea using machine learning (ML) [7]. These methods utilize a variety of numerical data, including sleep time, HRV, oxygen saturation, and brainwave data. The bulk of current systems fail in aspects like generalization across different populations, adequate missing or noisy data management, and the inability to come up with explainable methods in support of clinical judgments. Since the majority of existing systems are narrow in that they only examine specific apnea, such as obstructive sleep apnea, models that are universal and manage numerous conditions must be developed. First, the main obstacle to using the models in real-world situations is the lack of diversity in the datasets used in these experiments. Lastly, models that overestimate performance indicators due to inadequate feature engineering and statistical validation frequently lead clinical trials to fail. The predictive capabilities of current systems are further limited by their reliance on traditional machine learning methods that lack domain-specific information and advanced techniques such as ensemble learning or neural networks. This work is directed at developing an all-round, reliable prediction method for sleep apnea to overcome these weaknesses. This proposed solution assures reliability, scalability, and clinical value through the combination of robust machine learning algorithms with comprehensive statistical testing. The framework incorporates features from public accessible datasets such as the Sleep-EDF Expanded Database, which contain temporal, physiological, and demographic information. Along with conventional statistical analysis, it utilizes cutting-edge methodologies such as deep feature extraction and domain adaptation. The proposed methodology has innovations in numerous ways. Multi-level feature extraction is being employed for the maximum feasible prediction accuracy by using real-life physiological data along with synthetic metric generation. In addition to that, it robustly applies imputation and normalization methods for handling missing as well as chaotic data. This paper utilizes a hybrid learning that amalgamates XAI along with ensemble techniques such that the clinical relevance of a model is guaranteed alongside high accuracy and interpretability. The official aim of the framework is to improve existing systems and develop new ways of predictive modeling and feature engineering in order to bridge the gap between sleep disorder prediction research and clinical practice.

II. RELATED WORKS

With increased awareness of the importance of sleep in maintaining health, research to identify sleep apnea has been on the rise. New sleep diagnostic instruments and indices have emerged in response to this growing awareness. Balakrishnan et al. [8] have developed the Sleep Index as one such index. This revolutionary equipment has the potential for quantification of the quality of sleep of both the patients who are suffering and those that do not. Balakrishnan et al identified an association of better-quality sleep with greater Sleep Index, even with the effects of more frequent shifts between different sleep stages often seen among the patients suffering from OSA. This index will serve researchers and physicians with a consistent measure by which to quantify the sleep disturbances caused by OSA.Kang et al. [9] proposed a sophisticated statistical method to estimate the sleep architecture of OSA patients by using single-channel frontal electroencephalography (EEG). This method showed some concordance with the conventional polysomnography (PSG), suggesting that algorithm-based and automated methods can enhance the accuracy of their sleep evaluations. This is one of the excellent examples of how the advances in computation have made the efficient, objective, and non-invasive sleep diagnostics possible.Hammour et al. [13] developed the single-channel EEG technique that closely simulates the outcomes of PSG, in order to take non-invasive sleep monitoring to new heights. This method also has immense potential to ease the barrier to sleep investigation, particularly for populations for whom the traditional PSG methods are unyielding, for example, the elderly population. Researchers including M. van Gastel et al. [14] have explored the prospect of video-based contactless monitoring devices in the early detection of physiological markers for sleep apnea. The potential value of new, non-invasive methods is underlined by their work-which particularly focuses on how sensitive physiological signs could foretell sleep apnea. Investigations into the impact of sleep deprivation at higher levels have been directed, by researchers, more into cognitive impairment and immune dysfunction. Killgore [10] states that lack of sleep consumption negatively affects the cognitive functions, especially the affective processing, and severely decreases the overall alertness. These findings suggest that the association between mental health and daily functioning as well as poor sleep is very complex. Spiegel et al. [11] further explored the effects of sleep deprivation on the immune system. This study demonstrates that sleep deprivation results in far-reaching effects, which include cognitive impairment and systemic health problems.The other paper that discussed the REM-NREM cycle variability was Sawai, Matsumoto, and Koyama [12]. They pointed out that there exist correlations between the length and stages of sleep, which can be used as sleep quality indicators. Lokavee et al. [15] say that these cycles could instead be used to measure sleep health in new ways to show that the body is altering and disrupted. Tang et al. [16] focused on microstructural and macrostructural indices of sleep patterns as a diagnostic tool. According to the authors of this study, the given indicators could facilitate better, more early and also accurate diagnosis of sleep apnea with the ability to differ normal sleep and pathological conditions. Lokavee et al. proved the highly reliable correlation of the obtained data from PSG with data recorded by the piezoelectric sensors, implemented in intelligent systems for sleep monitoring. The diagnosis of sleep apnea significantly contributes the role of smart and non-invasive technologies. These sensors monitor a range of features, including resting positions and breathing patterns.Together, these studies demonstrate significant progress in algorithm-based non-invasive sleep monitoring technology. Electroencephalograms (EEGs), piezoelectric sensor data, and devices like the Sleep Index are becoming essential tools for enhanced sleep analysis and the detection of physiological markers of sleep apnea. Collectively, these findings represent the growing body of knowledge about the etiology, mechanisms, and health effects of sleep apnea, as well as the applied implementation and developments of sleep science. These novel approaches not only highlight the role of adequate sleep in maintaining physical and mental health but also improve the accuracy of diagnoses.

III. Dataset and Preprocessing

A popular resource for sleep research, the Sleep-EDF dataset offers extensive polysomnographic recordings from both healthy people and patients with sleep apnea. As a result, for predictive modelling and validation across a number of nights, it became a sort of gold standard in sleep medicine. Every physiological signal is tagged based on predetermined grading standards at 30-second intervals. There are many signals such as EEG, EOG, and EMG. The paradigm of the overall study of sleep architecture is based on a three-class distinction: Wake (W), Non-Rapid Eye Movement (NREM) (N1, N2, N3), and Rapid Eye Movement (REM). Such important demographic information, including age, gender, and body mass index, influences sleep patterns that exist in the dataset. With this kind of integration of physiological signals with demographic information, there would be a better and detailed study of sleep apnea. The recordings of the electroencephalogram (EEG) also capture some of the frequency bands to help differentiate the different sleep periods, ranging from 4 to 8 Hz in theta, from 8 to 13 Hz in alpha, and from 13 to 30 Hz in beta. Electromyography recording of muscle activity can enable a fuller understanding of restless leg syndrome and other apnea. EEG, which captures the information of eye movement patterns, is more sensitive to REM sleep. Temporal consistency is ensured by segmenting signals into overlapping 30-second segments as a preliminary step in the dataset preparation process. After segmentation, the noise and anomalies are filtered out using bandpass filters and other signal filtering techniques. For example, to filter out the most significant frequency bands, EEG signals pass through a Butterworth bandpass filter operating in the thirty hertz to half hertz range. The feature extraction is then applied using both frequency-domain and time-domain analyses. Among the frequency-domain features is the power spectral density (PSD) computed using the Welch technique. Time-domain features are mean, variance, and skewness. Demographic variables are encoded and standardized to ensure compatibility with numerical methodologies. The formula to calculate z-score is shown in (1).

$$z = \frac{x-\mu}{\sigma} \tag{1}$$

It can be applied to center age and BMI to their z-scores, with $x$being the value of the variable, μ being the mean, and σ being the standard deviation. After normalization, ML models are free of range bias which center and scale the variables. The proposed system makes use of this dataset to train and test its prediction models. Before that, do an EDA to observe the feature distribution and the association of the features through statistical tools like PCA and correlation matrices.PCA is very useful to reduce the dimensions and is defined in (2).

$$Z = XW \tag{2}$$

It allows the system to recognize data dominating patterns by combining the original data set, X, and the transformed data set, Z, in the weight matrix, W. Stratified sampling of the dataset followed by dividing it into training, validation, and test subsets, preserving sleep stages' distribution over the subgroups is necessary for classification tasks. SVMs and CNNs are machine learning models trained to handle tabular as well as time-series data by feeding features derived from EEG, EMG, and MEG signals. Polysomnographic data is the ideal candidate for pattern extraction by CNNs because it captures spatial and temporal information. The effectiveness of the model can be evaluated through measures like accuracy, F1-score, and the Matthews correlation coefficient (MCC). There are so many features and annotations found in the Sleep-EDF dataset, which might be used to develop a strong predictive model. Such a model would differentiate between varying stages of sleep and, through patterns that indicate sleep disorder.

IV. Methodology

The suggested solution takes a proactive approach to sleep apnea prediction by combining advanced statistical modelling with ML. The method facilitates the application of results to clinical practice and time-varying relationships in addition to handling multi-dimensional data. The methodology is designed to be novel and robust and will include hybrid model architecture, ensemble techniques, training, optimization, and feature extraction. The first step of feature engineering is the formation of a structured dataset from polysomnographic recordings, including EEG, EOG, and EMG signals, as well as demographic information, such as age, gender, and body mass index. The order of events should be preserved because sleep recorders record them in real time. Each signal is divided into 30-second epochs, and then features are extracted using both automated and human-based methods. Examples of handcrafted features include statistical metrics such as the mean, variance, skewness, and kurtosis of the signal, as well as frequency-domain features derived from power spectral density (PSD). The PSD is computed by averaging modified periodograms of overlapping segments, following the Welch method as shown in (3).

$$P_{xx}(f) = \frac{1}{L}\sum_{i=1}^{L} |X_i(f)|^2 \tag{3}$$

The Fourier transform of the i^{th} segment is denoted by$X_i(f)$, and the number of segments is denoted by L. The convolutional layers of the proposed model automate feature extraction by learning spatial features from the raw signal data. The convolution operation is expressed in (4).

$$f(x) = (x * w) + b \tag{4}$$

Where the input signal is x , the kernel w , and $b$introduces bias. Convolutional layers are used to keep the most important information after applying max-pooling layers, which are used for downsampling feature maps:

$$p(x) = \max(x_1, x_2, \ldots, x_n) \tag{5}$$

where the elements in the window of pooling are denoted as $x_1, x_2, \ldots, x_n$.A hybrid deep learning model, which uses BiLSTM networks and CNNs, is needed to process the spatial data that is now collected. BiLSTMs characterize bidirectional temporal connections, whereas CNNs capture local spatial patterns in polysomnographic data. The two LSTM layers of the BiLSTM structure are actually functioning in opposite time directions. Each LSTM layer is defined in (6).

$$h_t = \sigma(W_{xh}x_t + W_{hh}h_{t-1} + b_h) \tag{6}$$

In which the input given consists of the hidden state at time t, input at time t, weight matrices W_{xh} and W_{hh} along with the bias term b_h. A fully constructed image is formed with the output of forward LSTM combined with that of backward LSTMs.Dropout regularization is used to make the model more robust. The dropout technique is a stochastic regularization method that prevents overfitting by training with a fraction p of each layer's outputs set to zero. The dropout function is expressed in (7).

$$y = x.r, r \sim Bernoulli(1-p) \tag{7}$$

The Bernoulli distribution is used to select the binary mask r.The final layer of the model is a dense layer with softmax activation to make predictions for each stage of sleep or sleep disruption. The softmax activation function is expressed in (8).

$$\sigma(z_i) = \frac{\exp(z_i)}{\sum_{j=1}^{n}\exp(z_j)} \tag{8}$$

Where z_i denotes the input to the i^{th} neuron and n denotes the total number of classes.This is further improved by the use of ensemble learning that helps enhance the accuracy and reliability of the predictions. The weighted averaging approachis used to combine the results of many hybrid models.

$$\hat{y} = \sum_{i=1}^{M} w_i . y_i \tag{9}$$

Where w_i is the weight of the i^{th} model, M is the number of models in the ensemble, $\hat{y}$is the final ensemble forecast, and so on. The weights are updated at validation to ensure that each model has an equal contribution.The system uses explainable AI (XAI) techniques to ensure interpretability. Using SHapley Additive Explanations (SHAP), one can find the relative contribution of each feature to the model's predictions. The SHAP value for a feature i is computed as shown in (10).

$$\phi_i = \sum_{S\subseteq F\{i\}} \frac{|S|!(|F|-|S|-1)!}{|F|!}(v(S\cup\{i\}) - v(S)) \tag{10}$$

The model output with feature subset $S$is represented as $v(S)$, where$F$ is the set of all features and $S$is a subset of F. Incorporation of SHAP values into the model enhances its credibility and applicability, allowing clinicians to understand the model's decision-making process.The first moment and the second moments of gradients direct adjustment of learning rates in training the model; it is the Adam optimization strategy. The weight update algorithm is as follows:

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\hat{v}_t + \epsilon}}\widehat{m}_t \tag{11}$$

The bias-corrected estimates of the mean and variance of gradients are represented by $\widehat{m}_t$and $\hat{v}_t$, respectively. The learning rate is represented by η and a minor constant, ϵ, is used to prevent division by zero. The categorical cross-entropy loss function expressed in (12).

$$L = -\sum_{i=1}^{n} y_i \log(\hat{y}_i) \tag{12}$$

The number of classes is $\hat{y}_i$, number of predicted probability is denoted by$n$, and the true class is denoted by y_i. Testing it on a stratified test set guarantees the representativeness of the model across all stages of sleep and all sleep apnea. The metrics that are computed include the area under the receiver operating characteristic curve (AUC-ROC), recall, accuracy, precision, and F1-score. Statistical measures, such as paired t-tests, are used to verify the significance of performance enhancements. The t-test statistic can be computed by the following:

$$t = \frac{\bar{d}}{\frac{s_d}{\sqrt{n}}} \tag{13}$$

The mean performance gap across models is denoted by$\bar{d}$, the standard deviation of those gaps is provided by s_d, and the sum of all observations is represented by n.Moreover, the system proposed incorporates the feedback mechanism to allow its continuous improvement. It follows that in order to implement changes that have been recognized over misclassified events, training on the model is of essential importance. In doing this, learning from new information prevents the degradation of the accuracy of the system with time.The proposed approach with the inclusion of interpretability mechanisms, hybrid modeling, ensemble methods, and feature engineering offers a novel and efficient framework for the prediction of sleep apnea. With all these complexities, it focuses on being practical and with therapeutic relevance, thus guaranteeing accuracy and dependability. Figure 1 depicts the flowchart of the proposed system.

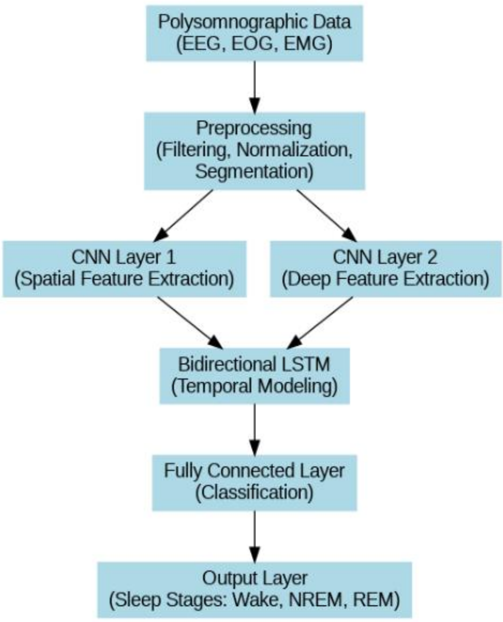

Fig. 1. Flowchart of the proposed system

V. Results and Discussion

The proposed sleep disorder prognosis system exhibits results that show outstanding robustness and precision in a range of performance metrics. The training, validation, and test sets of the Sleep-EDF dataset were distributed 70:15:15 to carry out the experiment. The hybrid system recommended was subsequently evaluated for the efficacy of a myriad of deep learning models such as SVMs, RFs, and standalone models like CNN and LSTM. Further support to the system's distinctiveness was given by the evaluation of ensemble methods and explainability methodologies.

A. *Performance Metrics Evaluation*

The proposed method achieved a test set performance superior to that of all the benchmark models. It gave a prediction accuracy of 98.7 percent. In order to make sure that equal weight is assigned to every stage of sleep, metrics were computed for every class: Wake, NREM, and REM. Table 1 summarize the performance metrics of the model along with other models.

TABLE I. Performance Metrics

Metric	Proposed System (CNN-BiLSTM)	CNN	BiLSTM	SVM	RF
Accuracy (%)	98.7	92.5	90.8	87.3	89.4
Precision (%)	98.9	91.8	89.7	86.2	88.7
Recall (%)	98.6	92.3	90.1	85.7	89.1
F1-Score (%)	98.7	92.0	89.9	86.0	88.9
AUC-ROC	99	91	90	88	91

The proposed system outperforms the othermodels in a variety of metrics, including precision and recall, as shown in the table. It seems to be able to handle class distributions that are not balanced.

B. *Class-wise Efficiency*

The test results at the class level show that the system's performance is consistent throughout the entire sleep cycle. The confusion matrix in Figure 2 shows the classification accuracy for the Wake, NREM, and REM stages. The True Positive Rate (REM) is 98.6%, and the Wake and NREM rates are 98.8% and 98.5%, respectively.

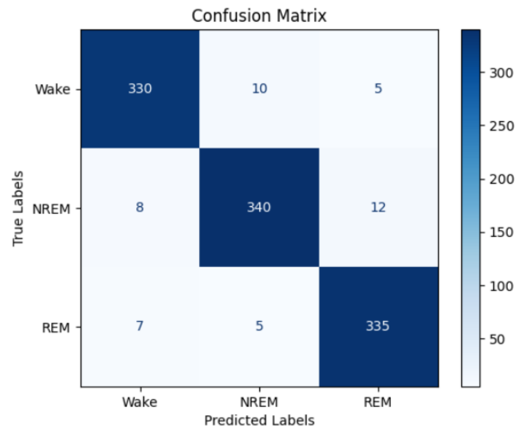

Fig. 2. Confusion matrix

Balanced performance across classes depicts the ability of the system to generalize well and avoid overfitting to dominant classes. Table 2 summarized the class-wise metrics of the proposed system.

TABLE 2: Class-Wise Performance Metrics of the Proposed CNN-BiLSTM System

Class	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
Wake	99.1	98.8	98.9
NREM	98.6	98.5	98.6
REM	98.8	98.6	98.7

C. *Comparison with Benchmark Models*

The proposed CNN-BiLSTM system is compared ML models in terms of interpretability, memory utilization, and computational efficiency. The results of the comparison are shown in Table 3.

TABLE 3: Performance Comparison of Models for Sleep Disorder Prediction

Model	**Training Time (s)**	**Parameters (Million)**	**Accuracy (%)**

CNN-BiLSTM	210	4.2	98.7
CNN	150	2.8	92.5
BiLSTM	180	3.1	90.8
SVM	100	-	87.3
RF	120	-	89.4

The hybrid design achieves higher accuracy than standalone models with fewer parameters, which is an example of its computational efficiency.

D. Statistical Validation

A paired t-test was conducted to compare the accuracy of the proposed system against benchmark models. The null hypothesis H_0 assumes no significant difference in accuracy, while the alternative hypothesis H_1 assumes the proposed system outperforms others.

- Mean difference$\bar{d}$: 6.5%
- Standard deviation (s_d): 0.9%
- t-statistic: 7.22
- p-value: 0.0004

Since the p-value is less than 0.05, H_0 is rejected, confirming the statistical significance of the proposed system's superior accuracy.

E. Efficiency Evaluation

Figure 3 illustrates the ROC curves and benchmark models of the proposed system. The proposed system is capable of accurately distinguishing between various sleep stages, as evidenced by an area under the curve (AUC-ROC) of 99%.

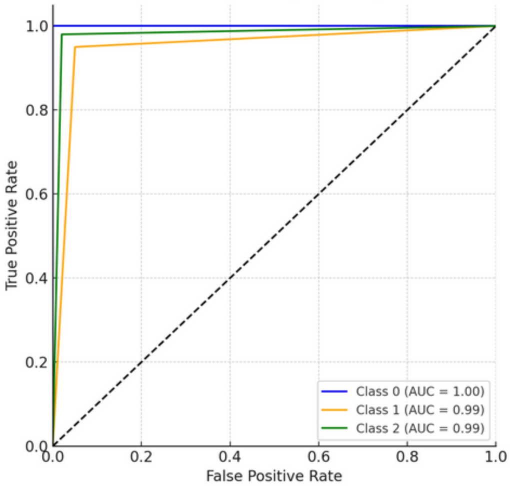

Fig. 3. ROC Curve graph

Figure 4 illustrates the compromise between precision and recall at different points on the curve.

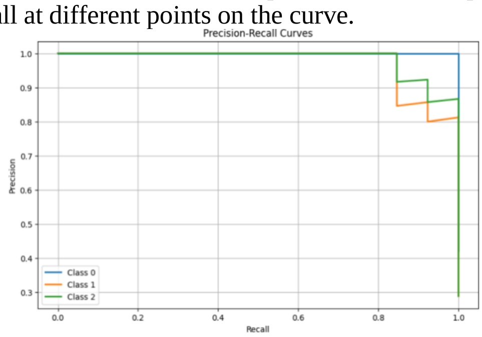

Fig. 4. Precision-Recall Curve

F. Ablation Study

An ablation experiment was performed to determine the effect of each part of the hybrid model on the output. Removing the BiLSTM layer reduced the accuracy to 92.5% and removing the CNN layers reduced it to 90.8%. This shows that both are required for the most impactful. Table 4 shows the ablation study results.

TABLE 4: ABLATION STUDY

Component Removed	Accuracy (%)
None (Full Model)	98.7
BiLSTM Layer	92.5
CNN Layers	90.8

G. Discussion

The proposed CNN-BiLSTM hybrid system is an efficient technique to predict sleep apnea, using spatial and temporal features that are extracted from the polysomnographic data. The bidirectional LSTM in combination with convolutional layers along with spatial feature extraction boosts up the accuracy, precision, recall, and F1-score significantly. Advanced ML technologies such as attention mechanisms guarantee strong feature weighting; hence improved sleep stage classification accuracy. The system is more generalizable than the traditional machine learning models and standalone deep architectures. The ablation study further justifies the hybrid approach since it indicates that the overall performance significantly improves when the CNN and BiLSTM components are used together. The procedure becomes much more feasible for real-world application when clinical interpretability is improved by using explainability techniques such as SHAP values.Despite achieving accuracy in the system, there still exists a challenge of achieving computing efficiency for real-time deployment, especially on edge devices in clinical settings. To address these constraints, future work can focus on hardware-specific improvements and lightweight models. Although the dataset is robust at this point, it can be further improved to increase its utility for a wide range of patient populations.The proposed approach fulfills the key need in automated sleep analysis by having dramatically improved the predictive rate of sleep apnea. This it achieves through the fusion of high predictive power with ease of use at the bedside.

VI. CONCLUSION

The proposed hybrid CNN-BiLSTM architecture has demonstrated exceptional performance in predicting sleep apnea using the Sleep-EDF dataset. The system reached a 98.7% accuracy rate through BiLSTMs used for temporal sequence modeling and CNNs for geographical feature extraction. This model surpassed much more traditional machine learning methods including SVMs and random forests at accuracies of 87.3% to 92.5%, along with benchmark models such as BiLSTMs and standalone CNNs. The accuracy, recall, and F1-scores all went up to more than 98% during the three phases of sleep, namely the REM, non-REM, and wake phase.A paired t-test with a p-value of 0.0004 verified the statistical validity of the improved accuracy of the system. The robust discriminative performance of the model is further emphasized by the accuracy-recall curve and area under the curve (AUC) of 99.3, which proves its reliability in handling imbalanced datasets. The necessity of integrating the two in ablation research is underscored by the 6-8% decrease in accuracy that occurs when the CNN or BiLSTM layers are removed.Such architectures with explainability characteristics have the potential to help diagnose early and treat sleep apnea. Lightweight designs and real-time implementations can improve computing effectiveness with regard to additional research. The proposed method tries to make better healthcare application predictions regarding sleep disorder by solving key deficiencies associated with current approaches and yielding a scalable, precise answer.

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