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A Deep Learning Approach to Automated Sleep Stages Classification Using Multi-Modal Signals

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Abstract

Sleep is one of the elements most vital to human life. However, the modern lifestyle continues to push people to neglect this critical requirement. With a vast majority of people falling victim to various sleep disorders, it has become increasingly essential to have a robust system for diagnosing and treating such ailments. Sleep stage classification is one of the primary steps for identifying sleep-related anomalies. Sleep stages are classified according to the frequency and nature of signals received during a polysomnography test. Since the early days, this has been performed manually with the help of trained technicians. However, manual scoring is often prone to error and subjectivity and requires tremendous time and effort. It is, therefore, essential to automatize this process. Several challenges from the correct selection of features remain to be faced in the machine learning-based sleep stage classification system. As an alternative, Deep Learning, capable of automatic feature extraction, proves far more reliable for this task. This experimental study analyses both techniques to compare and decide on a better approach. Three popular Machine Learning classifiers, namely Random Forest (RF), K-Nearest Neighbours (KNN), and Support Vector Machines (SVM), and a neural network comprising CNN and LSTM, have been trained on a vast base of diverse data. The proposed model reported an accuracy of 87.4% with CNN + LSTM.

Keywords: Sleep Staging; Electroencephalogram; Machine Learning; Deep Learning

1. Introduction

It has been observed that 62% of the adult population worldwide has reported continued dissatisfaction with their sleep quality due to various factors (Philips Global Sleep Survey, 2019). Statistics show that insomnia affects about 38 to 40 percent of older adults, and about 15-30% of males and 10-30% of females have been diagnosed with Obstructive Sleep Apnea (OSA) [1, 2]. Insufficient sleep has become a pervasive problem in modern society. It is now a global public health crisis frequently underestimated and has a relatively sizeable economic aftermath. Moreover, issues in falling asleep, as well as daytime drowsiness and exhaustion, impact even wider sectors of the community, creating a significant encumbrance when it comes to sickness and death, besides considerable societal

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costs in industrialized countries by adversely affecting its human capital, from taking toll of its healthy citizens to reducing their capacity of contributing to the nation's social and economic welfare [3]. Accurate and timely diagnosis of sleeping disorders is thus one of the significant challenges facing the medical fraternity today. One of the first steps in diagnosing sleep-related diseases is a polysomnographic test conducted on asleep patients. It is carried out using electrodes connected to patients that measure various physiological parameters that give an insight into bodily function during sleep. Three important channels of signals comprise the PSG are collected, namely EEG (Electroencephalography), which supervises brain activity during this period of rest, and EOG (Electrooculography), which refers to eye movements during the inactive state and EMG (Electromyography), which tracks muscle movement while sleeping [4]. A graphical representation of these sleep stages as a function of time, known as a hypnogram, is the first and most significant tool in helping clinicians thoroughly evaluate the sleep cycle of subjects. This technique is often prone to errors and misclassification and raises several concerns due to a human practitioner's complete reliability. Entirely dependent on the human ability of judgment, the entire process is considered highly time-consuming and grueling, not to mention the subjective bias involved [5-6]. The advent of Machine Learning has provided new hope for sleep studies. However, several challenges remain, including choosing the correct algorithm and selecting an appropriate technique for feature extraction from the raw data. As a counter approach to manual feature extraction, which requires a lot of experimentation and expertise to figure out the optimal features possessing the most excellent weightage, researchers nowadays are resorting to the application of Deep Learning algorithms involving neural networks to classification models, which make them capable of automatic feature extraction, and able enough to deduce and tune the essential features from the supplied data alone without human intervention.

Therefore, this research aims to introduce a robust Deep Learning classifier for automated sleep stage classification using CNN and LSTM. This experimental work thus entails the results achieved with Machine Learning, and Deep Learning approaches. The outcome obtained using CNN + LSTM is compared with the results derived from Machine Learning techniques. Sufficient training on a wide variety of sleep data has allowed the model to become experienced enough in detecting a host of sleep abnormalities. This project-based research thus aims to inspire multiple opportunities for future work involving artificial intelligence in sleep medicine.

Further, the research work presents in different sections. Section 2 offers a very brief review of related works. Section 3 presents the proposed architecture. The details of the proposed methodology and algorithmic explanation discuss in Section 4. Section 5 offers a description of the result analysis. At last, the concluding remarks for our research work are discussed in Section 6.

2. Literature Survey

Since the 1980s, following the establishment of polysomnography as the chief diagnostic tool to quantify sleep time and assess sleep quality, researchers have conducted numerous experiments worldwide to progress toward automatizing sleep classification. This area remains of prime interest to the medical fraternity. In this respect, significant work has been done by testing various classifiers upon various input data channels to boost the accuracy achieved using such artificially designed models.

Widasari et al. devised a sleep staging model using the ECG signal alone for classification [7]. This model went with a Decision-Tree Support Vector Machine (DTB-SVM) for sleep stage detection and chose an ensemble of bagged tree classifiers for categorizing sleep data into various sleep disorders, achieving an overall accuracy of 86.27% and a Cohen's kappa value of 0.70. Previously, Koley et al. proposed an ensemble model for sleep stage scoring using single-channel EEG [8]. After extracting 39 features from the frequency domain, time domain, and non-linear analysis, an SVM-based Recursive Feature Elimination (RFE) technique was applied to select the dominant features. Binary SVMs with One-Against-All (OAA) strategy was used as classifiers, resulting in a classification error of 8.9% and 10.61% for the training and testing dataset, respectively. Adnane et al.[9] who used a vital quality measure, sleep efficiency, as the performance evaluator of the classifier model. Detrended Fluctuation Analysis (DFA), Windowed DFA (WDFA), and Heart Rate Variability were the three methods used to extract all the essential features from the heart rate series, summing up to a total of 10 optimal ones, selected by the Support Vector Machine Recursive Feature Elimination (SVM-RFE) system. The training and classification using SVM yielded an accuracy of 79.99%. Previously, Koley et al.[10] proposed an ensemble model for sleep stage scoring using single-channel EEG. After extracting 39 features from the frequency domain, time domain, and non-linear analysis, applied binary SVMs with One-Against-All (OAA) strategy were used as classifiers, resulting in a classification error of 8.9% and 10.61% for the training and testing dataset, respectively. Cong Liu et al.[11] proposed an automated sleep staging system based on the EEG signal of a single channel driven by data. They used EEMD to decompose EEG epochs, extracted numerous features from calls, and decomposed IMFs. The testing was done using a five-fold cross-validation technique on the Dreams, Sleep-EDF, and SHHS databases. Their outputs showcased that the five-class sort obtained 83.4%, 91.9%, and 85.8% for all three datasets, respectively. Zhang et al. [12] proposed a Hidden Markov Model to consider the temporal dependency of data. Their work achieved an accuracy of 91% and an F-1 score of 86-96%. On raw EEG signals, Tsinalis et al. [13] applied a one-dimensional convolutional neural network, which could perform both feature extraction and classification with an accuracy of 82% and an F1 score of 81%. In the latest contribution by Supratak et al.[14], a combination of two Convolutional Neural Networks was used for feature extraction. The one having larger filters was important to catch slow oscillations. The CNN with smaller filters was more appropriate to accommodate shorter recording events. The outcome of this technique turned out to be at par with other solutions, giving an accuracy of 86% and an F-1 score of 82%.

While multiple techniques have been experimented upon, a simple yet effective model doesn't exist to date, owing to the complex nature of polysomnography signals and the challenging design of such artificial models, inspiring the need for further research. This project-based research is thus another step in this direction to address the limitations of existing literature.

3. Proposed System

The proposed automated sleep stage classification system is based on traditional machine learning (ML) and deep Learning (DL) principles. The use of the convolutional neural network (CNN) along with long short-term memory (LSTM) serves as an accurate means of autonomously extracting significant features from the data supplied to the model while also considering the outputs of a few of the past epochs using LSTM, as is the tradition in manual sleep stage scoring, resulting in a model quite closely resembling the conventional approach while at the same time, drastically enhancing the reliability of the whole procedure. A notable highlight of our model is the incorporation of multi-channel polysomnography signals, which is challenging to implement owing to its complexity. With this robust CNN + LSTM classifier, the results achieved are at par with those obtained on careful scoring performed manually by skilled technicians. All three channels ensure that no information loss occurs, leading to more convincing results. The following steps briefly describe the work process involved. The steps given below are executed in order:

Step 1: PSG test conducted on asleep subjects to obtain sleep behaviors.
Step 2: The extracted signals are pre-processed and filtered to remove undesired information from the raw inputs.
Step 3: Applying the CNN model to recognize the changes in sleep behavior characteristics automatically.
Step 4: The obtained dataset is split into two categories, the training set and the testing set, in an 80:20 ratio, respectively.
Step 5: The model is trained using different ML algorithms and the DL model.
Step 6: Final hypnogram is reported as an output on classifying sleep data into sleep stages.
Step 7: The model's performance is evaluated using several metrics.

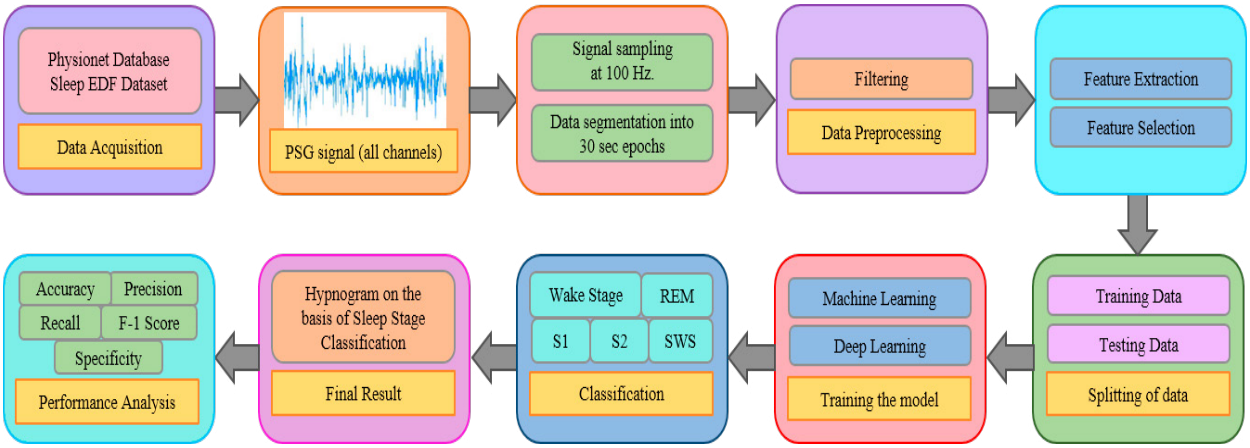

Fig. 1. Model Workflow

4. Methodology and Algorithmic Explanation

The current section focuses on implementing the Deep Learning methods described to construct a fully automated sleep scoring model. The technical concepts involved shall also be briefly discussed in addition to a logical flow of explanation concerning each stage of the workflow diagram.

4.1. Data Acquisition

PhysioNet [15] is a resource website supported by the National Academy of General Medical Sciences and the National Academy of Biomedical Imaging and Bioengineering. Sleep-EDF was the 2013 version of the Sleep Cassette (SC) subset in the Sleep-EDF Expanded dataset, consisting of 30 healthy subjects aged 25 to 34. The obtained patient details are described in Table 1. Similarly, Table 2 presents the distribution of epochs of each sleep stage. Fig. 2 (a, b) illustrates a sample PSG signal of a patient having record number SC4002E0, and Fig. 2 (c) shows the hypnogram scoring for the same record.

Table 1. Data Acquisition Details (Sleep-EDF Dataset)

Patients	Female/Male	Patients Age	Sleep Rule	Recorded Epochs	EEG channel	Sample freq. (EEG/EMG)	Sample freq. (EOG)
30	19/20	21-101	R & K	50559	Fpz-Cz/ Pz-Oz	100 Hz	100 Hz

Table 2. Dataset Description

Database	Sleep Stages						Total Samples
	W	S1	S2	S3	S4	REM	
Sleep-EDF	8055 (53.03%)	604 (3.97%)	3621 (23.84%)	672 (4.42%)	627 (4.12%)	1609 (10.59%)	15188

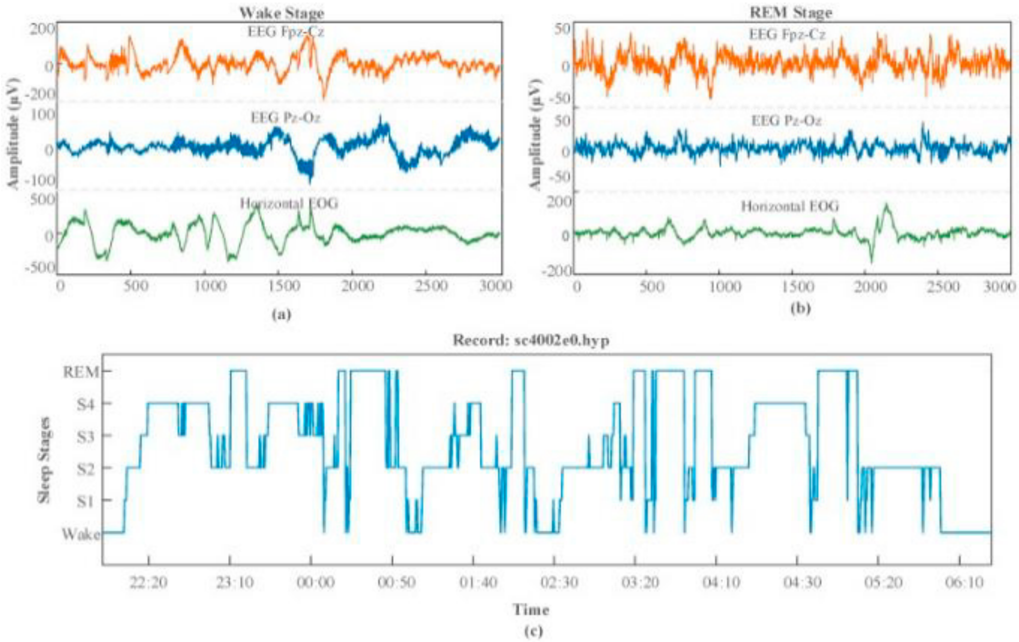

Fig. 2. Dataset Contents

4.2. Data Preprocessing

The recorded information from the patients was contaminated with a different type of noise and irrelevant artifacts. We used a Butterworth Band-pass filter of order eight to clean this unwanted information from the recorded raw signals [16].

4.3. Feature Extraction and Selection

Features are generally classified into four categories [17]:

a) Spectral features: Spectral features generally indicate the frequency domain features. The frequency component is extracted from signals using various methods, including Fourier transform or wavelet transformation. For instance, Slow Wave Sleep (SWS) derives its name from the slow waves in the delta band with a frequency ranging from 0.5 Hz to 4 Hz.

b) Temporal features: Temporal features consider the aspect of time involved in sleep staging. In the case of EEG signals, the activation changes in the brain over a specific duration are considered significant determiners in classification.

c) Statistical features: Simple statistical features can often be used to define signals. Signal maximum and minimum, or the number of times zero crossing occurs in the case of eye movements about the EOG signal, median of the signal value, etc., are all statistical characteristics.

d) Complexity features: Complexity features give a quantitative measure of the complexity of signals, which in simple terms, refers to the number of bits required to express the exact content of the movement in a compressed manner. For instance, Slow Wave Sleep is likely to have much less complexity than the Wake stage.

The next step after feature extraction is to find the best combination of features that must be selected as final inputs for the classification models. By choosing the most significant variables and discarding the unnecessary parts, feature selection enhances the prediction capacity of Machine Learning classifiers. This experimental study uses a Recursive Feature Elimination (RFE) technique to achieve this objective.

4.4. Classification Algorithm

4.4.1 Support Vector Machine

Like Random Forest Classifier, a Support Vector Machine or SVM is also a supervised learning technique, and it is also used for both classification and regression problems [26]. The main goal of the SVM is to create the best line, called a Decision boundary, that can divide the dataset into two or more classes, with the condition that the distance between the data points and the best line should be as far as possible. There are two types of SVM one is Linear SVM, and the other is Non-Linear SVM.

4.4.2 K Nearest Neighbor

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K Nearest Neighbor Algorithm is a Supervised Learning Algorithm. It is one of the simplest machine learning algorithms. KNN classifies a data point based on how its neighbor's classification. In simple words, we do feature similarities in KNN. KNN stores all available cases and organizes new topics based on a similarity measure [22]. That's why KNN is also known as Lazy Learner Technique. Here we use the Euclidean distance formula to count the distance between two points.

4.4.3 Random Forest Classifier

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Random Forest Classifier builds multiple decision and then combine all the results [25]. It is one of the most popular algorithms. This algorithm gives more accurate and stable results. This algorithm trained the data using the 'bagging' method. We can have more accuracy if the numbers of trees are more too.

4.4.4 Convolutional Neural Networks

In its most basic architecture, a Convolutional Neural Network consists of an input layer, a convolutional kernel, and an output layer [18]. The convolutional kernel is applied to the input pulse; each entry contains a neural weight. Via backpropagation, these weights are trained to learn and adapt according to the input signal's characteristics. Each kernel scans the input and returns to its filter kernel the region's activation. Multiple layers can be mounted, where each layer can construct a more complex feature representation building on the preceding layer's features. Thus, it is feasible to derive abstract feature representations from unprocessed original data, be it images or PSG signals.

4.4.5 Long Short-Term Memory

CNN and other neural networks do not possess any memory. On the other hand, neural networks such as RNN are the kind that can remember all the previous data provided to it while training and are capable of using it to assist future predictions made by the model, thereby significantly increasing the accuracy. However, the problem with RNNs is that the most significant weight or importance is placed on the most recent inputs, resulting in an issue known as the 'Vanishing Gradient.' Since the relevance of the initial inputs would have become almost negligible by the time the model receives all the information, it would have thus forgotten the values fed to it initially. To resolve this issue, LSTM is used. The LSTM comprises three sections known as gates, as illustrated in the diagram below, where each of those serves a different purpose. The first portion, the Forget gate, determines whether the data it receives from the initial timestamp could be helpful for future predictions and thus should be stored or whether it is unnecessary and can be ignored. The cell attempts to make sense of the new information it receives from the first part in the second section, called the Input gate. Finally, the last component, the Output gate, is used to send the revised information to the upcoming timestamp [19].

4.4.6 Experimental Setup and Network Architecture Training Parameters

In this section, we briefly discuss the experimental implementation and training parameters of the proposed model. The execution is compiled with the MATLAB 2019b version and Python packages with the following system configuration: Intel(R) Core (TM)i5-905H processor with 8GB memory capacity and NVIDIA GeForce GTX 1050 GPU with windows-10 operating system. The proposed CNN model has a filter size of 50, keeping in mind the need for the network to capture the lower range of frequency, i.e., 0.5Hz, representing the waves in the SWS stage. The more complex layers ensure accurate feature extraction. Max-pooling and strides decrease the high cost of computation and help in regularization. Furthermore, the abstractions of the convolutional layers are used as an input to an LSTM recurrent neural network consisting of two layers. The LSTM network's training uses a length of six epochs, which implies that on every new classification, it sees six previous sequential ages. This is by the human scoring standards of referring to the last five epochs every time before making a new classification. For training, the data has been split into two sections, 80% belonging to the training set and 20% comprising the testing set. Adam Optimizer was used for training. The learning rate was set to be 0.0001, and the model would end its execution in case of no improvement for 15 continuous epochs. The input consists of 2800 samples per epoch for all three channels. The Keras library for python is used as a CNN training framework using Tensorflow. Fig. 3 represents the network architecture.

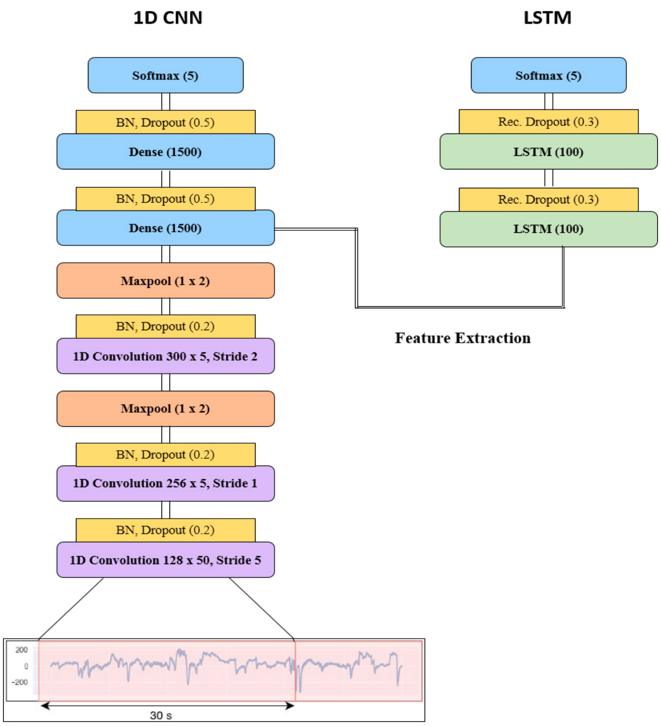

Fig. 3. Proposed Network Architecture

5. Results

The experiments are carried out on a machine with Processor Intel(R) Core (TM) i5-1035G1 CPU @ 1.00GHz machine. RAM: 8.00 GB, 64-bit operating system, x64-based processor. A confusion matrix is a table for the classifier that depicts its performance on the collective test data set. It is a summary of prediction results on classification problems.

$$Accuracy = \frac{(TR_{POS} + TR_{NEG})}{(TR_{POS} + TR_{NEG} + FL_{POS} + FL_{NEG})} \quad (1)$$

$$Precision = \frac{TR_{POS}}{(TR_{POS} + FL_{POS})} \quad (2)$$

$$Recall = \frac{TR_{POS}}{(TR_{POS} + FL_{NEG})} \quad (3)$$

$$Specificity = \frac{FL_{POS}}{(FL_{POS} + TR_{NEG})} \quad (4)$$

$$F1Sc = \frac{2 * Precision * Recall}{(Precision + Recall)} \quad (5)$$

5.1. Model Accuracy

The proposed CNN+LSTM model achieved an accuracy of 87.4%, CNN + LSTM, similarly by KNN and SVM algorithm, the model reported with an accuracy of 83.65% and 76.04% respectively. The graphical presentation is shown in Fig. 4. Fig.5 presents the reported confusion matrix for all the classification models considered in this research work. The performance metrics results are shown in Fig. 6. Fig. 7 demonstrates our model's comparative chart in between manual and automated sleep scoring. The red marking is the standard against which the model's performance is compared.

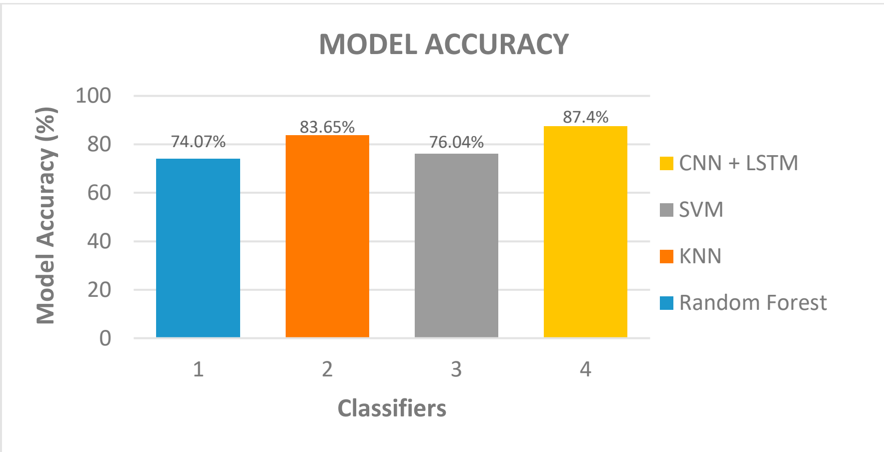

Fig. 4. Model Accuracy

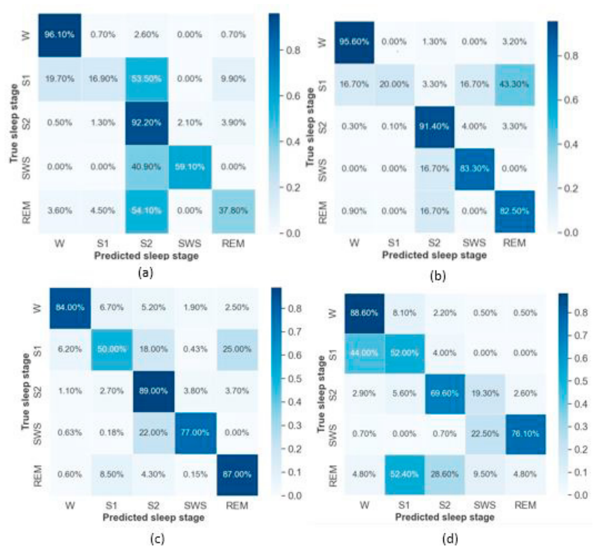

Fig. 5. Generated Confusion Matrix : (a) RF (b) KNN (c) SVM (d) CNN + LSTM

Fig. 6. Performance Metrics

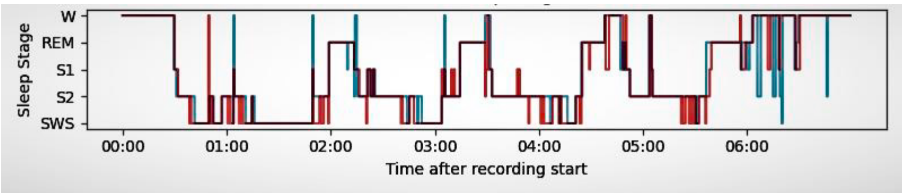

Fig. 7. Performance of sleep staging between manual and automated using hypnogram

5.2. Comparative Analysis

To validate our proposed methodology, we have analyzed the results of proposed model and existing contributed methods. The complete analysis is presented in Table 3.

Table 3. Comparisons with the recently contributed works

Author	Classifier	Classification Accuracy
Ref [1] 2022	Adversarial Learning	80%
Ref [2] 2019	LSTM+GRU	76%
Ref [16] 2019	CNN	85.22%
Ref [18] 2019		87%
Ref [19] 2019		84.6%
Proposed Work	**CNN+LSTM**	**87.4%**

6. Conclusion

In this article, we proposed a sleep staging model based on Machine Learning and Deep Learning. The proposed model is trained using sleep-related disorders and healthy controlled subjects using 80:20% training and testing data. The proposed model was tested through different baseline machine learning algorithms like RF, KNN, and SVM as classifiers and deep learning algorithms like CNN+LSTM. Various performance parameters were considered for measuring the model's effectiveness, like accuracy, precision, recall, specificity, and F1score. The proposed

CNN+LSTM achieves an accuracy of 87.4%, while the baseline ML algorithms ranged from 74.07% to 83.65%. In comparison with state-of-the-art works, CNN combined with LSTM reached the highest accuracy of 87.4%.

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