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Transforming Sleep Science – Deep Learning: Powered Automated Sleep Stage Detection and Classification

Nalla Akash, Vikas Sontakke, Prof. Anil Walke

ABSTRACT

The body needs sleep to heal physically, but sleep disturbances can lead to a number of issues. The diagnosis and treatment of such illnesses depend on the determination of sleep stages. Signals from the polysomnography (PSG) record the activity of the brain, muscles, eyes, and other physiological systems while a subject is sleeping. However, manually examining PSG signals can be error-prone and time-consuming. Convolutional Neural Networks (CNN), which is one type of Deep Learning Model, can be used to automate PSG signal interpretation. Long-Short Term Memory (LSTM) comes after CNN when using CNN as a stack ensemble technique to identify patterns in the correspondingto many phases and experiences of sleep. These models can identify the abnormalities at the sleep stages because they were trained on big datasets of PSG signals. The PSG signals in the dataset were taken from the PhysioNet Sleep-EDF dataset. The accuracy attained with CNN and CNN-LSTM utilizing separate training and testing data is 95.15% and 83.9%, respectively, and the overall accuracy is raised by 1% with the use of metadata classifier. Future improvements to the project could take heartrate, EEG Pz-oz signals, and EEG Pz-oz in addition to EEG Fpz-cz into account.

Keywords: Electroencephalography (EEG), REM, NREM, Long-Short Term Memory (LSTM), Deep Learning, Convolutional Neural Network (CNN), Metadata Classifier, Sleep Stage Classification.

INTRODUCTION

Sleep is a complex biological process that reenergizes our bodies, aids in maintaining good health, and helps people assimilate new knowledge. For optimal functioning, our bodies require both sleep and wakefulness. Even when you are asleep, your brain is still active. It also keeps the immune system and metabolism healthy, among other body functions. Ensuring adequate rest for the body and mind is crucial. We go through several phases as we sleep. Certain phases support recuperation and vigor the following day, while others support learning and memory enhancement. Either maintaining or decreasing weight is aided by getting enough sleep. Less than 7 hours of sleep each night can cause weight growth and increase in the BMI (body mass index). Additionally, getting enough sleep can enhance productivity, focus, and problem-solving abilities. Optimizing athletic performance can also be aided by getting adequate sleep. In addition to strengthening our hearts, getting enough sleep lowers our chance of heart disease.

There are three stages in the sleep cycle: N1, N2, and REM (rapid eye movement). While you sleep, your brain goes through its regular cycles of activity. There are two phases to the four stages of sleep: The first type of sleep has three stages and is called non-REM sleep. You are fully asleep in the final two stages of non-REM sleep. An hour or an hour and a half after falling asleep is when REM sleep starts. Your body switches between REM and non-REM sleep when you sleep. The first stage of non-REM sleep is when the sleep cycle starts for most people. You move through the various non-REM sleep stages before going into a brief REM sleep cycle. After that, the cycle restarts at step 1. The initial stage of non-REM sleep lasts five to ten minutes. Everything starts to slow down, including movement of the muscles and the eyes.

Figure1: Classification of Sleep Stages (Courtesy: Source [6])

In the second stage of non-REM sleep, your body temperature drops, your heart rate slows, and your eye movement stops. The brain waves become less rapid. Rarely, a short wave burst known as a sleep spindle will occur. Your body gets ready for a deep slumber. Stage three is deep sleep. Your brain generates delta waves, which are sluggish brain waves, at this time. Right now, it's hard to wake you up. Vibrant dreams happen during REM (rapid eye movement) sleep, which usually happens 90 minutes after falling asleep. During this phase of sleep, the eyes move quickly, the brain is working harder, and the arms and legs are temporarily paralyzed. About ten minutes make up the first REM cycle, and as the sleep cycle goes on, the length of the successive REM stages usually increases. Machine learning methods like Random Forest (RF), Support Vector Machine (SVM), Convolutional Neural Networks (CNN), and Long Short-Term Memory Networks (LSTM) can be used to streamline this process.

LITERATURESURVEY

The following section summarizes the significant factor regarding the literacy of existingapproaches.

In order to categorize Sleep Stages (SS), Zhu, Luo, and Yu [1] proposed CNN integrated with Attention-based Neural (AN) Network employing the window feature learning, intra-feature learning, and inter-feature learning components. The two datasets Sleep-EDF and Sleep-EDFX, which include individual PSG recordings of 197 subjects' whole nights, were employed in the current method. According to the study's findings, classifying SS using Deep Learning methods like CNN and AN network produced good results. With this method, a 93.7% accuracy rate was attained.

Zhou and his colleagues [2] proposed the Ensemble model, which uses machine learning algorithms—RF and LightGBM (LGBM)—to categorize SS. The N1 state might now be recognized more accurately thanks to the current model. The Sleep-EDF dataset includes 197 subjects' full night PSG recordings. The study found that combining RF and LGBM enhanced the ability to identify SS. An accuracy of 82.8% was obtained with this method.

LGBM and XGBoost were proposed by Radhakrishnan, Ezra, and Immanuel [3] as ensemble techniques to classify SS utilizing Tsfresh for Feature Extraction. The suggested technique classified sleep stages using the Sleep-EDF dataset, which includes EEG and EOG signals. The study found that the current model's ability to classify SS performed better when features were extracted using Tsfresh. With this method, 91.2% accuracy was attained.

For the purpose of classifying SS, Qing and his colleagues [4] proposed a Graph Temporal (GT) coupled with Dual-input CNN. Using a dual input CNN, the authors mapped every epoch of a Limited Penetrable Visibility Graph (LPVG) to acquire a Degree Sequence (DS) in addition to the raw epoch input. There are 197 whole-night PSG sleep recordings pertaining to brain activity in the Sleep-EDF database. 197 whole-night PSG signals representing brain activity are included in the Sleep-EDF database. According to the study's findings, dual-input CNN performs better. A success rate of 88.8% was attained with this method.

A deep learning approach was proposed by Mousavi, Afghah, and Rajendra Acharya [5] for automated sleep rating. Using a technique called SleepEEGNet, which is composed of Deep Convolutional Neural Networks (DCNNs), the objective was to determine the sleep scoring. In order to appropriately categorize the sleep stages, the misclassified stages are found using novel loss functions, which are then corrected in additional training data. This method addresses the issue of class disparity. The aforementioned issue was resolved by using the PhysioNet Sleep-EDF dataset. According to the study's findings, the suggested approach had a success rate of 84.26%.

A Deep Learning Model utilizing PSG signals for Automatic Categorization for Sleep Scoring was presented by Yildirim, Baloglu, and Acharya [6]. The goal was to categorize and track the many stages of sleep that can be used to identify neurological conditions. For the purpose of classifying sleep stages, they employed a One-Dimensional CNN (1D-CNN) that was created utilizing EEG and EOG signals. The sleep-edf and sleep-edfx datasets were used to assess the current methodology. The model obtained accuracy values of 98.06%, 94.64%, 92.36%, 91.22%, and 91.00% for between two and six sleep classes, respectively, using the sleep-edf dataset.

CNN was proposed by Sathish, Woo, and Edmond [7] as a way to predict sleep quality. The goal was to categorize and track the stages of sleep that aid in the identification of neurological conditions. They made advantage of the Sleep-Study, Sleep Deprivation, and Sleep Cycle Data sleep datasets that were readily available. The accuracies obtained for the Sleep-Study dataset were 63.46%, 56.22%, 55.33%, 53.69%, 59.21%, respectively; for the Sleep Deprivation dataset, they were 58.02%, 61.26%, 59.40%, 59.65%, and 62.66%; and for the Sleep Cycle Data dataset, they were 55.11%, 51.33%, 55.94%, 56.03%, and 59.26%, respectively. These results were obtained using machine learning techniques such as Logistic Regression (LR), Decision Trees (DT), k-Nearest Neighbour (k-NN), Naïve Bayes (NB), and SVM.

PROBLEMSTATEMENTANDOBJECTIVES

One of the best things we can do each day to rebalance the health of our physical and mental faculties is to get enough sleep. Early detection of sleep disorders and the classification of sleep stages are critical for improving both the quantity and quality of our sleep. Understanding PSG, which tracks blood oxygen levels, respiration, heart rate, and eye movements, is crucial to achieving this. However, the process of comprehending the PSG is difficult, and manual sleep scoring by skilled humans takes a lot of time. The project's goal is to create an automated sleep stage classification system in order to replace the manual sleep grading system. The goal of this project is to create an automated sleep phase classification system based on machine learning using PhysioNet sleep data.

Objectives

The division of sleep phases into categories can provide light on the duration and patterns of distinct sleep phases, such as REM and non-REM sleep. This information can be used to detect irregularities in sleep, monitor the success of treatment, and improve overall sleep quality.

Classification of sleep stages can help with the diagnosis of insomnia, narcolepsy, and sleep apnea, among other sleep disorders. The kind and severity of a sleep problem can be determined with the aid of an accurate sleep stage categorization, which can inform treatment choices.

The success of sleep interventions, such medication or behavioral therapy, can be monitored using the classification of sleep stages. Precise categorization of sleep stages can improve patient outcomes and optimize treatment plans.

PROPOSED METHOD

The project's foundation is an identification of sleep stages using CNN and LSTM, two machine learning algorithms. The PhysioNet Sleep-EDF dataset is utilized to manage this research.

The recordings in the dataset are of different kinds of PSG signals. The system uses a combination of machine learning algorithms and signal processing techniques to evaluate the EEG data and detect patterns unique to each stage of sleep. A classification model can accurately discriminate between each stage of sleep once it has been developed utilizing these features. The Sleep Track project's ultimate goal is to develop a machine learning algorithm that can accurately recognize and classify different sleep stages in real-time. This system may be used to diagnose and treat sleep disorders.

Architecture Diagram

1. The EEG echoes are first split into 30-second epochs.
2. After that, only the pertinent characteristics are chosen from the signals by feature extraction.
3. We use the CNN classifier to convey the signals in the first method.
4. The second method uses CNN and LSTM in order of application.
5. To acquire the best accuracy from the used ways, we employ a metadata classifier after acquiring accuracy from all the approaches.

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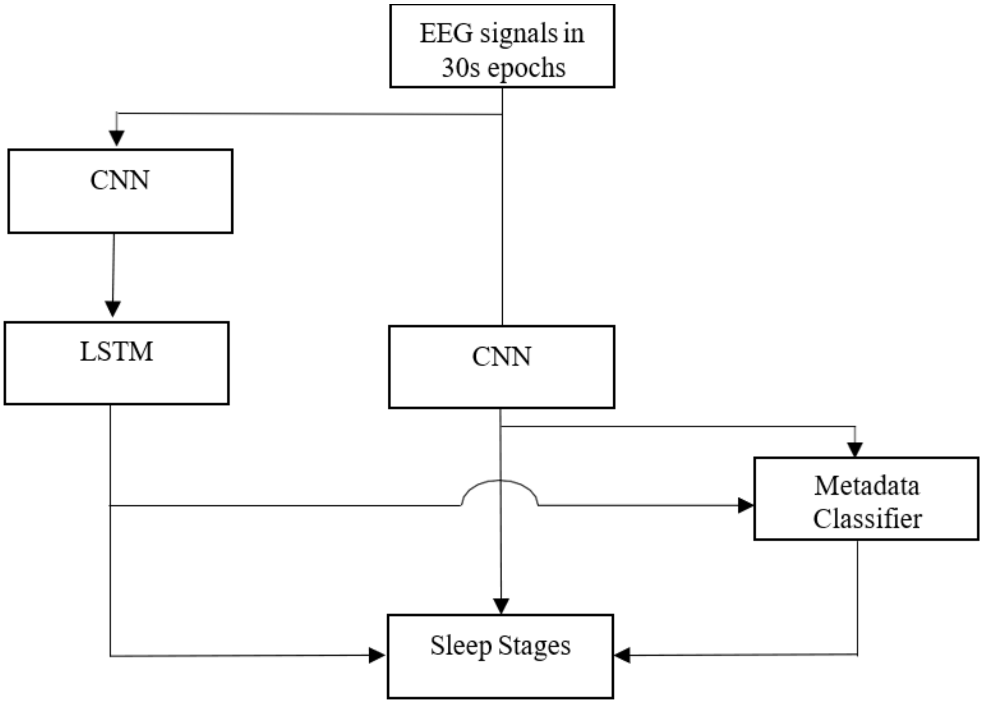

Figure2: Architecture Diagram

Modulesandits Description

CNN

CNNs are among the most popular deep learning algorithms that have changed the area of sleep tracking in recent years. CNNs are very good at processing time-series data, such EEG signals, which are frequently utilized in sleep monitoring. The capacity of CNNs to automatically recognize and remove features from unprocessed data without requiring for human feature engineering is one of their primary advantages. For evaluating complicated signals with a wide variety of frequency and spatial patterns, like EEG, CNNs are especially well-suited.Nevertheless, when employing CNNs to track sleep, such as the requirement for substantial volumes of labeled data, possible bias caused by algorithms, and the comprehensibility of the model. Further study and development are also required to maximize CNN performance and investigate the possibilities of novel deep learning techniques in this area. One of the main benefits of CNNs is their capacity to extract temporal as well as spatial data directly from an unprocessed EEG signal. As a result, the network can capture intricate connections and trends between different channels and time periods without the need for manual feature extraction. A second benefit is that variable length input patterns can be handled using methods like pooling layers and 1D convolutional layers.This aids in the processing of EEG data, which can vary depending upon the duration of the recordings or the event under study.

The 12-layer model is intended to process one-dimensional data, including EEG signals. The initial layer of input receives data in the input shape (3000,1), which stands for one channel electrode and three thousand time points. The first layer consists of a convolutional layers with 32 filters of size 3 and ReLU activation function capabilities. A batch normalizing layer will then be applied to the output in order to speed up and improve training reliability.

Design Architecture of CNN

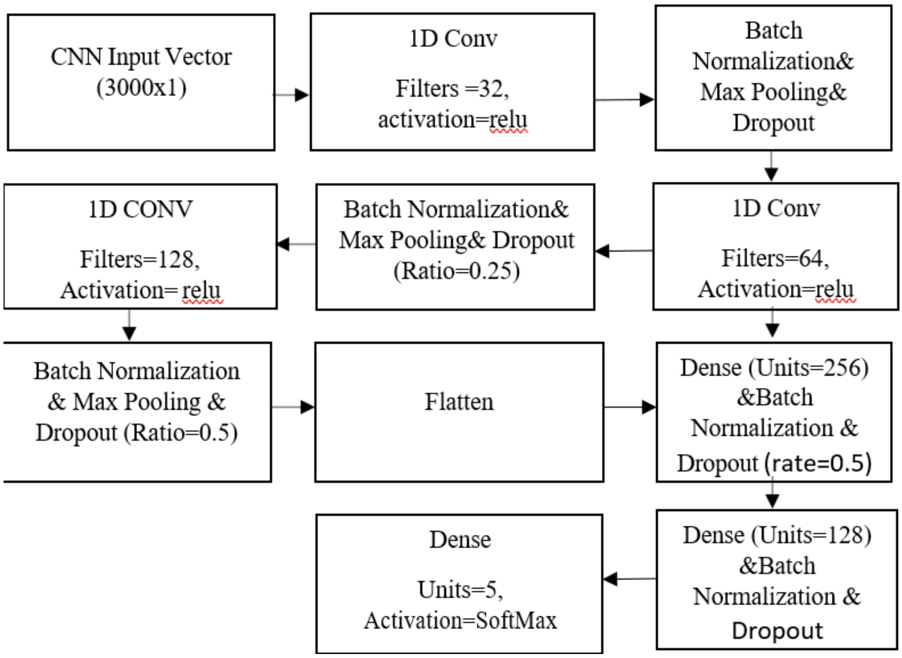

Figure3CNNDesignArchitecture

CNN and LSTM

With the raw EEG signals, CNN can extract relevant data like frequency elements and temporal patterns. CNN is used to extract the topological properties, which are helpful in categorizing the stages of sleep. A topological feature in signal processing is a mathematical characteristic of a signal's structure or form that defies certain modifications, including translation, rotation, and scaling. These features make it possible to meaningfully characterize and analyze signals, providing information about their fluctuation and architecture. LSTM networks are particularly useful in instances of time-series data, when the signal values are continuously changing.To retain knowledge for a longer amount of time, the LSTM makes use of LSTM cells. These networks are also utilized in time series forecasting, where their ability to forecast trends and patterns in the signal over a specific amount of time allows for the prediction of future values.

The long-term dependencies and temporal patterns that are used to categorize sleep stages are handled by LSTM. The relationships and patterns that exist within a signal that vary from one component to another, separated by appreciable amounts of time, are known as long-term dependencies. These dependencies aid in forecasting subsequent segments based on preceding segments of signal data. On the other hand, the signal's structural and dynamic information is covered by the patterns of time.The CNN-LSTM neural network combines the best features of both CNN and LSTM. CNNs are typically used in video and image processing because of their exceptional performance in extracting spatial characteristics from input data. LSTMs, on the other hand, are frequently employed with time series data because of their superior capacity to capture transitional patterns as well as long-term dependencies. In order to identify sleep stages, we employ CNN-LSTM architecture, taking into account the benefits of both CNN and LSTM.

Design Architecture of CNN-LSTM

Two legs make up this model; one has long filters and the other has short filters. To generate the final predictions, the output from both layers is combined and fed into the SoftMax layers. 3000 is the input vector that our model uses. The model's input shape is defined by the first input layer as a 1D array with a single channel and an input length number of samples. This initial leg of the network consists of four layers of convolution with 64, 128, 128 and 128 filters respectively. There will be two Max layers of pooling with a 0.5 dropout rate in addition to this leg. With higher filters and shorter strides of 400 and 50 samples, respectively, the second leg is comparable to the first. The output from both legs needs to be joined with Keras' Concatenate layer. Combine results are sent through the last dense layer using a SoftMax activation function in order to generate predictions. The input shape, 5, 2688, suggests five times as many steps, with 2688 characteristics overall for each step. The input must initially travel through the dropout layer at a rate of 0.5 to avoid overfitting. Two bidirectional LSTM layers, each with 512 units, are stacked over the top of each other. Return sequences = True in the first layer means that it provides the output for every time step, not just the last one. After preprocessing, the CNN model's intermediate result is fed as input into the LSTM model. The input data is then utilized to construct sequences of five clips using a sliding window method. The clips are subsequently included as the inputs to an LSTM model in order to forecast a general sequence and derive temporal dependencies. A strong tool for modeling the temporal and spatial properties of the EEG-provided data is the CNN-LSTM structure.

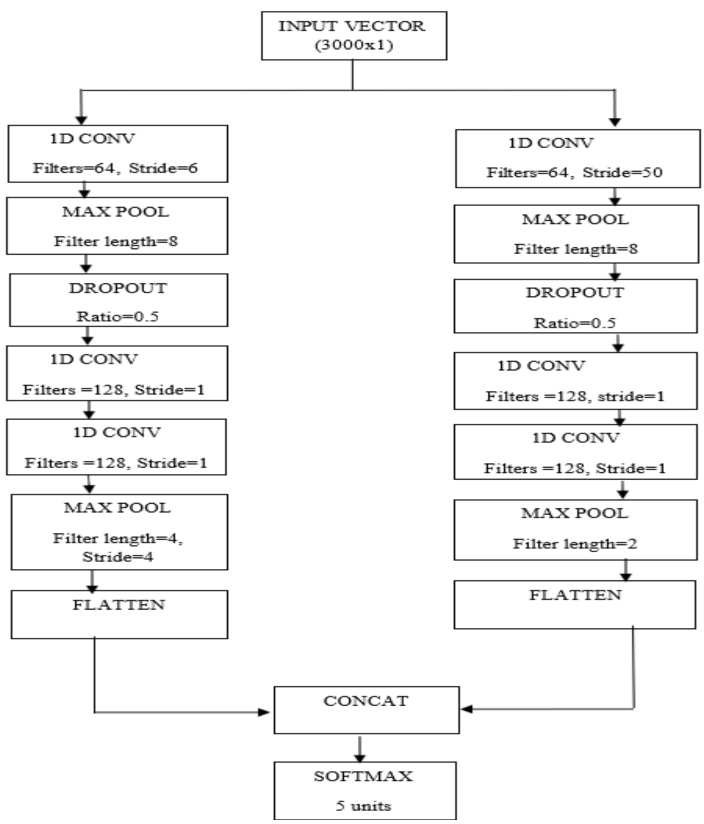

Figure4CNNArchitecture for CNN-LSTMModel

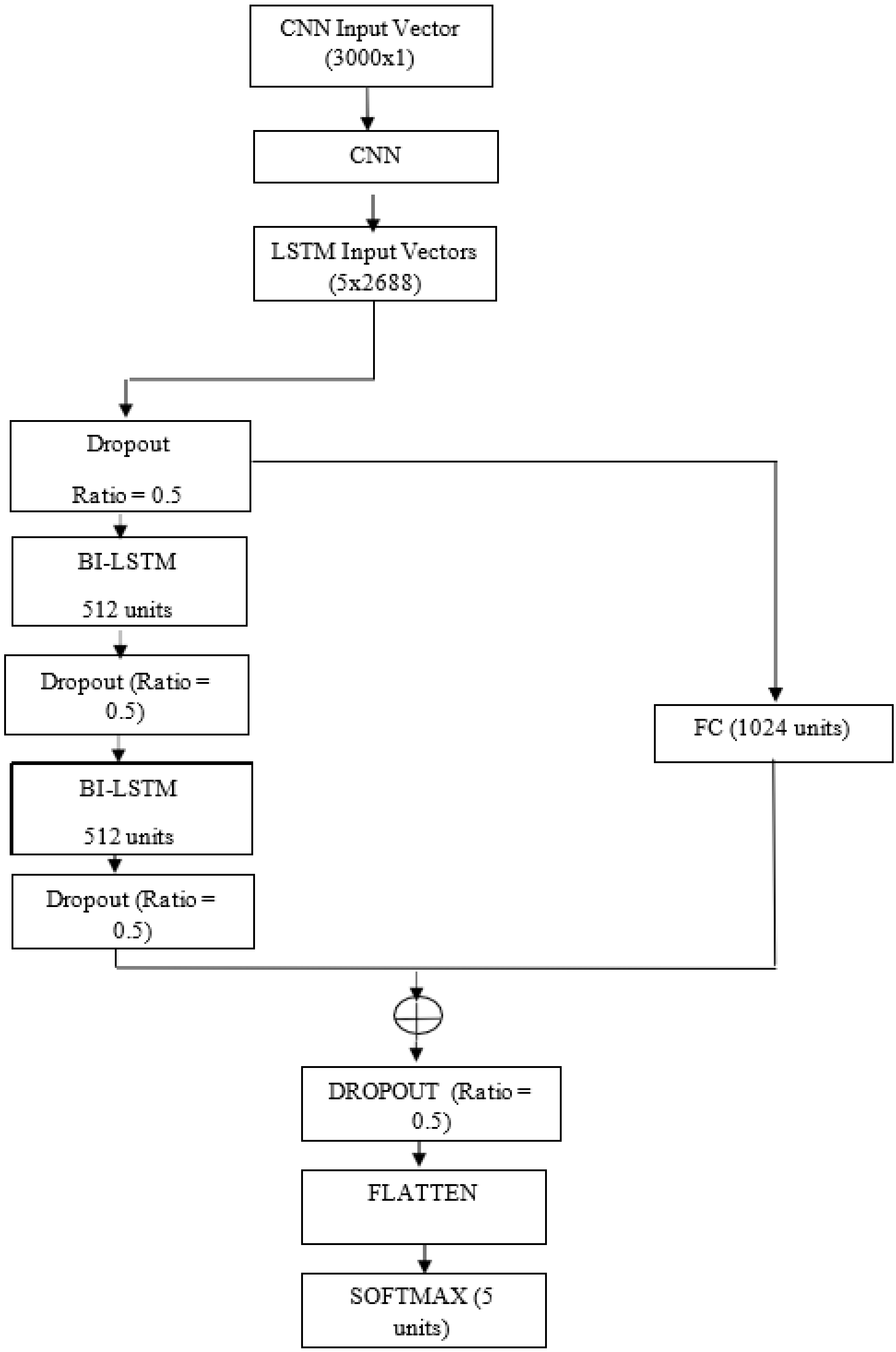

Figure5: CNN-LSTM Design Architecture

Metadata Classifier

Using EEG data, a stack ensemble learning technique can be applied to categorize sleep stages using a meta-data classifier. Stack ensemble learning aims to improve overall classification accuracy by integrating the predictions of multiple base classifiers using a meta-classifier. CNN and CNN-LSTM are the base classifiers employed in this design. These classifiers use EEG signals to predict the stages of sleep. The metadata classifier receives all of the output from the base classifiers, and uses a voting process to classify the final sleep stage. The meta classifier would then use the outputs from the basis classifiers to forecast the sleep stage. The meta-data classifier may receive as inputs the raw EEG signal or additional features not included in the base classifiers. By combining the best features of many classifiers, the usage of a meta-data classifier in stacked ensemble learning has the benefit of increasing the accuracy of sleep stage prediction. Using EEG data to combine the projections of many base classifiers, a meta-data classifier can be used as part of a stack ensemble-learning approach for sleep stage classification in order to improve overall classification accuracy.We experimented with many meta classifiers in this model. We experimented with various meta classifiers in our model. Using our basic models, we estimated the probability of each class in the first method. While our starting point predicts the class with the highest probabilities, each prediction contains five possibilities. Consequently, we examined the predicted probabilities from each of the two base classifiers in place of this. The final prediction is the one with the highest probability out of all the predictions.

RESULTS AND DISCUSSION

Description of Dataset

Neuroscience and biomedical engineering researchers frequently use the European Data Format (EDF) database. Over 35,000 recordings from different clinical and research settings worldwide are available in the EDF database. Because the recordings are kept in a common file format, sharing and data analysis are made simple. There is a header and a data record in an EDF file format. The recording's parameters, including length, number of channels. Thus, sampling rate, and signal kinds, are all listed in the header. The physiological signals that were really obtained during the recording are contained in the data record.

The EDF database includes data from a variety of physiological conditions and signals, including:

1. **EEG:**Recordingsofbrainactivityusingelectrodesplacedonthescalp
2. **ECG:**Recordingsofheartactivityusingelectrodesplacedonthechest
3. **EMG:**Recordingsofthemuscleactivityusingelectrodesplacedontheskin
4. **EOG:**Recordingsofeyemovementsusingelectrodesplacedaroundtheeyes
5. **Respiratorysignals:** Recordingsofbreathingpatternsusingvarioussensors
6. **Bloodpressure:**Recordingsofbloodpressureusingvarioussensors

Apart from the Sleep-EDF Database, there exist other EDF-formatted databases that contain data on sleep tracking. The Sleep-EDF database, a collection of polysomnographic recordings of human sleep, includes data from 153 subjects. that contains one recording lasting with eight hours or more. The database contains patients with a variety of sleep problems, most likely narcolepsy, sleep apnea, and insomnia. It also includes healthy individuals. A range of sample rates and recording techniques were used to capture the recordings. The goal of the Sleep Track project is to create an automated system that uses

EEG data to identify and categorize different stages of sleep. Data from the EDF is being used to train and test the system.

Experimental Results

The five classifications used in this study to categorize the various stages of sleep are N1, N2, N3, REM, and Awake. The models used to categorize the stages of sleep are CNN and CNN-LSTM. According to the results of the experiment, CNN performs better with smaller data and CNN-LSTM performs better with greater data.

Module1:CNN

CNN yielded an accuracy of about 95.15%. CNN receives the raw data; no intentional feature extraction is performed. Convolutional layers are used by the CNN itself to extract features and classify the stages of sleep from the extracted data. CNN uses several layers of convolutional processing to extract distinctive characteristics.

	precision	recall	f1-score	support
0	0.9725	0.9504	0.9613	2418
1	0.8964	0.7991	0.8450	1115
2	0.9531	0.9761	0.9644	6765
3	0.9505	0.9691	0.9597	2039
4	0.9500	0.9407	0.9453	2767
accuracy			0.9515	15104
macro avg	0.9445	0.9271	0.9351	15104
weighted avg	0.9511	0.9515	0.9510	15104

Figure7: Classification Report for CNN model

Module2: CNN-LSTM

CNN yielded an accuracy of about 83.9%. From the original EEG data, CNN retrieves the spatial features and LSTM recovers the temporal relationships. Since each of the two models has a unique set of benefits, the best model is produced by merging the two. The LSTM input receives the CNN output and uses it to categorize the stages of sleep. For analyzing the time series data, LSTM is already held.

	precision	recall	f1-score	support
0	0.9156	0.9066	0.9111	407
1	0.5333	0.0672	0.1194	119
2	0.9238	0.9287	0.9262	561
3	0.9300	0.8304	0.8774	112
4	0.5994	0.9043	0.7210	230
accuracy			0.8390	1429
macro avg	0.7804	0.7275	0.7110	1429
weighted avg	0.8372	0.8390	0.8179	1429

Figure8: Classification Report for CNN-LSTM model

Figure 8 shows that the accuracy is 83.9%. CNN-LSTM's performance is 83.9%. The CNN-LSTM is doing better for the larger data. Since less data was used to train the model, CNN-LSTM efficiency is higher than CNN in this instance.

Module3:Metadata Classifier

The CNN and CNN-LSTM base classifier outputs are compared and provided as the final output in this module. The class predicted is the one with the highest likelihood in this case, which is the weighted average of the probabilities of the classes from the two models. Figure 9 shows an accuracy of 94.57%, which is somewhat better than CNN but less accurate than CNN-LSTM and CNN. The metadata classifier performs best when compared to both models when their respective performances are lower. The outcome was that classifier is taken into consideration when both models are unable to execute metadata.

All of the models' performances are displayed in Table 2. Out of all the models, CNN performs the best. On the other hand, the metadata classifier, which performs somewhat worse than the CNN model, comes in second. However, the metadata classifier performs better when both models fail. Although the CNN-LSTM performs worse, it performs better with larger data sets.

Table2: Model comparison using the categorization report

Approaches	Accuracy	Precision	Recall	F1-Score
CNN	95.15%	0.9445	0.9271	0.9351
CNN-LSTM	83.9%	0.7804	0.7275	0.711
MetadataClassifier	94.57%	0.9431	0.9175	0.9289

	precision	recall	f1-score	support
0	0.9687	0.9621	0.9654	3347
1	0.9035	0.7732	0.8333	1477
2	0.9389	0.9796	0.9589	9277
3	0.9511	0.9832	0.9669	2552
4	0.9535	0.8895	0.9204	3756
accuracy			0.9457	20409
macro avg	0.9431	0.9175	0.9289	20409
weighted avg	0.9455	0.9457	0.9448	20409

Figure9: Report on Classification for Metadata Classifier

CONCLUSION AND FUTUREENHAN CEMENT

A vital biological function, sleep aids in preserving health, processing new data, and revitalizing the body. Generally, there are five different sleepstages : awake, N1, N2, N3, and REM. The body uses sleep for a range of physiological and psychological processes, such as mood control, memory consolidation, and physical and mental rejuvenation. Classifying the stages of sleep, however, is important. It aids in the detection and diagnosis of sleep disorders such narcolepsy, sleep apnea, and insomnia. Although PSG signals can be used to detect a variety of sleep problems, manual analysis of the signals can be laborious and error-prone.Signal patterns that correlate to distinct sleep stages and events can be identified using a variety of machine learning models, including deep learning models. Enhancing the capacity to categorize sleep stages using a range of machine learning techniques, such as CNN with LSTM and CNN, is the project's main objective. CNN was employed as a classifier, followed by LSTM, as two distinct techniques. A shorter epoch of the raw EEG signal is separated from it during the data pre-processing step. After removing noise and artifacts, each epoch is assigned a corresponding sleep stage by the use of professional annotations.

Around 95.15% accuracy is achieved with CNN. The CNN classifies sleep stages by extracting different information from the raw signal. The accuracy of 83.9% was achieved with CNN-LSTM. For huge data, the CNN-LSTM model performed better than all the other models in terms of categorizing the stages of sleep, but CNN performed better for smaller data. In this model, CNN is utilized to extract features, while LSTM is used to classify sleep stages. The final prediction is obtained by comparing all of the models' predictions using the metadata classifier. The metadata classifier outperforms the other two methods in terms of accuracy when both models are performing at a lower level. Previous research classified sleep stages primarily using CNN and CNN-LSTM models independently. However, the benefits of the base models are used in our work to the classification of sleep stages. To get the final projections, the predictions from the original models are compared once more.

FUTURE ENHANCEMENT

Some potential areas for further improvement with the suggested approach include:

- Combining other physiological signal types, such EEG, EOG, and EMG, could enhance the project's accuracy in classifying sleep stages.
- The suggested approach performs less well in identifying the N1 sleep state. Thus, utilizing novel approaches could improve output.
- This strategy uses a small amount of data to train the model. Given the volume of data, the model may be able to discover new patterns for classifying sleep stages. This could improve performance all around.
- Tracking a person's daily activities can aid in determining the quality of their sleep.

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