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Transforming Sleep Science: Powered Automated Sleep Stage Detection and Classification

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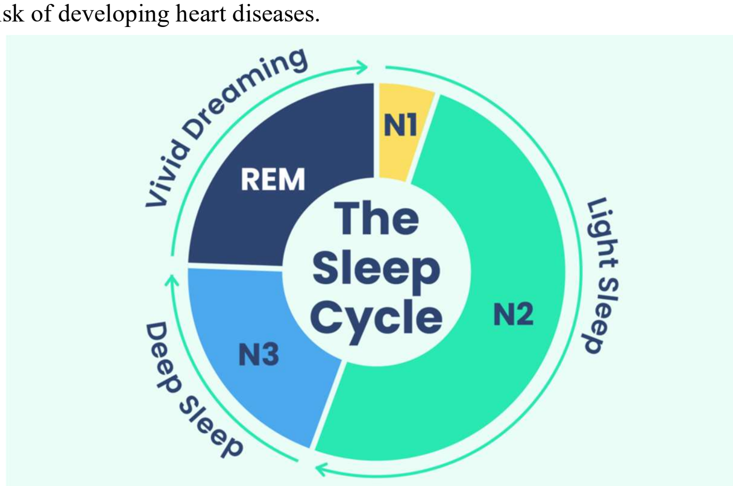
Abstract*: Sleep is vital for the body's physical restoration, but sleep disorders can cause various problems. Determining sleep stages is important for diagnosing and treating such disorders. Polysomnography (PSG) signals are recordings of brain activity, eye movements, muscle activity and other physiological signals that are collected during a sleep study. Insomnia, Sleep Apnea, and Restless Legs Syndrome are some of the sleep problems that can be identified using these signals. However, analyzing PSG signals manually can be time-consuming and prone to errors. Deep Learning Models such as Convolutional Neural Networks (CNN), can be used to automate the analysis of PSG signals. CNN is followed by Long-Short Term Memory (LSTM) and CNN are used as a stack ensemble method to recognize patterns in the signals that correspond to different sleep stages and events. By training these models on large datasets of PSG signals, they can detect the disorders from the sleep stages. The dataset is collected from PhysioNet Sleep-EDF dataset which consists of PSG signals.*

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

I. INTRODUCTION

Sleep is a complicated biological process that helps people maintain good health, process new information, and also re-energies our body. Our bodies need both sleep and wakefulness to function properly. Your brain is still working even while you are asleep. In addition, it maintains the health of other bodily systems like the immune system and metabolism. It also helps in cleaning of toxins in our brain that are generated while we are awake.Getting a good amount of sleep helps in maintaining or losing weight. Sleeping fewer than 7 hours per night may lead to weight gain and increase in Body Mass Index (BMI). Good sleep can also improve concentration, problem solving skills, and productivity. Getting enough sleep can also help in maximizing athletic performance. Proper sleep can also help in strengthening our heart, by not doing so may lead to risk of developing heart diseases.



Classification of Sleep Stages

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The sleep cycle consists of different stages namely N1, N2, N3, Rapid Eye Movements (REM).
Your brain goes through its normal cycles of activity as you sleep. The four stages of sleep are separated into two phases: First comes non-REM sleep, which has three stages. You fall asleep deeply during the latter two stages of non-REM sleep. Approximately an hour to an hour and a half after falling asleep, REM sleep begins. The brain waves associated with REM sleep marked in red outlined as in Figure 1.2. You often have vivid dreams during REM sleep. Your body shifts through REM and non-REM sleep when you're asleep. Stage 1 of non-REM sleep is often where the sleep cycle begins for most people. You move through the remaining non-REM sleep stages before entering a brief REM sleep cycle. The cycle then starts over at stage 1 once more. The first stage of non-REM sleep lasts for 5 to 10 minutes. Everything begins to slow down, including muscular and ocular activity. You keep your eyes shut. If stage 1 sleep is disrupted, you may feel as if you haven't slept at all. Some images may be vaguely remembered. You may feel as though you're ready to fall and then abruptly feel a muscle contract. Medical practitioners call this motion hypnic myoclonic or hypnic jerk. Hypnic jerks are common but not cause for concern because they rarely cause difficulties or have unpleasant side effects.

II. LITERATURE SURVEY

Zhu, Luo and Yu [1] suggested CNN integrated with Attention-based Neural (AN) Network to classify Sleep Stages (SS) using the window feature Learning, Intra-feature Learning and Inter-feature Learning components. The current method used two datasets Sleep-EDF and Sleep-EDFX which comprises individual PSG recordings of whole night for 197 subjects. The study concluded that the Deep Learning techniques like CNN and AN network showed positive results for classifying SS.
Zhou and his team members [2] suggested the Ensemble model to classify SS using Machine Learning algorithms namely, RF and LightGBM (LGBM). The present model resulted in improved performance in recognizing the N1 state. The dataset Sleep-EDF comprises whole night PSG recording corresponding to 197 subjects. The study concluded that integrating RF and LGBM improved the performance in detecting the SS.
Radhakrishnan, Ezra, Immanuel [3] suggested LGBM and XGBoost as Ensemble approaches to classify SS using Tsfresh for Feature Extraction. The dataset Sleep-EDF contains 197 whole-night PSG sleep recordings, containing EOG, EEG, chin EMG, and event markers. The study concluded that using Tsfresh for feature extraction improved the performance of the present model to classify SS.
Qing and his team members [4] suggested a Graph Temporal (GT) fused with Dual-input CNN for classifying SS. Authors used dual input CNN where one input is raw epoch and other Degree Sequence (DS) obtained after mapping each epoch of a Limited Penetrable Visibility Graph (LPVG). The Sleep-EDF database contains 197 whole-night PSG sleep recordings dealing with brain activity. The study concluded that Dual-input CNN has improved performance.
Mousavi, Afghah and Rajendra Acharya [5] suggested automated sleep stage scoring using Deep Learning. The objective was to find the sleep stage scoring using a method called SleepEEGNet that composed of Deep Convolutional Neural Networks (DCNNs). They used innovative loss functions to have an equal misclassified error for each sleep stage during training the network to lessen the impact of the class imbalance problem that was presented in the existing sleep datasets. The PhysioNet Sleep-EDF dataset was used to evaluate the performance of the proposed method. The study concluded that the proposed method achieved the best annotation performance with an
Tim Schluter and Stefan Conrad [6] suggested Automated sleep scoring using Fourier Transform (FT) and Wavelet Transform (WT) for Apnea-Hypopnea Detection. The objective was to predict the automatic sleep stage score and Apnea-Hypopnea using FT and WT, DDTW and waveform recognition. The window feature frequencies and special patterns from EEG, Electrocardiogram (ECG), EOG and EMG data, on which a decision trees classifier is built for classifying epochs into their sleep stages and annotating occurrences of apnea-hypopnea. Special patterns which are important for sleep stages, i.e., k-complexes, sleep spindles, sawtooth waves, α- and δ-waves, V (vertex sharp) waves, SEMs (slow eye movements) and REMs, are extracted via waveform recognition and Derivative Dynamic Time Warping.
Khald Ali, Aboalayon and Faezipour [7] put forward Sleep stage Classification in real time using Single channel EEG method. The goal was to forecast sleep disorders, which have been identified as one of the major human life issues in recent years. As a result, efficient and automated systems capable of distinguishing sleep stages and assisting physicians/neurologists in the diagnosis and treatment of sleep-related problems are in great demand.. The proposed set of rules is primarily based totally on statistical features implemented to single-channel EEG signals. The dataset used was

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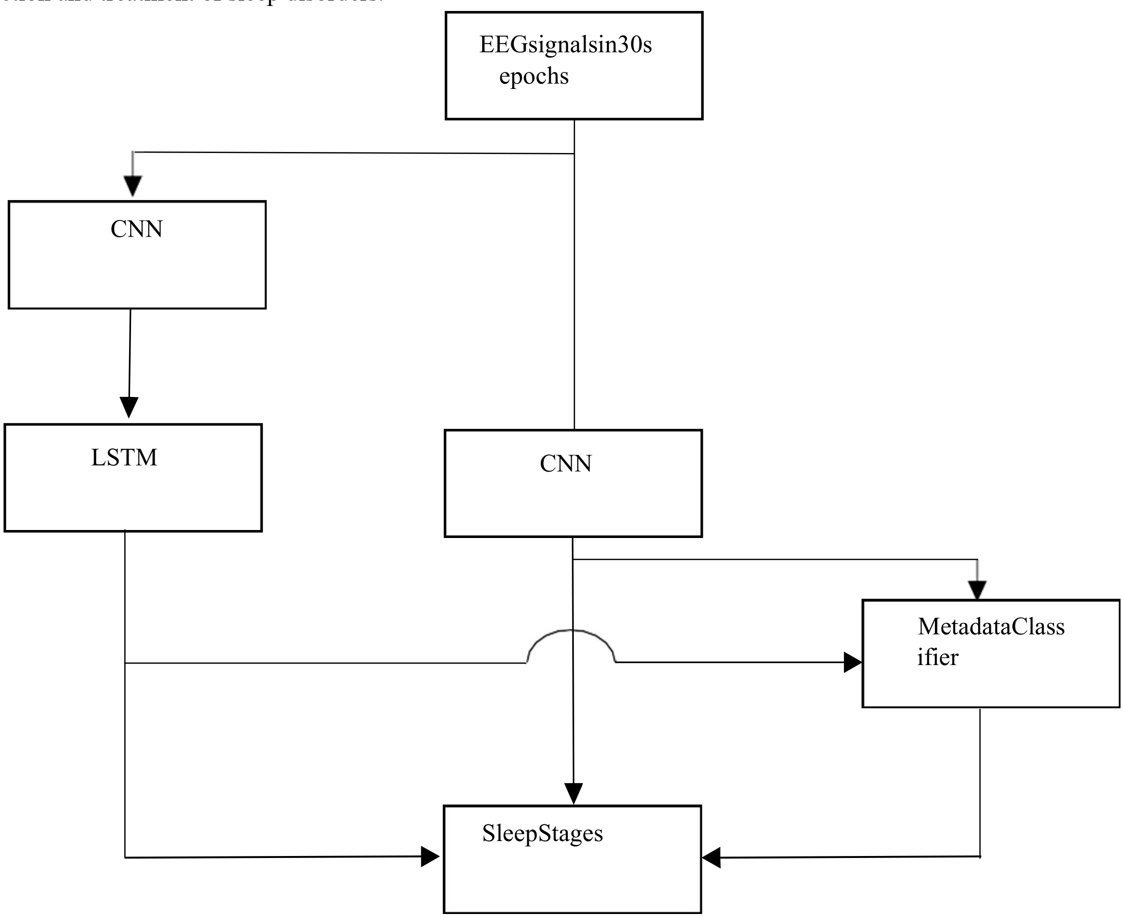
EEG Mindware. The study concluded real-time system to detect sleep stages using the single-channel EEG signal. The proposed system employs single NeuroSky dry-sensor EEG electrode to acquire EEG samples

III. PROPOSED METHOD

The paper is based on the classification of sleep stages using Machine Learning Algorithms namely, CNN and LSTM. In this paper, the PhysioNet Sleep-EDF dataset is used. The data set consists of recordings of various types of PSG signals. The EEG data are analyzed by the system to identify features that are specific to each stage of sleep using a combination of signal processing methods along with machine learning algorithms. Once a classification model has been trained using these features, it can successfully distinguish between each stage of sleep. The ultimate objective is to create an automated and feasible system that can precisely identify and categorize various sleep stages in real-time, which can be used in the detection and treatment of sleep disorders.



Proposed System Architecture

CNN and it's Architecture:

Sleep tracking is a field that has been revolutionized by deep learning techniques in recent years, with CNNs being one of the most widely used approaches. CNNs are particularly effective in analyzing time-series data, such as EEG signals, which are commonly used in sleep tracking. One of the main advantages of CNNs is their ability to automatically learn and extract features from raw data, without the need for manual feature engineering. This makes CNNs particularly well-suited for analyzing complex signals such as EEG, which contain a wide range of frequencies and temporal patterns.

However, there are still challenges that need to be addressed when using CNNs for sleep tracking, including the need for large amounts of labelled data, potential algorithmic bias, and the interpretability of the models. Additionally, there is a

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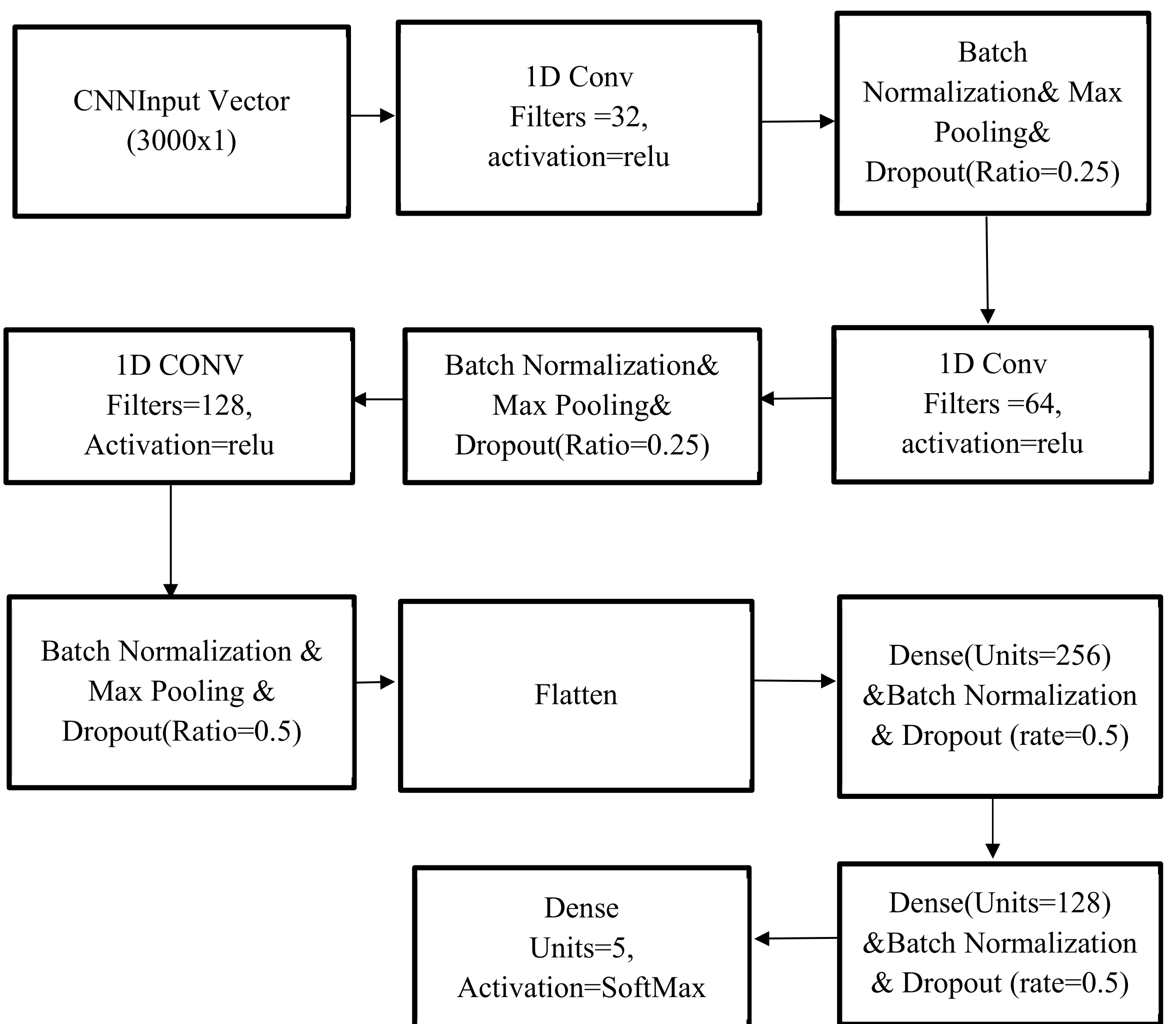
need for continued research and development to optimize the performance of CNNs and to explore the potential of new deep learning approaches in this field. The ability of the CNNs to pick up Spatial and Temporal Information Right from a Raw EEG signal is one of its key advantages. This enables the network to record complex patterns and relationships between various channels and time points, without requiring any manual feature extraction. A second advantage is that using techniques like 1D convolutional layers and pooling layers, you can handle variable length input sequences. This helps with EEG processing, where signals may differ according to the recording length or duration of an event being studied.

Design Architecture of CNN

The model consists of 12 layers and is designed to process one Dimensional data, such as EEG signals. The first input layer takes data of input shape (3000,1) which corresponds to 3000 time points and 1 channel electrode. A convolutional layer with 32 filters in size 3, as well as Rectified Linear Activation Unit (ReLU) activation capabilities is the 1st layer. In order to increase the stability and speed of training, the output shall then be transmitted through a batch normalization layer. A new convolutional layer with the same number of filters and activation functions, another batch normalization layer, and a maximum pooling layer with a pool size of 2 is then added. To avoid over fitting, a dropout layer must be inserted with a rate of 0.25. With the number of filters increasing from 32 to 64, then to 128, and the dropout rate increasing from 0.25 to 0.5, the process is repeated with two more pairs of convolutional, batch normalization, and max pooling layers.



CNN and LSTM:

CNN performs signal processing tasks like Image Processing, Speech Recognition and Audio classification. Extracting features are more important in signal related tasks. CNN can be able to extract features from the raw signal data. The convolutional layers learn features from the training data provided using filters and these learned filters are applied to the input signals which captures local patterns and spatial correlations. The convolutional layer checks the input filters to the existing trained data filters. If any one of the trained data matches the input filters, then the input is assigned with the class label of the matched training data.

CNN Design Architecture

In case of Time Series data, where the signal values change continuously, LSTM networks are especially helpful. LSTM Network overcomes the vanishing gradient design problem in traditional approaches of Recurrent Neural Network (RNN) making difficult to update network weights as the gradient signals becomes very small almost zero. The LSTM uses LSTM cells to store the information for longer period. In time series prediction, LSTM networks are also used where they can be used to predict trend and trends in the signal for a given period of time thus predicting subsequent values. LSTM can handle long term dependencies and temporal patterns which are used to classify sleep stages. Long-term dependencies are the relationship and patterns which exist within a signal that differ from one part to another, separated by significant periods of time. These dependencies help to predict the later parts from the previous parts of signal information.

The strengths of CNN and LSTM are combined as CNN-LSTM neural network. CNNs are usually applied in image and video processing, where they have a very high degree of performance when it comes to determining spatial features from input data. In contrast, LSTMs are widely used for time series data where they provide an excellent ability to capture both long term dependencies and transitional patterns. So, considering the strengths of CNN and LSTM we use CNN-LSTM architecture to classify sleep stages.

Design Architecture of CNN-LSTM

This model contains two legs one with short filters and other with long filters. The output of both the layers are concatenated and fed into SoftMax layers to produce final predictions. Our model takes input vector of 3000. The first input layer defines input shape of the model as a 1D-array with input length number of samples and single channel. Four convolution layers with 64, 128, 128 and 128 filters are included in this first leg of the network. A batch normalization layer, and a rectified linear activation function are added to each convolutional layer. This leg will be accompanied by two Max pooling layers with a dropout rate of 0.5. This leg also has four convolutional layers with 64, 128, 128, and 128 filters, each followed by batch normalization and rectified linear activation function. In order to produce predictions, concatenate outputs are sent through the final dense layer with a SoftMax activation function.

The intermediate output from the CNN model is preprocessed and passed into the LSTM model as input. A sliding window approach is then used to create sequences of five clips from the input data. The window size is 5, and a clip containing five consecutive sequences of feature vectors representing a short time temporal sequence in the overall features are generated for each window. For the purposes of deriving temporal dependencies and forecasting a general sequence, these clips are then added as inputs to the LSTM model. Overall, the performance is increased in classifying sleep stages.

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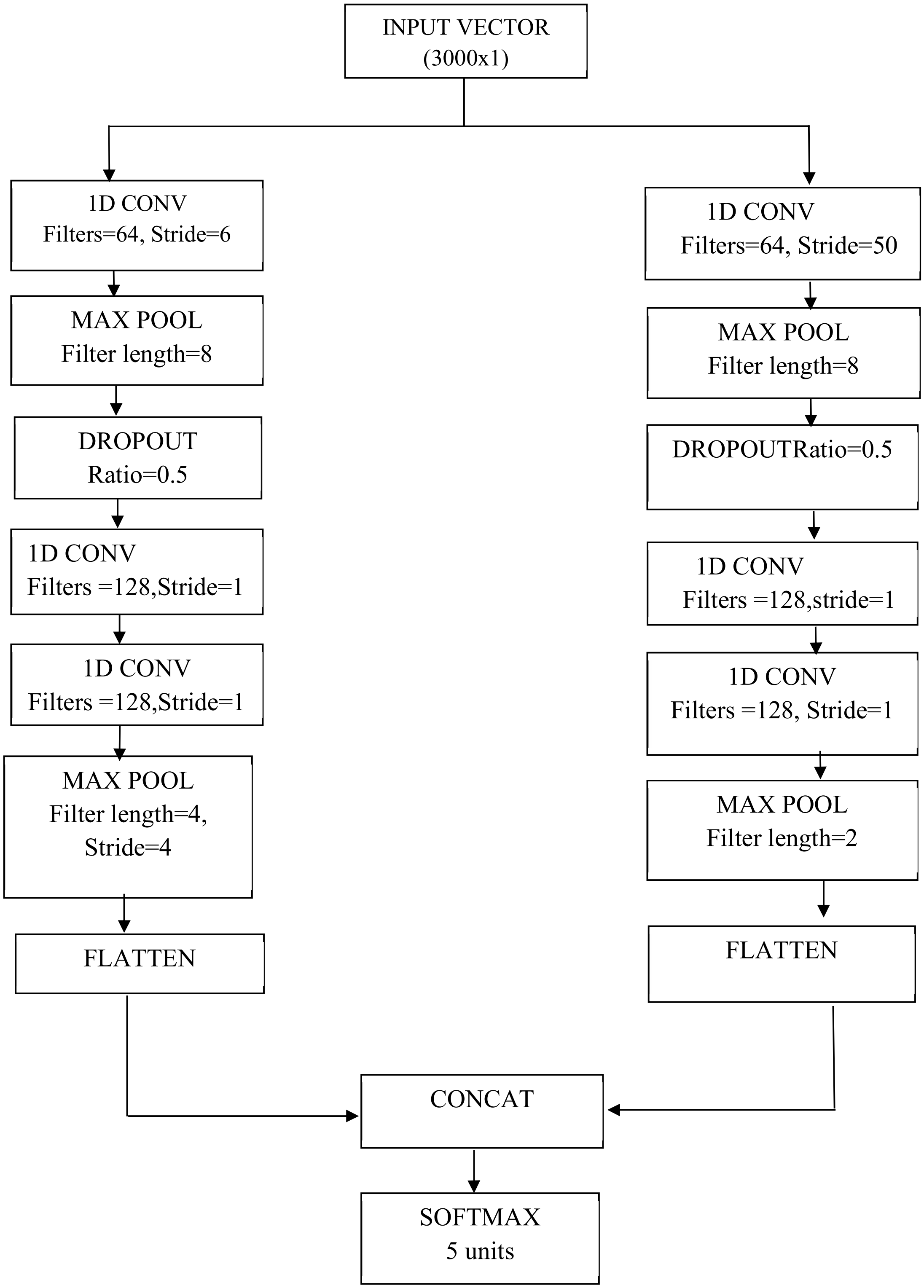

CNN Architecture for CNN-LSTM Model

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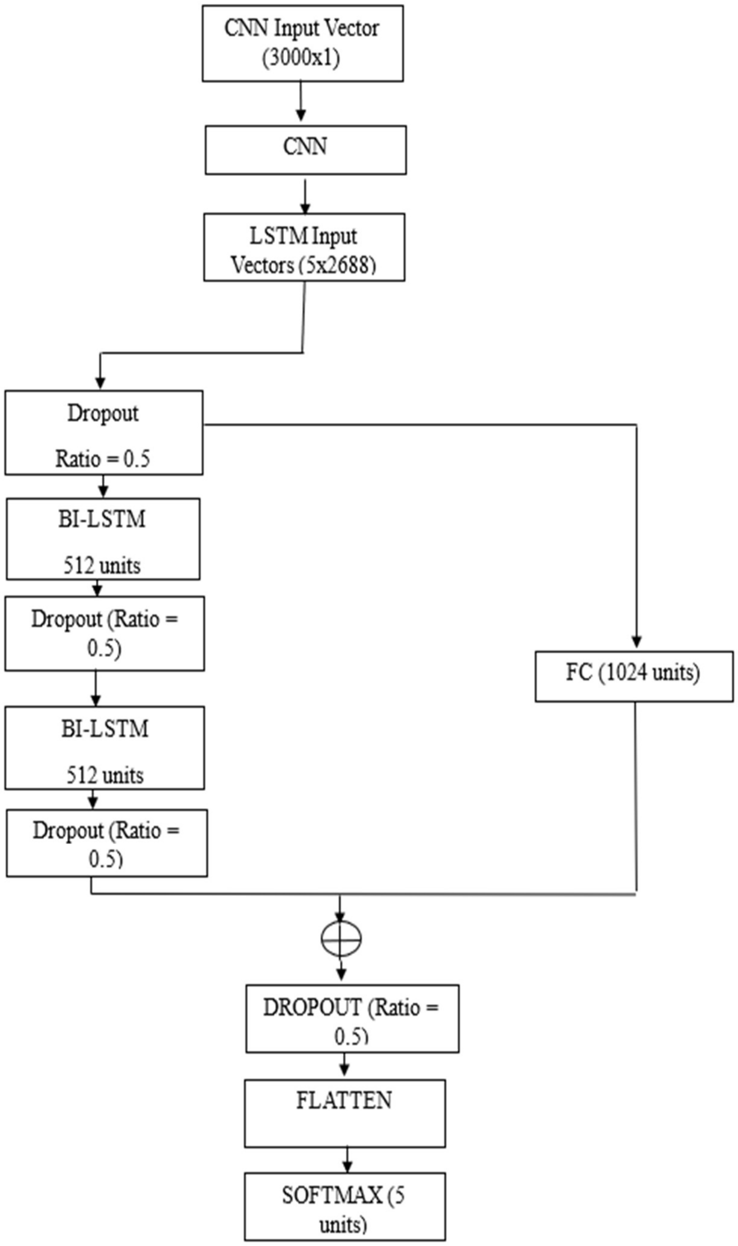

CNN-LSTM Design Architecture

Metadata Classifier:

A meta-data classifier can be utilized as part of a stack ensemble learning strategy to classify sleep stages using EEG data. The goal behind stack ensemble learning is to use a meta-classifier to integrate the predictions of numerous base classifiers to enhance overall classification accuracy. The base classifiers used in this architecture are CNN and CNN-LSTM. These classifiers predict the sleep stages from EEG signals. All the results of base classifiers are fed into metadata classifier where the final sleep stage is classified by using voting mechanism.

The outcomes of the base classifiers would then be sent into the meta classifier, which would then predict the sleep stage. The raw EEG signal or extra features that are not present in the base classifiers could be used as inputs to the meta-data classifier. The use of a meta-data classifier in stack ensemble learning has the advantage of improving sleep stage prediction accuracy by integrating the strengths of numerous classifiers. Furthermore, it can help to mitigate the impact on individual classifiers that may be inaccurate or biased towards specific sleep stages. To increase overall classification accuracy, a meta-data classifier can be employed as part of a stack ensemble learning strategy for sleep stage classification using EEG data to aggregate the predictions of multiple base classifiers.

IV. CONCLUSION

Sleep is a crucial biological process that helps maintain good health, process new information, and re-energize the body. Generally, sleep stages are classified into 5 different stages namely, Awake, N1, N2, N3, and REM. Different stages of sleep provide the body with a variety of physiological and mental health functions, including bodily and mental regeneration, consolidations in memory as well as emotion regulation. However, classifying sleep stages has a significant role. It helps to diagnose and observe sleep disorders such as insomnia, narcolepsy, and sleep apnea. Signals like PSG can be used to diagnose various sleep disorders but analyzing them manually can be time taking. Deep Learning Models and various Machine Learning models can be used to recognize patterns in the signals that correspond to different sleep stages and events. The motive of the paper is to improve the classification of sleep stages using various machine learning algorithms such as CNN with LSTM and CNN. Two approaches were taken: CNN followed by LSTM and CNN as a classifier. The data pre-processing stage involves segmenting the raw EEG signal into shorter epochs, filtering out noise and artefacts, and assigning each epoch a corresponding sleep stage using expert annotations

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