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Automated sleep stage classification in sleep apnoea using convolutional neural networks

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A R T I C L E I N F O

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A B S T R A C T

A sleep disorder is a condition that adversely impacts one's ability to sleep well on a regular schedule. It also occurs as a consequence of numerous neurological sicknesses. These types of disorders can be investigated using laboratory-based polysomnography (PSG) signals. The detection of neurological disorders is exact and efficient thanks to the automated monitoring of sleep relegation stages. This automation method publicly presents a flexible deep learning model and machine learning approach utilizing raw electroencephalogram (EEG) signals. The deep learning model is a Deep Convolutional Neural Network (CNN) that analyses invariant time capacities and frequency actualities and collects assessment adaptations. It also captures the inviolate and long brief length setting conditions between the epochs and the degree of sleep stage relegation.

This method uses an innovative function to calculate data loss and misclassified errors found while training the network for the sleep stage, considering the restrictions found in the publicly available sleep datasets. It is used in conjunction with machine learning techniques to forecast the best approach for the process. Its effectiveness is determined by using two open-source, public databases available from PhysioNet: two recordings with 5402 epoch counts. The technique used in this approach achieves an accuracy of 90.70%, precision of 90.50%, recall of 92.70%, and F-measure of 90.60%. The proposed method is more significant than existing models like AlexNet, ResNet, VGGNet, and LeNet. The comparative study of the models could be adopted for clinical use and modified based on the requirements.

1. Introduction

Sleep is defined by neurobiological activity, exhalation, heart rate, pulse rate, and other metabolic responses. Its impact on human physical and cognitive exercises makes it a significant factor in human wellbeing. As a result of the ramifications of gruelling and contrivance life, sleep disruption is becoming more prevalent in modern societies. S. Biswal et al., 2017 suggested andragogy to know about the combination of neurological and psychological disorders that can impair standard sleep patterns [1]. One category of effects are Sleep Disorders, which have become a widespread phenomenon in the majority of the population. According to a study conducted by Wakefield Research (U. R. Acharya et al., 2018 [2]; R. B. Berry et al., 2012 [3]; A. Rechtschaffen 1968 [4]), more than half (51%) of the adult ecumenical community lament that they get less sleep than they desire on an average night. Many discrete sleep disorders have been discovered, according to the sine qua nons of the *International Classification of Sleep Disorders*. S. Miran et al., 2018 [5] and Miller, M.A 2015 [6] suggested that sleep disorders, in addition to reducing insalubrious, cogitation and reminiscence. Authors such as J. Chen et al., 2017 [7], J. Chen et al., 2018 [8], and B. Koley and D. Dey 2012 [9] analyzed the significant side effects of these disorders, including the incremental risk of cardiovascular diseases, neuro-cognitive and extortionate. L. Fraiwan et al., 2012 [10], A. P. Moghaddam and S. Mousavi 2012 [11], and Y.-L. Hsu et al., 2013 [12]

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recommended accurate tenacity and treatment influenced by several vital records, and regarded precise sleep scoring as a critical process component. They proposed a visual assessment method, which is the most relevant approach but requires visual interpretation of various signal data. However, qualitative scoring has some drawbacks, such as the experts' experience, which results in different scoring results by foreign experts. Furthermore, in whole-night EEG labelling, visual vetting is a time-consuming process, making automated scoring more efficient.

Sutskever et al., 2014 [13] and S. S. Mousavi et al., 2016 [14], writing about the computerized treatment of sleep disorders, argued that polysomnography (PSG) can be considered the foremost approach for implementing electrophysiological signals to analyse body functions during sleep [15,16]. PSG is a multivariate rubric spanning recordings of signals such as electroencephalograms (EEG), electrocardiograms (ECG), electrooculograms (EOG), and electromyograms (EMG). Conventionally, EEG is primarily utilized to screen the encephalon activities to diagnose sleep and other prevalent disorders. S. S. Mousavi et al., 2017 [17] and S. S. Mousavi et al., 2017 [18] suggested that EEG signals are divided into illimitably predefined fixed length segments, referred to as epochs and labelled by the standards of sleep scoring proposed by the American Academy of Sleep Medicine (AASM) in conjunction with the standards of Rechtschaffen and Kales; each EEG recording spans around 8 h on average.

Numerous studies have focused on developing automated sleep-stage scoring algorithms. These are commonly known as feature extraction approaches, and are primarily divided into two categories. S. S. Mousavi et al., 2014; A. Shamsoshoara et al., 2019 [19]; and A. L. Goldberger et al., 2000 [20] proposed hand-engineered feature-predicated strategies that require precursory cognizance of EEG analysis to extract the most germane features. These procedures extract specific aspects, such as time, frequency, and the time-frequency domain of single channel-EEG waveforms. Some canonical Machine Learning (ML) algorithms, such as Random Forests (RF), Support Vector Machines (SVM), and Neural Networks (NNs), incorporate the fundamental construct for sleep scoring based on the extracted features.

Although these methods have demonstrated reasonable performance, they have several limitations, including a requirement for prior knowledge of sleep analysis and the inability to generalize more massive datasets from multiple patients with different sleep patterns. Second, automated feature extraction–based methods are similar to deep learning algorithms, in that the machine automatically extracts all relevant features. O. Yildirim et al., 2019 [21]; A. Supratak et al., 2017 [22]; O. Tsinalis et al., 2016 [23]; and Dang T. T. Hien et al., 2015 [24] have suggested, over the last few years, deep neural networks protractible from reinforcement learning, and natural language processing to computer vision. N. Michielli et al., 2019 [25] and M. Johnson et al., 2017 [26] addressed one of the critical reasons for the increased use in these domains of deep learning–based methods: the availability of massive data dimensions grasp the underlying concave pattern of the data sets. Because of the existence of these extensive sleep EEG recordings, deep learning algorithms can also be used for sleep stage classification and other purposes. Despite the remarkable increase in the utilization of deep learning models with bromidic machine learning methods for sleep disorder prediction, they still suffer from the imbalance of class, quandary impending in the datasets. K. M. Sagayam et al., 2021 [27] suggested the use of deep learning techniques and a pervasive machine learning technique, allowing the model to reach an expert-level capability for sleep stage classification.

This study proposes a novel approach to deep learning for the automation of sleep scoring by using a single-channel EEG and the sequential nature of this problem. As a result, in addition to applying a sequence-to-sequence model corresponding to a deep learning model, the following building blocks are required:

a) A Bidirectional Recurrent Neural Network (BiRNN) to capture transient data from clusters while considering the reference point and future input data.
b) Conditional Arbitrary Fields (CRF), statistical methods to facilitate representation and explicate the essential relevant components of the input arrangement while planning.
c) A nascent inability to minimize the consequences of lopsidedness perusal quandary by treating the failure of each misclassified test equally, regardless of whether it belongs to the majority or minority class.

This research article is organized as follows: Section II describes the methodology. Section III discusses the dataset and experimental results, as well as comparing performance to advanced calculations. Section IV concludes the research, along with outlining future work.

2. Methodology

The following section describes the proposed conceptual framework to automatically score each stage of sleep from a given EEG signal in detail.

2.1. Pre-processing

The input to the previously mentioned construct can be obtained by grouping 30s EEG epochs. Two simple steps extract EEG epochs from an EEG signal:

a) Fragment the continuous new single-channel EEG into a set of 30s epochs and conduct operations such as transferring and classifying into epochs, based on the comment file.
b) Standardize EEG epochs of the 30s so that each has a zero mean and a change of unity.

Note that the specific steps of pre-processing for the sleep score extraction are minor and do not include any frame of filtering or distortion deliberation strategies.

2.2. Proposed architecture

According to the corollaries of neural machine translation, this sequence-to-sequence model is trotted out to be very noteworthy, approximately similar to human-level performance. This sequence-to-sequence network ordinarily consists of two components, namely a type of Recurrent Neural Network (the encoder) and Convolutional Neural Network (the decoder), to initiate the automated sleep scoring relegation suggested by Shibin David et al., 2020 [28].

The CNN model has the same characteristics recommended by recent studies. The proposed deep learning architecture with a sequence-to-sequence approach is shown in Fig. 1. It is divided into two segments: tiny channels for extricating temporal data and a much larger one for releasing frequency data. This method utilizes variable-size filters, which originate from the signal processing community and are used to swap between time-space and frequency domain features. Within the classification assignment, it highlights the fact benefits from both frequency- and time-domain features. Each CNN portion comprises four sequential uni-dimensional layers of convolution. Every single layer of the convolution is passed to a nonlinear ReLU layer. A max-pooling layer and a block of dropout are tagged, along with the first mantle layer. Furthermore, the last convolutional layer is followed by a single dropout block. Clustered 30s epochs of EEG are fed into the CNN feature extraction at the respective timestamps of training or testing the model. The outputs of the CNN components are concatenated within the cessation and followed by a dropout block to organize the encoder for encoding the input arrangement. The sequence-to-sequence model is streamlined to predict the representations of encoder-decoder

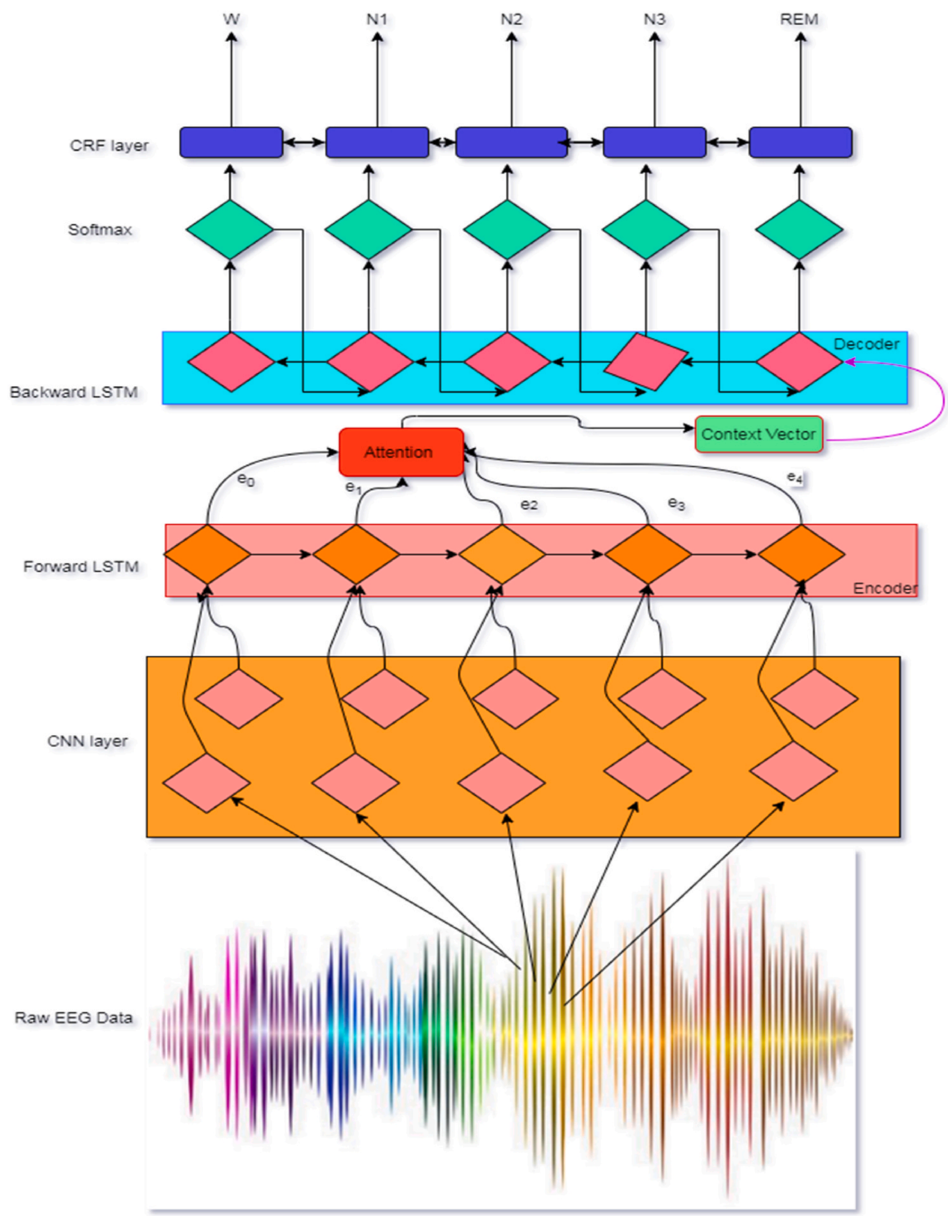

Fig. 1. Deep learning architecture with sequence-to-sequence approach.

abstraction. The layout of the CNN model with feature extraction is shown in Fig. 2.

While the encoder garbles the input sequence, the decoder evaluates the category of each 30s, single-channel EEG. A Long Short-Term Memory (LSTM) retrieval begins with the encoder by capturing long short-term setting conditions and the involute curve between the targets and the inputs. It captures the state of nonlinearity exhibited within the whole-time arrangement whereas prognostication the target. The time-series input features are fed to the LSTMs, and the firms the ability to calculate LSTM are then considered as the encoder representation and fed to the attention network.

2.3. Bidirectional recurrent neural network

A diagrammatic representation of Bidirectional LSTM (BiLSTM) architecture appears in Fig. 3. The model uses a bidirectional recurrent neural network rather than the standard LSTM, which is unidirectional and thus limited to a behavioural input state. To overcome this obstacle, the BiRNN was proposed, which can prepare information in both forward and reverse bearings. As a result, the current state has simultaneous access to both future and past information. The input sequence is supplied into the forward network in mundane time order = 1 T, and for the backward network, in inverse time order = T... 1. The sum of the outputs of the two networks is then weighted and computed as the output of the BiRNN.

2.4. Attention decoder

The encoder-decoder model for recurrent neural networks is designed to anticipate grouping-to-grouping problems.

2.5. Encoder

The encoder can venture through the input time steps and encode the whole arrangement into a fine-tuned length vector called a setting vector.

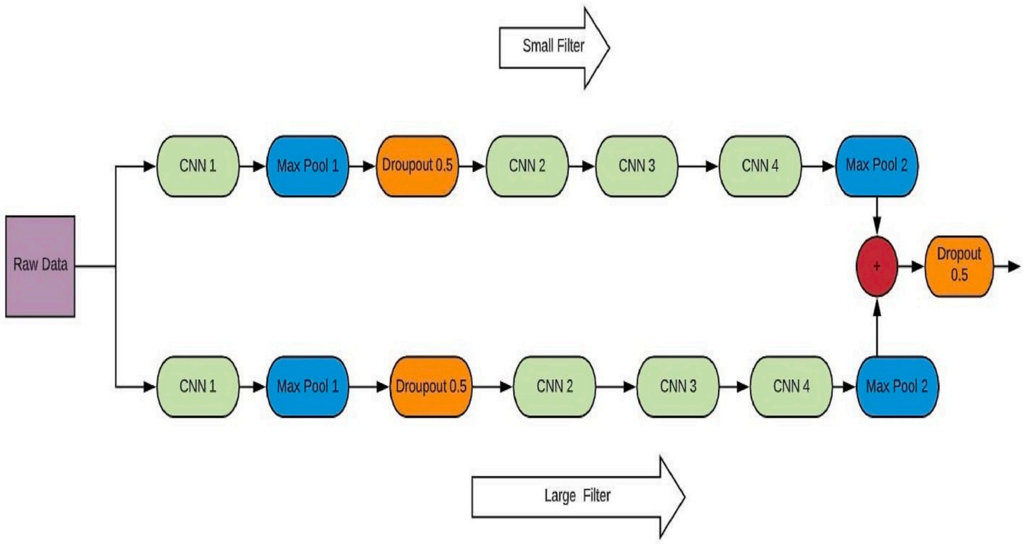

Fig. 2. The CNN model showing feature extraction.

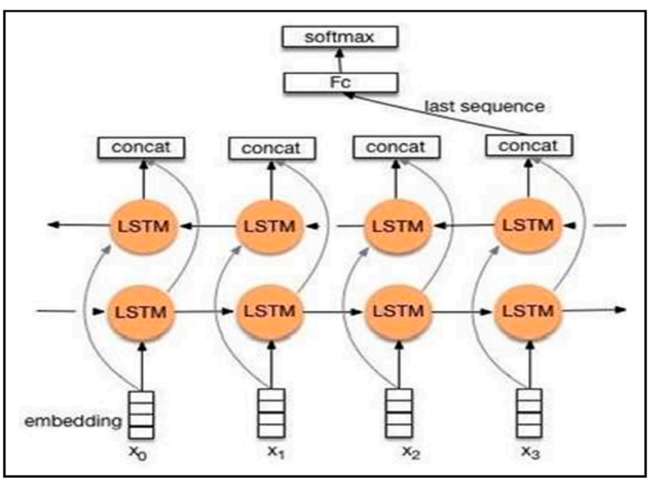

Fig. 3. General structure of BiLSTM.

2.6. Decoder

The decoder can venture through the yield crossroads steps, scanning from the setting vector. A problem with the design is that execution is poor on long input or yield arrangements due to the fine-tuned size inside the representation utilized by the encoder. Consideration is an expansion to the design that addresses this restraint. It liberates the encoder-decoder from the fine-tuned length of the internal representation. It operates by providing a relatively rich setting from the encoder LSTM to the decoder LSTM. Later, a cognition component is included, in which the decoder LSTM can understand where to focus within the richer encoding. These forecast time steps within the yield arrangement (Shibin David et al., 2020 [28]; G. Rajesh et al., 2020 [29]).

2.7. Conditional random fields (CRFs)

These are probabilistic systems for denominating and sectioning organized information, such as arrangements, trees, and cross-sections. The underlying idea is to define a conditional probability distribution over label groupings given a categorical optical insight arrangement rather than a joint dispersion over both name and visual acumen groupings.

The fundamental advantage of Conditional Random Fields over hidden Markov models is their conditional character, which allows hidden Markov models to relax the independence postulates required for tractable inference. CRFs, on the other hand, eliminate the label partialness problem that affects Maximum Entropy Markov Models (MEMMs) and other conditional Markov models based on directed graphical models (Mhathesh T.S.R. et al., 2021 [30]; Sathish Nirala et al., 2019 [31]).

2.8. Algorithm

Step 1:Pass raw EEG signal through convolutional layer (32 feature maps, ReLU activation function)

$$y = \max(0, x) \quad (1)$$

Step 2: Output of the previous layer passed through LSTM network (Recurrent
Step 3: Input signal is pre-processed to extract the optimal features from the signal data using the discrete wavelet transform method
Step 3: The extracted features are analyzed for the statistical test.
Step 4: The optimal features are selected using PCA.
Step 4: Output of the previous layer passed through a 2D max-pooling layer of dimensions 2x2.
Step 5: For the proposed model, the optimal features are passed through a convolutional layer with 32 markers and a sigmoid activation function.
Step 6: Output of the previous layer passed through a fully connected dense layer with 186 perceptrons (Rectifier activation).
Step 7: The model is build utilizing Adam optimizer by applying a learning rate of 0.05, categorical cross-entropy loss, and rectifier activation.

The cross-entropy loss function for binary classification can be given as equation (2),

$$\text{CEL(Cross-Entropy Loss)} = -(z\boldsymbol{log}(a) + (\mathbf{1} - z)\,\boldsymbol{log}\,(\mathbf{1} - a)) \quad (2)$$

where z is the binary indicator (0 or 1), and a is the predicted probability.

3. Experimental results

3.1. Dataset and data preparation

The dataset used in this study is the second adaptation of the PhysioNet Sleep-EDF dataset, which was created in 2018 and contains 197 polysomnograms (PSG) to evaluate the performance of the proposed model for sleep stage assignment. The Sleep-EDF dataset contains two types of data: (1) those that evaluate the effects of age on sleep in healthy persons, and (2) those that investigate the effects of temazepam (sleeping pills) on sleep. The dataset comprises whole-night polysomnogram (PSG) sleep recordings at a 100 Hz testing rate. Each record includes EOG, EEG, chin EMG, and occasion markers. An inadequate document conventionally contains oronasal breath and rectal body temperature. The hypnograms were physically labelled by professionals according to Rechtschaffen and Kales standards, which were assigned to a different class at each level. The American Academy of Sleep Medicine (AASM) norms for these classes are W, REM, N1, N2, and N3. In the evaluations, single EEG channels from the group of both versions were considered in the integration. The total number of stages in the dataset used for evaluation is 65,971-W (wake), 21,522- N1, 96,132-N2, 13,039 N3–N4 (where N1, N2, N3, and N4 record eye movement time), and 25,835-REM (Rapid Eye Movement).

3.2. Experimental design

Despite the non-uniform distribution of sleep stages in the Sleep-EDF database, the numbers of the W and N2 phases are far higher than those of the other stages. The performance of Machine Learning algorithms degrades when a dataset has a class imbalance problem; to solve this, a loss function, in conjunction with a synthetic recollection over-sampling strategy, generates the values between existing minority samples by considering artificial data points. This demonstration was evaluated using k-fold cross validation, with the k value set to 20 for this database and the database divided into k folds. For each unique fold, one fold is taken as a testing set and the remaining folds serve as a training set. Then, the training set is used to train the model, the testing set is used to evaluate the model, and all evaluation results are combined. The term "20-fold" refers to the number of groups that the given dataset can be split into. This helps evaluate the performance of the algorithm. The dataset is divided into 20 folds. Each fold is taken as a test set, the remaining folds serve as the test set, and the proposed model are evaluated using the test set. Table .1 shows the performance achieved by the training and testing dataset for a single EEG signal.

The nexus was trained with a maximum of 400 epochs. An optimizer named RMSProp was developed to operate with the L_{MFE} haplessness, with smaller than expected clusters of size 20 and a cognition rate of $\alpha = 0.0001$. In addition, along with the CRF algorithm, an adverbial L2 regularisation component was applied to the haplessness work to alleviate overfitting.

Google Tensorflow deep learning library and Python programming language were utilized to execute the proposed approach.

3.3. Evaluation metrics

The measures used to assess the performance of the proposed model are accuracy, precision, recall, and F-score. Accuracy is one measure used to determine the stages of sleep apnoea disease. A higher accuracy leads to improved prediction of the stages of apnoea.

The classification accuracy of the sleep stages of apnoea is validated using accuracy. The prediction in the steps of sleep apnoea should be predicted positively. The prognosis of an actual negative patient as positive and of positive patients as negative will affect the outcome of the prediction model. Precision shows the correctness achieved in positive prediction (out of all positive classes, how often have correct classes been predicted – i.e. how many are positive?). High precision indicates an example labelled as positive is indeed positive (there is only a small number of false positives). F-score is a good alternative for balancing precision and recall. It helps to compute recall and precision in a single equation to distinguish between models with low recall and high precision or vice versa.

$$\text{Accuracy} = (\text{true}(+\text{ve}) + \text{true}(\text{-ve})) \,/\, ((\text{true}(+\text{ve}) + \text{true}(\text{-ve}) + \text{false}(+\text{ve}) + \text{false}(\text{-ve})) \quad (3)$$

$$\text{Precision(P)} = \text{true}(+\text{ve}) / ((\text{true}(+\text{ve}) + \text{false\_}(+\text{ve})) \quad (4)$$

$$\text{Recall(R)} = \frac{\text{true}(+\text{ve})}{\text{true}(+\text{ve}) + \text{false}(-\text{ve})} \quad (5)$$

$$\text{F} - \text{score} = 2 \text{ x} \frac{\text{R} \times \text{P}}{\text{R} + \text{P}} \quad (6)$$

3.4. Result and discussion

True Positive (TP) values indicate the number of stages accurately scored, which are used to identify the most components in each confusion network. Externally and visually, the tables (the perplexity matrices' details) show that TP values are higher than other values within the same columns. These tables appear in the forecast execution (i.e., the exactness, review, specificity, and F1 score) of the demonstration for each progression. Among all stages, the model's performance is better for the REM (Rapid Eye Movement), W1, N2, and N3 stages than the N1 stage. The number of N1 stages in the dataset is lower than the number of other stages. The constructed model is made transparent by comparing the CNN-BiLSTM-CRF (CBC) model and Random Forest (RF) model, which uses the Welch algorithm along with Spectral Density Mapping for feature extraction, it is the most widely used approach for Sleep Stage Relegation.

The performance of the two classifiers was assessed using 20-fold cross-validation, which measured the following execution measures: exactness, accuracy, F1-measure, and recall. Whereas precision is an assessment degree that can be concretely calculated to appear by massive execution among the two classes, the precision, F1-score and recall are measured per class. It can be seen that CBC outperformed the RF comprehensive performance tests, achieving 90% accuracy as compared to 82% for AlexNet. In general, it can be assumed that the execution of a classifier essentially predicts the lion's quota class, which in our case will be 50% precision, as the two classes are similarly

Table 1
Performance achieved by training and testing with single EEG channel of Sleep EDF database.

Predicted					Pre-class Performance (%)				
	W1	N1	N2	N3	REM	Pre	Rec	Spe	F1
W1	7258	484	87	35	314	90.15	90.45	96.88	90.55
N1	580	1589	525	21	526	55.15	55.11	95.85	48.68
N2	423	769	14,581	1235	1108	92.58	84.21	94.12	84.94
N3	54	15	812	4985	7	80.98	82.57	96.54	88.27
REM	253	352	551	43	6985	82.10	88.77	95.94	84.89

distributed. Hence, both CBC and AlexNet altogether defeat this pattern. The tremendous advantage of CBC over AlexNet is that it doesn't require highlight designing to build and acquire valuable highlights. Instead, it only takes the first 960 features as input and can naturally select the most instructive ones. AlexNet highlights, on the other hand, required the use of wavelet adjustment, followed by highlight extraction and removal. An accuracy of 90% could be an auspicious result in practice, if it could be used as a single marginal signal – the nasal wind stream. In the future, designers intend to use other types of movements, such as the thoracic, abdominal, and chest streams. Table 2 displays the minor standard deviations of the findings over the 20 cross-validation runs for both CBC and AlexNet, as well as all execution steps for the two. There are a few visible differences between CBC and AlexNet: CBC has higher precision for the eccentric course than the traditional methods, while AlexNet tends to be the inverse. Furthermore, CBC has better judgement for mundane than for anomalous improvement, and the inverse is true for AlexNet. The cost of misidentifying everyday events as rare ones and vice versa may be considered in a cost-sensitive evaluation.

Table 2 shows the performance comparison of the proposed model with existing CNN models. Note that the proposed approach produces an accuracy gain of about 8.7% over AlexNet, 14.1% over ResNet, 15.7% over VGGNet, and 17.5% over LeNet. In terms of precision, the proposed model produces an improvement of 8.39% over AlexNet, 10.3% over ResNet, 10.9% over VGGNet, and 10.3% over LeNet.

In terms of recall, the proposed approach produces an improvement of 10.7% over AlexNet, 11.1% over ResNet, 16.3% over VGGNet, and 14.5% over LeNet. For the F1-score, the proposed model produces an improvement of 8.6% over AlexNet, 11.3% over ResNet, 12.6% over VGGNet, and 12.6% over LeNet. Figs. 5 and 6 illustrate the proposed model's average accuracy and loss for the training and validated datasets over 50 epochs. The accuracy measures for various CNN models are compared in Fig. 4. As shown in Fig. 4, the proposed method outperforms AlexNet by 10.7%, Resnet by 14.1%, VGGNet by 15%, and Lenet by 17.5%.

4. Scope for future work and conclusion

4.1. *Future work*

Although the primary goal of programmed sleep stage classification strategies is to detect abnormal EEG signals in patients, none of the proposed plans managed to persuade the understanding group. In this way, creating personalized EEG-based highlights to detect EEG arrhythmia is critical. These signal-processing strategies tend to be effective for analysing artificial and quasi-rhythmic signals. However, they are insufficient for a chaotic-shaped signal, such as EEGs from patients with sleep disorders. Note that the pre-processing and extraction components are more important than the classification part. The main comparative rest stages are N1, N2, and REM, which seem not to be well-segmented by the conventional communication-based signal processing highlights. This does not imply that the REM material can move about during the other stages of sleep.

There is a degree of similarity between REM and all other rest stages, which causes the REM classification precision to decrease. In any case, the similarity of N2, REM, and N1, as compared to others, is significant. This combinatorial highlight captures the rigorousness, recurrence groups, and abundant varieties of an EEG epoch, which can be significant and amend sleep stage performance. Some other highlights are optimizing the training epochs, tackling unbalanced datasets, N1 stage shows drastic results comparing to different stages, decreasing the average F1 score, preventing over- and under-sampling, increasing model complexity, combining LSTM and GRU layers, and examining multi-channel input with an additional CRF layer. With sleep stage classification, deep learning is the best approach for training on massive datasets from organizations like MASS and SHHR, and for the use of

Table 2
Performance measures obtained in each model.

MODEL	Accuracy(%)	Precision(%)	Recall(%)	F1-Score(%)
CNN-BiLSTM-CRF	90.70	90.50	92.70	90.60
AlexNet	82.00	82.11	82.00	82.00
ResNet	76.6	80.2	81.6	79.3
VGG Net	75	79.6	76.4	78
LeNet	73.2	80.2	78.2	79

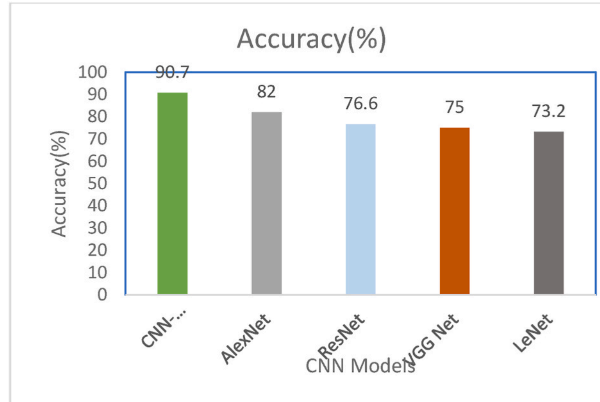

Fig. 4. Performance of various CNN models for each class (20-fold cross-validation).

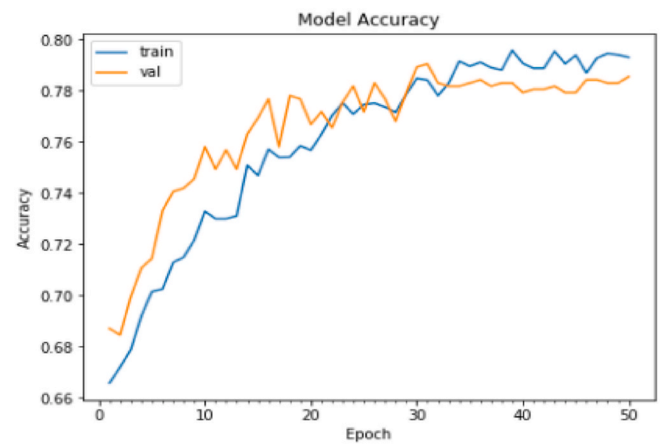

Fig. 5. Model accuracy of the proposed model.

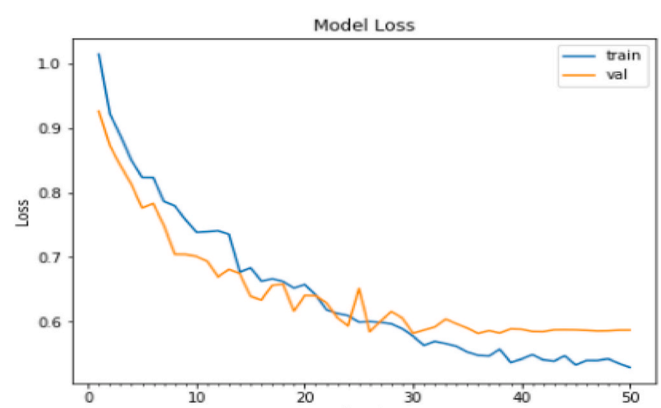

Fig. 6. Model loss of the proposed model.

handcrafted expert-defined features across multiple platforms. The BiLSTM-CNN model can be trained and tested on a single patient's data, allowing for customized sleep stage scoring.

5. Conclusion

The proposed strategy makes use of deep convolutional neural network and encoder-decoder architecture, along with bidirectional perpetual neural systems and considerations operating as its building blocks. The proposed early loss calculation, combined with Conditional Random Fields approaches, successfully reduces the impact of the class-imbalance problem and improved execution, especially on stage N1, which is more difficult to score than other sleep stages. By yielding superior performance for the sleep stage scoring task, the proposed model effectively overcomes the existing methods.

For the most part, there would be an imbalanced knowledge problem when developing automated frameworks (mundane class has more information than infected class). The generated interface can be connected to biomedical applications, such as arrhythmia detection using ECG signals, epilepsy detection using EEG signals, and stance cogitates using EMG signals. The dataset is also found to be highly dimensional, necessitating nonlinear decision boundaries. Among Machine Learning approaches, Random Forest and Boosting perform well. The use of PCA/ feature cull to reduce dimensionality speeds up computational valves. Since it encodes raw time-invariant as well as transitional features, this problem verbal expression is well-suited for Deep Learning with its best model CNN-BiLSTM.

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Data availability

open-source, public databases available from PhysioNet: https://physionet.org/about/database/

Code availability

The code used during the current study is available from the corresponding author upon reasonable request.

Authors' contributions

All authors contributed in a substantial way to the writing process. All authors reviewed and edited the manuscript and approved the final version of the manuscript.

Ethical approval

applicable.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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