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Competitive Multi-Verse Optimization with Deep Learning Based Sleep Stage Classification

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Abstract: Sleep plays a vital role in optimum working of the brain and the body. Numerous people suffer from sleep-oriented illnesses like apnea, insomnia, etc. Sleep stage classification is a primary process in the quantitative examination of polysomnographic recording. Sleep stage scoring is mainly based on experts' knowledge which is laborious and time consuming. Hence, it can be essential to design automated sleep stage classification model using machine learning (ML) and deep learning (DL) approaches. In this view, this study focuses on the design of Competitive Multi-verse Optimization with Deep Learning Based Sleep Stage Classification (CMVODL-SSC) model using Electroencephalogram (EEG) signals. The proposed CMVODL-SSC model intends to effectively categorize different sleep stages on EEG signals. Primarily, data pre-processing is performed to convert the actual data into useful format. Besides, a cascaded long short term memory (CLSTM) model is employed to perform classification process. At last, the CMVO algorithm is utilized for optimally tuning the hyperparameters involved in the CLSTM model. In order to report the enhancements of the CMVODL-SSC model, a wide range of simulations was carried out and the results ensured the better performance of the CMVODL-SSC model with average accuracy of 96.90%.

Keywords: Signal processing; EEG signals; sleep stage classification; clstm model; deep learning; cmvo algorithm

1 Introduction

Sleep plays a vital role in the optimal performance of both the brain and the body [1]. But, a larger number of individual severely suffers from sleeping disorder, namely narcolepsy, insomnia, and sleep dyspnoea [2]. Efficient and feasible sleep assessment is made mandatory for analyzing nap related issues and making timely interference. Assessment of sleep commonly depends on the manual phasing of overnight polysomnography (PSG) signal, including electrocardiogram (ECG), electroencephalogram (EEG), blood oxygen saturation electrooculogram (EOG), electromyogram (EMG), and respiration [3], by well trained and authorized technicians. The more time-taking characteristics of manual doze phasing hamper the application zones on very huge datasets and restrict related research in this domain [4]. In addition to this, the inter-scorer accord is comparatively lesser than 90%, and its development remains a challenge. The several channel ranges of PSG also represent disadvantages in prevention of broader use for the general population, on account of difficult groundwork and acts as a disruption to participant' normal nap. Hence, the past decades have made evident that the development of automated nap phasing depends on one-channel EEG. These methodologies may eventually result in adequately exact, powerful, worthwhile, and fastest ways of doze scoring [5].

The conduct of most sleep stage classification (SSC) techniques mainly depends on choosing representative characteristics for various nap phases [6]. Frequency, time period, and time-frequency field decays are the few general steps for processing and functioning of time signals and extraction of characteristics straightforwardly. Several numerical designs have been well-established in the procedure of finding hidden characteristics. After the extraction of features, several machine learning algorithms were commonly used for categorization [7], namely ensemble learning, nearest neighbour classifier, linear discriminate analysis (LDA), support vector machine (SVM), random forest (RF), and so on. It also depicts the good outcomes with combinatorial machine learning (ML) techniques [8]. In recent times, deep learning (DL) methodology namely recurrent neural network (RNN), convolution neural network (CNN), and other forms of deep neural networks (DNN) have become a common tool in pattern identification in biomedical signal processing. Long short-term memory (LSTM) method that has taken advantageous factor of sequential data learning to advance categorization performance was highly recommended for automatic nap phase [9,10].

Eldele et al. [11] present new attention based DL framework named AttnSleep for classifying sleep stages utilizing single channel EEG signal. This infrastructure begins with the feature extracting element dependent upon multi-resolution CNN (MRCNN) and adaptive feature recalibration (AFR). The MRCNN is extracting minimal as well as maximal frequency features and the AFR is capable of improving the quality of extracting features by modeling the inter-dependency among the features. The authors in [12] present the primary DL technique to SSC which learn end-to-end with no computing spectrograms or removing handcrafted feature which activities every multi-variate and multi-modal PSG signals and exploits the temporal context of all 30-s window of data. The authors in [13] establish a new multi-channel method dependent upon DL network and hidden Markov model (HMM) for improving the accuracy of SSC in term neonates. The feature space dimensionality is then decreased by utilizing a developmental FS approach named MGCACO (Modified Graph Clustering Ant Colony Optimization) dependent upon the significance and redundancy analysis. The authors in [14] examine the strategy of deep RNNs to detect sleep stages in single channel EEG signals recorded at home by non-expert users. It can be reported the outcome of dataset size, infrastructure selections, regularization, and personalization on the classifier efficiency.

The authors in [15] presented an effectual approach for signal-strength-based combining (SSC) dependent upon EEG signal analysis utilizing ML techniques with assuming 10s of epochs. The EEG signal has played important role in automatic SSC. EEG signal is filtered and decomposed as to frequency sub-bands utilizing band-pass filter. In [16], a flexible DL method was presented utilizing raw PSG signal. A one-dimensional CNN (1D-CNN) was established utilizing EOG and EEG signals to classifier of sleep stages. The efficiency of the model was estimated utilizing 2 public databases. Fan et al. [17–19] present a novel sleep staging method utilizing EOG signals that are further convenient for obtaining than EEG. A 2-scale CNN initial extracting epoch-wise temporary-equal features in raw EOG signal. The RNN then captured the long-term sequential data.

This study focuses on the design of Competitive Multi-verse Optimization with Deep Learning Based Sleep Stage Classification (CMVODL-SSC) model using EEG signals. The proposed CMVODL-SSC model intends to effectively categorize different sleep stages on EEG signals. Primarily, data pre-processing is performed to convert the actual data into useful format. Besides, a cascaded long short term memory (CLSTM) model is employed to perform classification process. At last, the CMVO algorithm is utilized for optimally tuning the hyperparameters involved in the CLSTM model. In order to report the enhancements of the CMVODL-SSC model, a wide range of simulations was carried out and the results ensured the better performance of the CMVODL-SSC model interms of different metrics.

2 The Proposed Model

In this study, a new CMVODL-SSC model has been introduced to effectively categorize different sleep stages on EEG signals. Primarily, data pre-processing is performed to convert the actual data into useful format. Besides, a CLSTM model is employed to perform classification process. At last, the CMVO algorithm is utilized for optimally tuning the hyperparameters involved in the CLSTM model. Fig. 1 illustrates the overall process of CMVODL-SSC technique.

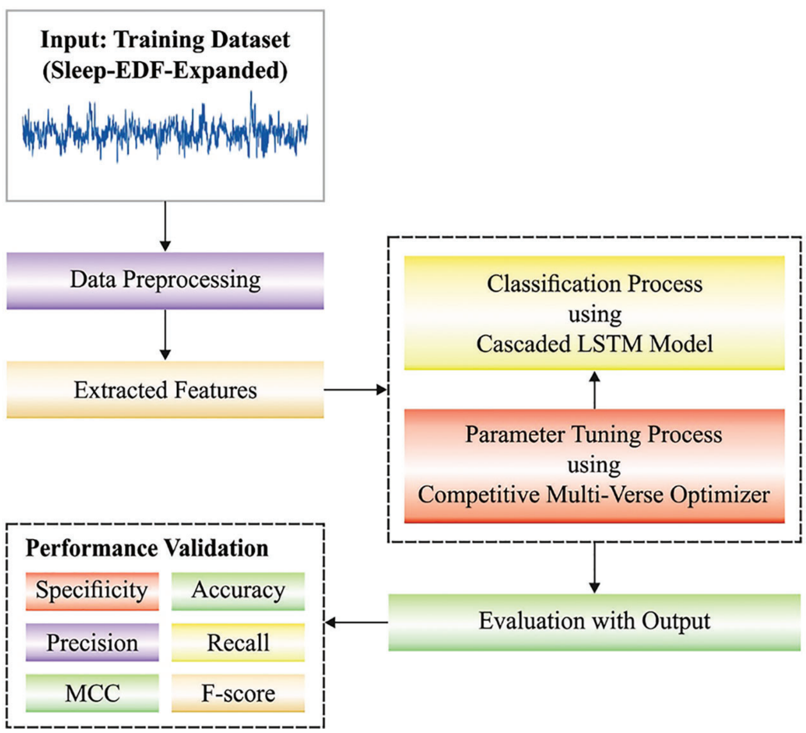

Figure 1: Overall process of CMVODL-SSC technique

2.1 Pre-Processing

At the initial stage, data pre-processing is performed to convert the actual data into useful format. The neural network (NN) trained develops further effectual on the reaching of few pre-processing steps on the network target and input. Usually, the feature was rescaled in the interval of 0 to 1 or from −1 to 1. It could be formulated as:

$$y' = (y_{\max} - y_{\min}) \times \frac{(x_i - x_{\min})}{(x_{\max} - x_{\min})} + x_{\min} \tag{1}$$

whereas $(y_{\max} - y_{\min}) = 0$; if $(x_{\max} - x_{\min}) = 0$ for a feature, it represents the constant rate that features from the data. Once the value of feature has been recognized by continuous value from the data, it could not be concern as it does not transport some data to NN. Once the min-max normalized is executed, every feature lies from the new range of values which remained unchanged.

2.2 CLSTM Based Sleep Stage Classification

Once the sleep stage data is pre-processed, the next level is to perform classification process using the CLSTM model [20]. A RNN is a sort of artificial neural network (ANN) neural network (NN) that comprises output, input, and hidden layers. There are two variances among traditional networks and RNN namely feed forward neural network (FFNN). In a similar hidden state, there are links among the nodes in RNN, while in the FFNN there is no one. The input of the hidden state in the present time contains the input neuron in the present time and the hidden state in the preceding time. The specific architecture of the RNN enables the best explanation of the temporal dynamic performance since it employs the preceding data it learns to design the pattern of the existing stage, i.e., advantageous for satisfactorily examining the feature of the existing time sequence. Consequently, in our work, RNN with memory process has been examined and employed in the time sequence predicting. Generally, an RNN could not preserve a better memory when the time interval is larger and has a vanishing gradient issue. Consequently, enhanced RNN model has been presented namely an LSTM with the easy architecture that is extensively employed for time sequence predicting in different domains. The LSTM calculates the memory unit through activation function. But, the application to hydrological information was constrained.

The LSTM unit using peephole connection comprises forget gate (FG), input gate (IG), and output gate (OG). Through the specific interaction process amongst three gates using a memory cell that assists an accumulator of the cells, the LSTM mitigates the vanishing gradient effects of long term dependency. The computation procedure of the LSTM using peephole connection is discussed in the following.

$$I_t = \sigma(w_{xi}x_t + w_{hi}h_{t-1} + w_{ci} \times c_{t-1} + b_i) \tag{2}$$

Simultaneously, the FG assesses that data to remove from the preceding cell state, through

$$F_t = \sigma\left(w_{xf}x_t + w_{hf}h_{t-1} + w_{cf} \times c_{t-1} + b_f\right) \tag{3}$$

The older cell state c_{t-1} would be upgraded toward the novel status

$$c_t = F_t \times c_{t-1} + I_t \times \tanh(w_{xc}x_t + w_{hc}h_{t-1} + b_c) \tag{4}$$

(4) The upgraded cell status c_{t-1} passes by "tanh" function and multiplied with the sigmoid activation function of the OG to describe the last output from LSTM unit h_t. It can be formulated by $h_t = O_t \times \tanh(c_t)$, whereas $O_t = \sigma(w_{xo}x_t + w_{ho}h_{t-1} + w_{co} \times c_t + b_o)$.

Here, w_{hi}, w_{hf}, w_{ho} denotes the recurrent weight; w_{xi}, w_{xf}, w_{xo} indicates the input weight; b_j, b_f, b_c, b_o denotes the bias vector; w_{ci}, w_{cf}, w_{co} indicates the peephole weights, and "$\times$" characterizes pointwise multiplication. Now, the LSTM discovers the long term feature.

Currently, the LSTM method was illustrated to be efficient at managing temporal correlation, even though certain limitation unavoidably exists. For example, the targeted value in the present time t is associated with the variable at preceding time (e.g., t-l), however, it is interconnected to the variable in the existing time t. But, variable in the present time is absent in actuality because they cohabit with the targeted value to be predicted. To resolve these issues, cascade modelling has been employed. The cascade method includes sub model that is complementary and independent in feature mapping and extraction. The C LSTM has k level, as well as the LSTM is employed for the time sequence predicting in all the levels through the input variable that is comprised of the learning outcomes from the preceding levels and the equivalent new input. With the cascade structure, the mixed time sequence features are recognized in distinct stages that might efficiently reject vague patterns. The presented technique is discussed below:

(1) Rescale and Collect the new information.

(2) Divide the information into testing (10%) and training (90%) datasets.

(3) Training the C-LSTM structure. The training dataset is separated into k classes based on pattern recognition according to the targeted value. For instance, $[P,\ E]$ is predicted by another parameter (LSTM 1), as well as the predicted value ($[P,\ E]$) is utilized for forecasting Q (LSTM 2). Since there exist two sub-targets, the data recognizes two patterns.

(4) Testing the trained C LSTM architecture by separating the testing dataset as in the preceding phase and predicting the targeted parameter.

2.3 CMVO Based Hyperparameter Optimization

Finally, the CMVO algorithm is utilized for optimally tuning the hyperparameters involved in the CLSTM model [21]. The presented method's aim is to attain solution with better quality and prevent early convergence of MVO approach. The presented method is inspired by the preceding study of CSO algorithm. In the modified approach, the dynamic method of object exchange among universes varies from that in the normal form of MVO where universe presents a competitive process.

The competition method is executed by the universe is attuned instead of based on the personal best universes and global. The competition model guarantees to prevent early convergence by maintaining population variety. In CMVO, the population is arbitrarily gathered according to bi-competition to generate two sets, losers, and winners. In all the competitions, the location of loser from the competition is attuned through learning from the winner instead of from the personal best and global locations. Followed by all the competitions, winner enters the following generation. Fig. 2 depicts the flowchart of CMVO technique.

Accordingly, universe might collectively converge toward the optimum solution. The competition conserves the best balance among exploitation and exploration as well as assist them to converge on optimum solution and preserve the diversity of every population. In the presented method, arithmetical equation of updating location are attuned by the subsequent approach:

$$X^i_{l,k} = \begin{cases} \begin{cases} r1 * TDR + r2 * \left(X_{w,k} - X_{l'k}\right) + r3 * \left((X_k) - X_{l,k}\right) + r3 * \left((X_k) - X_{l,k}\right) (rd1) < WEP \\ r1 * TDR + r2 * \left(X_{w,k} - X_{l,k}\right) + + r3 * \left((X_k) - X_{l,k}\right) (rd1) \geq WEP \end{cases} & (rd2) < WEP \\ X^i_{l,k} & (rd2) < WEP \end{cases}, \quad (5)$$

In which $X_{w,k}$ represents the winner universe in the kth; $X_{l,k}$ shows the loser universe in the kth; X^i_{lk} indicates the kth competition in the i-th of loser universe; the TDR and WEP denotes the two major coefficients; X_k represent the mean location value of the applicable universe; the value of rdl, $rd2$, $r2$, $r3$, $r4$ indicates arbitrary variable within $[0, 1]$. The common summary of CMVO approach is given in Algorithm 1.

Step 1 (Initial step): arbitrary universe is initialized according to the population size and dimension of searching region. Next, all the universes involved in population would be arbitrarily separated.

Step 2 (Bicompetition step): two sets of population at all the iterations (whereas CMVO chooses) are allowable to contribute to the bicompetition.

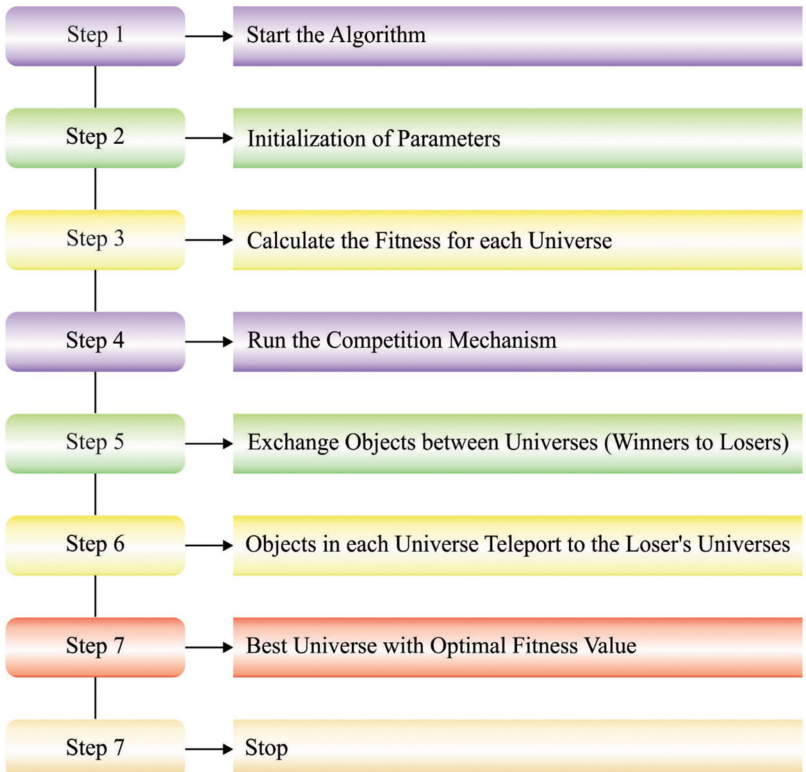

Figure 2: Flowchart of CMVO technique

Algorithm 1 Competitive multiple verse optimizer

Initiate the CMVO: WEP, TDR, lb, *ub*, Max Iteration, Nbr of individual.
Initiating a set of arbitrary populations depends on the problems.
for iteration $(t) <=$ Max $-iteration$ do do
Estimate the variable of : WEP, TDR.
Estimate the fitness of all the universes.
run the competitive method.
for all the individuals do
Exchange objects among universes (winner to loser).
Object in all the universe teleport to the loser universe.
end for
end for
The better universe with low fitness values.

3 Results and Discussion

In this section, the experimental assessment of the CMVODL-SSC model is carried out using the Sleep-EDF-Expanded dataset [22] comprises of 238976 samples with 71197 samples under W class, 25169 samples under N1 class, 88975 samples under N2 class, 19454 samples under N3 class, and 34181 samples under REM class as shown in Tab. 1. The proposed model is simulated using Python tool.

Table 1: Dataset details

Sleep-EDF-Expanded	
Class labels	No. of samples
W	71197
N1	25169
N2	88975
N3	19454
REM	34181
Total	238976

Fig. 3 shows the confusion matrices produced by the CMVODL-SSC model on 70% of training set (TRS) and 30% of testing set (TSS). On 70% of TRS, the CMVODL-SSC model has identified 48451 samples into W class, 16343 samples into N1 class, 60495 samples into N2 class, 12218 samples into N3 class, and 22486 samples into REM class. Similarly, on 30% of TSS, the CMVODL-SSC model has recognized 20786 samples into W class, 6949 samples into N1 class, 26097 samples into N2 class, 5345 samples into N3 class, and 9557 samples into REM class.

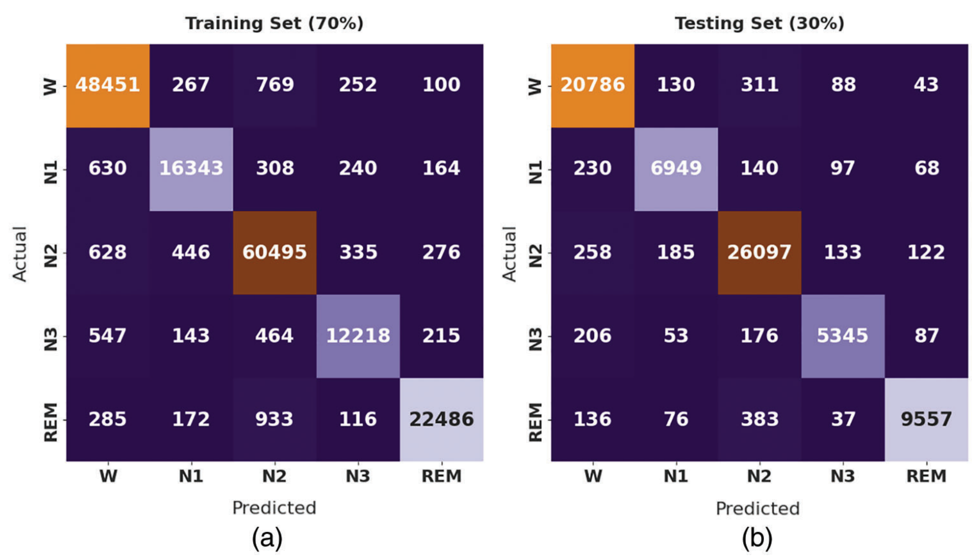

Figure 3: Confusion matrix of CMVODL-SSC technique on 70% of TRS and 30% of TSS

Tab. 2 highlights the performance of the CMVODL-SSC model on 70% of TRS and 30% of TSS.

Fig. 4 reports a detailed result of the CMVODL-SSC model offered on 70% of TRS. The CMVODL-SSC model has identified samples under W class with $accu_y$, $prec_n$, $reca_l$, $spec_y$, F_{score}, and MCC of 97.92%, 95.86%, 97.22%, 98.22%, 96.54%, and 95.05% respectively. Moreover, the CMVODL-SSC approach has identified samples under N2 class with $acc\mathrm{CMVODL} - \mathrm{SSC}\ u_y$, $prec_n$, $reca_l$, $spec_y$, F_{score}, and MCC of

97.51%, 96.07%, 97.29%, 97.65%, 96.68%, and 94.70% correspondingly. Eventually, the CMVODL-SSC system has identified samples under REM class with $accu_y$, $prec_n$, $reca_l$, $spec_y$, F_{score}, and MCC of 98.65%, 96.75%, 93.72%, 99.47%, 95.21%, and 94.44% correspondingly.

Table 2: Result analysis of CMVODL-SSC technique with distinct measures on 70% of TRS and 30% of TSS

Class labels	Accuracy	Precision	Recall	Specificity	F-score	MCC
Training set (70%)						
W	97.92	95.86	97.22	98.22	96.54	95.05
N1	98.58	94.08	92.41	99.31	93.24	92.45
N2	97.51	96.07	97.29	97.65	96.68	94.70
N3	98.62	92.83	89.92	99.39	91.36	90.62
REM	98.65	96.75	93.72	99.47	95.21	94.44
Average	98.26	95.12	94.11	98.81	94.60	93.45
Testing set (30%)						
W	98.04	96.16	97.32	98.35	96.74	95.34
N1	98.63	93.99	92.85	99.31	93.42	92.66
N2	97.62	96.27	97.40	97.75	96.83	94.93
N3	98.78	93.77	91.10	99.46	92.42	91.76
REM	98.67	96.76	93.80	99.48	95.26	94.50
Average	98.35	95.39	94.49	98.87	94.93	93.84

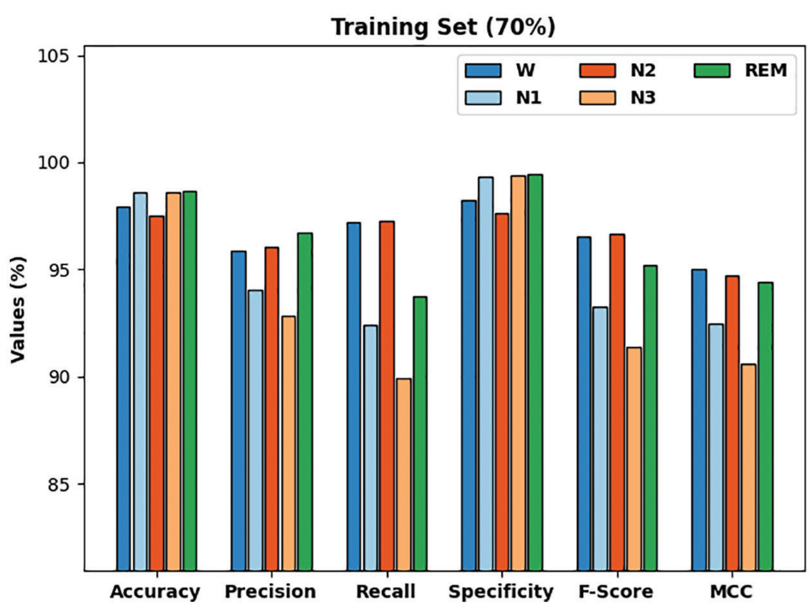

Figure 4: Result analysis of CMVODL-SSC technique on 70% of TRS

Fig. 5 demonstrates a detailed results of the CMVODL-SSC model offered on 30% of TSS. The CMVODL-SSC model has identified samples under W class with $accu_y$, $prec_n$, $reca_l$, $spec_y$, F_{score}, and MCC of 98.04%, 96.16%, 97.32%, 98.35%, 96.74%, and 95.34% respectively. Furthermore, the CMVODL-SSC method has identified samples under N2 class with $accu_y$, $prec_n$, $reca_l$, $spec_y$, F_{score}, and MCC of 97.62%, 96.27%, 97.40%, 97.75%, 96.83%, and 94.93% correspondingly. Finally, the CMVODL-SSC approach has identified samples under REM class with $accu_y$, $prec_n$, $reca_l$, $spec_y$, F_{score}, and MCC of 98.67%, 96.76%, 93.80%, 99.48%, 95.26%, and 94.50% respectively.

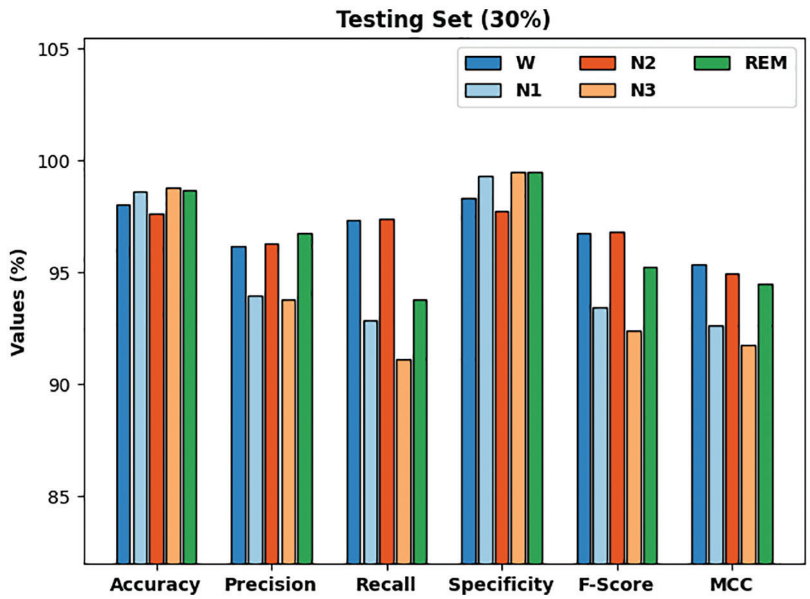

Figure 5: Result analysis of CMVODL-SSC technique on 30% of TSS

Fig. 6 illustrates the confusion matrices produced by the CMVODL-SSC approach on 80% of training set (TRS) and 20% of testing set (TSS). On 80% of TRS, the CMVODL-SSC model has identified 55198 samples into W class, 16564 samples into N1 class, 68645 samples into N2 class, 10829 samples into N3 class, and 25104 samples into REM class. Also, on 20% of TSS, the CMVODL-SSC technique has recognized 13988 samples into W class, 4203 samples into N1 class, 16986 samples into N2 class, 2689 samples into N3 class, and 6233 samples into REM class.

Tab. 3 examines the performance of the CMVODL-SSC technique on 80% of TRS and 20% of TSS. Fig. 7 defines a detailed results of the CMVODL-SSC model offered on 80% of TRS. The CMVODL-SSC model has identified samples under W class with $accu_y$, $prec_n$, $reca_l$, $spec_y$, F_{score}, and MCC of 97.25%, 93.77%, 97.19%, 97.27%, 95.45%, and 93.51% correspondingly. Additionally, the CMVODL-SSC systen has identified samples under N2 class with $accu_y$, $prec_n$, $reca_l$, $spec_y$, F_{score}, and MCC of 95.91%, 93%, 96.28%, 95.69%, 94.61%, and 91.35% correspondingly. At last, the CMVODL-SSC approach has identified samples under REM class with $accu_y$, $prec_n$, $reca_l$, $spec_y$, F_{score}, and MCC of 97.28%, 89.67%, 91.61%, 98.23%, 90.63%, and 89.05% respectively.

Fig. 8 demonstrates a detailed results of the CMVODL-SSC approach offered on 20% of TSS. The CMVODL-SSC model has identified samples under W class with $accu_y$, $prec_n$, $reca_l$, $spec_y$, F_{score}, and MCC of 97.23%, 93.88%, 97.13%, 97.27%, 95.48%, and 93.51% respectively. Besides, the CMVODL-SSC model has identified samples under N2 class with $accu_y$, $prec_n$, $reca_l$, $spec_y$, F_{score}, and MCC of 95.89%, 93.03%, 96.09%, 95.77%, 94.53%, and 91.27% correspondingly. Furthermore, the

CMVODL-SSC technique has identified samples under REM class with $accu_y$, $prec_n$, $reca_l$, $spec_y$, F_{score}, and MCC of 97.29%, 89.25%, 91.97%, 98.17%, 90.59%, and 89.02% correspondingly.

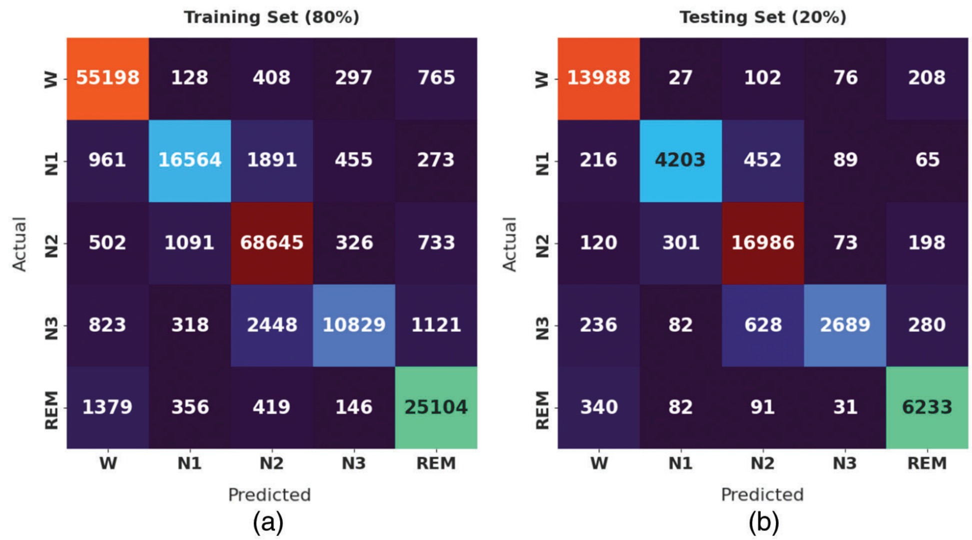

Figure 6: Confusion matrix of CMVODL-SSC technique on 80% of TRS and 20% of TSS

Table 3: Result analysis of CMVODL-SSC technique with distinct measures on 80% of TRS and 20% of TSS

Class labels	Accuracy	Precision	Recall	Specificity	F-score	MCC
Training set (80%)						
W	97.25	93.77	97.19	97.27	95.45	93.51
N1	97.14	89.74	82.23	98.89	85.82	84.33
N2	95.91	93.00	96.28	95.69	94.61	91.35
N3	96.90	89.84	69.69	99.30	78.49	77.57
REM	97.28	89.67	91.61	98.23	90.63	89.05
Average	96.90	91.21	87.40	97.88	89.00	87.16
Testing set (20%)						
W	97.23	93.88	97.13	97.27	95.48	93.51
N1	97.25	89.52	83.64	98.85	86.48	85.01
N2	95.89	93.03	96.09	95.77	94.53	91.27
N3	96.87	90.91	68.68	99.39	78.25	77.47
REM	97.29	89.25	91.97	98.17	90.59	89.02
Average	96.91	91.32	87.50	97.89	89.07	87.26

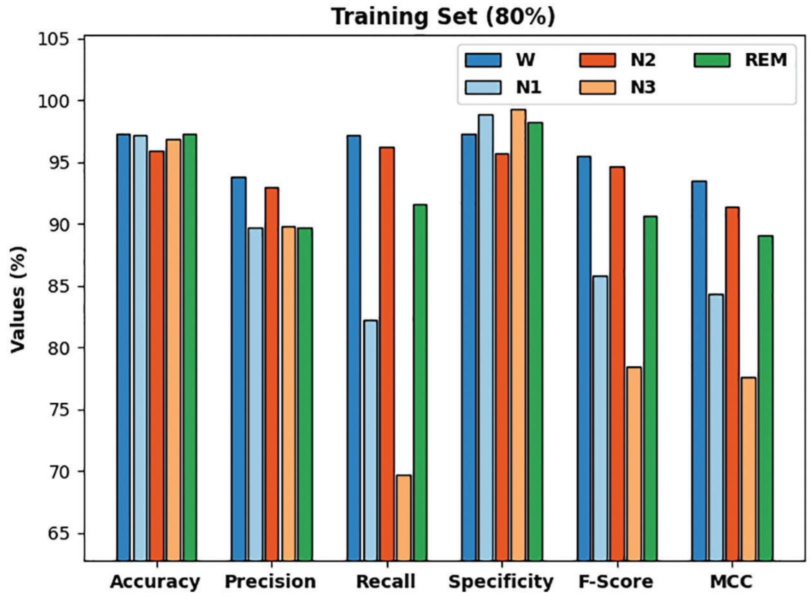

Figure 7: Result analysis of CMVODL-SSC technique on 80% of TRS

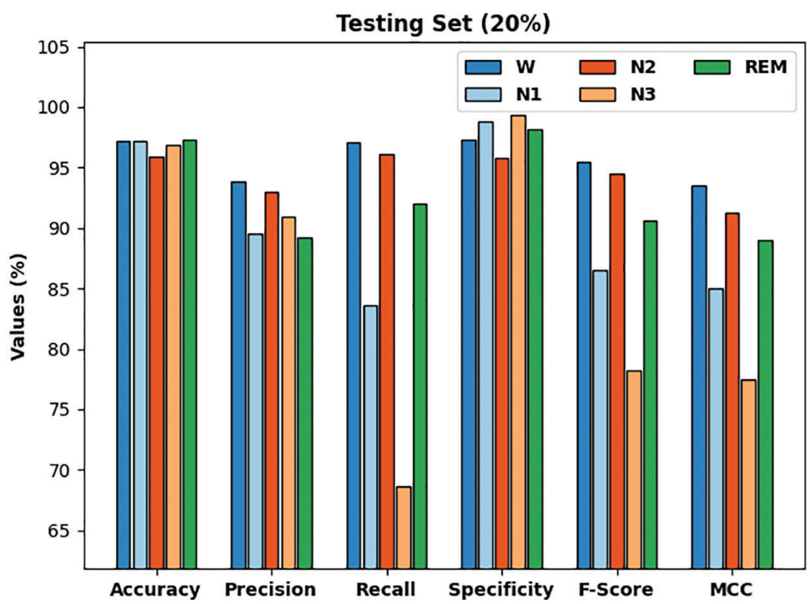

Figure 8: Result analysis of CMVODL-SSC technique on 20% of TSS

For ensuring the enhanced performance of the CMVODL-SSC model, a comparative analysis with MRCNN model interms of $accu_y$ is shown in Tab. 4 and Fig. 9 [23]. The results indicated that the MRCNN model has obtained reduced $accu_y$ of 94.13%, 85.78%, 86.83%, 96.67%, and 92.22% under W, N1, N2, N3, and REM classes respectively. However, the CMVODL-SSC model has showcased enhanced $accu_y$ of 97.23%, 97.25%, 95.89%, 96.87%, and 97.29% under W, N1, N2, N3, and REM classes respectively.

Table 4: Acc_y analysis of CMVODL-SSC technique with existing methods under distinct class labels

Accuracy (%)		
Class labels	MRCNN	CMVODL-SSC
W	94.13	97.23
N1	85.78	97.25
N2	86.83	95.89
N3	96.67	96.87
REM	92.22	97.29

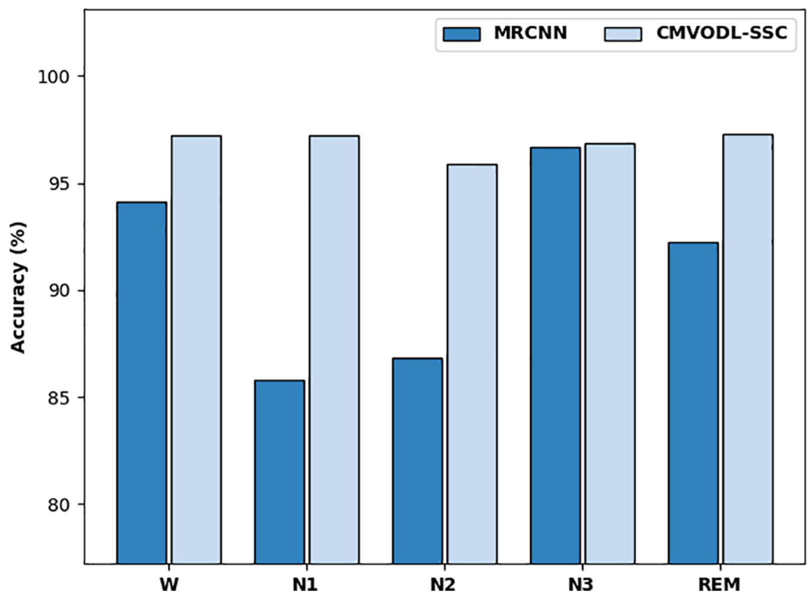

Figure 9: Acc_y analysis of CMVODL-SSC technique with existing methods

In order to ensure the enhanced performance of the CMVODL-SSC model, a comparative analysis with MRCNN model with respect to $reca_l$ is revealed in Tab. 5 and Fig. 10. The results indicated that the MRCNN technique has obtained reduced $reca_l$ of 88.56%, 60.17%, 70.10%, 82.92%, and 77.31% under W, N1, N2, N3, and REM classes correspondingly. But, the CMVODL-SSC method has outperformed higher $reca_l$ of 97.13%, 83.64%, 96.09%, 68.68%, and 91.97% under W, N1, N2, N3, and REM classes correspondingly.

Table 5: $Reca_l$ analysis of CMVODL-SSC technique with existing methods under distinct class labels

Recall (%)		
Class labels	MRCNN	CMVODL-SSC
W	88.56	97.13
N1	60.17	83.64
N2	70.10	96.09
N3	82.92	68.68
REM	77.31	91.97

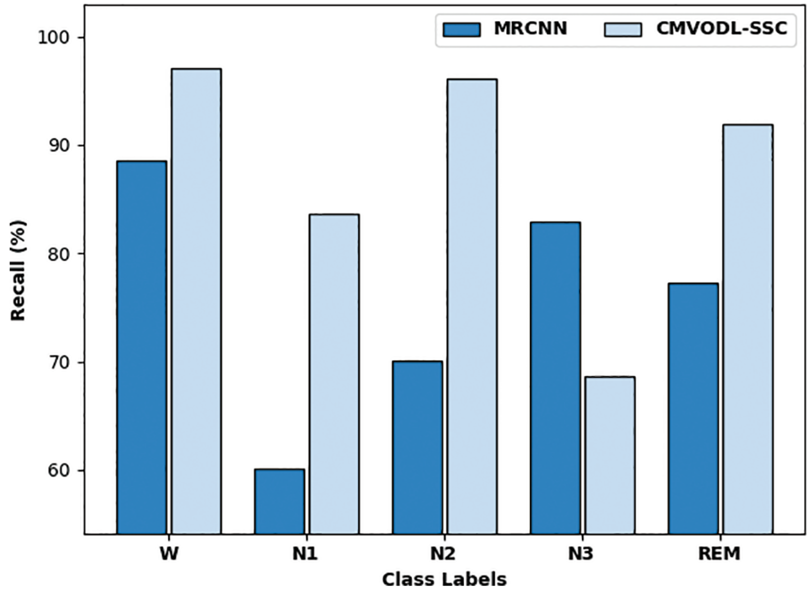

Figure 10: *$Reca_l$* analysis of CMVODL-SSC technique with existing methods

For demonstrating the enhanced performance of the CMVODL-SSC model, a comparative analysis with MRCNN technique interms of $spec_y$ is shown in Tab. 6 and Fig. 11. The results exposed that the MRCNN approach has obtained lower $spec_y$ of 97.55%, 88.73%, 95.07%, 97.67%, and 92.24% under W, N1, N2, N3, and REM classes respectively. At last, the CMVODL-SSC model has exhibited maximal $spec_y$ of 97.27%, 98.85%, 95.77%, 99.39%, and 98.17% under W, N1, N2, N3, and REM classes correspondingly.

Table 6: *$Spec_y$* analysis of CMVODL-SSC technique with existing methods under distinct class labels

	Specificity (%)	
Class labels	MRCNN	CMVODL-SSC
W	97.55	97.27
N1	88.73	98.85
N2	95.07	95.77
N3	97.67	99.39
REM	94.24	98.17

After looking into the above mentioned tables and discussion, it can be concluded that the CMVODL-SSC model has outperformed the other methods on sleep stage classification.

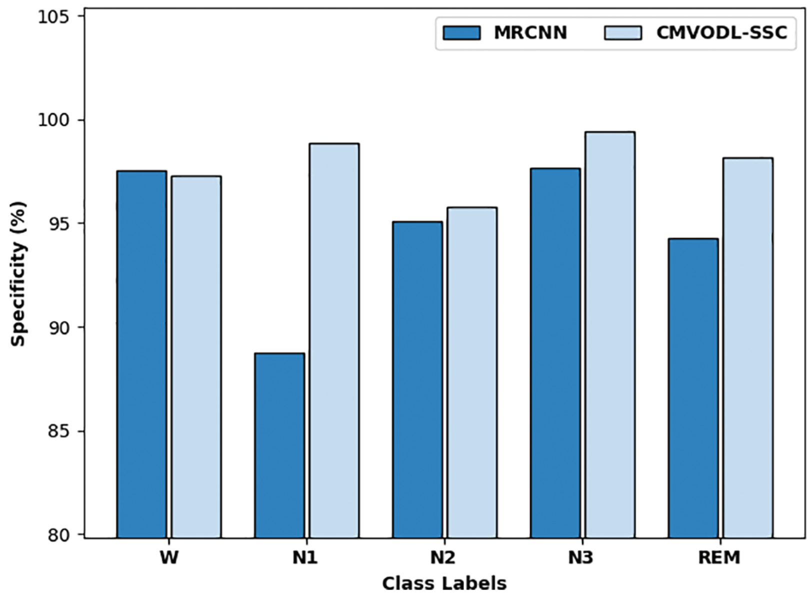

Figure 11: $Spec_y$ analysis of CMVODL-SSC technique with existing methods

4 Conclusion

In this study, a new CMVODL-SSC model has been introduced to effectively categorize different sleep stages on EEG signals. Primarily, data pre-processing is performed to convert the actual data into useful format. Besides, a CLSTM model is employed to perform classification process. At last, the CMVO algorithm is utilized for optimally tuning the hyperparameters involved in the CLSTM model. In order to report the enhancements of the CMVODL-SSC model, a wide range of simulations was carried out and the results ensured the better performance of the CMVODL-SSC model interms of different metrics. In future, the performance of the CMVODL-SSC model can be improved by the design of hybrid metaheuristic optimization algorithms.

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