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RESEARCH ARTICLE

Modified Bald Eagle Search Algorithm With Deep Learning-Driven Sleep Quality Prediction for Healthcare Monitoring Systems

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ABSTRACT Sleep habits are strongly related to health behaviors, with sleep quality serving as a major health indicator. Current approaches for evaluating sleep quality, namely polysomnography and questionnaires, are often time-consuming, costly, or invasive. Thus, there is a pressing need for a more convenient, nonintrusive, and cost-effective method. The applications of deep learning (DL) in sleep quality prediction represent a groundbreaking technique for addressing sleep-related disorders. In this aspect, the article offers the design of a Modified Bald Eagle Search Algorithm with Deep Learning-Driven Sleep Quality Prediction (MBES-DLSQP) for Healthcare Monitoring Systems. The MBES-DLSQP technique combines the strengths of a DL model with a hyperparameter tuning strategy to provide precise sleep quality predictions. At the primary stage, the MBES-DLSQP technique undergoes data pre-processing. Besides, the MBES-DLSQP technique uses a stacked sparse autoencoder (SSAE)-based prediction model, which can extract and encode high-dimensional sleep data. The MBES-DLSQP incorporates MBESA-based hyperparameter tuning which assures its optimal configurations to further boost the efficiency of the SSAE model. The experimental outcome of the MBES-DLSQP algorithm is tested on the sleep dataset from the Kaggle repository. The experimental value infers that the MBES-DLSQP technique shows promising performance in sleep quality prediction with a maximum accuracy of 98.33%.

INDEX TERMS Sleep quality prediction, healthcare monitoring, deep learning, parameter tuning, artificial intelligence.

I. INTRODUCTION

The significance of sleep is paramount to health. Lack of sleep may affect emotional, mental and physical well-being [1]. This causes many health complications like high blood pressure, insulin resistance, metabolic syndrome, cardiovascular disease, mood disorders (anxiety or depression), and reduced cognitive function for judgement and memory [2].

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Numerous indicators of sleep quality are available but sleep efficiency (SE) is more important [3]. Poor SE causes a lack of sleep which is a major health problem like obesity and diabetes. In addition, sleep behavior is found to be an effect on adolescent health. In the present scenario, most people pay attention to their quality of sleep [4]. Moreover, to enhance individual sleep quality, they want to distinguish the accurate condition of their sleep; that is they require techniques to observe their sleep conditions. The latest and novel technologies produced the most convenient methods for individuals to monitor themselves as well as boost sleep in their everyday lives [5]. Sleep quality can be evaluated by behavior perception and objective physical indicators.

Many types of sleep are accessible in the sleep cycle [6]. Stages 1 and 2 called light sleep and stages 3 and 4 called dream sleep, are classified into non-rapid eye movement (NREM) and rapid eye movement (REM) sleep. During the sleep cycle, the sleep processes include light sleep, wake condition, deep sleep, and REM which are frequent numerous times at night time and sometimes each cycle is crossed by short-term wake situations [7]. In addition, there are many kinds of sleep disturbances such as awakening in the early morning, maintaining sleep and difficulty falling asleep [8]. For evaluating sleep in clinical studies, Polysomnography (PSG) has been usually employed but it has numerous disadvantages intrusive, time-consuming, expensive and impractical. Smart bracelets and Smartphones are utilized for sleep activity observation [9].

Moreover, these kinds of devices are prominent as well as clumsy because while sleeping the user needs to put or wear them to their body [10]. Additionally, these techniques are only used to extend people's sleep quality that are asleep, making it tiresome to function in some conditions [11]. For instance, these methods cannot be able to employ in physical checks of the common population [12]. Machine Learning (ML) is a commonly utilized methodology that has become an effective core technology of artificial intelligence (AI) and data science [13]. Concerning sleep data and other kinds of clinical data, many researchers have employed ML in order to create prediction techniques for a range of sleep disorders [14]. Some researchers have proven that DL and long short-term memory (LSTM) were effective tests for the prediction of a range of sleep disorders [15].

The article offers the design of a Modified Bald Eagle Search Algorithm with Deep Learning-Driven Sleep Quality Prediction (MBES-DLSQP) for Healthcare Monitoring Systems. The MBES-DLSQP technique integrates the benefits of the DL algorithm with a hyperparameter tuning strategy for providing accurate sleep prediction results. At the primary stage, the MBES-DLSQP technique undergoes data pre-processing. Besides, the MBES-DLSQP technique uses a stacked sparse autoencoder (SSAE)-based prediction model, which can extract and encode high-dimensional sleep data. To further boost the efficiency of the SSAE model, the MBES-DLSQP incorporates MBESA-based hyperparameter tuning which assures its optimal configurations. The stimulation outcome of the MBES-DLSQP technique is tested on a sleep dataset from the Kaggle repository. In short, the key contributions of the study are summarized as follows.

- The MBES-DLSQP technique offers a novel method for predicting sleep quality, leveraging data preprocessing, SSAE-based prediction, and MBESA-based hyperparameter tuning for extensive sleep data to provide a more accurate and efficient solution. To the best of our knowledge, the MBES-DLSQP technique never existed in the literature.
- The MBES-DLSQP technique contributes to healthcare monitoring systems by enabling the accurate evaluation and prediction of sleep quality, with potential applications in the early detection and management of sleep-related disorders and their impact on overall health.
- The integration of hyperparameter tuning through MBESA enhances the efficiency and performance of the SSAE model, improving the accuracy of sleep quality predictions.

II. RELATED WORKS

The author in [16], a new attention-based DL architecture called AttnSleep is developed. The feature extraction is mainly executed by utilizing Adaptive Feature Recalibration (AFR) and multi-resolution convolutional neural network (MRCNN). The Temporal Context Encoder (TCE) is the next model which influences a multi-head consideration device. This organizes causal difficulties to perfect the sequential relations in the input features. In [17], developed a new architecture for predicting the existence of apnea from single-lead electrocardiogram (ECG) by using a Deep recurrent neural network (DRNN). ECG R-R intervals and R-peak amplitudes are removed and then arranged by employing influence spectral analysis. The recurrent DL methods are mainly designed to abstract the predictive ECG feature and estimate the event of apnea.

In [18], a novel model was developed to identify differences in the sleep habits of the person. This technique is mainly based on generating a novel database of patients. Then it is divided into five dissimilar habits. Next, this dataset was employed to verify the classification of the patient by utilizing the mean-shift clustering methodology. Lastly, the AE model is made to detect the anomalies. The research can able to attain satisfying results by using the AE AE-based LSTM system. John et al. [19] developed a new technology for apnea detection from ECG signals attained from wearable devices. This innovation branches from the high perseverance of apnea recognition. Then, this is accomplished by executing a one-dimensional convolutional neural network (CNN) for the detection and feature extraction of sleep apnea actions.

In [20], an effective CNN framework (SleepFCN) method is developed. The design of SleepFCN contains two main parts for removal of features and sequential series encoding like residual dilated causal convolutions (ResDC) and multi-scale feature extraction (MSFE). The implementation of the developed technique is executed by employing datasets of Sleep-EDF and sleep heart health study (SHHS). Yang et al. [21] present an effectual attention-based lightweight DL technique named LWSleepNet. A depthwise CNN is proposed in order to examine the input mapping features and seizure features at many frequencies by utilizing two various-sized convolution kernels.

A programmed sleep stage scoring network with a patch-type wearable electroencephalogram (EEG) sensor-based DL technique was developed in [22]. The presented method is easy to use, inexpensive, and lightweight. The method applied a model based on the modern DL technique for the training framework and specifically projected for automatic sleep performance. The model is learned and verified on the leave-one-out and cross-validation model. Hilal et al. [23] mainly emphasise the strategy of Competitive Multi-verse Optimization with the based Sleep Stage Classification (CMVODL-SSC) method. Initially, the data preprocessing is executed to renovate the actual information into the normal format. In addition, the cascaded LSTM (CLSTM) technique is used to execute the detection procedure. Lastly, the proposed approach is employed for tuning the hyperparameters optimally which is difficult in the CLSTM method.

III. THE PROPOSED MODEL

In this manuscript, we have established the automated sleep quality prediction using the MBES-DLSQP technique for Healthcare Monitoring Systems. The MBES-DLSQP technique integrates the benefits of the DL algorithm with a hyperparameter tuning strategy for providing accurate sleep prediction results. The data preprocessing, SSAE-based prediction, and MBESA-based hyperparameter tuning are the three major processes of the MBES-DLSQP technique. The overall working process of the MBES-DLSQP model is demonstrated in Fig. 1.

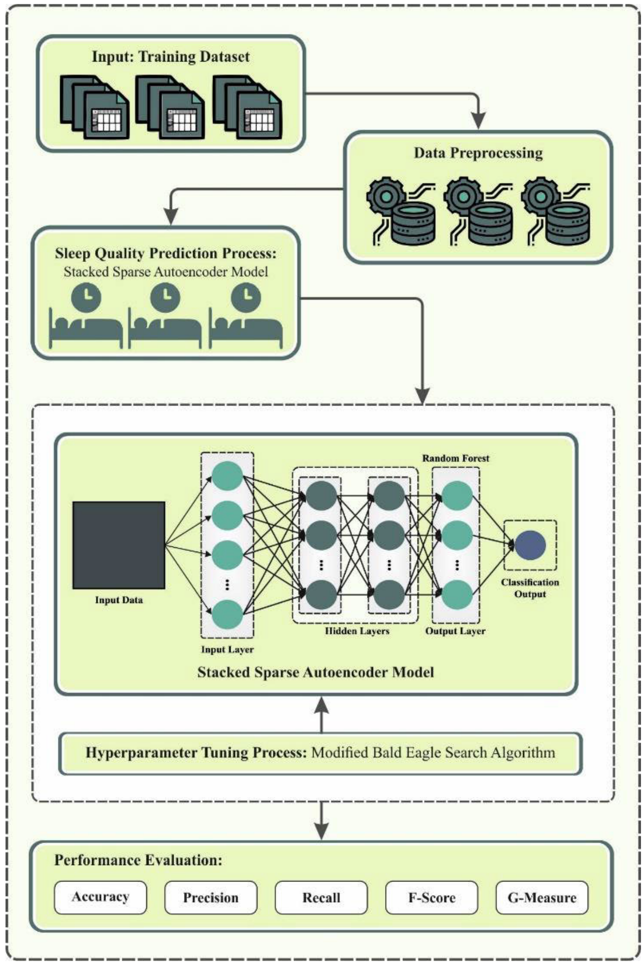

FIGURE 1. The overall flow of the MBES-DLSQP algorithm.

A. PRE-PROCESSING

In the initial phase, the MBES-DLSQP method undergoes data preprocessing. The data collected by smartwatches do not estimate sleep onset latency (time required to reduce sleeping after in time bed). For example, wake-up time is recorded by the watch as 34 minutes, and the next is considered to be 17 minutes.

B. PREDICTION USING THE SSAE MODEL

Next, the MBES-DLSQP technique applied the SSAE-based prediction model. Consider $X = (x(1), x(2), \ldots, x(N))^T$ as the series of unlabelled initial face image features for training [24], where $x(k) \in R^{d_x}$ and the features number is represented as N, and the amount of pixels in an image is d_x. Next, the l-layer learning feature was calculated by Eq. (8) with k^{th} features. Hidden unit and existing layer l are used during the computation of d_h.

$$h^l(k) = \left(h_1^l(k), h_2^l(k), \ldots, h_{d_h}^l(k)\right)^T \tag{1}$$

Now, hidden units and neurons are described by the subscripts and superscripts. $h_i^{(1)}$ is the 1st hidden layer (HL) of i^{th} units, HL l process x and $h^{(l)}$ amount of features to detect the output values. The encoder has *an* x input layer and *an* h hidden layer that calculates the output. In these processes, the optimum parameter is used to decrease the deviation between the outcomes. The variation is decreased to minimise the reconstructed output.

$$\mathcal{L}_{SAE}(\theta) = \left[\frac{1}{N}\sum_{k=1}^{N}\left(L\left(x(k), d_{\widehat{\theta}}\left(e_{\widetilde{\theta}}(x(k))\right)\right)\right)\right] + \left[\alpha\sum_{j=1}^{n} KL\left(\rho \| \hat{\rho}_j\right)\right] + \left[\beta \|W\|_2^2\right] \tag{2}$$

In Eq. (2), the sum of the mean-squared error (SMSE) of idioms that describe the contradiction amongst rebuilding $\hat{x}(k)$ and incoming $x(k)$ is the overhead of the overall data sequence. Moreover, $e_{\tilde{\theta}}(\cdot)$ maps incoming $x \in R^{d_x}$ to the latent representation $h \in R^{h_x}$, which is calculated by $h = e_{\tilde{\theta}}(x) = s(Wx + b_h)$, where $b_h \in R^{d_h}$ where bias b_h and W are the weight of $d_h \times d_x$ matrices. The encoder is denoted by $\tilde{\theta} = (W, b_h)$ whereas decoder $d_{\hat{\theta}}(\cdot)$ plots the outcoming hidden illustration h into the reconstructed space $\hat{x}$. $\hat{x} = d_{\hat{\theta}} = s\left(W^T h + b_x\right)$, where $b_x \in R^{d_x}$ is described as biased and W^T is a $d_x \times d_h$ represented by the weight matrix. An activation function is indicated as $s(\cdot)$; now, $s(z) = \frac{1}{1+e^{-z}}$, is used as an activation function for z neuron [25]. Thus, $\left(W^T, b_x\right)$ as the decoder. The transition of weight matrix W leads to weight matrix W^T. The AE reduces the matrix of weight. The pre-activation of the output layer of the AE, $=(W, b_h, b_x)$, can be expressed as $y = W^T s(Wx + b_h) + b_x$ using 3 parameters. Thus, the reconstruction of the decoder, X, is defined by $= s(y)$. The training of AE aims to minimize the reconstructed error at the initial part while improving the parameter $= (W, b_h, b_x)$.

The index j is the second idiom which represents the total hidden units of the network and the number n to characterize the amount of units in $KL(\rho||\hat{\rho}_j)$ is the KullbackLeibler (KL) divergence amongst $\hat{\rho}_j$, which describes the mean activation of j^{th} hidden units and desired activation ρ_j, expressed as:

$$\rho \log \frac{\rho}{\hat{\rho}_j} + (1 - \rho) \log \frac{1 - \rho}{1 - \hat{\rho}_j} \tag{3}$$

The weight decay is a third idiom that applies Eq. (4) to decrease the weight magnitude and helps to prevent overfitting:

$$||W||_2^2 = tr\left(W^T W\right) = \sum_{l=1}^{n_l} \sum_{i}^{s_l - 1} \sum_{j}^{s_l} \left(w_{i,j}^{(l)}\right)^2 \tag{4}$$

In Eq. (4), $w_{i,j}$ shows the connection among the i^{th} neurons at $l - 1$ along with j^{th} neurons at l. Moreover, the amount of layers is n_l and the amount of neurons in layer l is s_l. The SAE is $n_l = 2$, and $s_1 = 1680$ for the OLR dataset and $s_1 = 5280$ for the Extended Yale-B dataset, $s_2 = 1200$.

The SSAE includes multiple SAE layers with the output connected to the subsequent input layers: a deep neural network (DNN). The two important SAEs are fused to generate 2 layers of SSAE. The SSAE generates the function: $R^{d_x} \to R^{d_h}(2)$ that transforms the input pixel for the initial features into a new feature illustration as $h^{(2)} = f(x) \in R^{d_{h^{(2)}}}$.

C. HYPERPARAMETER TUNING USING THE MBES ALGORITHM

Finally, the MBES-DLSQP incorporates MBESA-based hyperparameter tuning which assures its optimal configurations of the SSAE model. BES is a new method that searches for emulating the hunting performances of bald eagles (BEs) for the collative work of hunting [26]. This method is divided into 3 parts that define the BE's hunting performance namely Search, Swooping, and Selection. In the selection step, the BE recognizes and selects the optimum region under the searching space chosen but it hunts its prey. Eq. (5) defines this step:

$$P_{new}, i = P_{best} + \alpha . r \left(P_{meon} - P_i\right) \tag{5}$$

The term "P_{best}" represents the existing search area represented by the BE, but the better position can presented by referencing the earlier recognized optimum place. The parameter "p_{mean}" represents the model that the eagle combines insights in the preceding position.

During this stage, the BE approach integrates a control variable that manages the extent of place alterations and spans an interval of [1.5-2]. Simultaneously, an arbitrary number r, interval of [0-1] is employed. During this phase, this method pinpoints a region dependent upon the data collected from the previous stage. Afterwards, the eagles progress to arbitrarily choose another proximate searching region in the preceding one. By leveraging the average and the optimum location, a primary phase considerably bolsters the possible candidate solution [27].

In the search phase, BE looks for the target in the selected hunting region and moves in dissimilar directions in the search space to improve the search range. The optimum dive location is defined as follows:

$$\begin{aligned} &P_{i,new} = P_i + y(i).(P_i - P_{i+1}) + x(i).(P_i - P_{meon}) \\ &x(i) = \frac{xr(i)}{\max(|xr|)}, \quad y(i) = \frac{yr(i)}{\max(|yr|)} \\ &x(i) = r(i).\sin(\theta(i)), \quad yr(i) = r(i).\cos(\theta(i)) \\ &\theta(i) = a.\pi.rand \\ &r(i) = \theta(i) + R.rand, \end{aligned} \tag{6}$$

Algorithm 1 Pseudocode of BES Algorithm

```
Randomly produce NP_i solutions.
Compute the cost function for the population initialization.
Define the optimum location: P_best and the mean P_mean
While (The condition for ending are not met)
Stage 1: Selection stage
For (Each single point i of the population)
Compute the newest solution, Pnew Eq. (5)
Update the solution's location:
If f (P_new) < f (P_i) then P_i = P_new
Update the optimum solution's location:
If f (P_new) < f (P_best) then P_best = P_new
End If
End If
End For
Stage 2: Search process
For (Each point i of the population)
Compute the newest solution Pnew Eq. (6)
Update the solution's location:
If f (P_new) < f (P_i) then P_i = P_new
Update the optimum solution's location:
If f (P_new) < f (P_best) then P_best = P_new
End If
End If
End For
Stage 3: Swooping stage
For (Each point i of the population)
Compute the newest solution, P_new Eq. (7)
Update the solution's location:
If f (P_new) < f (P_i) then P_i = P_new
Update the optimum solution's location:
If f (P_new) < f (P_best) then P_best = P_new
End If
End If
End For
End While
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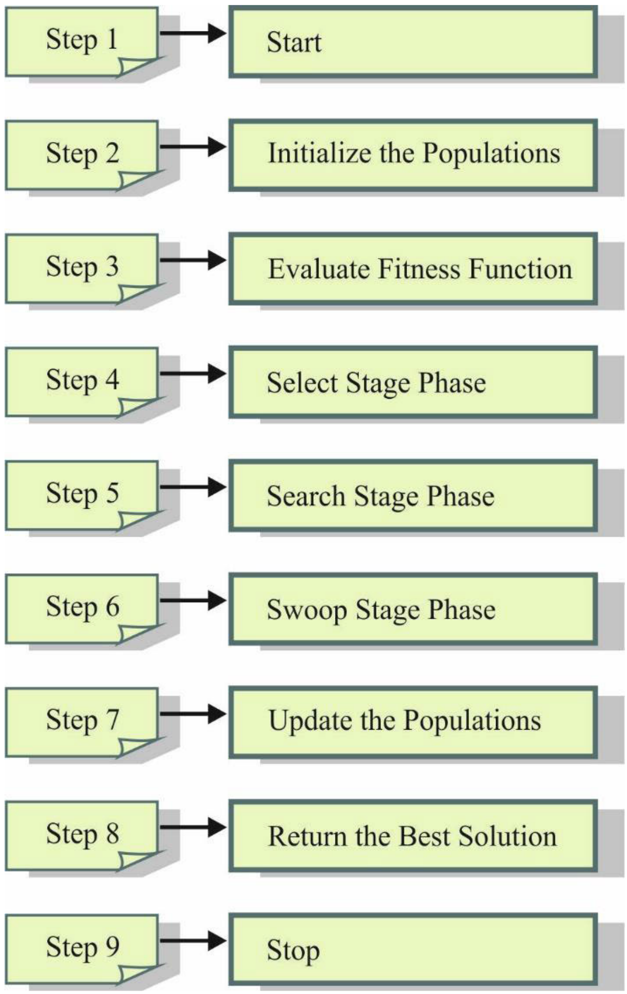

FIGURE 2. Steps involved in BESA.

In Eq. (6), 'a' is a number that ranges from 5 to 10. The parameter 'R' ranges from 0.5 and 2. The procedure of Branch and Eliminate Spiral (BES) extends the search range as we tweak 'a' and 'R'. This prevents from getting trapped in local solution. Fig. 2 depicts the steps involved in BESA.

The third phase is eagle shifts its focus towards the prey can be defined as follows:

$$\begin{aligned} P_{i,new} &= rand.P_{best} + x1\,(i)\,.\,(P_i - c1.P_{\text{mean}}) + y1\,(i) \\ x1(i) &= \frac{xr(i)}{\max(|xr|)},\ y1(i) = \frac{yr(i)}{\max(|yr|)} \\ xr\,(i) &= r\,(i)\,.\sinh\,[\theta\,(i)]\,,\ yr(i) = r(i).\cosh\,[\theta\,(i)] \\ \theta(i) &= a.\pi.rand \\ r\,(i) &= \theta\,(i)\,, \end{aligned} \tag{7}$$

The MBES model is derived by using chaotic concepts. The MBES algorithm is a nature-inspired optimization algorithm that draws inspiration from the predatory hunting behaviour of bald eagles in a chaotic environment. It incorporates chaos theory to introduce randomness and diversity into the search process, enhancing its ability to explore complex search spaces efficiently [28]. The chaotic sequences introduced by MBES during the perturbation phase help diversify the search, while the exploration and exploitation steps balance the exploration of new regions and the exploitation of promising solutions. The MBESA's strength lies in its ability to handle complex, multimodal optimization problems by harnessing the chaotic dynamics and adaptively adjusting the search strategy. The fitness selection is a major factor which influences the efficacy of the MBES method. The hyperparameter selection approach includes the solution encoding process to assess the performance of the candidate solution. Here, the MBES technique considers accuracy as the primary criterion to design the fitness function (FF) that is given below.

$$Fitness = \max\,(P) \tag{8}$$

$$P = \frac{TP}{TP + FP} \tag{9}$$

where the true and false positive values are TP and FP.

TABLE 1. Details on database.

Class	No. of Samples
Insufficient	100
Mild	100
Moderate	100
Sufficient	100
Total No. of Samples	400

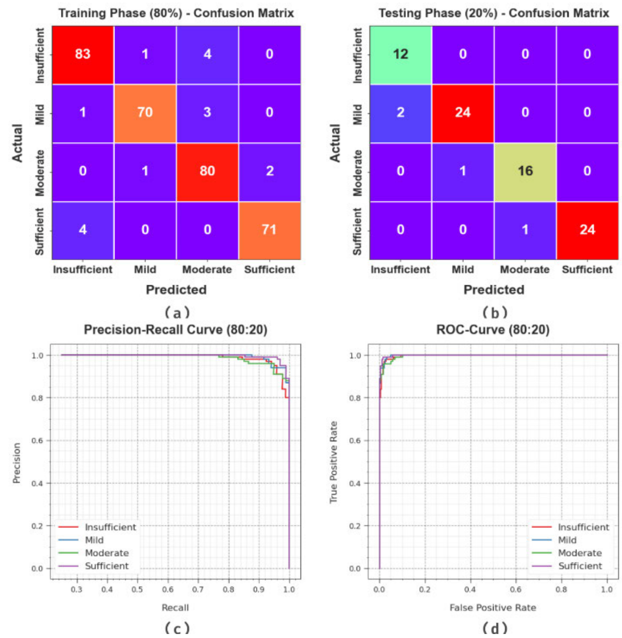

FIGURE 3. Classifier outcome (a-b) Confusion matrices, (c) PR curve, and (d) ROC.

IV. RESULTS AND DISCUSSION

The proposed model is simulated using the Python 3.8.5 tool on PC i5-8600k, GeForce 1050Ti 4GB, 16GB RAM, 250GB

TABLE 2. Sleep quality recognition outcome of BES-DLSQP technique at 80:20 of TRP/TSP.

Class	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}	$G_{measure}$
TRP (80%)					
Insufficient	96.88	94.32	94.32	94.32	94.32
Mild	98.12	97.22	94.59	95.89	95.90
Moderate	96.88	91.95	96.39	94.12	94.14
Sufficient	98.12	97.26	94.67	95.95	95.95
Average	97.50	95.19	94.99	95.07	95.08
TSP (20%)					
Insufficient	97.50	85.71	100.00	92.31	92.58
Mild	96.25	96.00	92.31	94.12	94.14
Moderate	97.50	94.12	94.12	94.12	94.12
Sufficient	98.75	100.00	96.00	97.96	97.98
Average	97.50	93.96	95.61	94.63	94.70

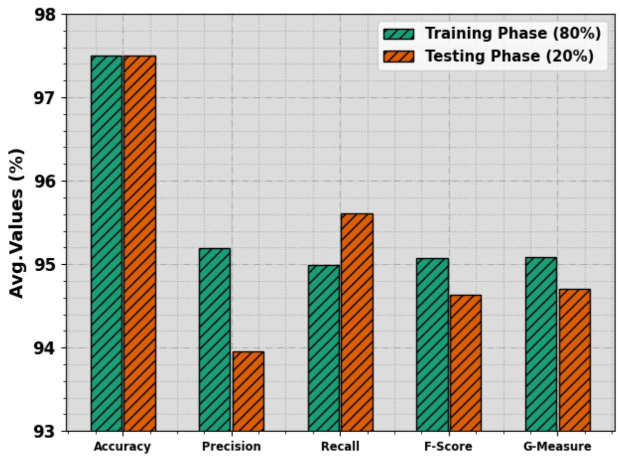

FIGURE 4. Average of BES-DLSQP technique at 80:20 of TRP/TSP.

SSD, and 1TB HDD. The parameter settings are given as follows: learning rate: 0.01, dropout: 0.5, batch size: 5, epoch count: 50, and activation: ReLU. The sleep quality prediction outcomes of the MBES-DLSQP method are tested using a Sleep dataset [29] including 400 samples and 4 classes as shown in Table 1. The dataset includes 4 classes with 100 samples under all the classes and 8 attributes. For experimental validation, we have used 80:20 and 70:30 of the training/testing dataset.

The classifier performance of the ABCFS-OHML method under 80:20 of the Training phase (TRP)/Testing phase (TSP) is shown in Fig. 3. The confusion matrices presented by the ABCFS-OHML method are exhibited in Figs. 3a-3b. The outcome indicated that the ABCFS-OHML system has accurately recognized and categorized all 4 class labels. At the same time, the PR outcome of the ABCFS-OHML technique is illustrated in Fig. 3c. The stimulation value indicated that the ABCFS-OHML technique has achieved the highest precision-recall (PR) values in 4 classes. Finally, Fig. 3d validates the Receiver operating characteristic (ROC) examination of the ABCFS-OHML method. The outcomes indicated that the ABCFS-OHML technique has resulted in promising outcomes with the maximum ROC values on 4 class labels.

FIGURE 5. $Accu_y$ curve of BES-DLSQP technique at 80:20 of TRP/TSP.

FIGURE 6. Loss curve of BES-DLSQP technique at 80:20 of TRP/TSP.

The sleep quality detection outcomes of the MBES-DLSQP method on 80% of TRP and 20% of TSP are portrayed in Table 2 and Fig. 4. The experimental outcome denotes that the MBES-DLSQP system effectually recognizes the sleep classes. On 80% of TRP, the MBES-DLSQP system offers average $accu_y$, $prec_n$, $reca_l$, F_{score}, and $G_{measure}$ of 97.50%, 95.19%, 94.99%, 95.07%, and 95.08%, correspondingly. Additionally, on 20% of TSP, the MBES-DLSQP technique offers average $accu_y$, $prec_n$, $reca_l$, F_{score}, and $G_{measure}$ of 97.50%, 93.96%, 95.61%, 94.63%, and 94.70%, correspondingly.

As demonstrated in Fig. 5, we have generated accuracy curves for the TRP and TSP to compute the effectiveness of the BES-DLSQP model at 80:20 of TRP/TSP. This curve provides essential insights into the model's learning progress and its generalization capability. A noticeable improvement in TR and TS accuracy curves becomes evident as we increase the number of epochs. This enhancement indicates the model's capability to better identify patterns within both the TR and TS datasets.

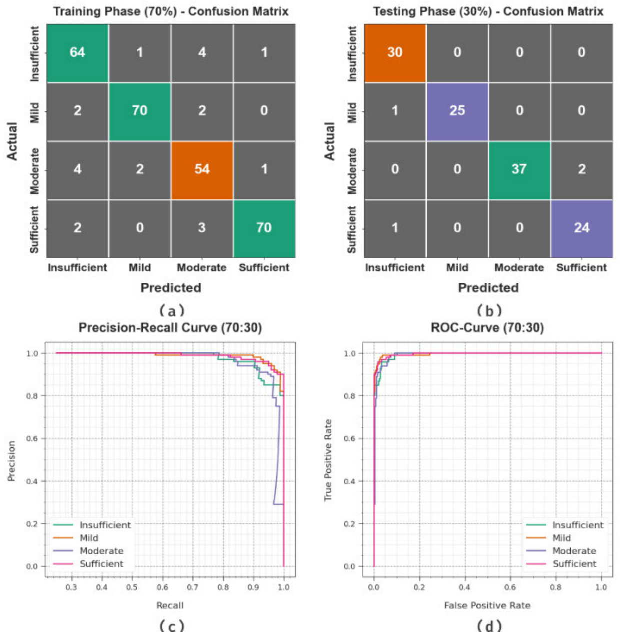

FIGURE 7. Classifier outcome (a-b) Confusion matrices, (c) PR curve, and (d) ROC.

TABLE 3. Sleep quality recognition outcome of BES-DLSQP technique at 70:30 of TRP/TSP.

Class	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}	$G_{measure}$
TRP (70%)					
Insufficient	95.00	88.89	91.43	90.14	90.15
Mild	97.50	95.89	94.59	95.24	95.24
Moderate	94.29	85.71	88.52	87.10	87.11
Sufficient	97.50	97.22	93.33	95.24	95.26
Average	96.07	91.93	91.97	91.93	91.94
TSP (30%)					
Insufficient	98.33	93.75	100.00	96.77	96.82
Mild	99.17	100.00	96.15	98.04	98.06
Moderate	98.33	100.00	94.87	97.37	97.40
Sufficient	97.50	92.31	96.00	94.12	94.14
Average	98.33	96.51	96.76	96.57	96.61

Fig. 6 also demonstrates an overview of BES-DLSQP method loss values throughout the training process. The decreasing trend in TR loss over epochs denotes that the model continually refines its weights to diminish the predictive errors on TR and TS datasets. These loss curves reflect how well the model fits the training dataset. Particularly, the TR and TS loss consistently decrease, indicating the model's effective learning of patterns present in both datasets. Furthermore, it portrays the model's adaptation in minimalizing discrepancies between predictions and the original training labels.

Fig. 7 shows the classifier performances of the ABCFS-OHML method under 70:30 of TRP/TSP. Figs. 7a-7b depicts the confusion matrices provided by the ABCFS-OHML model. The outcome indicated that the ABCFS-OHML

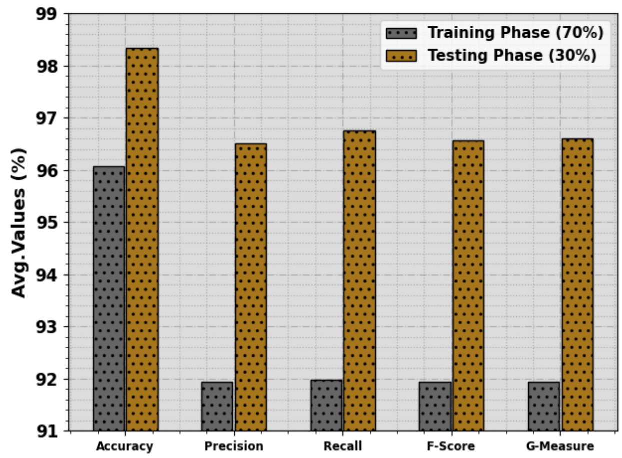

FIGURE 8. Average of BES-DLSQP method at 70:30 of TRP/TSP.

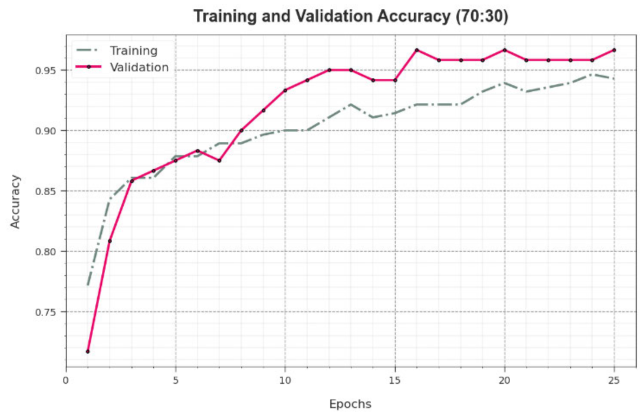

FIGURE 9. $Accu_y$ curve of BES-DLSQP method at 70:30 of TRP/TSP.

technique has accurately identified and categorized all 4 class labels. Simultaneously, Fig. 7c exhibits the PR investigation of the ABCFS-OHML technique. The outcome indicated that the ABCFS-OHML model has obtained the highest PR values in the 4 classes. Finally, Fig. 7d shows the ROC inspection of the ABCFS-OHML method. The experimental outcome indicated that the ABCFS-OHML technique has resulted in promising outcomes with the highest values of ROC on 4 class labels.

In Table 3 and Fig. 8, the sleep quality recognition outcomes of the MBES-DLSQP system on 70% of the TRP and 30% of the TSP are portrayed. The outcomes show that the MBES-DLSQP method effectually detects the sleep classes. On 70% of TRP, the MBES-DLSQP method offers average $accu_y$, $prec_n$, $reca_l$, F_{score}, and $G_{measure}$ of 96.07%, 91.93%, 91.97%, 91.93%, and 91.94%, respectively. Additionally, on 30% of TSP, the MBES-DLSQP technique offers average $accu_y$, $prec_n$, $reca_l$, F_{score}, and $G_{measure}$ of 98.33%, 96.51%, 96.76%, 96.57%, and 96.61%, correspondingly.

As illustrated in Fig. 9, we have generated accuracy curves for the TRP and TSP to compute the efficiency of the BES-DLSQP model at 70:30 of TRP/TSP. This curve provides essential insights into the model's learning progress and its generalization capability. A noticeable improvement

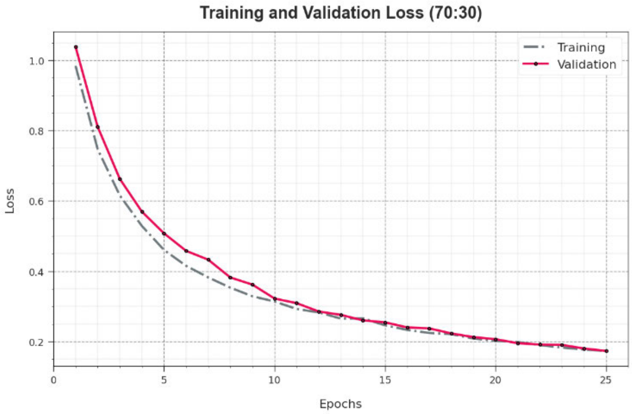

FIGURE 10. Loss curve of BES-DLSQP technique at 80:20 of TRP/TSP.

TABLE 4. Comparative outcome of MBES-DLSQP methodology with existing algorithms.

Methods	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}
MBES-DLSQP	98.33	96.51	96.76	96.57
WSHMSQP-ODL	97.50	95.36	94.87	95.02
MLP Algorithm	92.46	92.53	91.35	92.40
CNN Model	92.01	91.39	92.03	91.69
LR	92.21	91.79	92.11	92.31
RNN Model	93.08	92.39	94.61	91.33
LSTM Model	91.67	92.33	91.99	92.79

in TR and TS accuracy curves becomes evident as we increase the number of epochs. This enhancement signifies the model's capacity to better identify patterns within the TR and TS datasets.

Fig. 10 presents an overview of the BES-DLSQP model loss values throughout the training process. The decreasing trend in TR loss over epochs indicates that the model continually refines its weights to diminish predictive errors on TR and TS datasets. These loss curves reflect how well the model fits the training dataset. Notably, the TR and TS loss consistently decrease, illustrating the model's effective learning of patterns present in both datasets. Additionally, it shows the model's adaptation in minimizing discrepancies between predictions and the original training labels.

Table 4 and Fig. 11 exhibit the sleep quality classification outcomes of the MBES-DLSQP method with existing techniques [30]. The experimental result indicated that the MBES-DLSQP method accomplishes enhanced classification performance. Based on $accu_y$, the MBES-DLSQP technique offers an increased $accu_y$ of 98.33% whereas the MWHMSQP-ODL, MLP, CNN, LR, RNN, and LSTM models obtain decreased $accu_y$ of 97.50%, 92.46%, 92.01%, 92.21%, 93.08%, and 91.67%, respectively.

Moreover, based on $prec_n$, the MBES-DLSQP technique offers an increased $prec_n$ of 96.51% whereas the MWHMSQP-ODL, MLP, CNN, LR, RNN, and LSTM models obtain decreased $prec_n$ of 95.36%, 92.53%, 91.39%, 91.79%, 92.39%, and 92.33%, respectively. Furthermore, based on F_{score}, the MBES-DLSQP technique offers an increased F_{score} of 96.57% whereas the MWHMSQP-ODL, MLP, CNN, LR, RNN, and LSTM models obtained decreased F_{score} of 95.02%, 92.40%, 91.69%, 92.31%, 91.33%, and 92.79%, respectively. The experimental outcome showed the superior performance of the MBES-DLSQP approach on the sleep quality prediction process.

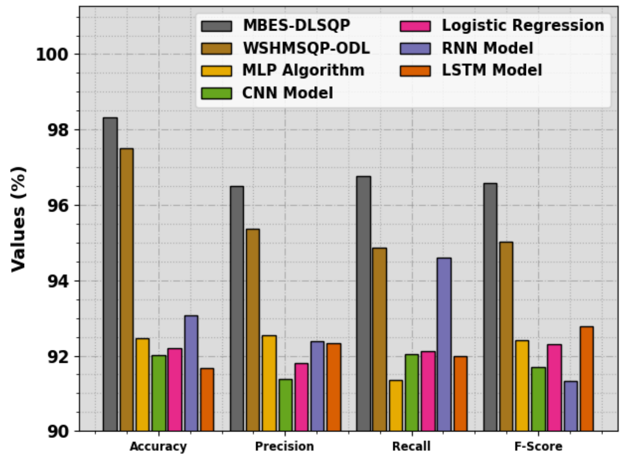

FIGURE 11. Comparative outcome of MBES-DLSQP algorithm with existing methods.

V. CONCLUSION

In this manuscript, we have established the automated sleep quality prediction using the MBES-DLSQP technique for Healthcare Monitoring Systems. The MBES-DLSQP technique integrates the benefits of the DL algorithm with a hyperparameter tuning strategy for providing accurate sleep prediction results. To further boost the efficiency of the SSAE model, the MBES-DLSQP incorporates MBESA-based hyperparameter tuning which assures its optimal configurations. By harnessing the capabilities of deep learning and innovative hyperparameter tuning strategies, this technique provides cost-effective, nonintrusive, and accurate techniques for assessing an individual's sleep quality. The experimental outcomes, with a high accuracy of 98.33%, highlight the potential and promising performance of the MBES-DLSQP method. It characterizes a valuable contribution to the field of sleep-related health monitoring and holds great promise in enhancing the well-being of individuals suffering from sleep-related disorders. Future work for the MBES-DLSQP method may include improving its adaptability for real-time sleep monitoring and extending its applicability to diverse healthcare contexts. Furthermore, the incorporation of advanced data sources and the development of user-friendly interfaces could further enhance its effectiveness and practicality.

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