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Internet of Things Assisted Sleep Quality Recognition using Hunger Games Search Optimization with Deep Learning on Smart Healthcare Systems

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Abstract

Rapid urbanization needs major cities that change into smart cities to increase our lifestyle with respect to transportation, people, government, environmental sustainability, and more. In recent times, Internet of Things (IoT) and healthcare wearables have played a vital play in the progress of smart cities by providing enhanced healthcare services and an entire standard of living. Wearables offer real-time health records to individuals and healthcare providers, permitting for proactive management of chronic conditions and early recognition of health problems. While sleep is of major importance for a healthy life, it can be required to forecast sleep quality. Insufficient sleep affects mental health, physical, and emotional, and is a solution to many illnesses like heart disease, insulin resistance, stress, heart disease, and so on. Recently, deep learning (DL) techniques can be deployed to forecast the quality of sleep dependent upon the wearables data in the awake duration. Therefore, this paper presents an automated sleep quality recognition using hunger games search optimization with deep learning (ASQR-HGSODL) technique in the IoT-assisted smart healthcare system. The ASQR-HGSODL technique allows the IoT devices to perform a data collection process, which collects the data related to sleep activity. For the feature selection process, the ASQR-HGSODL technique applies an arithmetic optimization algorithm (AOA). For the prediction of sleep quality, the ASQR-HGSODL technique implements a convolutional long short-term memory (ConvLSTM) approach. Lastly, the HGSO technique has been applied for the optimum hyper parameter selection of the ConvLSTM approach. To exhibit the effectual prediction results of the ASQR-HGSODL approach, a range of simulation can be carried out. The investigational outputs highlight the improved outcome of the ASQR-HGSODL. technique with other DL methodologies.

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Keywords: Sleep quality prediction; Internet of Things; Deep learning; Hunger Games search algorithm; Wearables; Smart cities

1. Introduction

IoT permits an individual to gather and analysis of data in numerous surroundings, objects, and devices combined in general day-to-day activities [1]. The objects with IoT typically are sensors that generate large quantities of data, which is inaccurate and heterogeneous. The big data analytics domain offers the required mechanisms and tools to analyze these data. IoT is employed for both indoor objects such as domestic appliances and indoor self-location devices and outdoor objects like groundwater sensors. IoT is also utilized to monitor patients in the medical field [2]. Especially, IoT develops its potential for the remote monitoring of patients. In medical services, wearable IoT sensors are extremely common with various applications. A current study proposes that IoT can provide major developments in nursing care in the future [3]. Figure 1 illustrates the process of wearable sensor systems assisted by IoT for healthcare sector.

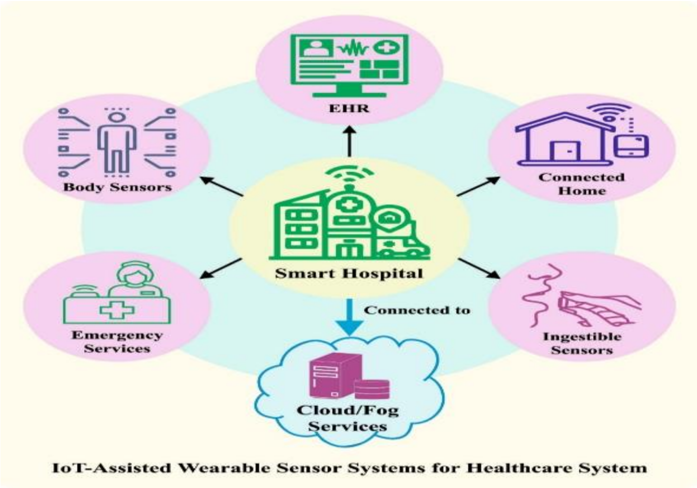

Figure 1. IoT-assisted wearable sensor systems for healthcare system

The majority of persons allocate from 5 to 9 hours of sleep daily. A few researches indicate that sleep quality and time are correlated with clinical results. For instance, long and short-sleepers are at higher risks of acquiring specific diseases than normal-length sleepers [4]. Sleeping disorder activated through physiological causes leads to various mental issues such as depression and concern. Presently, anxiety is the primary reason of several difficulties. Short-term disease differs the system of biological, which disturbs the sleep of an individual, therefore, resulting in long-term impacts [5]. This can also occur because of disruption in the body's metabolism, cardiac system, and nervous system. The final one is the environmental factor that comprises physical properties namely moisture, brightness in the room, environmental temperature, and other ambient features such as comfort-level of room and quiet in the room [6]. Advanced sleep monitoring tools implement different sensing technologies. In addition, these sensors are also exploited for sleep staging [7].

The identification of sleep quality needs the information relevant to locating the subject and any methods for classifying this data [8]. The data can be obtained remotely through IoT-allowed sensors and numerous techniques have been in place for sleeping pattern classification containing dual-tree, support vector machine (SVM), ANN, and means clustering. However, these standard methodologies need significant feature extraction from the pre-processed signals and are vulnerable to local optimization [9]. Nowadays, researchers developed a deep learning (DL) approach named CNN, which decreases the complexity of the network and quantity of weights due to its shared-weight network model. It is provided widely exploited in the field of image segmentation and object identification [10].

This paper presents an automated sleep quality recognition using hunger games search optimization with deep learning (ASQR-HGSODL) technique in the IoT-assisted smart healthcare system. The ASQR-HGSODL technique allows the IoT devices to perform a data collection process, which collects the data related to sleep activity. For the feature selection process, the ASQR-HGSODL technique applies an arithmetic optimization algorithm (AOA). For the prediction of sleep quality, the ASQR-HGSODL technique implements a convolutional long short-term memory (ConvLSTM) approach. Lastly, the HGSO technique was applied for the optimum hyperparameter selection of the ConvLSTM approach. To exhibit the effectual prediction results of the ASQR-HGSODL approach, a range of simulation can be carried out.

2. Related Works

Hamza et al. [11] proposed a new wearables-enabled smart health monitoring for quality of sleep prediction by employing the optimum DL (WSHMSQP-ODL) technique. This technique primarily permits the wearables to gather sleep-activity-relevant information. For predicting sleep quality, this framework employs the DBN algorithm. In [12], a non-intrusive and low-priced sleep monitoring technique was developed through commodity WiFi devices like WiFi-Sleep. The authors utilize the fine-grained channel state data in numerous antennas and present innovative signal processing and integration techniques for extracting accurate body movement and respiration data. A DL algorithm could be presented to incorporate medical sleep drug previous experience for achieving a 4-phase sleep monitoring with restricted data sources.

Shen et al. [13] introduced a wearable SAS identification approach that depends on a 1D multi-task multi-attention residual shrinkage-CNN (1D-MMResSNet) technique and cost-sensitive (CS) method. Primarily, a collection of photo plethysmography (PPG) sleep information. Lastly, the AdaCost cost-sensitive method was proposed. Han et al. [14] introduced a new systematic and approach IoT framework (IoT-V2E) for retrieving major equivalent EEG signal illustrations in a dataset that provided an IR visual query for sleep-based evaluation. Primarily, cross modal retrieval databases are gathered. Secondarily, a new uncertainty-aware hashing retrieval technique was developed that offers higher memory efficacy, effective performances, and adequate interpretability.

In [15], the emergence of a new learning algorithm was presented employing a deep neural network (DNN), which forecasts the indoor thermal comfort of disabled persons in the real world. In addition, the framework comprises a data gathering method for ensuring an effectual gathering system, allowing a huge amount of targeted information before transmitting it to cloud servers for additional data analysis. Nijaguna et al. [16] suggested a method for screening Obstructive Sleep Apnea utilizing analysis of HRV of ECG data when an individual is at sleep. This research aims to generate computational methodologies to recognize OSA depending on extraction features in HRV signals acquired under sleep ECGs. Liu et al. [17] recommended a single-input, multi-output-CNN. The inputs to NNs are the phase and amplitude of channel state data gathered via a WiFi device pair. Additionally, a 2-DL-based-NN classification approach was established and analyzed to classify four categories of sleep phases. In [18], a new architecture employing actigraph recordings of motor activity was developed. An over-lapping sliding window was exploited to input sequences into LSTM. The prediction capability of the integrated feature vectors is estimated by the SVM method.

3. Proposed Model

In this article, a novel ASQR-HGSODL technique for precise and automatic sleep quality detection in the IoT-assisted smart healthcare system is presented. The ASQR-HGSODL methodology allows the IoT devices to perform a data collection process, which collects data related to sleep activity. It incorporates several sub processes namely pre-processing, AOA-based feature selection, ConvLSTM-based classification, and HGSO-based tuning process. Figure 2 portrays the overall working flow of ASQR-HGSODL methodology.

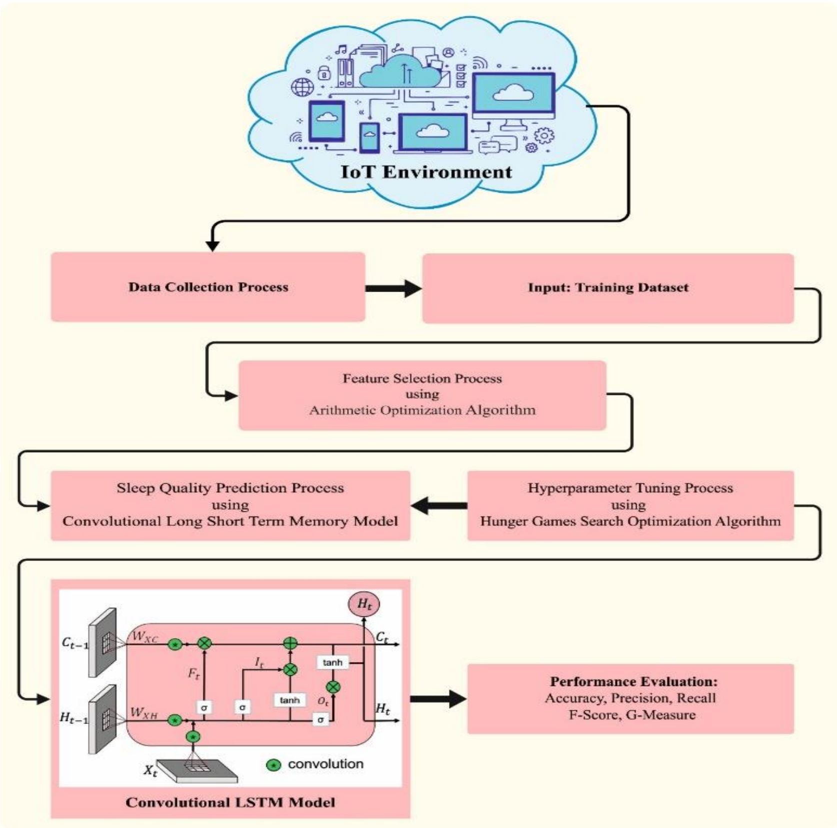

Figure 2. Overall flow of ASQR-HGSODL approach

A. Data Preprocessing

At an initial level, the ASQR-HGSODL approach executes preprocessing. The data gathered by smartwatches determine sleep onset latency (time required to reduce sleep after bedtime). It involves the total spending time in minutes to wake up and comprises sleep onset latency. Then, half of the time, spent wake-up is considered sleep onset latency. For example, a watch notes one sample of wake-up time as 34min, and the next sleep onset latency is considered that 17min.

B. Feature Selection using AOA

To choose features, the AOA is used. AOA is one of the novel meta-heuristic optimizer algorithms that depend on the functions of the arithmetical operator in the mathematics or processor of the PC [19]. Addition (A), multiplication (M), subtraction (S), and Division (D) are the four major operators used in the calculation. The exploration and exploitation stages are based on the concept of math-accelerated optimizer (MOA). Using the following equation, the MOA function can be defined:

$$MOA(iter) = \text{Min} + iterx\left(\frac{\text{Max} - \text{Min}}{\text{Max}_{iter}}\right) \tag{1}$$

In Eq. (1), $iter$ and Max_{iter} correspondingly represent the existing and the maximum iterations, and the minimal and maximal values of accelerated functions are defined using Min and Max correspondingly.

Exploration stage: In the original AOA, using the math operator, the position is updated toward the optimal area. The division (D) and the multiplication (M) are the two fundamental strategies of the exploration stage. The study aims to find the optimum solution. Using the following equation, the location is updated in the exploration phase:

$$x_{i,j}(iter+1)s = \begin{cases} best(x_j) \div (MOP+\epsilon)x\left((ub_j - lb_j)x\mu + lb_j\right) \\ \quad r2 > 0.5(a) \\ best(x_j)x(MOP+\epsilon)x\left((ub_j - lb_j)x\mu + lb_j\right) \\ \quad otherwise(b) \end{cases} \tag{2}$$

In Eq. (2), $x_{i,j}(iter+1)$ represents the j^{th} location of the i^{th} solution at the existing location, and $best(X)$ represents the better solution at the j^{th} location. The probability math optimizer and the control parameter are defined as MOP and u correspondingly. Using the following equation, the MOP function can be defined:

$$MOP(iter) = 1 - \left(\frac{iter^{\frac{1}{\propto}}}{\text{Max}\_iter^{\frac{1}{\propto}}}\right) \tag{3}$$

Exploitation stage: The subtraction (S) and the addition (A) are the two main operators used in the exploitation stage. The study aims to attain optimal and high-dense solutions:

$$x_{i,j}(iter+1) = \begin{cases} best(x_j) - (MOP+\epsilon)x\left((ub_j - lb_j)x\mu + lb_j\right), r3 > 0.5 \\ best(x_j) + (MOP+\epsilon)x\left((ub_j - lb_j)x\mu\ lb_j\right), \quad otherwise \end{cases} \tag{4}$$

The FF of the AOA adopts the accuracy of classifier and the amount of nominated factors. It enhances the accuracy of classifier and mitigates the set dimension of the feature elected. So, the next FF has been applied to estimate individual performances, as expressed in Eq. (5).

$$Fitness = \alpha * ErrorRate + (1-\alpha) * \frac{\#SF}{\#All\_F} \tag{5}$$

Whereas $ErrorRate$ portrays the error of classifier deploying the selected factors. $ErrorRate$ is calculated as the percentage of unsuitable classifier to the classifier amount made, depicted as a value between [0, 1]. $\#SF$ represents the amount of elected features and $\#All\_F$ suggests the complete count of elements in the novel dataset. α is used for altering the effect of sub-set length and the excellence of the classifier.

C. Sleep Quality Prediction by employing ConvLSTM

To recognize the sleep quality, the ConvLSTM model is applied. ConvLSTM is an NN structure that combines a non-linear CNN and LSTM to process information with spatial-temporal data [20], for instance, time series signals or video analysis. Replace the memory unit of LSTM with external operation is the fundamental concept, using the advantages of CNN while processing spatial information like videos and images. Its structure contains an LSTM, outer, and output layers. All the units from the LSTM layer have memory unit, forget, input, and output gates, which control the data that needs to be memorized, forgotten, and outputted to procedure the time sequence data. Lastly, the resultant layer transforms the LSTM output layer into the preferred method. The ConvLSTM is mathematically modelled as:

$$i_t = \sigma(W_{xi} * X_t + W_{hi} * H_{t-1} + W_{ci} o C_{t-1} + b_i) \tag{6}$$

$$f_t = \sigma\left(W_{xf} * X_t + W_{hf} * H_{t-1} + W_{cf} o C_{t-1} + b_f\right) \tag{7}$$

$$C_t = f_t o C_{t-1} + i_t o \tanh(W_{xc} * X_t + W_{hc} * H_{t-1} + b_c) \tag{8}$$

$$O_t = \sigma(W_{xo} * X_t + W_{ho} * H_{t-1} + W_{co} o C_t + b_0) \tag{9}$$

$$H_t = o_t \, o \tanh(C_t) \tag{10}$$

Where i_t, f_t, and 0_t signify the input, forget, and output gates, correspondingly; X_t, H_{t-1}, and C_{t-1} characterize the input of existing cell, output, and layer of the latter cell, correspondingly; b and W signify the bias and Conv kernel, respectively; and σ denotes the function that considers the shape of s.

D. Hyperparameter Tuning utilizing HGSO Algorithm

In the ASQR-HGSODL model, the HGSO model can do the tuning process of the ConvLSTM approach. For some organisms, neuroscientists usually approve that hungriness is an energy, which creates living circumstances more permanent, exceed, and stimulate competition-driven states [21]. Thus, Hunger Games Search has been planned depending on the hunger-connected behaviors of organisms. The model of hunger can be utilized for establishing adaptive weights and outcomes of hunger can be executed for all the steps of a searching method for achieving effectual search.

The animal behavior approaching food is defined as (11).

$$X(t+1) = \begin{cases} X(t) \cdot \left(1 + randn(1)\right), r_1 < l \\ W_1 \cdot X_b + R \cdot W_2 \cdot |X_b - X(t)|, r_1 > l, r_2 > E \\ W_1 \cdot X_b - R \cdot W_2 \cdot |X_b - X(T)|, r_1 > l, r_2 < E \end{cases} \tag{11}$$

Whereas, $X(t+1)$ implies the upgraded performance in $(t+1)^{th}$ iteration. $randn(1)$ denotes to the randomly generated number following the standard normal distribution. t defines iteration counts. r_1 and r_2 represent both random numbers in [0, 1] range. $X(t)$ implies the existing solution in t^{th} iteration. W_1 and W_2 imply the weight of hunger. X_b stands for the global optimum performance. l denotes the fixed-valued parameter. R and E implies the distance and variance control parameter. The mathematical calculation of E is measured in Eq. (12):

$$E = sech(|F(i) - BF|) \tag{12}$$

In which, $F(i)$ denotes the fitness of existing performance. BF implies the fitness of optimum performance. $sech$ represents the hyperbolic secant function measured as $sech(y) = \frac{2}{e^y + e^{-y}}$.

R is estimated as Eqs. (13) and (14).

$$R = 2 \times a \times rand - a \tag{13}$$

$$a = 2 \times \left(1 - \frac{t}{\mathrm{Max}_{iter}}\right) \tag{14}$$

At this point, $rand$ denotes an arbitrary integer in [0, 1] and Max_{iter} denotes the maximal iteration counts.

$|X_b - X(T)|$ represents the range of actions. W_1 and W_2 denote the hunger weights estimated as Eqs. (15) and (16).

$$W_1(i) = \begin{cases} hungry(i) \cdot \dfrac{N}{SHungry} \times r_4, if r_3 < l \\ 1, if \ r_3 > l \end{cases} \tag{15}$$

$$W_2(i) = (1 - exp(-|hungry(i) - SHungry|)) \times r_5 \times 2 \tag{16}$$

In Eqs. (13) and (14), $hungry$ denotes the hunger of every subject, N represents the amount of subjects, $SHungry$ implies the sum of hunger feelings of every individual and $r_3, r_4, and\ r_5$ denote the random integers in [0, 1] range. The equation for $hungry(i)$ is as Eq. (17):

$$hungry(i) = \begin{cases} 0, AllFitness(i) == BF \\ hungry(i) + H, AllFitness(i)! = BF \end{cases} \tag{17}$$

If the fitness of individuals is better, it cannot assumed that hungry, and their value of hunger is 0. Or else, a novel value of hunger is along with the existing hunger value. The value of H is measured as Eqs. (18) and (19).

$$TH = \frac{F(i) - BF}{WF - BF} \times r_6 \times 2 \times (UB - LB) \tag{18}$$

$$H = \begin{cases} LH \times (1 + r), & if\ TH < LH \\ TH, & if\ TH \geq LH \end{cases} \tag{19}$$

BF denotes the best fitness acquired in the existing iteration and WF stands for the worst fitness achieved in the existing iterations. $WF - BF$ implies the entire individual's hunting size under this iteration. $F(i)$ stands for the fitness value (FV) of all individuals. UB and LB exemplify the upper and lower limits of searching spaces. LH denotes a lower bound to limit the hunger sensation H. r_6 refers to the arbitrary integer in [0, 1] range.

There is no certain upgrade approach for HSG that elects the worst and best parameters based on FV, upgrades the next-generation parameters, followed by directly creates a novel population for replacing the novel population.

In Eqs. (20) and (21) compute the hunger of all the positions and variation control of every position.

$$c = (Allfitness(i) - D\_fitness)/(W\_fitness - D\_fitness) * rand * 2 * (ub - lb) \tag{20}$$

$$VC1 = \left(abs(Allfitness(i) - D\_fitness)\right) \tag{21}$$

In Eqs. (20) and (21), $D\_fitness$ denotes the finest fitness and $W\_fitness$ exemplifies the worse fitness. $rand$ stands for the arbitrary number from the range between 0 and 1.

In the searching model, any one is applied for completing the global as well as local searches, correspondingly.

Algorithm1: HGSO Pseudocode
Initialized the parameters N, Max$_iter$, $l, D, SHungry$
Initialized the Individual positions $X_i (i = 1,2, \ldots, N)$
Determine the optimum individual X_b
While ($r \leq$ Max$_iter$)
Compute the fitness of every Individual.
Upgrade BF, WF, X_b, BI
Estimate the Hungry by Eq. (17)
Evaluate the W_1 by Eq. (15)
Determine the W_2 by Eq. (16)
For each individual
Analyze E by Eq. (12)
Upgrade R by Eq. (13)
Upgrade positions by Eq. (11)
End For
$r = r + 1$
End While
Return BF, X_b

The fitness optimum is a crucial factor of HGSO model. An encoded accomplishment is exploited to progress the best solution for candidate results. Currently, the value of accuracy is a primary state utilized in FF.

$$Fitness = \max(P) \tag{22}$$

$$P = \frac{TP}{TP + FP} \tag{23}$$

Where FP and TP signifies the values of false and true positive.

4. Results and Discussion

In this study, the sleep quality prediction results of the ASQR-HGSODL approach are verified on the Kaggle database [22], containing 400 samples with 4 class labels as portrayed in Table 1. The original database contains the values of sleep quality in 0–100% range. In this case, it can be separated the database into 4 classes depending on the level of sleep quality.

Table 1: Dataset Specification

Classes	No. of Instances
Insufficient (0-40)	100
Mild (41-60)	100
Moderate (61-80)	100
Sufficient (81-100)	100
Total No. of Instances	400

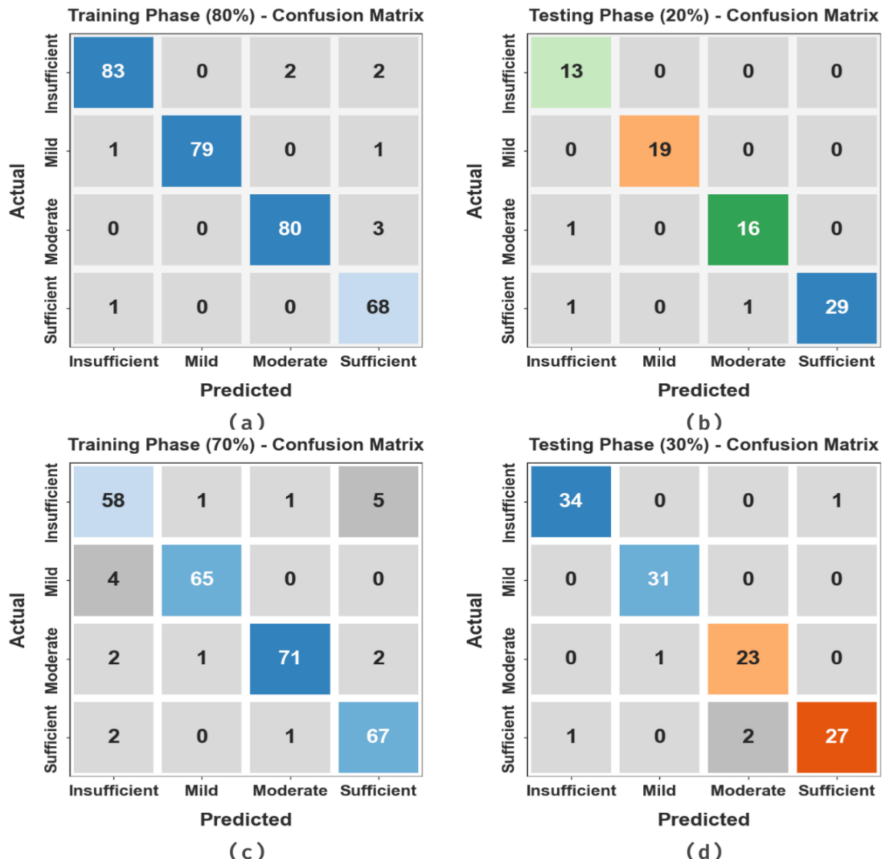

Figure 3. Confusion matrices of TR/TS set (a-b) 80:20 (c-d) 70:30

Figure 3 reveals the confusion matrices created by the ASQR-HGSODL approach of the TR/TS set under diverse measures. The outputs signified effectual detection and categorization of the overall classes.

In Table 2 and Figure 4, the sleep quality prediction output of the ASQR-HGSODL approach is demonstrated under 80:20 set. The result indicates the effectual enhancement of the ASQR-HGSODL approach under overall classes. On the 80% TR set, the ASQR-HGSODL approach obtains average $accu_y$, $prec_n$, $reca_l$, F_{score}, and $G_{measure}$ of 98.44%, 96.77%, 96.97%, 96.83%, and 96.85% respectively. Additionally, on the 20% TS set, the ASQR-HGSODL methodology gains average $accu_y$, $prec_n$, $reca_l$, F_{score}, and $G_{measure}$ of 98.13%, 95.20%, 96.92%, 95.91%, and 95.98% correspondingly.

Table 2: Sleep quality prediction outcome of ASQR-HGSODL approach on 80:20 of TR/TS set

Class	$Accu_y$	$Prec_n$	$Reca_l$	F_{Score}	$G_{Measure}$
TR set (80%)					
Insufficient	98.12	97.65	95.40	96.51	96.52
Mild	99.38	100.00	97.53	98.75	98.76
Moderate	98.44	97.56	96.39	96.97	96.97
Sufficient	97.81	91.89	98.55	95.10	95.16
Average	98.44	96.77	96.97	96.83	96.85
TS set (20%)					
Insufficient	97.50	86.67	100.00	92.86	93.09
Mild	100.00	100.00	100.00	100.00	100.00
Moderate	97.50	94.12	94.12	94.12	94.12
Sufficient	97.50	100.00	93.55	96.67	96.72
Average	98.13	95.20	96.92	95.91	95.98

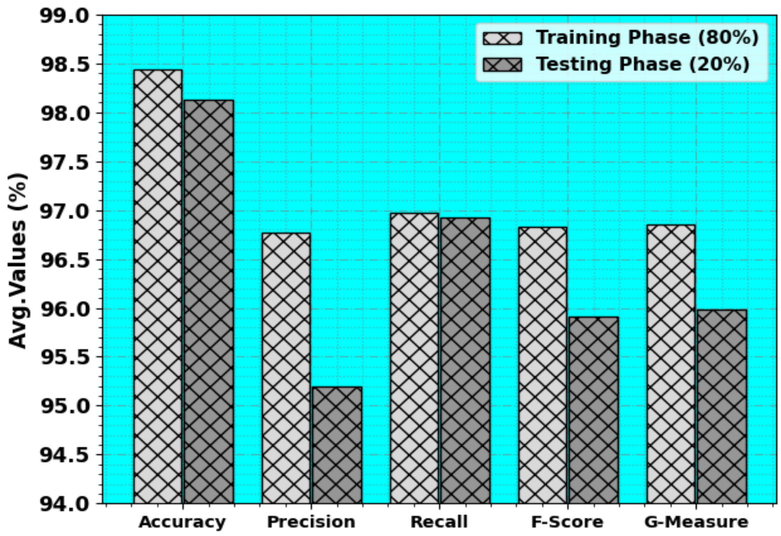

Figure 4. Average of ASQR-HGSODL approach on 80:20 of TR/TS set

In Table 3 and Figure 5, the sleep quality prediction output of the ASQR-HGSODL methodology is portrayed under 70:30 set. The outputs indicate the effectual enhancement of the ASQR-HGSODL method with 4 classes. Under the 70% TR set, the ASQR-HGSODL method obtains average $accu_y$, $prec_n$, $reca_l$, F_{score}, and $G_{measure}$ of 96.61%, 93.17%, 93.14%, 93.12%, and 93.14% subsequently. Additionally, on 30% TS set, the ASQR-HGSODL method achieves average $accu_y$, $prec_n$, $reca_l$, F_{score}, and $G_{measure}$ of 97.92%, 95.61%, 95.74%, 95.63%, and 95.66% correspondingly.

Table 3: Sleep quality prediction outcome of ASQR-HGSODL approach on 70:30 of TR/TS set

Class	$Accu_y$	$Prec_n$	$Reca_l$	F_{Score}	$G_{Measure}$
TR set (70%)					
Insufficient	94.64	87.88	89.23	88.55	88.55
Mild	97.86	97.01	94.20	95.59	95.60
Moderate	97.50	97.26	93.42	95.30	95.32
Sufficient	96.43	90.54	95.71	93.06	93.09
Average	96.61	93.17	93.14	93.12	93.14

TS set (30%)					
Insufficient	98.33	97.14	97.14	97.14	97.14
Mild	99.17	96.88	100.00	98.41	98.43
Moderate	97.50	92.00	95.83	93.88	93.90
Sufficient	96.67	96.43	90.00	93.10	93.16
Average	97.92	95.61	95.74	95.63	95.66

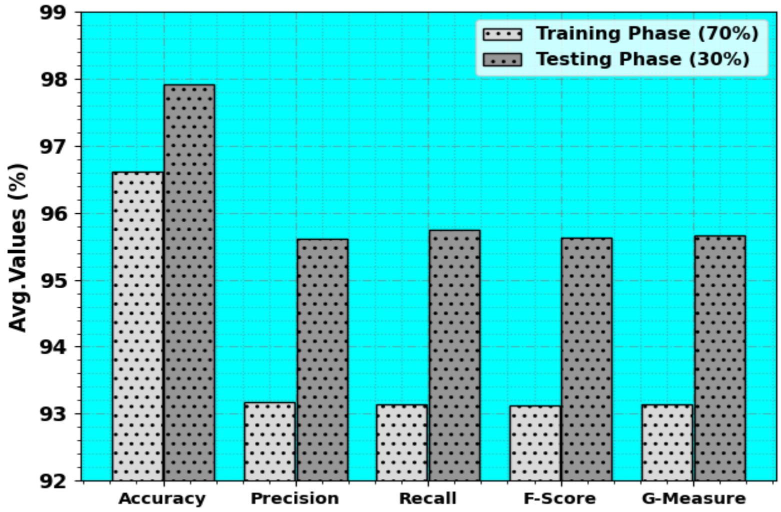

Figure 5. Average of ASQR-HGSODL approach on 70:30 of TR/TS set

To estimate the achievement of the ASQR-HGSODL model under 80:20 of TR/TS set, $accu_y$ curves of TR/TS set are determined, as shown in Figure 6, and depicts the achievement of the ASQR-HGSODL approach over various epochs. The figure portrays the learning task and generalization capabilities of the ASQR-HGSODL approach. As epoch count rises, it is noted that the TR and TS $accu_y$ curves are increased. It is seen that the ASQR-HGSODL approach attained improved testing accuracy that has the capability for recognizing the TR/TS data patterns.

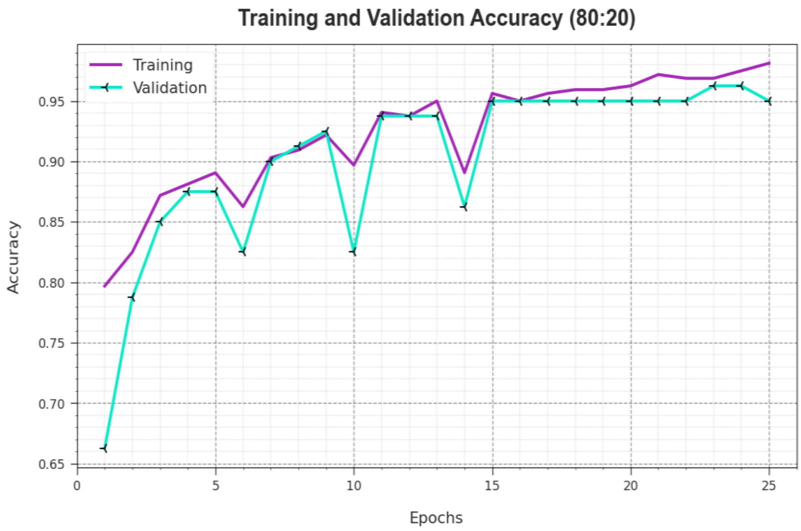

Figure 6. $Accu_y$ Curve of ASQR-HGSODL approach on 80:20 of TR/TS set

Figure 7 exhibits the complete TR/TS values of loss of the ASQR-HGSODL model on 80:20 of the TR/TS set over epochs. The TR loss displays that the loss is diminished over epochs. Primarily, the values of loss get minimal as the technique adapts the weight for mitigating the TR/TS data prediction error. The loss curves portrays the extent in which the model fits the data of training. It is seen that the TR/TS value of loss gradually dropped and signified that the ASQR-HGSODL approach efficiently learned the patterns depicted in the TR/TS data. It is also detected that the ASQR-HGSODL approach alters the parameters for minimizing the divergence among the original and predicted trainings.

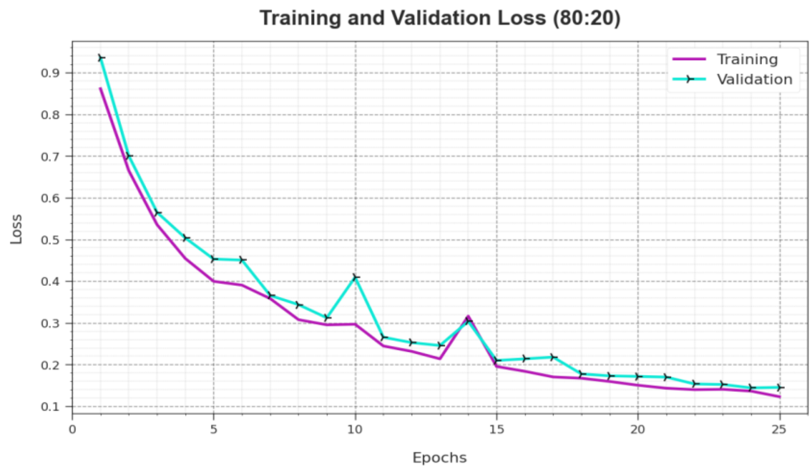

Figure 7. Loss curve of ASQR-HGSODL approach on 80:20 of TR/TS set

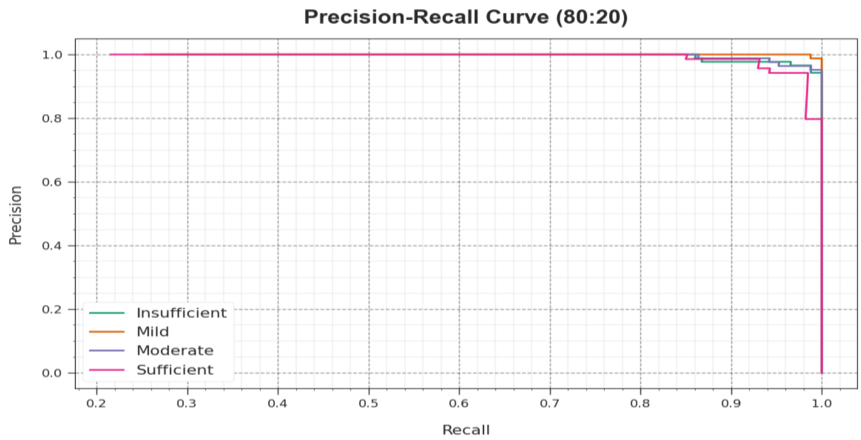

Figure 8. PR curve of ASQR-HGSODL approach on 80:20 of TR/TS set

The PR curve of the ASQR-HGSODL technique on 80:20 of the TR/TS set is portrayed by plotting $Prec_n$ against $Reca_l$ as illustrated in Figure 8. The results confirm that the ASQR-HGSODL technique gets increased PR values under the overall classes. The figure depicts that the technique learned to detect several classes. The ASQR-HGSODL method achieves enhanced outcomes in the positive sample recognition with minimum FP.

The ROC curves depicted by the ASQR-HGSODL approach on 80:20 of the TR/TS set are exemplified in Figure 9 that has the ability for discriminating the classes. The figure points out notable understandings into the trade-off amongst the rates of TPR and FPR over discrete and changing classification thresholds and epoch numbers. It signifies the precise anticipated achievement of the ASQR-HGSODL approach on the distinct class classification.

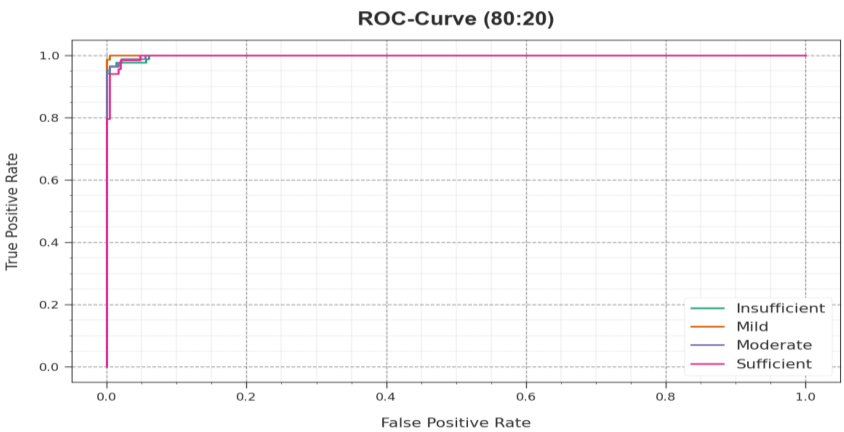

Figure 9. ROC curve of ASQR-HGSODL approach on 80:20 of TR/TS set

A comparative result of the ASQR-HGSODL approach with recent methods in Table 4 and Figure 10 [11]. The outputs inferred that the LSTM approach attains poor performance while the MLP, CNN, and LR algorithms attain somewhat enhanced results. Along with that, the RNN model gains moderate performance. Although the WSHMSQP-ODL model reaches considerable results, the ASQR-HGSODL technique accomplishes higher $accu_y$ of 98.44%, $prec_n$ of 96.77%, $reca_l$ of 96.97%, and F_{score} of 96.83%. Therefore, the ASQR-HGSODL technique can be employed for automated sleep quality prediction.

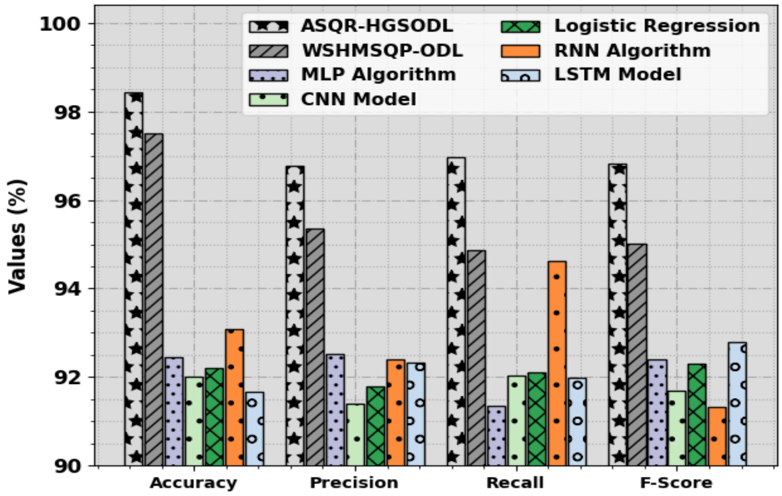

Figure 10. Comparative outcome of ASQR-HGSODL approach with recent methods

Table 4: Relative output of ASQR-HGSODL approach with existing techniques

Techniques	$Accu_y$	$Prec_n$	$Reca_l$	F_{Score}
ASQR-HGSODL	98.44	96.77	96.97	96.83
WSHMSQP-ODL	97.50	95.36	94.87	95.02
MLP	92.46	92.53	91.35	92.40
CNN	92.01	91.39	92.03	91.69
Logistic Regression	92.21	91.79	92.11	92.31
RNN	93.08	92.39	94.61	91.33
LSTM	91.67	92.33	91.99	92.79

5. Conclusion

In this study, a novel ASQR-HGSODL methodology for accurate and automated sleep quality detection in the IoT-assisted smart healthcare system is presented. The ASQR-HGSODL methodology allows the IoT devices to perform a data collection process, which collects the data related to sleep activity. It incorporates several sub processes namely pre-processing, AOA-based feature selection, ConvLSTM-based classification, and HGSO-based tuning process. Here, the ASQR-HGSODL technique applied the AOA to elect a subset of features. For sleep quality prediction, the ASQR-HGSODL technique utilized the ConvLSTM approach. Finally, the HGSO method has been employed for optimum hyperparameter selection of the ConvLSTM method. To exhibit the effectual prediction results of the ASQR-HGSODL approach, a wide range of simulations can be applied. The investigational results highlight the improved outcome of the ASQR-HGSODL approach with other DL methodologies.

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References

[1] Zhang, L., Chen, S., Jin, X. and Wan, J., 2021. Smart Home Based Sleep Disorder Recognition for Ambient Assisted Living. In Artificial Intelligence and Security: 7th International Conference, ICAIS 2021, Dublin, Ireland, July 19–23, 2021, Proceedings, Part II 7 (pp. 466-475). Springer International Publishing.

[2] Rajeswari, S.V.K.R. and Ponnusamy, V., 2022. Internet of Things and Artificial Intelligence in Biomedical Systems. In Artificial Intelligence for Innovative Healthcare Informatics (pp. 153-177). Cham: Springer International Publishing.

[3] Yang, F., Wu, Q., Hu, X., Ye, J., Yang, Y., Rao, H., Ma, R. and Hu, B., 2021. Internet-of-things-enabled data fusion method for sleep healthcare applications. IEEE Internet of Things Journal, 8(21), pp.15892-15905.

[4] Rangasamy, S., Rajamohan, K., Lavan, V.S., Mayur, C. and Lalitha, M.F., 2023. Evolutionized Industry With the Internet of Things. In Handbook of Research on Machine Learning-Enabled IoT for Smart Applications across Industries (pp. 407-434). IGI Global.

[5] Sun, Z., Kadry, S.N. and Krishnamoorthy, S., 2021. Internet of things-assisted advanced dynamic information processing system for physical education system. Technology and Health Care, 29(6), pp.1263-1275.

[6] Anu, V.M., Jagadeesh, M., Gladence, L.M., Srinivasulu, S., Revathy, S. and Rani, V.N., 2022. Tuning Hyper Parameters of Deep Learning Model to Monitor Obstructive Sleep Apnea (OSA). Sleep Epidemiology, 2, p.100031.

[7] Wang, Y., Hu, M., Zhou, Y., Li, Q., Yao, N., Zhai, G., Zhang, X.P. and Yang, X., 2020. Unobtrusive and automatic classification of multiple people’s abnormal respiratory patterns in real time using deep neural network and depth camera. IEEE Internet of Things Journal, 7(9), pp.8559-8571.

[8] Jaworski, D.J., Park, A. and Park, E.J., 2021. Internet of Things for sleep monitoring. IEEE Instrumentation & Measurement Magazine, 24(2), pp.30-36.

[9] Azman, N., Abd Ghani, M.K.B., Wicaksono, S.R., Kurniawan, B. and Repi, V.V.R., 2020. Insomnia analysis based on internet of things using electrocardiography and electromyography. TELKOMNIKA (Telecommunication Computing Electronics and Control), 18(3), pp.1406-1415.

[10] Sahu, K.S., Majowicz, S.E., Dubin, J.A. and Morita, P.P., 2021. NextGen public health surveillance and the internet of things (IoT). Frontiers in Public Health, 9, p.756675.

[11] Hamza, M.A., Abdalla Hashim, A.H., Alsolai, H., Gaddah, A., Othman, M., Yaseen, I., Rizwanullah, M. and Zamani, A.S., 2023. Wearables-Assisted Smart Health Monitoring for Sleep Quality Prediction Using Optimal Deep Learning. Sustainability, 15(2), p.1084.

[12] Yu, B., Wang, Y., Niu, K., Zeng, Y., Gu, T., Wang, L., Guan, C. and Zhang, D., 2021. WiFi-sleep: Sleep stage monitoring using commodity Wi-Fi devices. IEEE internet of things journal, 8(18), pp.13900-13913.

[13] Shen, Q., Yang, X., Zou, L., Wei, K., Wang, C. and Liu, G., 2022. Multitask residual shrinkage convolutional neural network for sleep apnea detection based on wearable bracelet photoplethysmography. IEEE Internet of Things Journal, 9(24), pp.25207-25222.

[14] Han, J., Men, A., Liu, Y., Yao, Z., Zhang, S., Yan, Y. and Chen, Q., 2023. IoT-V2E: an Uncertainty-Aware Cross-Modal Hashing Retrieval between Infrared-Videos and EEGs for Automated Sleep State Analysis. IEEE Internet of Things Journal.

[15] Brik, B., Esseghir, M., Merghem-Boulahia, L. and Snoussi, H., 2021. An IoT-based deep learning approach to analyse indoor thermal comfort of disabled people. Building and Environment, 203, p.108056.

[16] Nijaguna, G.S., Kumar, S., Devika, S.V., Lal, B. and Kumar, P., 2023, February. Internet of Things Based Tired Detection using Deep Learning Techniques. In 2023 IEEE International Conference on Integrated Circuits and Communication Systems (ICICACS) (pp. 1-7). IEEE.

[17] Liu, M., Lin, Z., Xiao, P. and Xiang, W., 2022. Human biometric signals monitoring based on wifi channel state information using deep learning. arXiv preprint arXiv:2203.03980.

[18] Arora, A., Chakraborty, P., Bhatia, M.P.S. and Kumar, A., 2023. Deep-SQA: A deep learning model using motor activity data for objective sleep quality assessment assisting digital wellness in healthcare 5.0. Expert Systems, p.e13321.

[19] Ghith, E.S. and Tolba, F.A.A., 2023. Tuning PID Controllers Based on Hybrid Arithmetic Optimization Algorithm and Artificial Gorilla Troop Optimization for Micro-Robotics Systems. IEEE access, 11, pp.27138-27154.

[20] Jia, F., Tan, J., Lu, X. and Qian, J., 2023. Radar Timing Range–Doppler Spectral Target Detection Based on Attention ConvLSTM in Traffic Scenes. Remote Sensing, 15(17), p.4150.

[21] Zhan, B. and Gu, W., 2023. A Multi-Stage Adaptive Sequential Parameter Exploration Hunger Games Search Algorithm for solving complex optimization problems. IEEE Access.

[22] https://www.kaggle.com/code/jumpingmandt/sleepdata-study/data.