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Original article

The prediction of sleep quality using wearable-assisted smart health monitoring systems based on statistical data

Abu Sarwar Zamani [a,b,*], Aisha Hassan Abdalla Hashim [a], Md. Mobin Akhtar [c], Faizan Samdani [d], Ahmad Talha Siddiqui [e], Adel Alluhayb [f], Manar Ahmed Hamza [b], Naved Ahmad [g]

[a] Department of Electrical and Computer Engineering, International Islamic University Malaysia, Kuala Lumpur 53100, Malaysia
[b] Department of Computer and Self Development, Preparatory Year Deanship, Prince Sattam bin Abdulaziz University, AlKharj, Saudi Arabia
[c] Department of Basic Sciences, Riyadh Elm University (REU), Riyadh, Saudi Arabia
[d] Department of Computer Engineering, Asia Pacific University, Bukit Jalil, Kuala Lumpur, Malaysia
[e] Department of CS & IT, Maulana Azad National Urdu University, India
[f] IT & Computer Science Department, College of Science and Humanities, Al Quwaiiyah, Shaqra University, Saudi Arabia
[g] College of Applied Sciences, AlMaarefa University, P.O.Box 71666, Riyadh 13713, Saudi Arabia

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ABSTRACT

The technology, which plays a significant role in our lives, has made it possible for many of the appliances and gadgets we use on a daily basis to be monitored and controlled remotely. Health and fitness data is collected by wearable devices attached to patients' bodies. A number of parties could benefit from this technology, including doctors, insurers, and health providers. This technology, including smartwatches, smart ring, smart cloth wristbands, and GPS shoes, is frequently used for fitness and wellness since it allows users to track their day-to-day health. Devices that compute the sleep characteristics by storing sleep movements fall within the category of wearables worn on the wrist. In order to lead a healthy lifestyle, sleep is crucial. Inadequate sleep can harm one's physical, mental, and emotional well-being and increase the risk of developing a number of ailments, including stress, heart disease, high blood pressure, insulin resistance, and other conditions. Deep learning (DL) models have recently been used to forecast sleep-quality based on wearables information from the awake hours. Deep learning has been demonstrated to be capable of predicting sleep efficiency based on wearable data obtained during awake periods. In this regard, this study creates a novel deep learning model for wearables-enabled smart health monitoring system (DLM-WESHMS) for the prediction of sleep quality. The wearables are initially able to collect data linked to sleep-activity using the described DLM-WESHMS approach. The data is then put through pre-processing to create a standard format. Using the DLM-WESHMS, sleep quality is predicted using the deep belief network (DBN) model. The DBN model uses the auto-encoders algorithm (AEA) to predict popularity, which improves the accuracy of its predictions of sleep quality. The experimental outcomes of the DLM-WESHMS approach are investigated using several metrics. The DLM-WESHMS model performs significantly better than other models, according to a thorough comparison analysis.

1. Introduction

Sleep performs a crucial function in helping the frame to relaxation, regenerate, and repair power for correct performance of the organs, specially the mind. Human sleep and wake cycles are controlled by biological clocks in the brain, which maintain a balance between sleep and wakefulness (Pardamean et al., 2022). Higher sleep will become an important a part of a healthful individual and helps in enhancing all body capabilities and intellectual states. It is possible to suffer from a wide range of fitness complications if you do not get enough sleep (Strine and Chapman, 2005, Colten and Altevogt, 2006), including insulin resistance (Knutson et al., 2006; Nilsson et al., 2004), high blood pressure (Palagini et al., 2013), cardiovascular complications (Kasasbeh et al., 2006; Meier-Ewert et al., 2004, compromised immune or metabolic system (Cohen et al., 2009; Opp and Toth, 2003) temper problems (Peterman et al., 2015; Murphy and Peterson, 2015), and decreased

* Corresponding author.
E-mail address: a.zamani@psau.edu.sa (A.S. Zamani).
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ability to reminisce and. Among many factors that indicate sleep quality, sleep performance is one of the most important. It is a measure of how much sleep you get, how long it takes to fall asleep, and how long you are asleep even when you are woken up. The performance of sleep may be adversely affected by poor sleep quality, which is linked to conditions such as diabetes and obesity. Adolescent health has also been associated with sleep patterns (Arora and Taheri, 2015; Paruthi et al., 2016). Physical pastime can directly affect sleep quality and performance, according to the latest systematic critiques (Kredlow et al., 2015; Chennaoui et al, 2015). There is a strong and complex correlation between bodily activities and sleep, even though it can't be fully understood. As a result, there is a greater prevalence of lifestyle diseases including type 2 diabetes mellitus and obesity (Kredlow et al., 2015; Chennaoui et al., 2015). Sleep and bodily activities are associated with different mechanisms, but the exact explanation is still unknown. The negative consequences of sleep deprivation are significantly more severe when there is a poor quality of sleep or when decreased sleeping hours occur on a daily basis, rather than as a one-time occurrence (Phan et al., 2020). The polysomnogram (PSG) is the gold standard for sleep size, requiring a sleep technician, sleep lab, and examination of numerous physiological variables. As a result, polysomnography has become typically restricted to the evaluation of sleep across numerous nights (Sadeghi et al., 2019). In addition to people who suspect they have sleep problems, longitudinal sleep measurements, particularly those that are ambulatory and longitudinal, may also help employees who are at high risk (such as transportation workers) as well as healthy individuals who want to perform better and stay fit through better sleep (Shen et al., 2022). It is estimated that 30% of the population experiences sleep disturbances, according to the National Institutes of Health (NIH). 10% of persons with a diagnosis of insomnia experience both sleep disturbance and daytime problem (Ramachandran and Karuppiah, 2021). Sleep deprivation contributes to depression, obesity, insomnia, diabetes, hypertension, acute myocardial infarction, and atherosclerosis, as well as depression and obesity. It is also possible that physical activity can have health-related benefits (nicely-being, effectiveness, and a better quality of sleep) (Palotti et al., 2019). Exercise regimens are a beneficial function for people who do not get enough or enough sleep. Physical sports are thought to be a non-pharmacological treatment for insomnia that is easily accessible. However, the most useful confined research were conducted on how physical exercise improves sleep quality, from both an evaluation and a prediction standpoint. (Akhtar et al., 2022; Liang and Chapa-Martell, 2021). Many studies have recently become available establishing sleep excellent as a crucial component for sleep satisfying assessment using various technologies (Gashi et al., 2022). Studies are being undertaken to determine whether sleep health and environmental characteristics like pollution, mental health, and physical fitness are associated, or whether forecasting sleep quality is possible. Data acquired from wearable devices is currently being used in a number of deep learning algorithms to anticipate sleep quality (Sadeghi et al., 2020). The study analyzed wakeful interval wearable records to predict good sleep or unfavorable sleep performance using six neural networks. Furthermore, this paper indicates the utility of DL in anticipating the quality of sleep. The assessment conclusions of the study methodologies include effective applications in e-health solutions for sleep, particularly with CNN achieving the best results (Bahrami and Forouzanfar, 2022), as well as using wearable devices to extract projections.

For a wearables-enabled smart health monitoring system (DLM-WESHMS) model, this study creates a brand-new, innovative deep learning model. The wearables can initially collect data linked to sleep-activity using the DLM-WESHMS technique that is being demonstrated. To format the data uniformly, data pre-processing is then carried out. The DLM-WESHMS model predicts sleep quality using a deep belief network (DBN) model. The DBN model uses the auto-encoders algorithm (AEA) to forecast popularity, which boosts the precision of its predictions of sleep quality. This improves the performance of the DBN model's sleep quality prediction capabilities (Hamza et al., 2023). Several metrics are used to analyze the experimental results of the DLM-WESHMS technique. The following are, in brief, the paper's main contributions:

- AEA algorithm is combined with pre-processing, sleep quality prediction based on DBN, and an intelligent DLM-WESHMS technique. DBN-based sleep quality prediction, and an AEA algorithm are all components of an intelligent DLM-WESHMS technique that is given. As far as we are aware, the DLM-WESHMS model has never been discussed in the literature;
- Autoencoders are designed to take in data and turn it into a different representation. Autoencoders are utilized in a variety of applications, including pharmaceutical discovery, popularity prediction, and image processing.
- DLM-WESHMS model predicts unobserved data more accurately when cross-validated and optimized using the AEA algorithm.

2. Related work

By utilizing DL techniques, (Arora et al., 2020, 2022) goal is to forecast sleep quality from wearable sensors. Three sleep markers were modeled so they could be calculated using the information automatically gathered via wearable technology. These sleep markers include sleep regularity, daily and weekly sleep quality. The developed metrics led to the use of DL approaches such as the multilayer perceptron (MLP) and CNN to forecast sleep quality. A reasonably priced wearable multisensor device to gather the subject's cardiorespiratory signal. Throughout the feature extraction procedure, three additional features were created. Following that, to forecast the four sleep classes, the authors developed a bidirectional RNN structure that uses LSTM (BLSTM). A novel method for identifying apnea (stop in breathing) from ECG data obtained by wearable technology is presented by (John et al., 2021). (Hidayat et al., 2018). To better utilize these data, a simple K-NN technique is implemented for pre-processing data and machine learning methods to project changes in sleep quality according to the amount of physical activity he or she is performing. This methodology faces a problem in predicting variations in five clinically recognized indicators of sleep quality using information generated by current consumer-grade wrist wearable technology. (Khoa et al.,2022; Paricherla et al., 2022) used multi-modal data from wearables and federated multiple CNNs (FedMCRNNs) to predict sleep quality in their study. The efficiency of FedMCRNN in many-to-many and many-to-one scenarios is calculated by the authors using a number of measures, and they compare it to traditional ML methods. By applying adaptive neuro-fuzzy inference systems (Arora et al., 2022) Research focusing on how smartphones and wearables (ANFISs) can be used to assess sleep quality and health. A user's smartwatch can collect real-time sleep data and physical activity information. For the purpose of gathering data about smartphone usage in real-time, a smartphone application can be created. A sleep quality indicator (SleepQual) is used to estimate daily sleep quality using sleep attributes obtained from smartwatches. Using Pearson's correlation, the link between smartphone usage and physical activity and SleepQual was evaluated. Deep-ACTINet is a wrist actigraphy-based end-to-end DL structure introduced by (Cho et al., 2019) In order to automate the detection of sleep-wake activity, the raw activity signals recorded during sleep must be noise-canceled and do not involve any feature engineering. Four feature-engineering-related ML strategies and two conventional fixed sleep-wake score approaches were compared to the modelled Deep-ACTINet. Although ML and DL algorithms for predicting sleep quality are available, it is still necessary to improve the predictive outputs. The number of DL model parameters rises as a result of the constant deepening of DL models, leading to model overfitting. The effectiveness of the CNN model is simultaneously significantly impacted by a variety of hyperparameters. It is highly recommended to take hyperparameters like batch size, epoch count, and learning rate selection into consideration when determining a top-notch result. Due to hyperparameter tuning's time-consuming and inaccurate nature, metaheuristic algorithms can replace trial and error (Al Duhayyim et al., 2022). Consequently, in this study, we use the AEA algorithm to choose the DBN model's parameters.

3. Proposed model

For evaluating sleep quality in a connected healthcare setting, this study developed a novel DLM-WESHMS algorithm. The wearables are initially able to collect data linked to sleep-activity using the described DLM-WESHMS approach. The data is then put through pre-processing to create a standard format. Additionally, the DLM-WESHMS technique uses the AEA algorithm and DBN model to predict sleep quality. The general operating process of the DLM-WESHMS system is depicted in Fig. 1. Here you can see how the suggested model is fed training data as input. A pre-processing step is performed on the data before it can be used for prediction using this model. The suggested model then uses the DBN model to forecast the quality of the sleep, and the AEG algorithm can select the hyperparameters of this model in the best way possible.

3.1. Data pre processing

The DLM-WESHMS approach employs data pre-processing at the preliminary stage. Smartwatch data did not disclose sleep onset latency (the time necessary to stop sleeping after coming to bed). This measure includes the sleep onset delay and includes all the minutes spent waking up. Therefore, half of the waking time indicates a sleep start delay in this study. It makes sense to expect a sleep onset latency of 20 min if a watch records a waking time of 40 min.

3.2. DBN prediction of sleep quality

In this paper, the Deep Belief Network is used to extract sleep quality features for the purpose of identifying key sleep quality characteristics within a cross-sectional study. The %top level of the model handles pre-processing tasks, and the relevant data is then input into the DBN model. The DBN model utilizes the abstract features learned and obtained from training in the lower layers as input, and predicts sleep quality based on those features. Additionally, the DBN model undergoes a fine-tuning process to optimize its parameters. This fine-tuning step helps in further refining the model's ability to accurately predict sleep quality features.

Using DBN, a learned dataset can be represented in a highly hierarchical fashion using a multi-layer probabilistic generative model. DBN is composed of many RBM layers, with categorization added on the topmost layer (Almanaseer et al., 2021). DBN is swiftly trained by using a greedy layer-wise unsupervised training technique to train multiple RBM. The network parameters are fine-tuned using supervised learning after network pre-training to produce the best classification results. The RBM mechanism attaches only the visible-invisible layer to the hidden-hidden layer, leaving

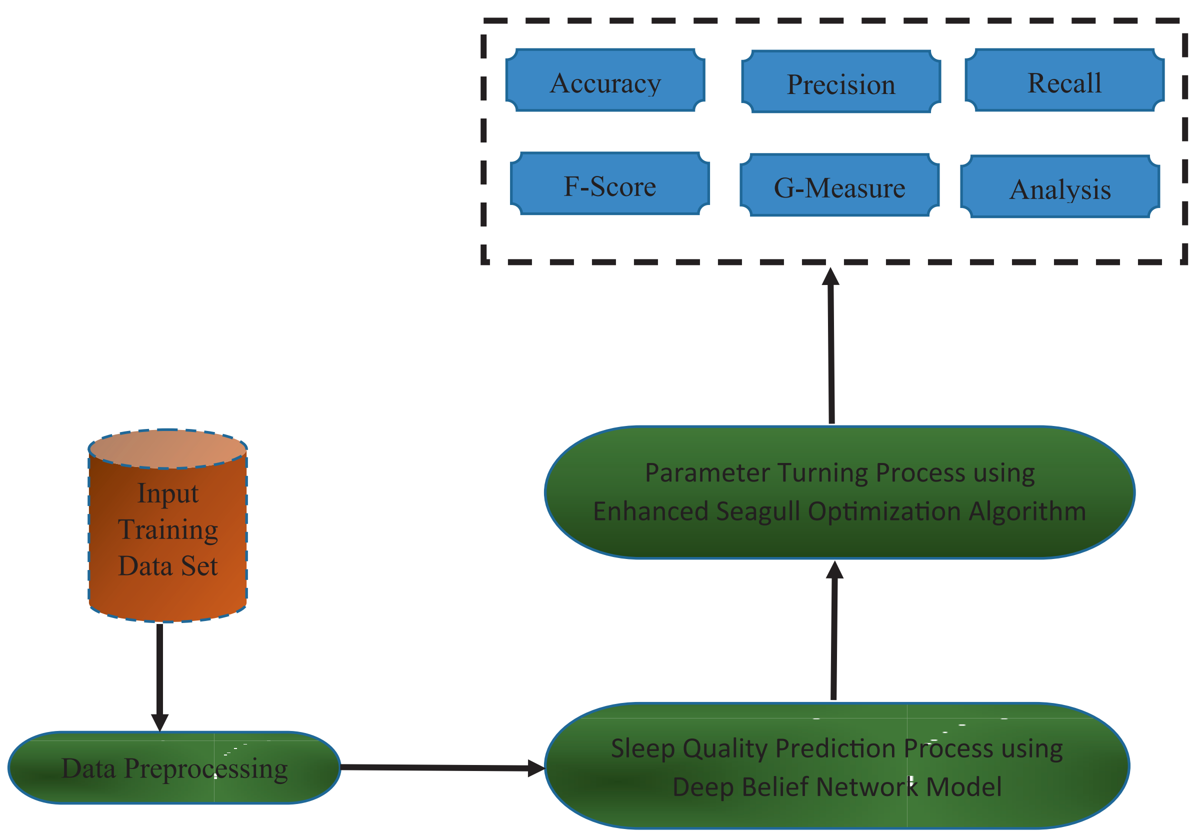


Fig. 1. Overall DLM-WESHMS technique operating procedure.

the visible-hidden layer detached. Topic modeling, collaborative filtering, and feature extraction are the most common applications of RBM. A RBM contains hidden and visible Bernoulli random values, as well as sample datasets that map m-dimensional input spaces into n-dimensional output spaces, where n < m. The RBM is an energy-based generative model that consists of a layer of visible nodes ($v_1, v_2\ldots\ldots v_i\ldots v_m$) that represent the data and a layer of hidden nodes (h_1, h_2, h_j, h_n) that learn to characterize features, with every $v_i \in \{0,1\}$ and $h_j \in\in \{0,1\}$. The bias of the visible node is then determined to be ($b_1, b_2\ldots bi\ldots bm$), whereas the bias of the hidden node is determined to be ($c_1, c_2\ldots cj\ldots cn$). The following expression [41] can be used to define the energy function $E(v, h)$ of a joint configuration (v, h).

$$E(v,h) = -\sum_{i=1}^{m} bjvj - \sum_{j=1}^{n} cjhj - \sum_{j=1}^{n}\sum_{i=1}^{m} vjwijhj \tag{1}$$

Here is an example of how the joint probability distribution for hidden and visible units can be constructed using the energy function (v, h):

$$P(v,h) = \frac{1}{Z}\exp(-E(v,h)) \tag{2}$$

Z represents the partition function that can be summed up across each pair of hidden and visible units in Eq. (2).

$$Z = \sum_{v}\sum_{h}\exp(-E(v,h)) \tag{3}$$

The chance assigned to the v visible unit can be obtained by adding up all possible binary hidden vectors h in the manners described below:

$$P(v) = \sum_{b} p(v,n) = \frac{1}{Z}\sum\nolimits_{h} Exp(-\mathrm{E}(\mathrm{v},\mathrm{h})) \tag{4}$$

The hidden unit (HU) is a visible unit that is independently given, however in an RBM there are no direct connections between similar levels. Based on the assumption that v is the visible unit, the conditional chance of h is as follows:

$$P(h|v) = \prod_{j=1}^{n} P(hj|v) \tag{5}$$

The conditional probability of the v visible unit, assuming the h HU, can be given as follows:

$$P(v|h) = \prod_{i=1}^{m} P(h|v) \tag{6}$$

Under the premise of a v visible vector, each HU's activation state is conditionally independent. We currently define hj E [0,1] and j-th Hus activation probability as follows:

$$P(hj = 1|v = sigm\sum\nolimits_{i=1}^{m} wijvi + cj \tag{7}$$

where $sigm(x) = \frac{1}{1+e^{-x}}$ refers to the logistics sigmoid function. As a result, when the h HU is assumed, the activation Probability of every observable vector might be conditionally independent.

$$P(vi = 1 \mid h = sigm\sum\nolimits_{j=1}^{n} wijvi + bj \tag{8}$$

RBM can be trained to minimize energy in Eq. (1) by calculating the value of Network Parameter = (W, b, c). In Eq. (1), the probability is maximized after the RBM is trained, so the network energy is minimized. Following equations are used to evaluate the gradient of P(v) with respect to network parameters θ:

$$\frac{\partial \log P(v)}{\partial\theta} = -Ep(h|v)\left[\frac{\partial E(v,h)}{\partial\theta}\right] + Ep(v',h')\left[\frac{\partial E(v\prime,h\prime)}{\partial\theta}\right] \tag{9}$$

The expectation operator E is represented in Eq. (1). Calculating the LHS expectation had no problem, but determining the RHS expectation is more challenging. In order to approximate the log-likelihood gradient, the contrastive divergence (CD) method is employed. The CD-k model predicts the expectation in Equation (J) using k (k = 1) iterations of Gibbs sampling to improve the network parameter θ (iV, b,c). The CD is a persistent contrastive divergence (PCD) model, which makes the training process particularly effective. The variable's θ upgrade mechanism is as follows:

$$\frac{\partial logP(v)}{\partial wij} = P(hj = 1|v).vi - \sum_{v'} P(v')P(hj' = 1|v').v'i\prime \tag{10}$$

$$\frac{\partial \log P(v)}{\partial bi} = vi - \sum_{v\prime} P(v').vi\prime \tag{11}$$

$$\frac{\partial \log P(v)}{\partial cj} = P(hj == 1|v) - \sum_{v\prime} P(v\prime)P(h'j = 1|v') \tag{12}$$

It is common for one RBM to be trained first, followed by another RBM. The intricate design of the dataset is reflected in the layers of RBMs that extract various features automatically.

3.3. Process for adjusting parameters

The AEA method is also used by the DLM-WESHMS approach to tune the parameters. The AEA is a SI metaheuristics method that is based on seagull colony behavior (Dhiman and Kumar, 2019), especially the migrating and attacking (hunting) strategies. Initially, during their migration, they attack other birds over the water. They then move in a spiral pattern to assault the victim successfully. There is no doubt that AEA performs the best in global bound-constrained optimization problems. Therefore, take into account that it has been successfully applied to a number of real-world problems. The convergence rate is increased by conducting a more in-depth analysis of the CEC test suite, but the basic AEA still achieves notable results for unrestricted benchmarks. Even if the first AEA was able to identify the ideal search region in each run, a few runs result in an unsatisfactory convergence, which lowers the quality of the final result. The OBL approach was created to alleviate these drawbacks. The previous study showed that intensification and diversification could both be greatly increased using the OBL technique. Following the determination of the best solution, $X_{best,}$ the best alternative solution, X^0_{best} can be generated using the following equation for all the parameters, j:

$$X^0_{best,j} = lj + uj - X_{best,j} \tag{13}$$

The lower and upper bounds of the j-th variable are represented by l_j and u_j in Eq. (13), respectively, and $X^0_{best,j}$ represents the opposite j-th parameter optimum solution. The fitness function states that greedy selection can be applied to both the primary and opposing optimal solutions, and that the better of the two solutions was preserved for the following iteration. The pseudocode for the proposed method, dubbed AEA, is shown in Algorithm 1. Finally, AEA appears to contribute to some of the perceived computational complexity, particularly since additional processing is added to each iteration (Asiri et al., 2022). OBL's greedy selection method selects between $X_{best,j}$ and $X^0_{best,j}$ Or to put it another way, O ((N + (N + 1)) $\mathrm{Max}_{iterations}$), where N stands for individual amount and $\mathrm{Max}_{iterations}$ for iterative amount.

Table 1
Data set Details.

Label 1	Class	Scale (%) –8h	No. of Sample
CLS 1	Insufficient	0–35	100
CLS 2	Mile	35–55	100
CLS 3	Moderate	55–75	100
CLS 4	Sufficient	75–100	100
Total No. Samples			400

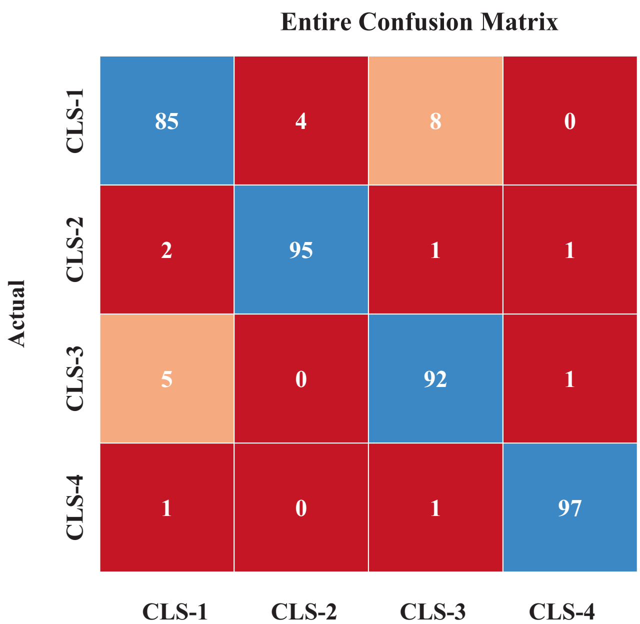


Fig. 2. Shows the DLM-WESHMS system's confusion matrix for the whole database.

Algorithm 1.

Algorithm 1 Pseudocode of AEA

Input: Auto Encoders Population P_{EA}
Output: Optimal Search Agent P_{BS}
Initial Parameters: A, B and $Max_{iteration}$
Consider $fc \leftarrow 2$
Consider $u \leftarrow 1$
Consider $v \leftarrow 1$
While $\times$ < $Max_{iterations}$ do
For i = 1 to n, do
FIT_s [i] $\leftarrow$ Fitness Function (P_s (i,:))
End for
Best = FIT_s [0]
For i = 1 to n do
If FIT_s [i] < Best then
Best FIT_s [i]
End if
End for
  Pbs = Best
  $rd \leftarrow$ Rand (0,1)
  $k \leftarrow$ Rand (0,2)
  $r = U \times e^{kv}$
  $D_s = C_s + M_s$
  P $\leftarrow x' * y' * z'$
  $P_s(x) = (D_s \times P) + P_{bs}(x)$
    $X \leftarrow +1$
Perform OBL technique
Choose X_{best} and X^{0}_{best} through greedy selection
End while
Return P_{bs}

4. Performance validation

This section examines the DLM-WESHMS model's predictions for sleep quality on a dataset of 400 samples, as specified in Table 1.

Entire Data Set						
Labels	**Accuracy**	**Analysis**	**Precision**	**Recall**	**F-Score**	**G-Measure**
CLS 1	93.50	95.62	91.62	85.00	87.87	88.89
CLS 2	95.62	96.75	92.50	95.00	94.54	94.52
CLS 3	94.74	89.39	90.59	92.00	92.62	92.63
CLS 4	98.99	98.00	98.00	98.00	98.00	98.00
Average	**95.71**	**94.94**	**93.17**	**85.00**	**93.26**	**93.51**

Fig. 3. Shows the overall classification of sleep quality using the DLM-WESHMS algorithm for the complete dataset.

With 100 samples per class (CLS), the dataset is divided into four classes. Kaggle repository was used to download the data set (found at https://www.kaggle.com/code/jumpingmandt/sleep-data-study/data (accessed on 15 September 2022)). A sleep quality score ranging from 0 to 100 is included in the original data set, we split the dataset into four classes for our study.

Fig. 2 displays the confusion matrix generated by the DLM-WESHMS approach for the complete dataset. 85 samples are divided into CLS 1, 95 samples into CLS 2, 92 samples into class 3, and 97 samples are divided into CLS 4, according to the DLM-WESHMS method.

Fig. 3 provide detailed results for the DLM-WESHMS method's classification of sleep quality over the full dataset. The simulation results demonstrate that the DLM-WESHMS technique achieves improved classification results across all classes. It is noted that the DLM-WESHMS model achieves an average $Accurac_y$ of 95.71%, $Anal_{ys}$ of 94.94%, $Prec_n$ of 93.17%, $Reca_l$ of 85.00%, F_{score} of 93.26%, and $G_{measure}$ of 93.51%.

Fig. 3 shows the classification results for the full dataset using the DLM-WESHMS system for sleep quality, with several classes.

Fig. 4 displays the confusion matrix that the DLM-WESHMS model produced for 70% of the TR databases. 57 samples are sorted into CLS 1 using the DLM-WESHMS model technique, 63 samples into CLS 2 and 3, and 73 samples into CLS 4.

Fig. 5 show the results of the DLM-WESHMS method's short sleep quality categorization for 70% of the TR database. The DLM-WESHMS methodology's simulation values lead to improved classification outcomes across all classes (CLS). It is noteworthy that the DLM-WESHMS algorithm achieves an average $Accurac_y$ of 96.54%, $Anal_{ys}$ of 95.83, $Prec_n$ of 92.83%, $Reca_l$ of 92.86%, F_{score} of

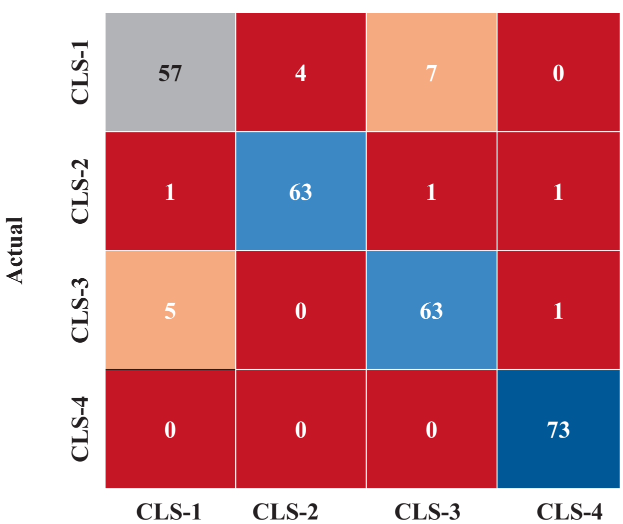


Fig. 4. DLM-WESHMS system for 70% confusion matrix.

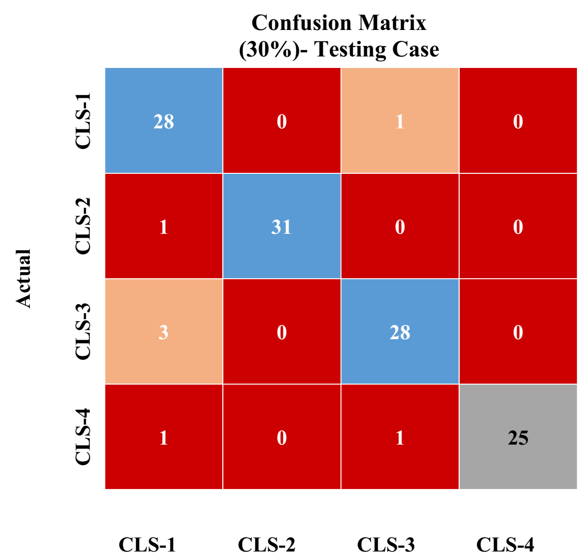


Fig. 6. DLM-WESHMS system confusion matrix for 30% of the TS database.

Training Phase (70%)						
Labels	**Accuracy**	**Analysis**	**Precision**	**Recall**	**F-Score**	**G-Measure**
CLS 1	93.95	94.65	92.05	82.97	87.56	87.86
CLS 2	96.96	95.35	92.85	95.65	93.98	93.39
CLS 3	95.86	94.85	88.98	92.85	90.68	90.69
CLS 4	99.39	98.50	97.47	99.99	98.76	98.78
Average	**96.54**	**95.83**	**92.83**	**92.86**	**92.74**	**92.83**

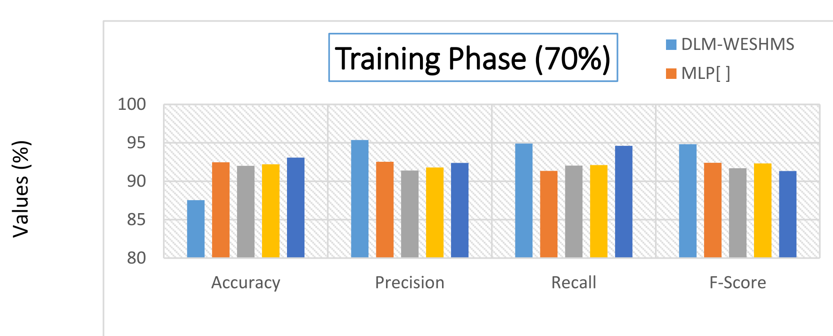


Fig. 5. Shows the results of the DLM-WESHMS system's classification of overall sleep quality for 70% of the TR database.

Table 2
Shows the DLM-WESHMS system's sleep quality classification results for 30% of the TS database with different classes.

Testing Phase (30%)						
Labels	**Accuracy**	**Analysis**	**Precision**	**Recall**	**F-Score**	**G-Measure**
CLS 1	95.81	94.91	87.85	96.76	92.08	92.18
CLS 2	99.18	95.95	100.00	96.95	97.65	97.85
CLS 3	96.85	94.75	93.65	93.55	93.55	93.55
CLS 4	98.35	95.65	100.00	92.41	96.00	96.07
Average	**97.54**	**95.31**	**95.37**	**94.91**	**94.82**	**94.91**

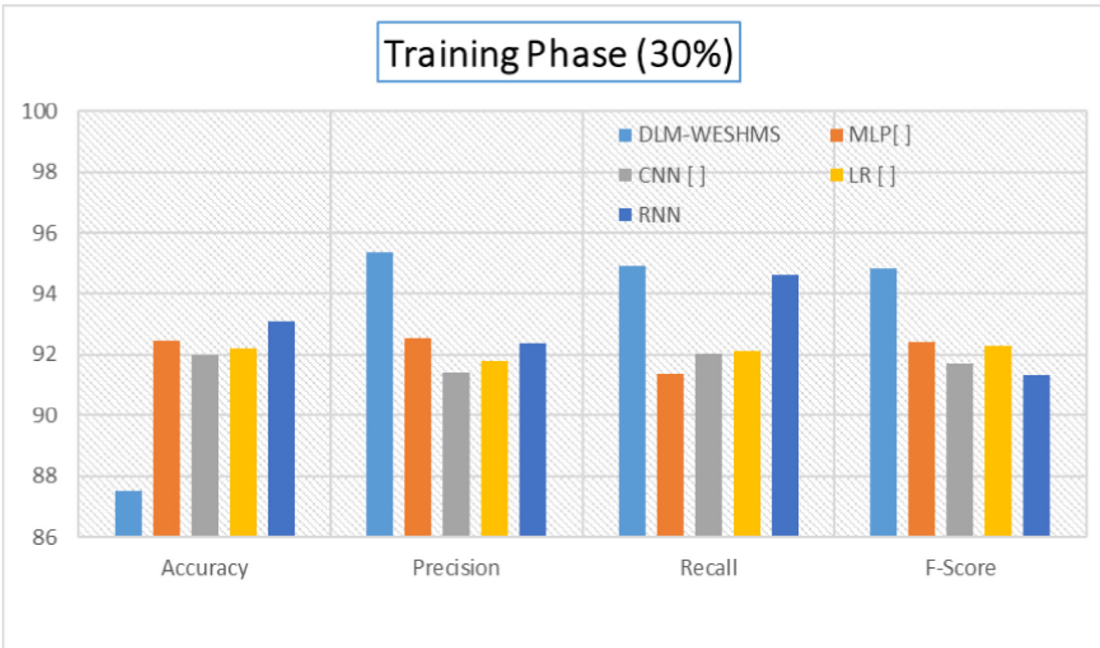
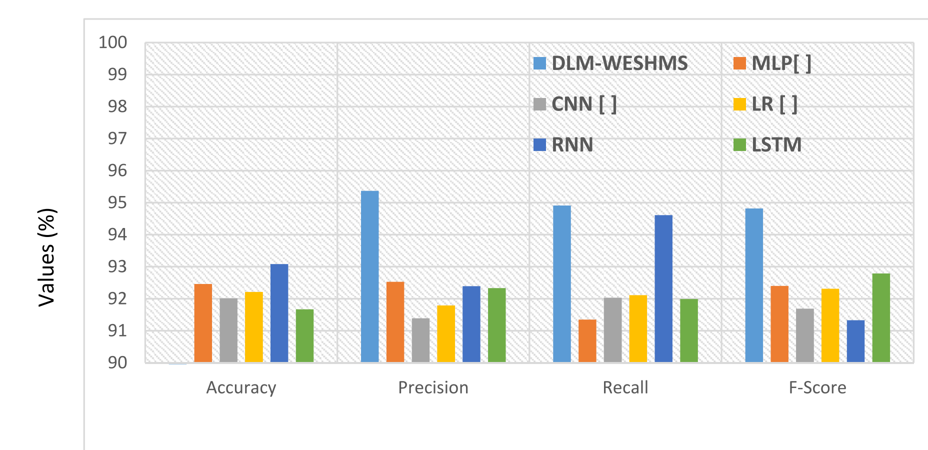


Fig. 7. Shows the overall sleep quality categorization result of the DLM-WESHMS method for 30% of the TS database.



Methods	Accuracy	Precision	Recall	F-Score
DLM-WESHMS	97.54	95.37	94.91	94.82
MLP[33]	92.46	92.53	91.35	92.40
CNN [33]	92.01	91.39	92.03	91.69
LR [43]	92.21	91.79	92.11	92.31
RNN [43]	93.08	92.39	94.61	91.33
LSTM [43]	91.67	92.33	91.99	92.79

Fig. 8. Compared with other existing approaches, the WSHMSQP-ODL system is analyzed (Arora et al., 2020, Sathyanarayana et al., 2016).

92.74%, and $G_{measure}$ of 92.83% as well Fig. 5 shows the results of the DLM-WESHMS system's classification of sleep quality for 70% of the TR database into separate classes.

Based on the DLM-WESHMS approach, a confusion matrix was produced for 30% of the TS database as shown in Fig. 6. The DLM-WESHMS algorithm categorizes 28 samples as CLS 1, 31 samples as CLS 2, 28 samples as CLS 3, and 25 samples as CLS 4. Table 2 and Fig. 7 show the DLM-WESHMS method's comprehensive sleep quality categorization results for 30% of the TS database. DLM-WESHMS achieves improved classification results in all simulated class labels compared to other techniques. The DLM-WESHMS Algorithm achieves an average $Accurac_y$ of 97.54, $Anal_{ys}$ of 95.31, $Prec_n$ of 95.37, $Reca_l$ of 94.91, F_{Score} of 94.82, and $G_{Measure}$ of 94.91.

Finally, Fig. 8 present a comparison analysis of the DLM-WESHMS model on sleep quality categorization (Arora et al., 2020). The simulation results reveal that the LSTM model performs poorly, with the lowest $Accurac_y$ of 91.67%. MLP, CNN, and LR techniques yield slightly closer classification results simultaneously. With a maximum $Accurac_y$ of 97.54%, the DLM-WESHMS model surpasses the other models. These findings support the DLM-WESHMS model's superior sleep quality categorization results when compared to other models.

This Figure shows the DLM-WESHMS system's sleep quality prediction results in comparison to other available techniques.

5. Conclusion

A unique DLM-WESHMS algorithm was proposed, using smart healthcare environments, this study evaluated sleep quality. Data on sleep-activity can initially be collected by wearables with the DLM-WESHMS approach. Following that, to prepare the data for standardization, preprocessing is carried out. Furthermore, the DLM-WESHMS technique predicts sleep quality using the DBN model. Last but not least, high-performance prediction of sleep quality is provided by the AEA algorithm, through which fine-tuning of DBN hyperparameters is achieved. The data -based outcomes of the DLM-WESHMS model are evaluated using various criteria. A comprehensive comparison demonstrates that the DLM-WESHMS model outperforms other models, with a maximum accuracy of 97.54%, Precision of 95.37%, Recall of 94.91% and F-Score of 94.82%. The suggested model's improved performance is attributed to an optimal hyper parameter selection process using the AEA algorithm. Furthermore, incorporating the OBL approach into the regular AEA algorithm helps to improve the AEA algorithm's overall qualities. In the future, feature selection procedures could be used to improve the DLM-WESHMS model's performance.

Declaration of competing interest

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

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