scientific reports

OPEN

Revolutionizing sleep disorder diagnosis: A Multi-Task learning approach optimized with genetic and Q-Learning techniques

Soraya Khanmohmmadi[1], Toktam Khatibi[1]✉, Golnaz Tajeddin[1], Elham Akhondzadeh[1] & Amir Shojaee[2]

Adequate sleep is crucial for maintaining a healthy lifestyle, and its deficiency can lead to various sleep-related disorders. Identifying these disorders early is essential for effective treatment, which traditionally relies on polysomnogram (PSG) tests. However, diagnosing sleep disorders with high accuracy based solely on electroencephalogram (EEG) signals, rather than using various signals in a complex PSG, can reduce the time and cost required, and the need for specialized signal devices, as well as increase accessibility and usability. Previous studies have focused on traditional machine learning (ML) methods such as K-Nearest Neighbors (KNNs), Support Vector Machines (SVMs), and ensemble learning methods for sleep disorders analysis. However, these models require manual methods for feature extraction, and the prediction accuracy greatly depends on the type of feature extracted. Additionally, the EEG signal datasets are small and heterogeneous, challenging traditional machine learning and deep learning models. The study proposes an innovative multi-task learning convolutional neural network with a partially shared structure that uses frequency-time images generated from EEG signals to address these limitations. The proposed technique makes two predictions using non-shared features from time-frequency images created through Short Time Fourier Transform (STFT) and Continuous Wavelet Transform (CWT), one prediction from shared features, and the final prediction is a combination of these three predictions. The weights for this combination were optimized using the genetic algorithm and the Q-learning algorithm, aiming to minimize loss and maximize accuracy. The study utilizes a dataset involving 26 participants to examine the impact of Partial Sleep Deprivation (PSD) on EEG recordings. The outcomes demonstrated that the multi-task learning model using these two optimization methods, attained 98% accuracy on the test data for predicting partial sleep deprivation. This automated diagnostic model is an efficient supporting tool for rapidly and effectively diagnosing sleep disorders. It swiftly and precisely evaluates sleep data, minimizing the time and effort required by the patient and the physician.

Keywords Multi-Task learning, Genetic algorithm, Q-learning algorithm, Electroencephalogram, Sleep disorders

Sleep disorders are common diseases that disrupt the regular sleep-wake cycle, resulting in adverse impacts on both mental and physical well-being[1]. Sleep disorders, insufficient sleep, and poor sleep quality often occur together and can lead to similar negative outcomes. They are affected by different biological factors, individual behaviors, as well as social and economic pressures[2]. Sleep disorders can greatly affect an individual's overall health and quality of life. They can weaken the immune system, impair cognitive function and memory, hinder learning, and disrupt emotional well-being[3]. Studies indicate that sleep deficiency is linked to increased weight gain and obesity, as well as a higher risk of diabetes, dyslipidemia, hypertension, and other cardiovascular and metabolic disorders. Additionally, it affects cognitive function, behavior, and mood[2]. Numerous international studies indicate that approximately 10–30% of the global population experiences sleep disorders, with certain nations reporting figures as high as 60%. Additionally, the prevalence of sleep disorders is nearly 7% greater in women compared to men. Sleep disorders constitute a worldwide epidemic that jeopardizes the living conditions and health of nearly 45% of individuals across the globe[4].

[1]Faculty of Industrial and Systems Engineering, Tarbiat Modares University, Tehran, Iran. [2]Faculty of Medical Science, Tarbiat Modares University, Tehran, Iran. ✉email: toktam.khatibi@modares.ac.ir

Diagnosing sleep disorders early can improve their management and treatment[5]. Polysomnography (PSG) is the most effective method for assessing sleep status[6]. Polysomnography recordings are extensively used in clinics to detect sleep problems, utilizing various signal modalities[7]. It incorporates various physiological signals, including electroencephalogram (EEG), electrooculogram (EOG), electrocardiogram (ECG), and electromyography (EMG)[6]. Scoring based on PSG is a lengthy and laborious process, often revealing significant differences among raters[8]. Recent research has shown a considerable shift towards integrating EEG and EOG modalities for sleep studies. These modalities are the most and second most effective among PSG recordings, respectively[7]. The EEG is a widely used tool for monitoring brain activity and diagnosing sleep disorders[2]. The analysis of EEG signals conducted by physicians during sleep can often be problematic, labor-intensive, and prone to mistakes[9]. Bioengineers and clinicians are currently focusing on utilizing Machine Learning (ML) models to automate the processing of large volumes of electrophysiological data from sleep studies. These ML models, a type of Artificial Intelligence (AI), use algorithms to detect patterns in data, making prediction and classification easier. The increasing advancements in AI have made ML more popular for analyzing sleep studies[10]. Automated systems for detecting sleep disorders can enhance cost efficiency and reduce operator disagreement[5]. Most studies on automatic sleep disorder diagnosis are based on support vector machines and k-nearest neighbors, making them methods that require manual feature extraction, which is a laborious process. In recent years, studies have shifted towards deep learning models.

In this study, we propose an automatic diagnosis of sleep disorders using EEG signals. Due to two main limitations, EEG signals pose challenges that prevent the successful generalization of machine learning and deep learning models. The first limitation is the small sample size in the EEG datasets, while the second limitation is the heterogeneity of EEG signals. These signals can vary over time due to environmental, experimental, and individual physiological or psychological factors[11,12]. These limitations complicate the applicability of models trained on existing cases to new cases[12]. On the other hand, our dataset contains images from two different signal-to-image conversion methods, STFT and CWT. Due to the differences in how these two methods work, the resulting images have varying characteristics. These differences include time and frequency resolution and how signal details are displayed over time. Therefore, it can also be said that our dataset is heterogeneous in terms of this aspect. Due to the small-scale and heterogeneous nature of the datasets, it is not feasible to directly combine them for network training. Consequently, a multi-task learning network can be suitable. Multi-task learning enhances generalization by addressing multiple interconnected tasks simultaneously and utilizing shared information among them. Leveraging related tasks as an inductive bias helps improve the effectiveness of individual tasks[13].

We propose a novel and efficient multi-task learning model that learns from several tasks simultaneously to improve performance for analyzing EEG signals of individuals with Partial Sleep Deprivation (PSD). This model incorporates a sharing structure that enhances performance using features obtained from both datasets, including time-frequency images created through Short Time Fourier Transform (STFT) and Continuous Wavelet Transform (CWT) during training. The primary contributions of this paper are summarized as follows:

- We introduce a novel multi-task learning model with a partial sharing structure that utilizes information from two different tasks and sharing representations between them to optimize the outcome of the final task. Each of the three prediction pathways uses a distinct feature extraction approach, enabling the model to capture unique patterns in the EEG signals. These specialized pathways ensure that each prediction provides novel insights, ultimately influencing the final diagnosis more effectively. The final task for diagnosing PSD is formulated as a weighted linear combination of minimizing tasks loss and maximizing tasks accuracy. For the first time, we suggest two weighting schemes to solve this weighted linear combination: a genetic algorithm and a Q-learning algorithm.
- The input for the multi-task learning model includes EEG signal time-frequency images derived from two transformations: Short Time Fourier Transform (STFT) and Continuous Wavelet Transform (CWT), labeled dataset 1 and dataset 2. This helps to utilize the features extracted from two transformations simultaneously to achieve more accurate predictions.
- The PSD diagnosis model has been simplified by using only three EEG channels to decrease computational and hardware expenses.

This document is structured into five distinct sections. The second section addresses previous research concerning automated techniques utilized in sleep studies. In Sect. 3, we introduce a novel multi-task learning model with a partial sharing structure for diagnosing PSD, a method that has not been previously done. We describe the inputs utilized in our proposed multi-task learning model, which include EEG signal images obtained from two different transforms: the short-time Fourier transform and continuous wavelet transform. Section 4 analyzes the findings, and Sect. 5 presents the conclusion.

Related work

Sleep is critically important in influencing human performance. Therefore, it is essential to comprehend the impact of sleep deprivation and sleep disorders on overall health. Since the brain regulates different sleep patterns, sleep disorders are a significant factor in developing various neurological disorders[3]. Early diagnosis and prediction of illnesses are critical objectives in the healthcare sector, as they enable the implementation of timely preventive interventions[14]. Physicians use EEG signals to illustrate brain activity, aiding in diagnosing sleep disorders[15]. Electroencephalogram (EEG) analysis is considered the most effective, least invasive, and most dependable method for detecting neurological disorders[14]. The EEG signals show variations across different stages of sleep and display distinct patterns associated with various sleep disorders[15]. Experienced neurologists invest significant time and effort in analyzing EEG data that may span days, weeks, or even months[14]. Traditional diagnosis of sleep disorders is a process that is both time-consuming and labor-intensive, heavily reliant on the skills of the operator. This reliance often results in challenges when diagnosing such conditions. In artificial intelligence, numerous studies have been undertaken to explore the usage of ML in diagnosing sleep disorders[16].

K-nearest neighbor (KNN) and Support vector machine (SVM) are among the most frequently employed classifiers in the context of sleep classification problems[17]. Zhao et al.[17] proposed an automated classification system for distinguishing between sleep apnea and normal events, eliminating the necessity for expert intervention. The classification performance of the three classifiers, SVM, KNN, and RF, demonstrates that RF achieves the highest classification accuracy and exhibits the most effective classification results[17]. Ensemble techniques are a machine learning strategy aimed at enhancing model performance through the integration of multiple models. This approach contributes to improved accuracy and reduced variability in predictions[18]. Jayaraj and Mohan[19] proposed a support vector machine with kernels and a random forest classifier for classifying subjects with sleep apnea based on features extracted from EEG signals[19]. Satapathy et al.[20] employed traditional algorithms such as K-nearest neighbors (KNN), Support Vector Machines (SVM), and Random Forest (RF), and in their deep learning methodology, they utilized recurrent neural networks (RNNs) and convolutional neural networks (CNNs) for detecting sleep disorders through EEG brain signals. Their research revealed that deep learning algorithms perform better than traditional machine learning in diagnosing sleep disorders[20].

Deep learning (DL) techniques facilitate end-to-end training by directly correlating raw signals with target labels. This data-driven approach enables the automatic discovery of latent patterns without manual feature engineering[21]. The most commonly used DL techniques for sleep disorder diagnosis include MLP, Bidirectional LSTM, and R-CNN, with studies reporting a median accuracy of 90.1% under intra-subject validation[22]. A key advantage of DL is its ability to process complex signals, such as time-frequency representations, which are widely used for analyzing non-stationary multicomponent signals[23]. In line with recent advances in sleep disorder analysis using EEG spectrograms, a study proposes using the YOLOv8 deep learning model to classify sleep apnea syndrome based on STFT-transformed EEG segments. Their results showed that compared to traditional models like ResNet64 and YOLOv5, YOLOv8 achieves higher accuracy (93.7%) with fewer parameters and faster processing, offering an efficient solution for multi-class sleep apnea classification[24]. Kumar et al.[9] employed smoothed pseudo-Wigner-Ville distribution (SPWVD) and Morlet wavelet transforms to generate time-frequency scalograms from EEG signals, which were then fed into a convolutional neural network (CNN) for insomnia detection[9]. Furthermore, a novel swarm-sparse decomposition method (SSDM) was proposed to enhance time-frequency analysis of nonstationary signals by exploiting sparse spectral features. When combined with CNN and BiLSTM architectures, SSDM achieved over 96% accuracy in sleep apnea detection from EEG signals, demonstrating the synergy between time-frequency representations and DL[23]. Further advancing this field, Cheng et al. developed a multimodal and multilabel decision-making system (MML-DMS) using EEG, ECG, and EMG signals. Their framework combined deep CNNs with shallow perceptron networks, achieving 99.09% accuracy in classifying eight sleep disorders[25].

Sleep stages play a crucial role in the assessment of sleep health and the detection of related disorders. Due to the time-consuming and subjective nature of manual scoring, automated methods using EEG signals have gained significant attention. Li et al.[26] proposed EEGSNet, a deep learning model that combines CNN and Bi-LSTM networks to extract time and frequency features from EEG spectrograms, achieving high classification accuracy across multiple public datasets[26]. Similarly, another study used raw EEG signals and their time-frequency representations to explore deep learning architectures, such as 1-D CNN, SWT-CNN, and STFT-CNN. These models achieved classification accuracies above 83% on 20-fold subject-wise cross-validation[27].

These examples highlight how integrating time-frequency analysis with DL architectures can significantly enhance diagnostic performance in sleep medicine. While previous studies have shown promising results with deep learning techniques, these approaches often rely on having access to large, homogeneous EEG datasets - conditions that are rarely present in real-world situations. In reality, EEG datasets are typically small and diverse, mainly due to practical limitations such as expensive data collection procedures, differences in recording protocols, and variations in hardware setups. For example, the PSD dataset we used in our research has a limited number of subjects and recordings. Furthermore, inconsistencies between datasets, such as different channel setups, sampling rates, and demographic distributions, make it challenging to create models that can be effectively applied across different populations. Obtaining large and standardized EEG datasets is a time-consuming and complex process that often requires years of collaboration between multiple institutions.

These limitations underscore a critical gap in current research: the reliance of traditional deep learning models on large-scale labeled data, which hinders their applicability in realistic, low-resource settings. To address this issue, the present study introduces a multi-task learning framework with partial parameter sharing. This approach is designed to facilitate knowledge transfer across related tasks and enhance performance even when trained on small and diverse EEG datasets. It offers a more practical and scalable solution for automated EEG-based sleep disorder classification in clinical contexts.

Methodology

The proposed approach includes five phases: first, EEG signals are pre-processed; second, specific EEG channels are selected to identify sleep disorders; third, time-frequency images are created from the EEG signals; fourth, a diagnostic model for sleep disorders is developed using a multi-task learning model with a partial sharing structure; and finally, common evaluation metrics are used to assess the model's effectiveness. A flowchart illustrating the research methodology is provided in Fig. 1.

Data acquisition

The study utilizes a secondary dataset involving 26 participants (ages 22–36) to examine the impact of Partial Sleep Deprivation (PSD) on EEG recordings. Participants, both male and female, were recorded before and after

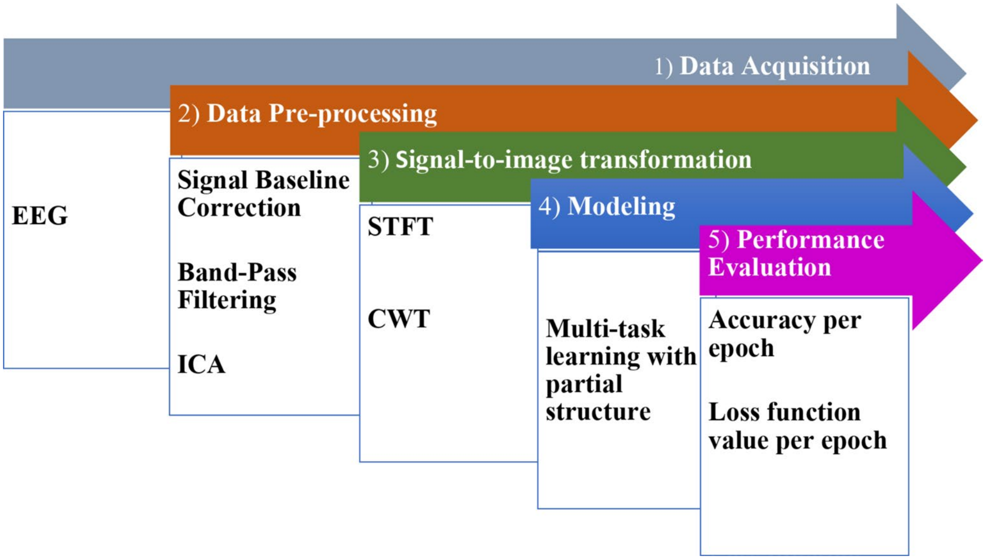


Fig. 1. Flowchart of the research methodology.

experiencing PSD, seated comfortably with their eyes open. The dataset was recorded under two conditions: normal sleep and after partial sleep deprivation. This resulted in 52 samples, evenly distributed between the two classes, ensuring a balanced dataset. EEG signals were recorded utilizing 31 electrodes positioned according to the international 10–20 system. The recordings were conducted with a bandpass of 0.1 to 100 Hz and a sampling rate of 250 Hz[28].

Data Pre-processing

After data acquisition, the first step is data preprocessing for EEG signals. This process includes baseline correction, applying a notch filter to remove power line artifacts, and band-pass filtering between 1 and 100 Hz using a zero-phase linear finite impulse response filter. Finally, Independent Component Analysis (ICA) employing the "runica" method is used to remove undesired artifacts such as EMG and ECG noises, as well as eye blinks and movements.

Transforming data

This study proposes the use of time-frequency images generated by Short-Time Fourier Transform (STFT) and Continuous Wavelet Transform (CWT) on preprocessed EEG signals to develop an automatic diagnosis model for sleep disorders. To reduce computational complexity, we focus on three key electrodes: F3, F4, and C4. A review of existing sleep studies indicates that these electrodes are commonly utilized in sleep-related analyses. The EEG signals are further analyzed by decomposing them into five standard frequency bands: delta, theta, alpha, beta, and gamma.

Electroencephalography is a sensitive tool for assessing brain activity and cognitive states during wakefulness, especially under conditions of sleep deprivation. Spectral power analysis has shown that partial sleep deprivation can cause significant changes in EEG activity. Some studies report increased absolute power in theta, alpha, and beta frequency bands following sleep deprivation, while others have observed reductions in alpha power, with elevated theta activity. Additional studies have documented decreased power across most frequency bands except delta, alongside significant theta power increases in frontal and temporal regions. Interestingly, some researchers have specifically noted enhanced alpha and beta power in occipital areas. These inconsistencies in EEG findings are likely due to methodological differences and individual variability[29]. This study used all EEG sub-bands, including delta, theta, alpha, beta, and gamma, to comprehensively evaluate partial sleep deprivation.

The Fourier transform (FT) serves to calculate the frequency spectra of signals, providing information in the frequency domain but lacking time domain details. To observe both domains simultaneously, the frequency spectra of short signal segments are arranged together. This process involves dividing the signal into frames using window functions, followed by applying the Fourier transform to each frame. The equation can be expressed as follows[30]:

$$STFT\left\{f\left(t\right)\right\} = \int_{-\infty}^{\infty} f\left(t\right) w\left(t-\tau\right) \exp\left(-i\omega\, t\right) dt \tag{1}$$

Where w is the window function.

A two-dimensional image generated by STFT is called a spectrogram image[31]. The Short-Time Fourier Transform was applied to the entire EEG signal of each channel. A Hamming window of 1000 samples was used

(4 s at a sampling rate of 250 Hz) with a 50% overlap. This setup allows for the capture of time-varying frequency components over the full signal duration without the need for additional segmentation.

The Continuous Wavelet Transform (CWT) serves as a fundamental tool in time-frequency analysis, utilizing a series of wavelet functions to examine a signal within the time-frequency domain. This method extends the localization concept initially introduced by the Short-Time Fourier Transform (STFT). Unlike STFT, CWT offers improved time resolution and reduced frequency resolution at high frequencies, while providing enhanced frequency resolution and reduced time resolution at lower frequencies through the adjustment of scale and translation parameters. The CWT for a signal with translation parameter b, scale parameter a, and wavelet function φ(t) is defined as follows[32]:

$$CWT_f^{\phi}\ (a, b) = \int_{-\infty}^{\infty} f\ (t)\ \frac{1}{\sqrt{a}}\phi\ \left(\frac{t-b}{a}\right) dt \tag{2}$$

A two-dimensional image generated by CWT is called a scalogram image[31]. In Eqs. (1) and (2), the function f(t) represents the EEG signal, which is a time-series signal recorded over time. For the Continuous Wavelet Transform, we used the full-length EEG signal for each channel without segmentation. We applied the complex Morlet wavelet across 127 scales, covering a wide frequency range to achieve both high and low-frequency resolution.

The use of a 2D data format offers the advantage of extracting a greater number of features compared to 1D data[33]. In this study, the short-time Fourier transform and continuous wavelet transform were used to convert 1D EEG signals into a 2D representation. The first step involved preprocessing the raw 1D EEG signals using various signal processing techniques. Following this, spectrogram and scalogram images were created using STFT and CWT, respectively, to visualize the 2D data. Figure 2 shows an example of the spectrogram and scalogram images generated from the EEG signals processed with STFT and CWT.

Modeling

Multi-task learning is a learning framework aimed at training several tasks simultaneously. Using shared representations improves the efficiency of learning all tasks compared to training them separately[34]. Multi-task learning involves training on several related tasks simultaneously, enabling the model to improve its performance on each task by utilizing insights gained from the others[35]. For modeling purposes, we introduce an innovative multi-task learning model characterized by a partial sharing structure. This architecture comprises two distinct types of networks: the Task Specific Network (TSNet) and the Shared Network (SNet). The TSNet is dedicated to learning features that are unique to individual tasks, whereas the SNet is responsible for acquiring informative representations that can be used for all tasks[36]. The proposed model efficiently extracts specific features from both STFT and CWT datasets, leveraging their shared characteristics and optimizing the utilization of all feature representations. $Task_1$ involves predicting PSD using time-frequency images obtained from STFT. $Task_2$ involves predicting the disorder using time-frequency images obtained from CWT. $Task_3$ involves predicting the disorder by sharing representations obtained from two datasets. In the proposed multi-task learning model, the final loss is a linear combination of task-specific losses and the loss of sharing task with tasks weightings $\lambda_{\ i}$ as follows:

$$final\ loss = \lambda_{\ 1}\ Task_1\ loss + \lambda_{\ 2}\ Task_2\ loss + \lambda_{\ 3}\ Task_3\ loss \sum{}_{i=1}^{3}\lambda_{\ i} = 1 \tag{3}$$

Also, the final accuracy is calculated as follows:

$$final\ accuracy = \lambda_{\ 1}\ \ Task_1\ accuracy + \lambda_{\ 2}\ Task_2\ accuracy + \lambda_{\ 3}\ Task_3\ accuracy \sum{}_{i=1}^{3}\lambda_{\ i} = 1 \tag{4}$$

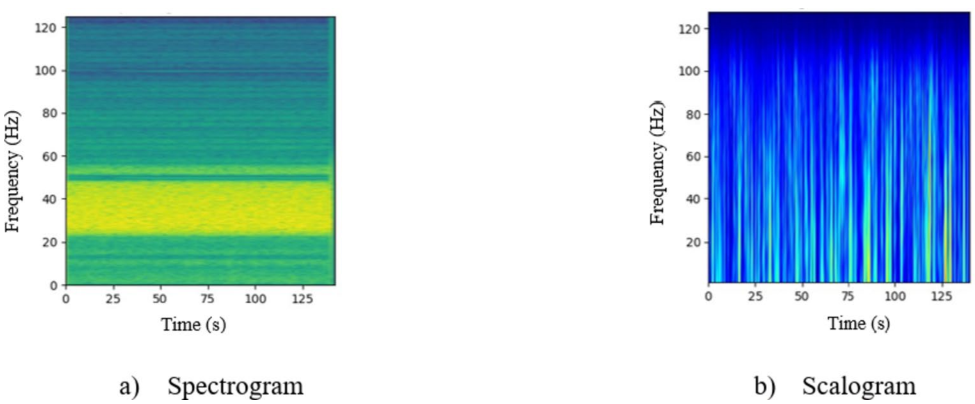


Fig. 2. Time-frequency images obtained by (**a**) short-time Fourier transform; (**b**) continuous wavelet transform.

The proposed multi-task learning model with a partial sharing structure is illustrated in Fig. 3. We have two sets of inputs: the STFT dataset and the CWT dataset. These two types of image transformations of the signal are in different frequencies and time domains and can provide comprehensive information for signal analysis. Each set passes through the network via a separate path. This means that the model utilizes the specific features of each set for learning. After the stage of feature extraction using convolutional and pooling layers, each of these two inputs makes predictions independently (i.e. $Task_1\ loss, Task_1\ accuracy\ and\ Task_2\ loss, Task_2\ accuracy$). There is also a sharing step where the STFT and CWT features are combined, resulting in a joint prediction ($Task_3\ loss, Task_3\ accuracy$). Therefore, this model processes the unique information from each source in separate initial steps. It then combines the features in an intermediate step, utilizing information from both sources jointly for prediction that reflects the partial sharing approach in multi-task learning.

Training various tasks within multi-task learning networks presents a significant challenge due to the necessity of achieving an appropriate equilibrium among the tasks[37]. Multi-task learning can be formulated as a multi-objective optimization problem, where the goal is to optimize a collection of objectives that may conflict with each other[38]. The objective function in this problem is written as a weighted linear combination of minimizing tasks loss and maximizing tasks accuracy. Our goal is to optimize the weights associated with the loss and accuracy of each task to ensure the model achieves optimal performance.

In this study, Genetic Algorithm (GA) and Q-Learning were utilized to optimize the combination weights of the three prediction tasks within the multi-task learning model. We also discussed and compared other optimization methods, such as Grid Search and Bayesian Optimization, to provide a more comprehensive analysis. When compared to Grid Search and Bayesian Optimization, the choice of Genetic Algorithm and Q-Learning provided distinct advantages for our specific problem. Grid Search necessitates evaluating all potential weight combinations, which can be computationally expensive. While Bayesian Optimization is more sample-efficient, it commonly assumes a stationary objective function. In contrast, in multi-task learning, particularly when adjusting loss weights, dynamic adaptation to model changes is often required. Genetic Algorithm, with its population-based search and ability to avoid local optima, and Q-Learning, due to its capability to learn optimal policies through trial and error, offer greater flexibility in exploring the non-linear and dynamic search space. Therefore, it can be concluded that these two methods are more appropriate than other approaches for

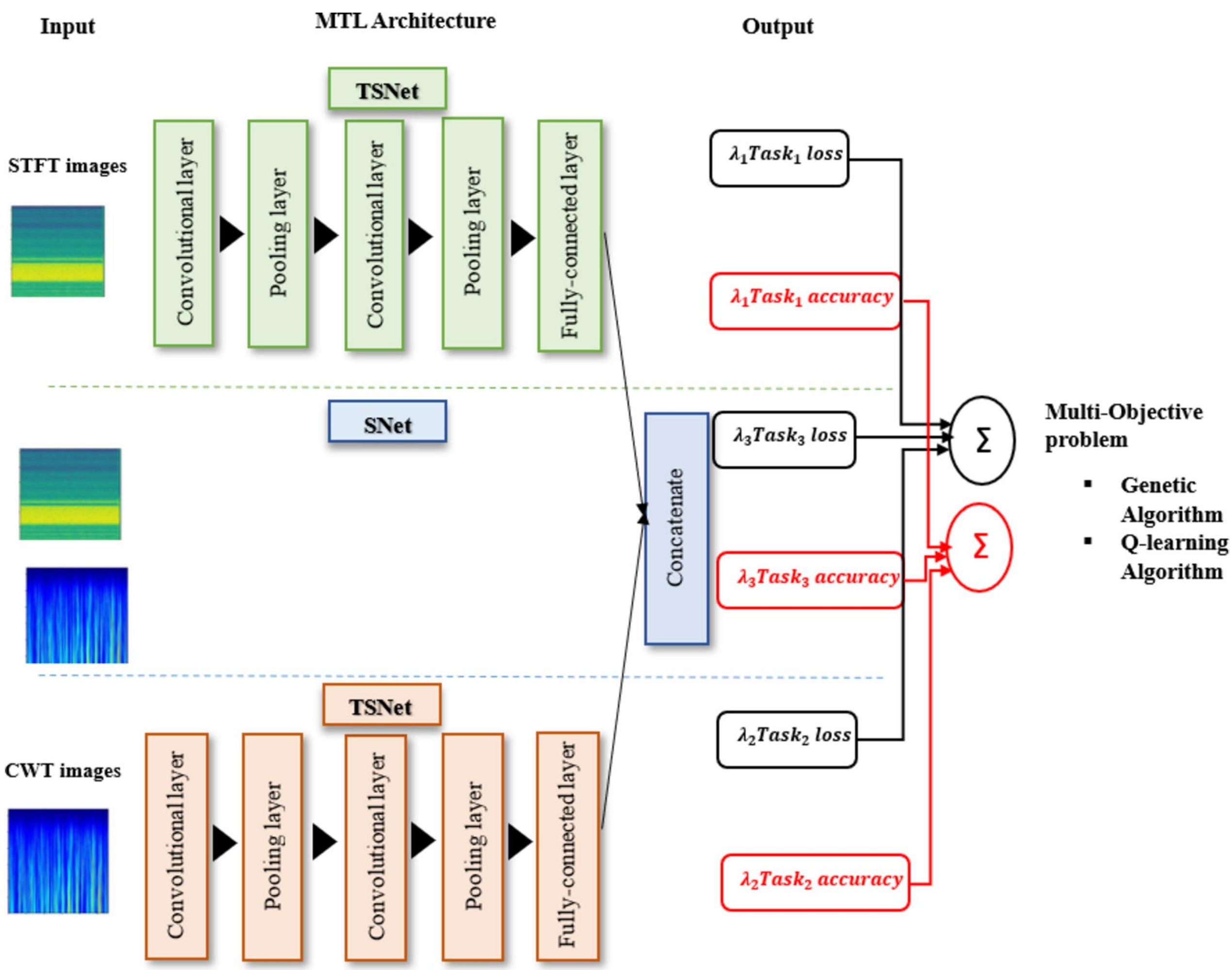


Fig. 3. The architecture of the suggested multi-task learning convolutional neural network.

optimizing the combination weights within the multi-task learning framework based on EEG-derived images for sleep disorder detection. Both algorithms adjust the final task weighting over time by considering the rate of change in the loss and accuracy associated with each task.

Genetic algorithm

The Genetic Algorithm (GA) is a global optimization technique that draws inspiration from the principles of biological evolution[39]. The genetic algorithm is a heuristic search method inspired by natural selection and genetic variation, commonly used for optimizing functions[40]. It starts with an initial population of possible solutions, represented as chromosomes or individuals. These individuals undergo iterative evolution, where the fittest are chosen and recombined to generate improved solutions for subsequent generations. This process continues until a predetermined number of generations is reached or the solutions achieve a satisfactory level[39].

During this research phase, we have used a genetic algorithm to optimize the chromosomes representing the weights associated with accuracy and loss for each task in the multi-task learning model. The objective is to achieve the highest accuracy and lowest loss for the final task. therefore, the fitness function, which serves as the main criterion for optimizing the selection of tasks weights is defined as the equation below.

$$Fitness\ function = \sum {}_{i=1}^{3} \lambda\ _i Task_i loss - \sum {}_{i=1}^{3} \lambda\ _i Task_i accuracy \tag{5}$$

To enhance accuracy and minimize loss, the fitness function combines accuracies with a negative sign and losses with a positive sign. Increasing accuracy and decreasing loss decrease the objective function value, making it more favorable. To enhance the efficiency of the genetic algorithm, a variety of values were established for its hyperparameters. These included the number of iterations, population size, mutation probability, selection ratio of elite individuals, crossover probability, crossover type, and parents' portion. These parameters offer a broad search space to achieve more optimal results. The random search method was utilized to determine the optimal combination of hyperparameters. In this approach, a random set of hyperparameters was chosen. The genetic algorithm was then executed using this set. Following each run, the accuracy and loss of the model were computed for each task, and the objective function was evaluated. The set of hyperparameters that yielded the highest score for the objective function was recorded as the optimal configuration. Table 1 displays the considered hyperparameters values and their corresponding optimal values.

Q-learning algorithm

Reinforcement learning is a model of algorithms that enables the development of optimal strategies through self-study learning in specific contexts. Q-learning is classified as a value-based algorithm within the realm of reinforcement learning. In this approach, $Q\ (s, a)$ represents the expected profit or reward from taking a certain action $a\ \ (a\, \epsilon\, A)$ in a given state $s\ \ (s\, \epsilon\, S)$. In other words, the value of $Q\ (s,\ a)$ shows how beneficial it is to perform an action $a\ \ (a\, \epsilon\, A)$ in state $s\ \ (s\, \epsilon\, S)$. After the agent acts, the environment provides feedback in the form of a reward r based on the action performed. This reward helps the agent to update the values of Q and progressively identify the best actions for each state, ultimately maximizing its cumulative reward over time. The Bellman formula for updating the Q value in the Q-Table is outlined as follows:

$$Q\ (s, a) \leftarrow\ Q\ (s, a) + \alpha\ \left[r + \gamma\ max_{\acute{a}} Q\ (\acute{s}, \acute{a}) - Q(s, a)\right] \tag{6}$$

Where α is the learning rate, r is the reward received, and γ is the discount factor[41].

In this research phase, the Q-Learning algorithm has been utilized to optimize the weights associated with accuracy and loss for each task in the multi-task learning model. This algorithm is based on the structure of Reinforcement Learning, to guide the model towards achieving maximum accuracy and minimizing loss in a multi-task learning environment. One of the most crucial components of this method is the definition of the reward function. The reward function is crafted to promote weighted accuracy of various tasks while also considering weighted loss with a more significant penalty. The reward function is shown in Eq. 7. In essence, as the accuracy of the tasks improves and the loss decreases, the model earns a higher score. This approach aids the model in prioritizing loss reduction and achieving the most optimal accuracy level.

$$Reward\ function = \sum {}_{i=1}^{3} \lambda\ _i Task_i accuracy - 2 \sum {}_{i=1}^{3} \lambda\ _i Task_i loss \tag{7}$$

The states represent the current performance of the multi-task learning model. A state is a dictionary of six values representing all tasks' current accuracy and loss. The actions determine how the weights assigned to the tasks are adjusted. Action 0: The weights remain unchanged. Action 1: Small random changes are handled by the normal distribution.

Iterations no.	Population size	Mutation probability	Elitism rate	Crossover probability	Crossover type	Parents' portion
50,100,200	20,50,100	0.01,0.1,0.2	0.01,0.05,0.1	0.3,0.5,0.7	Uniform, One-point, Two-point	0.2,0.3,0.4
200	**100**	**0.01**	**0.1**	**0.5**	**Two-point**	**0.2**

Table 1. The considered hyperparameters for the genetic algorithm and their corresponding optimal values.

Initially, the main parameters of the Q-Learning algorithm are set, including the learning rate, discount factor, and exploration rate. The learning rate (alpha) dictates the speed at which Q-values are updated during learning. The discount factor (gamma) determines the importance of future rewards compared to immediate ones. The exploration rate (epsilon) specifies the likelihood of choosing random actions to explore the environment rather than exploiting known information. This parameter helps the algorithm to prioritize exploration in the early stages of learning, gradually shifting toward exploitation as it gains more knowledge. The values considered for the parameters in the Q-learning algorithm are shown in Table 2.

First, the Q-table is initialized with small random values. The action is selected using the epsilon-greedy strategy. This strategy involves selecting a random action (exploration) with a probability of epsilon and selecting the action with the highest Q value (exploitation) with a probability of 1-epsilon. A random action means that the model randomly chooses one of two possible actions. This action is performed for exploration so that the model can gain new information about the environment. The best action means that the model selects the action with the highest Q value based on the current Q values. This is done for exploitation so that the model can exploit its current knowledge and earn more rewards. If the selected action is to change the weights, the weights change randomly and by normal distribution. This process gradually improves weighting and task prioritization. Then, the Q value for the current state and the selected action is updated using the Bellman equation.

As epsilon decreases gradually over time, the algorithm becomes more effective in exploiting the information it has gathered. Initially, random weights are assigned to the accuracy and loss of each task. These weights act as composite coefficients of accuracy and loss for the tasks. The algorithm adjusts these weights throughout the learning process to guide the model towards its optimal state. This enables the model to learn how to appropriately assign weights to each task to improve overall performance.

Performance evaluation

The performance of a deep learning model is evaluated using statistical parameters such as loss and accuracy. This research evaluates the proposed model by examining and comparing the loss and accuracy curves for both the training and testing phases. In deep learning, the loss function, which serves as the objective function, quantifies the error generated during the forward pass. Minimizing this loss is the key aim of model training[42]. For each task, a binary cross-entropy loss function is applied to optimize our model.

Accuracy is characterized as the proportion of accurately identified positive and negative samples (true positives and true negatives) to the total number of samples, which includes true positives, true negatives, false positives, and false negatives, as illustrated in the following equation[43]. Additionally, in order to evaluate the generalizability and stability of the results obtained, Precision, Recall, and F1-score metrics are calculated and reported using the Cross-Validation (CV) method. This approach enables an examination of the consistency of model performance across various datasets. The calculation formula for these metrics is outlined based on formulas 9 to 11.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{8}$$

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

$$Recall = \frac{TP}{TP + FN} \tag{10}$$

$$F1 - score = \frac{2 * Precision * Recall}{Precision + Recall} \tag{11}$$

Results and discussion

This study proposed a method for diagnosing sleep disorders automatically using EEG signals. The dataset used in the study consists of images from two different signal-to-image conversion methods, resulting in varied characteristics. Due to the heterogeneity and the small number of samples in the dataset, a multi-task learning model was developed. This model learns from multiple tasks simultaneously, utilizing features from both datasets to analyze EEG signals of individuals with partial sleep deprivation (PSD). This model added a sharing structure to enhance the performance of the final task of diagnosing PSD and suggested two genetic and Q-learning algorithm weighting schemes to solve the weighted linear combination of the final task.

Weighting scheme using the genetic algorithm

The multi-task learning model was implemented for 100 epochs. During each epoch, the model was trained on the training data, and the accuracy and loss were recorded for each task. Subsequently, new weights for each task were calculated using a genetic algorithm and optimal hyperparameters. After each epoch, the results, including optimal weights, accuracies, and losses obtained, were calculated to evaluate the progress and performance of the model. The graphs in Fig. 4 display the accuracy and loss of the model during each epoch. This multi-task

Alpha	Gamma	Epsilon
0.1	**0.9**	**0.1**

Table 2. The considered value for the parameters in the Q-learning algorithm.

model has been optimized using a genetic algorithm. In the graph on the left, the accuracy for both the training and testing data improved steadily over the epochs, eventually reaching a high value close to 1. After the 35 th epoch, accuracy values for both the training and testing sets stabilized, with only minor fluctuations in the test data, which is normal and indicates model convergence. In the graph on the right, the loss for both the training and testing sets decreased rapidly and eventually dropped below 0.1. After approximately 60 epochs, the training loss approached zero, and the testing loss stabilized below 0.1. This demonstrates good model performance and proper convergence. These graphs illustrate that optimizing the multi-task model with a genetic algorithm has resulted in high performance and successful convergence.

Weighting scheme using the Q-learning algorithm

The Q-Learning algorithm was executed in a 100-epoch loop, steadily improving the model's performance. Each epoch involves running the multi-task model to obtain accuracy and loss for each task. After extracting this information, the current state is recorded in the Q-table. At the end of each epoch, the reward is calculated based on the reward function, and the Q value is updated. Additionally, the exploration rate is decreased at the end of each epoch to make the algorithm more exploitative over time and prevent unnecessary exploration. This reduction in the exploration rate allows the algorithm to focus on exploiting the learning outcomes once it has gained enough knowledge of the environment. Figure 5 shows accuracy and loss graphs for the multi-task model optimized using the Q-learning algorithm. In the graph on the left, the accuracy of the model for both training and testing data increased over time and eventually reached a high value (approximately 0.98 and above). After around 90 epochs, the accuracy of both sets stabilized, indicating acceptable performance of the model and prevention of overfitting. In the graph on the right, the losses in both the training and testing sets have decreased over time and gradually approached low values. In contrast to the genetic algorithm implementation, the test loss slowly and steadily decreased and became closer to the training loss at higher periods. This indicates that the model with Q-learning adapted better to the test data over time.

We can focus on two aspects of the results to compare the performance of the two genetic algorithms and Q-learning: first, both algorithms have achieved high accuracy. However, it appears that the final accuracy of training and testing with the genetic algorithm is slightly higher and closer to one, while it remained slightly lower than 1 in Q-learning. This indicates that the genetic algorithm has achieved higher accuracy. Second, the Q-learning algorithm exhibits fewer fluctuations in the loss graph compared to the genetic algorithm. The reduction of the test loss has been gradual, bringing it closer to the training loss over time. This indicates that the Q-learning algorithm has performed better in preventing overfitting. In contrast, the genetic algorithm quickly achieved a small loss in the training data, but the test loss was slightly higher and showed more fluctuations.

In general, the results show that the multi-task model with genetic algorithm optimization has been more effective in achieving higher accuracy and faster convergence. On the other hand, the Q-learning algorithm has shown greater stability and compatibility with test data. The proposed multi-task learning model, which leverages both genetic algorithms and Q-learning for tasks weight optimization, has demonstrated promising results in the context of sleep disorder diagnosis. Specifically, the genetic algorithm has proven advantageous in achieving higher accuracy and faster convergence, suggesting its ability to quickly adapt to the relevant features within the dataset. In contrast, the Q-learning algorithm has shown enhanced stability, maintaining consistency across various test datasets, which indicates its robustness and suitability for real-world application scenarios.

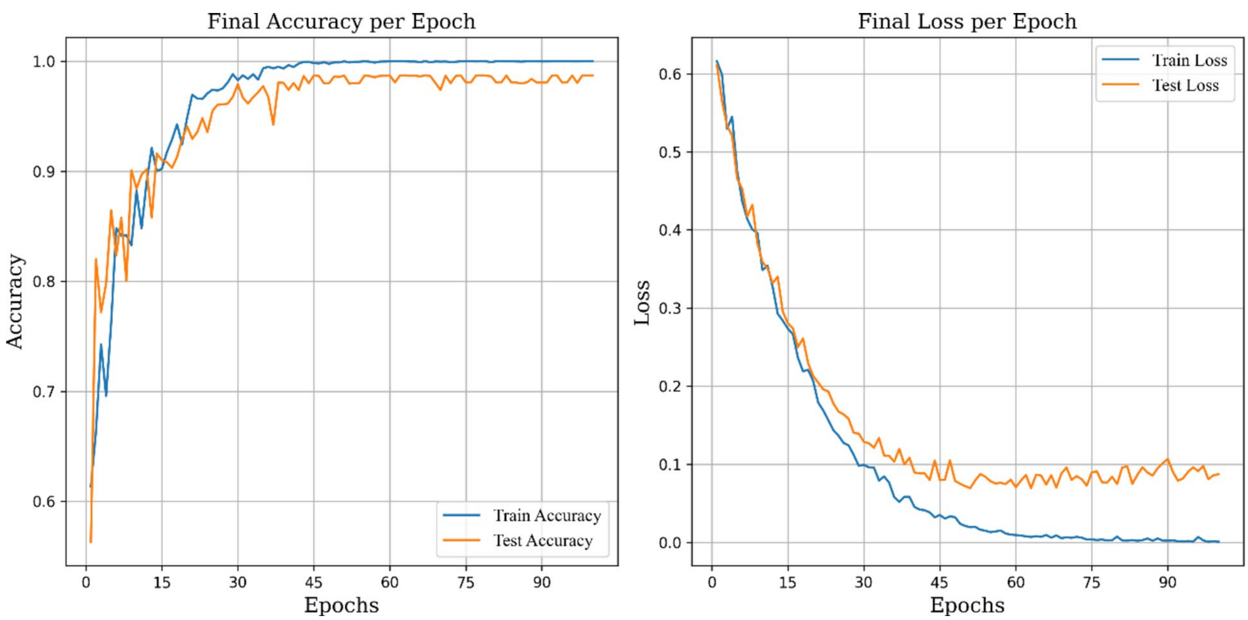


Fig. 4. Accuracy and loss curves per epoch for the training set and testing set of the multi-task learning model with optimization of weights using the genetic algorithm.

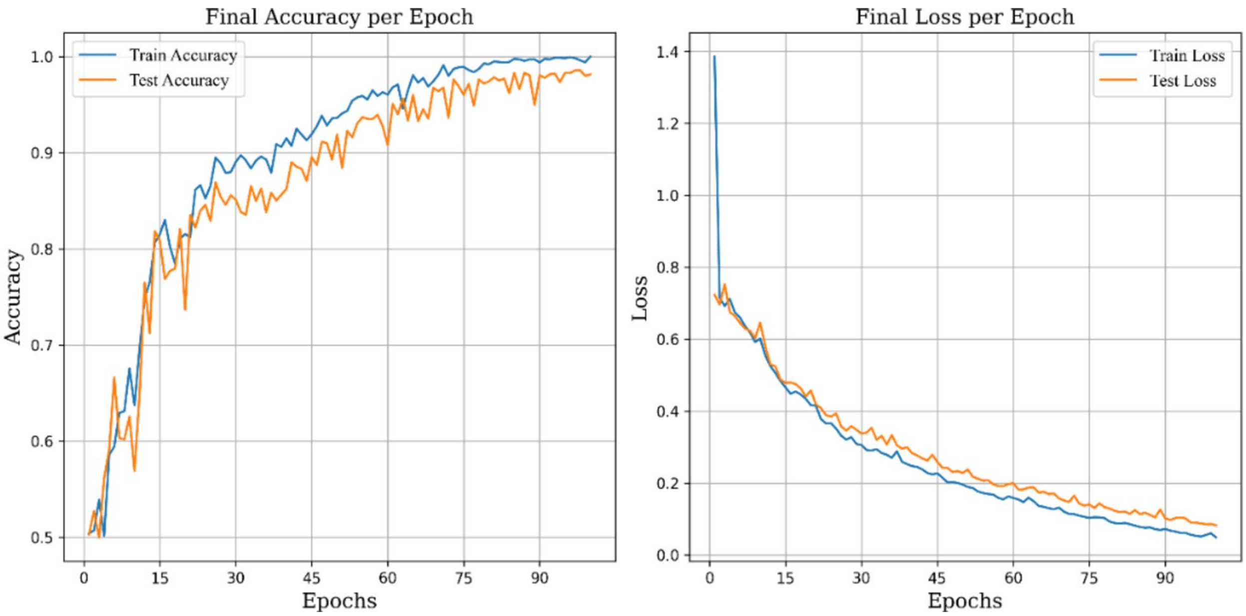


Fig. 5. Accuracy and loss curves per epoch for the training set and testing set of the multi-task learning model with optimization of weights using the Q-learning algorithm.

Layers	Number of multi-task model parameters	Genetic algorithm	Execution time	
Conv-stft_1	3*3*3*32 + 32 = 896		Total	Each Epoch
Conv-stft_2	32*3*3*64 + 64 = 18,496			
Task1_output	57,600*1 + 1 = 57,601		45 min	15 s
Conv-cwt_1	3*3*3*32 + 32 = 896			
Conv-cwt_2	32*3*3*64 + 64 = 18,496			
Task2_output	57,600*1 + 1 = 57,601			
Concatenate	115,200*64 + 64 = 7,372,864	Q-learning Algorithm	38 min	14 s
Task3_output	64*1 + 1 = 65			
Sum	7,526,915			

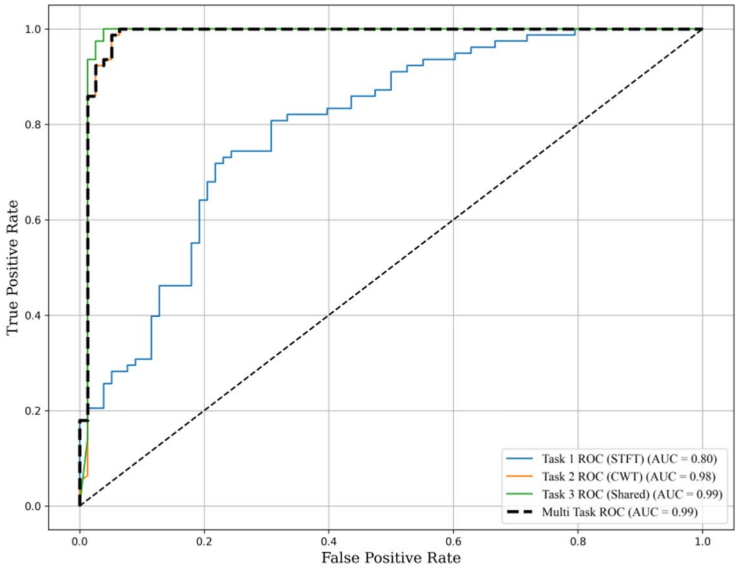
Table 3. The characteristics of the multi-task learning model, computational complexity, and comparison of execution time for two weighting methods.

These characteristics make the model particularly effective for handling the complexities and variability inherent in sleep disorder diagnosis, where both accuracy and stability are critical.

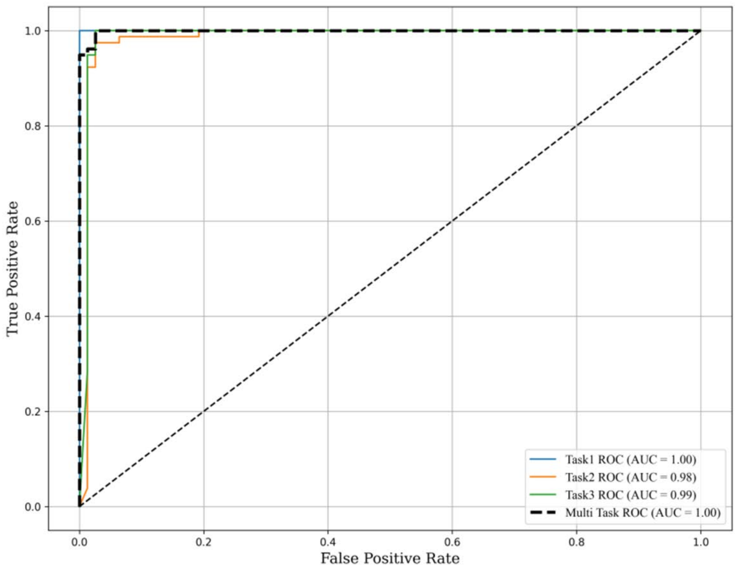
Table 3 displays the characteristics of the multi-task learning model created to classify partial sleep deviations using EEG signals. The weighting of the various tasks in this model is determined by two optimization algorithms: the genetic algorithm and the Q-learning algorithm. The table indicates the number of parameters for each layer and task, as well as the training time with each algorithm. The total number of model parameters is approximately 7.5 million. Training time with the genetic algorithm is noted as 45 min (15 s per epoch), while with the Q-learning algorithm it is reported as 38 min (14 s per epoch). Both algorithms boast short execution times, making them highly suitable for real-time applications such as quickly detecting moments of drowsiness while driving or in sensitive medical settings.

The ROC curves for the multi-task model whose weights were optimized during the training process using the genetic algorithm and Q-Learning are presented in Fig. 6a and b. The ROC curves illustrate the performance of a multi-task learning model applied to EEG-derived images for three prediction tasks. Task 1, which uses STFT features, Task 2, which uses CWT features, and Task 3, which uses shared features.

In the model optimized by the Genetic Algorithm, Task 1 achieves an AUC of 0.80, indicating moderate performance. Task 2 and Task 3 show significantly better results, with AUCs of 0.98 and 0.99, respectively. The overall multi-task model, optimized using weighted accuracy, achieves a high AUC of 0.99, demonstrating that shared learning effectively preserves and enhances task performance through joint optimization. In contrast, when the model is trained using Q-learning, performance improves across all tasks. Task 1 reaches a perfect AUC of 1.00, while Task 2 and Task 3 maintain strong results with AUCs of 0.98 and 0.99, respectively. The overall model also achieves an AUC of 1.00, highlighting the added benefit of reinforcement learning in optimizing both individual tasks and shared feature representations.



a) ROC Curve of the Multi-task Model with Weights Optimized by Genetic Algorithm



b) ROC Curve of the Multi-task Model with Weights Optimized by Q-Learning Algorithm

Fig. 6. ROC Curves of the Multi-task Model with Weights Optimized using (**a**) Genetic Algorithm, (**b**) Q-Learning Algorithm.

Cross-validation helps enhance our understanding of model performance and generalizability. Table 4 displays the values of the prediction model's performance evaluation metrics using two weighting methods while implementing the 3-fold cross-validation method. These values were captured for genetic weighting at epoch 40 and Q-learning weighting at epoch 90. The values of the metrics for each fold, their means, and standard deviations in different iterations confirm that there is low variation in results between folds. This suggests that the algorithms exhibit stable performance across varying data conditions. Overall, both algorithms have demonstrated the ability to maintain their performance effectively when presented with diverse datasets.

Subject-wise cross-validation, particularly the Leave-One-Subject-Out (LOSO) approach, is a robust evaluation method for assessing a model's ability to generalize across unseen individuals, especially in personalized domains such as EEG analysis. Figure 7a and b demonstrate the Leave-One-Subject-Out (LOSO) cross-validation accuracy of a multi-task learning model whose weights were optimized using Genetic Algorithm and Q-Learning. The model consistently achieves high accuracy across most subjects in both

Weighting type	Iteration	Metric	Fold 1 (%)	Fold 2 (%)	Fold 3 (%)	Mean (%)	SD
Genetic Algorithm	1	Accuracy	92	95	94	93.67	1.25
	1	Precision	93	91	91	91.67	0.94
	1	Recall	90	94	93	92.33	1.70
	1	F1-score	91.5	92.5	92	92	0.5
	2	Accuracy	94	91	91	92	1.73
	2	Precision	91	90	93	91.33	1.25
	2	Recall	92	91	93	92	1
	2	F1-score	91.5	90.5	93	91.67	1.25
	3	Accuracy	92	94	91	92.33	1.25
	3	Precision	93	93	90	92	1.73
	3	Recall	93	91	90	91.33	1.25
	3	F1-score	93	92	90	91.67	1.53
Q-learning Algorithm	1	Accuracy	91	93	90	91.33	1.25
	1	Precision	92	94	91	92.33	1.25
	1	Recall	90	93	89	90.67	2.05
	1	F1-score	91	93.5	90	91.5	1.75
	2	Accuracy	92	94	91	92.33	1.25
	2	Precision	93	95	92	93.33	1.25
	2	Recall	91	93	90	91.33	1.25
	2	F1-score	92	94	91	92.33	1.25
	3	Accuracy	93	92	90	91.67	1.53
	3	Precision	94	93	91	92.67	1.25
	3	Recall	92	91	90	91	1
	3	F1-score	93	92	90.5	91.93	1.25

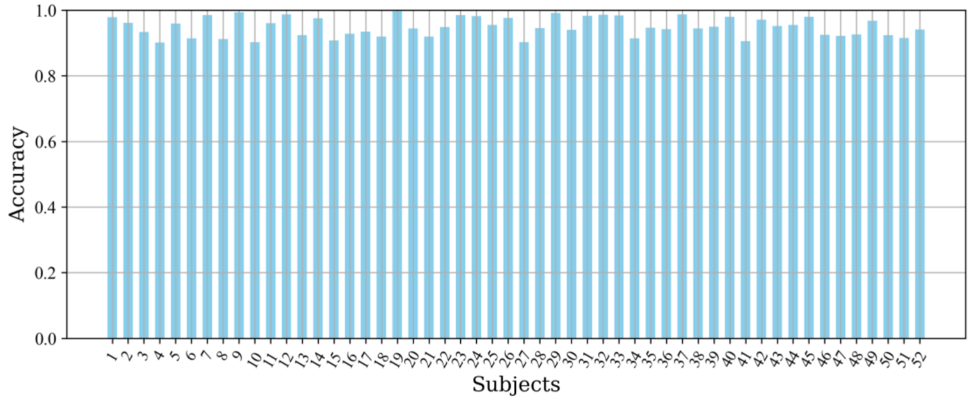
Table 4. Results of 3-fold cross-validation.

configurations, indicating strong generalization capabilities. However, as shown in Fig. 7a, the Genetic-based model demonstrates slightly more stable performance with less fluctuation between subjects, suggesting better convergence in identifying optimal task-weight configurations. In contrast, Fig. 7b shows greater variability in accuracy across subjects when using the Q-Learning Algorithm, which may be due to its stochastic nature and sensitivity to parameter tuning. Overall, both optimization strategies are effective in enhancing the model's performance.

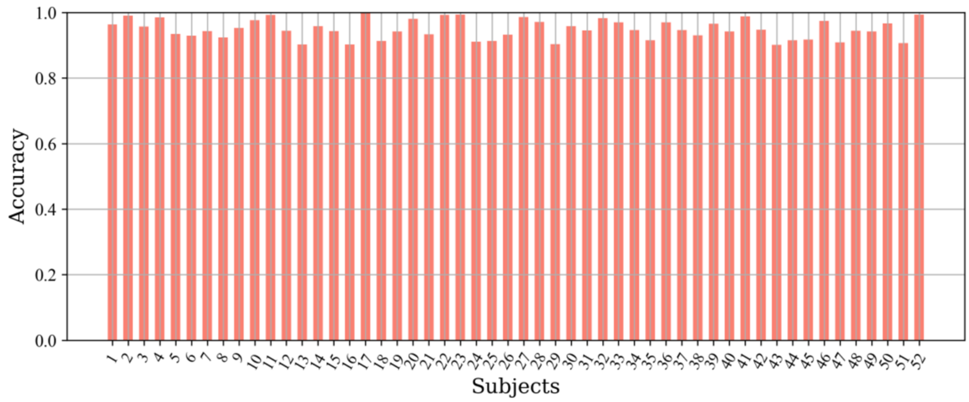
In recent years, there has been a significant increase in research focused on automated sleep analysis, which mirrors the progress made in comprehending sleep patterns and their effects on overall health. Techniques such as k-nearest neighbors, support vector machines, and ensemble learning methods have proven to be effective classifiers, demonstrating high levels of accuracy across various applications. Nevertheless, issues such as variability in performance and high computational costs have been recognized, emphasizing the importance of selecting classifiers carefully based on the specific characteristics of the dataset[44].

The methods mentioned above heavily rely on handcrafted feature extraction, a process that not only requires significant domain expertise but also increases computational complexity, potentially limiting generalizability. Furthermore, this manual intervention often fails to capture the full spectrum of intricate patterns present in the data, leading to suboptimal performance in certain cases. Deep learning methods have revolutionized the field by enabling the automatic extraction of complex features directly from raw data. This capability significantly reduces the reliance on manual feature engineering while improving both efficiency and accuracy.

Table 5 displays various studies that have utilized deep-learning methods to diagnose different sleep disorders. It includes the types of data used and the model performance. Unlike other studies that primarily focus on disorders like sleep apnea, OSA, and insomnia, our study delves into a less explored aspect of sleep patterns. This has the potential to bring added value to both the scientific and applied communities[52]. is the only study that utilized machine learning methods to detect sleep deprivation. They employed metabolic biomarkers and the random forest technique, achieving an accuracy of 94.7%. EEG, as a non-invasive and time-based method that directly measures instantaneous brain activity, provides more accurate information about the current sleep state and its changes than metabolic biomarkers. Our study utilized multi-task learning, deep learning, and EEG data to predict partial sleep deviation. We were able to achieve an accuracy of 98%, surpassing the random forest method and metabolic biomarkers, which only achieved 94.7% accuracy. This superiority demonstrates the greater efficiency of our multi-task model in analyzing complex physiological data. Out of all the studies conducted[48], is one of the few studies that utilized multi-task learning to diagnose a sleep disorder. They utilized multi-task learning to detect OSA, and their model achieved an accuracy of 91.13%. The other studies focused on using multi-task learning for sleep staging[53,54]. This suggests that the use of multi-task learning in sleep analysis is still in its early stages.



a) Leave-One-Subject-Out Cross-Validation Accuracy for the Multi-Task Learning Model Optimized with Genetic Algorithm



b) Leave-One-Subject-Out Cross-Validation Accuracy for the Multi-Task Learning Model Optimized with Q-Learning Algorithm

Fig. 7. Leave-One-Subject-Out Cross-Validation Accuracy for the Multi-Task Learning Model Optimized with **a**) Genetic Algorithm, **b**) Q-Learning Algorithm.

First Author, Year	Disorders name	Dataset	Type of neural network	Model performance (Accuracy)
Kuan, 2022[45]	Obstructive Sleep Apnea	Age, Sex, BMI	ANN	74.04%
Vaquerizo-villar, 2023[46]	Sleep Apnea	EEG	CNN	86.9%
Wallis, 2020[47]	REM sleep with Atonia	PSGs	CNN	91%
Cao, 2022[48]	Obstructive Sleep Apnea	ECG	Multi-task feature fusion CNN	91.13%
Kandukuri, 2023[49]	Obstructive Sleep Apnea	ECG	CNN	91.34
Stephansen, 2018[50]	Narcolepsy Type 1	PSGs	CNN	92%
Sharma, 2023[51]	Insomnia	EEG	Wavelet Scattering Network	97%
Kumar, 2024[9]	Insomnia	EEG	Morlet Wavelet-based CNN	98.9%
Cheng, 2023[25]	Eight sleep disorders	EEG, ECG, EMG	CNNs- shallow Perceptron Neural Networks	99.09%
Our Study	**Partial Sleep Deprivation**	**EEG**	**CNN-MTL**	98%

Table 5. Characteristics of studies that developed models for the automated diagnosis of sleep disorders.

Table 5 is included to provide a comparison of deep learning methods applied to EEG and other physiological signals in sleep-related studies. This comparison emphasizes the methodological relevance of our approach and situates our work within the expanding body of literature that utilizes multi-task learning in the field of sleep analysis. Additionally, it highlights the novelty of our study, which focuses on PSD using EEG-based multi-task deep learning, an area that has not been extensively explored.

This study introduces a novel multi-task learning (MTL) for automatically diagnosing sleep deprivation based on frequency-time images generated from EEG signals, marking an innovative step in this field. Our study adopted a novel approach by transforming the raw signals into time-frequency images, allowing us to exploit the powerful feature extraction capabilities of convolutional neural networks. This research is distinguished by its innovative use of two distinct transformations to generate these images, marking significant progress from previous works. By integrating multiple perspectives of the signal's time-frequency representation, we aimed to enrich the input data and capture a more comprehensive set of features, ultimately enhancing the accuracy and robustness of sleep disorder classification. This dual-transformation approach represents a pioneering step in the field and underscores the potential of combining domain knowledge with cutting-edge deep learning techniques to advance automated sleep analysis.

Additionally, the application of genetic and Q-learning optimization algorithms has improved the model's performance, enabling more accurate and efficient diagnosis of individuals with partial sleep deprivation (PSD). Compared to existing methods, this model utilizes a feature-sharing structure and combines data from two signal-to-image conversion methods. This overcomes the limitations of traditional models that typically rely on uniform and large datasets. The results show that the proposed approach effectively tackles the complexities of EEG analysis and shows significant potential for automatically diagnosing other EEG-based disorders.

The use of a multi-task learning model, capable of analyzing heterogeneous data and limited sample sizes of EEG signals, is a key strength of this research. This study represents a significant advancement in the diagnosis of sleep disorders and sets the stage for future innovations in automated healthcare and precision medicine. By utilizing automated methods like this model, specialists can reduce their workload, enhance diagnostic accuracy, and expedite treatment processes.

The current study shows promising results with data from 26 participants. However, future research should focus on validating the proposed method on larger and more diverse populations to assess its generalizability across different demographics and recording conditions. Furthermore, applying this approach to public EEG datasets like Sleep-EDF or MASS could provide broader benchmarking and reproducibility.

Conclusion

This research introduced a new multi-task learning model with partial structure for detecting partial sleep deprivation using three-channel F3, F4, and C4 EEG signals. In this study, signals were converted into time-frequency images using the STFT and CWT methods to take advantage of automatic feature extraction from images. This approach offers benefits such as increased accuracy, reduced costs, and saved time. The proposed multi-task learning model with a partial structure makes three predictions using non-shared and shared features. The final prediction is a combination of these three predictions. The genetic algorithm and Q-learning algorithm were used to optimize the weights of this combination, with the goal of minimizing loss and maximizing accuracy. Both of these optimization methods for finding optimal weights achieved notable results in terms of minimizing loss and maximizing accuracy. The results showed that the multi-task model, along with these two optimization methods, achieved 98% accuracy on the test data in predicting partial sleep deprivation. However, for stability in test data and to avoid overfitting, Q-learning would be a better option. Utilizing this automatic diagnostic model that only requires 3 EEG channels reduces the costs of diagnosing sleep disorders, eliminating the need for costly tests like polysomnography (PSG). This automatic diagnostic model can help diagnose sleep disorders faster and more effectively as a support tool. It quickly and accurately analyzes sleep data, requiring minimal time and effort from both the patient and the doctor. In summary, the proposed model offers a cost-effective, efficient, and accurate solution for sleep disorder diagnostics, presenting a viable alternative to traditional, resource-intensive methods.

Data availability

Data will be available upon reasonable request. if someone wants to request the data from this study, coauthor, Soraya Khanmohammadi, should be contacted through email.

Received: 16 January 2025; Accepted: 8 May 2025
Published online: 13 May 2025

References

1. Zhao, M., Tuo, H., Wang, S. & Zhao, L. The effects of dietary nutrition on sleep and sleep disorders. *Mediators Inflamm.* **2020** (3142874). https://doi.org/10.1155/2020/3142874 (2020).
2. Behzad, R. & Behzad, A. The role of EEG in the diagnosis and management of patients with sleep disorders. *J. Behav. Brain Sci.* **11**, 257–266. https://doi.org/10.4236/jbbs.2021.1110021 (2021).
3. Bishir, M. et al. Sleep deprivation and neurological disorders. *Biomed. Res. Int.* **2020** (5764017). https://doi.org/10.1155/2020/5764017 (2020).
4. Alazaidah, R. et al. Potential of machine learning for predicting sleep disorders: A comprehensive analysis of regression and classification models. *Diagnostics* **14**, 27. https://doi.org/10.3390/diagnostics14010027 (2023).
5. Xu, S. et al. A review of automated sleep disorder detection. *Comput. Biol. Med.* **150**, 106100. https://doi.org/10.1016/j.compbiomed.2022.106100 (2022).
6. Wang, J. et al. Narcolepsy diagnosis with sleep stage features using PSG recordings. *IEEE Trans. Neural Syst. Rehabil Eng.* https://doi.org/10.1109/TNSRE.2023.3312396 (2023).
7. Zhou, Y. et al. Simplifying multimodal with single EOG modality for automatic sleep staging. *IEEE Trans. Neural Syst. Rehabil Eng.* https://doi.org/10.1109/TNSRE.2024.3389077 (2024). .
8. Choo, B. P. et al. Benchmarking performance of an automatic polysomnography scoring system in a population with suspected sleep disorders. *Front. Neurol.* **14**, 1123935. https://doi.org/10.3389/fneur.2023.1123935 (2023).
9. Kumar, K. et al. Time frequency distribution and deep neural network for automated identification of insomnia using single channel EEG-signals. *IEEE Lat Am. Trans.* **22**, 186–194. https://doi.org/10.1109/TLA.2024.10431420 (2024).
10. Alattar, M., Govind, A. & Mainali, S. Artificial intelligence models for the automation of standard diagnostics in sleep medicine—a systematic review. *Bioengineering* **11**, 206. https://doi.org/10.3390/bioengineering11030206 (2024).

11. Saibene, A. & Gasparini, F. Genetic algorithm for feature selection of EEG heterogeneous data. *Expert Syst. Appl.* **217**, 119488. https://doi.org/10.1016/j.eswa.2022.119488 (2023).
12. Li, J. et al. A novel semi-supervised meta learning method for subject-transfer brain-computer interface. *Neural Netw.* https://doi.org/10.1016/j.neunet.2023.03.039 (2023).
13. Zheng, X. et al. Generalized scene classification from small-scale datasets with multitask learning. *IEEE Trans. Geosci. Remote Sens.* **60**, 1–11. https://doi.org/10.1109/TGRS.2021.3116147 (2021).
14. Jain, A. et al. Analysis of EEG signals and data acquisition methods: a review. *Comput. Methods Biomech. Biomed. Eng. Imaging Vis.* **12**, 2304574. https://doi.org/10.1080/21681163.2024.2304574 (2024).
15. Sohaib, M. et al. Automated analysis of sleep study parameters using signal processing and artificial intelligence. *Int. J. Environ. Res. Public. Health*. **19**, 13256. https://doi.org/10.3390/ijerph192013256 (2022).
16. Moridian, P. et al. Automatic diagnosis of sleep apnea from biomedical signals using artificial intelligence techniques: methods, challenges, and future works. *Wiley Interdiscip Rev. Data Min. Knowl. Discov*. **12**, e1478. https://doi.org/10.1002/widm.1478 (2022).
17. Zhao, X. et al. Classification of sleep apnea based on EEG sub-band signal characteristics. *Sci. Rep.* **11**, 5824. https://doi.org/10.1038/s41598-021-85138-0 (2021).
18. Satapathy, S. K., Bhoi, A. K., Loganathan, D., Khandelwal, B. & Barsocchi, P. Machine learning with ensemble stacking model for automated sleep staging using dual-channel EEG signal. *Biomed. Signal. Process. Control*. **69**, 102898. https://doi.org/10.1016/j.bspc.2021.102898 (2021).
19. Jayaraj, R. & Mohan, J. Classification of sleep apnea based on sub-band decomposition of EEG signals. *Diagnostics* **11**, 1571. https://doi.org/10.3390/diagnostics11091571 (2021).
20. Satapathy, S. K., Patel, V., Gandhi, M. & Mohapatra, R. K. Comparative Study of Brain Signals for Early Detection of Sleep Disorder Using Machine and Deep Learning Algorithm. *In IEEE International Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI)*. 2, 1–6; (2024). https://doi.org/10.1109/IATMSI60426.2024.10503066 (2024).
21. Perez-Pozuelo, I. et al. The future of sleep health: a data-driven revolution in sleep science and medicine. *NPJ Digit. Med.* **3**, 42. https://doi.org/10.1038/s41746-020-0244-4 (2020).
22. Rivera, M. J., Teruel, M. A., Mate, A. & Trujillo, J. Diagnosis and prognosis of mental disorders by means of EEG and deep learning: a systematic mapping study. *Artif. Intell. Rev.* 1–43. https://doi.org/10.1007/s10462-021-09986-y (2022).
23. Bhalerao, S. V. & Pachori, R. B. Sparse spectrum based swarm decomposition for robust nonstationary signal analysis with application to sleep apnea detection from EEG. *Biomed. Signal. Process. Control*. **77**, 103792. https://doi.org/10.1016/j.bspc.2022.103792 (2022).
24. Tanci, K. & Hekim, M. Classification of sleep apnea syndrome using the spectrograms of EEG signals and YOLOv8 deep learning model. *PeerJ Comput. Sci.* **11**, e2718. https://doi.org/10.7717/peerj-cs.2718 (2025).
25. Cheng, Y. H., Lech, M. & Wilkinson, R. H. Simultaneous Sleep Stage and Sleep Disorder Detection from Multimodal Sensors Using Deep Learning. *Sensors*. 23, 3468; (2023). https://doi.org/10.3390/s23073468
26. Li, C. et al. A deep learning method approach for sleep stage classification with EEG spectrogram. *Int. J. Environ. Res. Public. Health*. **19**, 6322. https://doi.org/10.3390/ijerph19106322 (2022).
27. Jadhav, P. & Mukhopadhyay, S. Automated sleep stage scoring using time-frequency spectra Convolution neural network. *IEEE Trans. Instrum. Meas.* **71**, 1–9. https://doi.org/10.1109/TIM.2022.3177747 (2022).
28. Riazi, H., Nazari, M., Raoufy, M. R., Mirnajafi-Zadeh, J. & Shojaei, A. Olfactory epithelium stimulation using rhythmic nasal Air-Puffs improves the cognitive performance of individuals with acute sleep deprivation. *Brain Sci.* **14**, 378. https://doi.org/10.3390/brainsci14040378 (2024).
29. Ferreira, C. et al. Electroencephalographic changes after one night of sleep deprivation. *Arq. Neuropsiquiatr.* **64**, 388–393. https://doi.org/10.1590/S0004-282X2006000300007 (2006).
30. Chen, H. Y. & Lee, C. H. Vibration signals analysis by explainable artificial intelligence (XAI) approach: application on bearing faults diagnosis. *IEEE Access*. **8**, 134246–134256. https://doi.org/10.1109/ACCESS.2020.3006491 (2020).
31. Rashed-Al-Mahfuz, M. et al. A deep convolutional neural network method to detect seizures and characteristic frequencies using epileptic electroencephalogram (EEG) data. *IEEE J. Transl Eng. Health Med.* **9**, 1–12. https://doi.org/10.1109/JTEHM.2021.3050925 (2021).
32. Wang, T. et al. Automatic ECG classification using continuous wavelet transform and convolutional neural network. *Entropy* **23**, 119. https://doi.org/10.3390/e23010119 (2021).
33. Fuad, N., Jailani, R., Omar, W. R. W., Jahidin, A. H. & Taib, M. N. Three dimension 3D signal for electroencephalographic (EEG). *In 2012 IEEE Control and System Graduate Research Colloquium*. 262–266; (2012). https://doi.org/10.1109/ICSGRC.2012.6287173
34. Upadhyay, R., Chhipa, P. C., Phlypo, R., Saini, R. & Liwicki, M. Multi-task meta learning: learn how to adapt to unseen tasks. *In International Joint Conference on Neural Networks (IJCNN)*. 1–10; (2023). https://doi.org/10.1109/IJCNN54540.2023.10191400 (2023).
35. Zhang, Y. & Yang, Q. A survey on multi-task learning. *IEEE Trans. Knowl. Data Eng.* **34**, 5586–5609. https://doi.org/10.1109/TKDE.2021.3070203 (2021).
36. Cao, J., Li, Y. & Zhang, Z. Partially shared multi-task convolutional neural network with local constraint for face attribute learning. *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.* **4290-4299** https://doi.org/10.1109/CVPR.2018.00451 (2018).
37. Liu, S., Johns, E. & Davison, A. J. End-to-end multi-task learning with attention. *In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. 1871–1880; (2019). https://doi.org/10.1109/CVPR.2019.00197
38. Sener, O. & Koltun, V. Multi-task learning as multi-objective optimization. *Adv. Neural Inf. Process. Syst.* **31** (2018).
39. Ali, W. & Ahmed, A. A. Hybrid intelligent phishing website prediction using deep neural networks with genetic algorithm-based feature selection and weighting. *IET Inf. Secur.* **13**, 659–669. https://doi.org/10.1049/iet-ifs.2019.0006 (2019).
40. Yang, S. S., Yang, X. H., Jiang, R. & Zhang, Y. C. New optimal weight combination model for forecasting precipitation. *Math. Probl. Eng.* **2012** (376010). https://doi.org/10.1155/2012/376010 (2012).
41. Sun, J. et al. A method of optimizing weight allocation in data integration based on Q-learning for drug-target interaction prediction. *Front. Cell. Dev. Biol.* **10**, 794413. https://doi.org/10.3389/fcell.2022.794413 (2022).
42. Poojary, R., Raina, R. & Mondal, A. K. Effect of data-augmentation on fine-tuned CNN model performance. *IAES Int. J. Artif. Intell.* **10**, 84. https://doi.org/10.11591/ijai.v10.i1.pp84-92 (2021).
43. Senan, E. M. et al. Classification of histopathological images for early detection of breast cancer using deep learning. *J. Appl. Sci. Eng.* **24**, 323–329. https://doi.org/10.6180/jase.202106_24(3).0007 (2021).
44. Yazdi, M., Samaee, M. & Massicotte, D. A. Review on automated sleep study. *Ann. Biomed. Eng.* **52**, 1463–1491. https://doi.org/10.1007/s10439-024-03486-0 (2024).
45. Kuan, Y. C., Hong, C. T., Chen, P. C., Liu, W. T. & Chung, C. C. Logistic regression and artificial neural network-based simple predicting models for obstructive sleep apnea by age, sex, and body mass index. *Math. Biosci. Eng.* **19**, 11409–11421 (2022).
46. Vaquerizo-Villar, F. et al. An explainable deep-learning model to stage sleep States in children and propose novel EEG-related patterns in sleep apnea. *Comput. Biol. Med.* **165**, 107419. https://doi.org/10.1016/j.compbiomed.2023.107419 (2023).
47. Wallis, P., Yaeger, D., Kain, A., Song, X. & Lim, M. Automatic event detection of rem sleep without Atonia from polysomnography signals using deep neural networks. *ICASSP 2020–2020 IEEE Int. Conf. Acoust. Speech Signal. Process. (ICASSP)*. **4112–4116** https://doi.org/10.1109/ICASSP40776.2020.9054506 (2020).

48. Cao, K. & Lv, X. Multi-task feature fusion network for obstructive sleep apnea detection using single-lead ECG signal. *Measurement* **202**, 111787. https://doi.org/10.1016/j.measurement.2022.111787 (2022).
49. Kandukuri, U. R. et al. Constant Q-transform-based deep learning architecture for detection of obstructive sleep apnea. *Int. J. Appl. Math. Comput. Sci.* 33. https://doi.org/10.34768/amcs-2023-0036 (2023).
50. Stephansen, J. B. et al. Neural network analysis of sleep stages enables efficient diagnosis of narcolepsy. *Nat. Commun.* **9**, 5229. https://doi.org/10.1038/s41467-018-07229-3 (2018).
51. Sharma, M., Anand, D., Verma, S. & Acharya, U. R. Automated insomnia detection using wavelet scattering network technique with single-channel EEG signals. *Eng. Appl. Artif. Intell.* **126**, 106903. https://doi.org/10.1016/j.engappai.2023.106903 (2023).
52. Jeppe, K. et al. Accurate detection of acute sleep deprivation using a metabolomic biomarker—A machine learning approach. *Sci. Adv.* **10**, eadj6834. https://doi.org/10.1126/sciadv.adj6834 (2024).
53. Chih, H. Y. et al. Multitask learning for automated sleep staging and wearable technology integration. *Adv. Intell. Syst.* **6**, 2300270. https://doi.org/10.1002/aisy.202300270 (2024).
54. Zan, H. & Yildiz, A. Multi-task learning for arousal and sleep stage detection using fully convolutional networks. *J. Neural Eng.* **20**, 056034. https://doi.org/10.1088/1741-2552/acfe3a (2023).

Author contributions

The conception and design of the study were conducted by S.K, T.K, and G.T. The acquisition and interpretation of data were done by A.S. The analysis of data was performed by S.K, T.K, and E.A. The drafting of the article was completed by S.K. and T.K. The article was critically revised for important intellectual content by T.K, G.T, E.A, and A.S. The final approval of the version to be submitted was given by T.K. All authors have read and approved the final version of the manuscript.

Funding

There is no funding issue in this study.

Declarations

Competing interests

The authors declare no competing interests.

Ethics statement

All experimental procedures were conducted following the principles embodied in the Declaration of Helsinki and were approved by the local Ethics Committee of Tarbiat Modares University, Faculty of Medical Sciences (approval no.: 1401.085; date of approval: June 6, 2022).

Additional information

Correspondence and requests for materials should be addressed to T.K.