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A Machine Learning Approach to Analyze Manpower Sleep Disorder

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Abstract

Introduction: Human resources play a pivotal role in determining the efficiency of a workplace and an organization. One major issue that significantly influences workforce productivity is sleep disorders. Machine learning can be applied to predict sleep disorders and analyze how various factors, such as lifestyle and environmental conditions, contribute to the development of these disorders, paving the way for more effective interventions and solutions.
Materials and Methods: In this research, by utilizing data analytic methods, some physical and medical-related features of manpower are investigated to make beneficial observations. Moreover, a combination of machine learning and metaheuristic algorithms such as eXtreme Gradient Boosting and particle swarm optimization are used to make an accurate predictive model. Also, the accuracy, recall, precision, and F1-score metrics are utilized to evaluate the model. The Python and Scikit-learn package are used to analyze the problem and implement algorithms.
Results: The outcome is a predictive model with 93.1% accuracy to predict the type of sleep disorder and some useful insights like the relationship of different variables like job and physical characteristics with the sleep disorder. It is observed that one's occupation has the most impact on insomnia (1.25) and BMI has the most effect on sleep apnea (1).
Conclusion: The implementation of a predictive model helps identify existing issues and enables proactive measures to prevent potential problems, allowing decision-makers to design targeted interventions and wellness programs. Continuous monitoring and adjustments based on the model's predictions ensure adaptive strategies that improve employee health and workplace efficiency, fostering a resilient workforce and enhancing overall organizational performance.

Keywords: Efficiency, Machine learning, Metaheuristic, Manpower, Sleep disorder

1. Introduction

In the fast-paced landscape of contemporary workplaces, the significance of adequate sleep in the realm of manpower has emerged as a critical consideration. Sleep, a fundamental pillar of well-being, not only affects an individual's health but also plays a crucial role in shaping workplace dynamics and organizational outcomes. Exhaustion exerts a significant economic toll, causing employers to incur billions of dollars in expenses annually [1]. It is approximated that declines in both productivity and motivation, coupled with healthcare expenditures linked to fatigue, result in an average cost of $1,967 per employee for individual employers each year [1]. Aggregating these productivity losses, workplace fatigue collectively amounts to approximately $136.4 billion annually for companies in the United States [2]. Therefore, this paper delves into the intricate interplay between sleeping issues and manpower, and identifies the effective factors, which can influence employee efficiency and overall performance, with the help of artificial intelligence methods. Thus, this will guide decision-makers to deal with regarding problems more efficiently.

The relationship between manpower performance and organizational efficiency is foundational in determining the overall success and competitiveness of a business [3]. Manpower performance, representing the collective skills, motivation, and engagement of the workforce, directly influences the efficiency of organizational operations [4]. When employees perform at their best, executing tasks with proficiency and dedication, the overall productivity as well as effectiveness of the organization rises [4]. Conversely, organizational efficiency, achieved through streamlined processes, resource optimization, and effective management practices, provides the infrastructure within which manpower performance can flourish [5]. By optimizing workflows, reducing bottlenecks, and leveraging technology, organizations can empower their workforce to achieve higher levels of performance and productivity [5]. Thus, a symbiotic relationship exists between manpower performance and organizational efficiency, with each element mutually reinforcing the other to drive innovation, growth, and sustained success [6].

Artificial intelligence (AI) stands as a cornerstone of Industry 4.0, revolutionizing traditional manufacturing and industrial processes [7]. In this era of digital transformation, AI plays a pivotal role in enhancing efficiency, productivity, and innovation across various sectors [7, 8]. Through advanced machine learning algorithms, AI enables predictive maintenance, optimizes production schedules, and improves quality control [9]. Furthermore, AI-powered robotics and automation systems streamline operations, reducing costs and minimizing human error [10]. Real-time data analytics facilitated by AI drives informed decision-making, facilitating agile responses to market fluctuations and customer demands [10]. The synergy between AI and Industry 4.0 fosters a dynamic ecosystem of interconnected smart technologies, empowering industries to thrive in an increasingly competitive and interconnected global landscape [11].

Some research focused on sleep quality and job performance. Park et al. [12] investigated some factors like countries' GDP and cultures and their relation with sleep quality and job performance by using statistical tools. They found that more than 50% of the variation in sleep quality is related to social factors. Wang et al. [13] proposed research in which they analyzed the effect of change in body mass index (BMI) on sleep quality by using machine learning and deep learning algorithms. Li et al. [14] worked on specifying the effective factors on the sleep quality and depressive symptoms of nurses in China by utilizing machine learning algorithms. Their model showed an 87.1% accuracy.

Furthermore, some research investigated sleep disorders by artificial intelligence methods. Sharma et al. [15] proposed a machine learning algorithm for the classification of various sleep problems like nocturnal frontal lobe epilepsy, periodic leg motion disorder, narcolepsy, quick eye motion behavior, insomnia, and sleep-disordered breathing based on EEG data. Alazaidah et al. [16] proposed a machine learning model to classify sleep disorders based on features like sleep exposure index, body weight, gestation time, predation index, brain weight, and danger index. Huang et al. [17] investigated the recognition of risk factors for insomnia disorder by machine learning algorithms and their model showed 87% accuracy for this purpose. Mencar et al. [18] trained predictive models by random forest and support vector machine to predict obstructive sleep apnea syndrome severity and their model had a 44.7% accuracy. They trained models based on factors like demographic characteristics, gas exchange, spirometry values, and symptoms. Cai et al. [19] proposed a deep learning model to predict sleep disorders like sleep apnea based on EEG data and their model had 71% accuracy. Widasari et al. [20] worked on a machine learning model trained based on EGG data and sleep quality features to predict sleep disorders and their model showed 86.27% accuracy. Cheng et al. [21] presented a convolutional neural network model to classify sleep stages and sleep disorders based on sensory data.

Since sleep disorders have a significant effect on human efficiency in the workplace, in our quest to understand and address the complexities of sleep disorders, we propose a comprehensive analysis of various features associated with these conditions. Recognizing the multifaceted nature of sleep disorders, we aim to delve into key parameters like sleep duration, quality, and physical factors. By meticulously examining these features, we aspire to unravel the intricate relationships between different variables and their potential impacts on overall sleep health. Our ultimate goal is to utilize the ability of machine learning methods and metaheuristics algorithms to construct a predictive model that can accurately forecast the classes of sleep disorders. This will be beneficial to the treatment of disorders and increase human efficiency in the workplace.

This paper explores sleep disorder issues and associated factors such as physical and medical aspects through an analytical approach to gain insights. Furthermore, machine learning and PSO algorithms are employed to develop a highly accurate predictive model for identifying the types of sleep disorder. As a result, this analysis facilitates the prompt identification of sleep-related problems, leading to expedited treatment and a more efficient work environment.

The rest of the paper is arranged as follows: Section 2 describes the XGBoost and PSO algorithms; Section 3 contains the numerical results and discussion, and the conclusion is detailed in Section 4.

2. Materials and Methods

In this section, the machine learning algorithm, the evaluation metrics, and the metaheuristic algorithm that is used to tune the hyperparameters of the machine learning model are introduced.

Data definition and preparation

Sleep disorder data and related factors such as physical and medical aspects are investigated through an analytical approach. To obtain a more accurate model, the features are selected based on the correlation of each dependent variable with the independent one. Also, since some of variables are categorical, the label encoding method is applied to deal with this issue. The features which will be utilized in this research are mentioned in Table 1.

Table 1. Factors of dataset

Variable	Type	Role
ID	Numerical	Int*
Gender	Categorical	Int
Age	Numerical	Int
Job	Categorical	Int
Sleep duration	Numerical	Int
Quality of sleep	Numerical	Int
Physical activity	Numerical	Int
Stress	Numerical	Int
BMI	Categorical	Int
Blood pressure	Categorical	Int
Heart rate	Numerical	Int
Daily steps	Numerical	Int
Sleep disorders	Categorical	Dt*

*Note: Int = Independent, Dt = Dependent

Metaheuristic algorithm

Particle swarm optimization (PSO) is an optimization algorithm categorized as a metaheuristic, which takes inspiration from the collective behavior observed in birds and fish. [22]. Renowned for its effectiveness and adaptability in addressing optimization problems, PSO simulates a social system where individuals, portrayed as particles, work together to discover the best solution within a given search space [23]. The problem-solving prowess of PSO is founded on a set of fundamental principles that guide its operations [24].

In the realm of optimizing a problem, particle swarm optimization (PSO) begins by randomly placing a population of particles within the solution space[25]. Each particle's location in this space signifies a possible solution, and its trajectory is influenced by two crucial factors: its individual history and the performance of the top-performing particle in its vicinity [26]. Through iterative adjustments of their positions, the particles aim to approach the global optimum, maintaining a delicate balance between exploration and exploitation [27]. This cooperative strategy enables PSO to efficiently explore and exploit the search space in a decentralized fashion [27]. The determination of particle movement involves calculating the change in speed using equation (1).

$$\vec{V}_{ij}(h+1) = \varphi_1 e_1 \left(\vec{z}_{ij}(h) - \vec{x}_{ij}(h)\right) + \varphi_2 e_2 \left(\vec{z}_{gi}(h) - \vec{y}_{ij}(h)\right) + W\,\vec{V}_{ij}(h) \qquad (1)$$

In this context, $\vec{V}_{ij}(h)$ represents the speed of particle i during the h-th iteration, while $\vec{y}_{ij}(h)$ denotes the location of particle i at the same iteration. The terms e_1 and e_2 are random numbers within the range (0,1), and φ_1 and φ_2 are constants. Additionally, $\vec{z}_{ij}(h)$signifies the best location of an individual particle, and $\vec{z}_{gi}(h)$denotes the best location of the entire particle swarm. The constant W remains fixed. The calculation for the new location of a particle is determined by equation (2).

$$\vec{y}_{ij}(h+1) = \vec{y}_{ij}(h) + \vec{V}_{ij}(h+1) \quad (2)$$

In this paper, PSO is used to optimize the hyperparameters of the machine learning model, aiming to enhance accuracy in task performance. The flowchart of the PSO is illustrated in Figure 1.

Machine learning

Supervised learning constitutes one of the three branches of machine learning, comprising two main components: (1) Regression and (2) Classification [28]. Within Classification, the prediction of a class label is made based on independent variables [28].

The XGBoost (eXtreme Gradient Boosting) algorithm is a popular and powerful machine learning algorithm that is a subcategory of ensemble learning [29]. Specifically, it is a boosting algorithm that integrates the forecasts of numerous weak learners, usually decision trees, to construct a robust predictive model [30]. One of the key strengths of XGBoost is its ability to handle both regression and classification tasks efficiently [31]. XGBoost has gained widespread popularity due to its high predictive accuracy and robustness.

At its core, XGBoost builds a series of decision trees consecutively, with each tree aiming to correct the errors done by the previous ones [31]. The algorithm minimizes a regularized objective function, which consists of two main components: the error function, measuring the difference between predicted and actual values, and a regularization term, preventing the model from becoming too complex and overfitting the training data [31]. The objective function for XGBoost can be expressed as:

$$Objective(\Theta) = \sum_{i=1}^{n} L(y_i, \hat{y}_i) + \sum_{s=1}^{S} \Omega(f_s) \quad (3)$$

where L is the error function; y_i is the true label for the *i*-th observation; $\hat{y}_i$ is the predicted value; S is the number of trees; $\Omega(f_s)$ is the adaptation term for the *s*-th tree; and Θ represents the set of parameters to be optimized.

The key advancement of XGBoost lies in its utilization of gradient boosting, wherein every subsequent tree is customized to match the negative gradient of the error function related to the current model's prediction [30]. This process allows XGBoost to emphasize the correction of errors made by the existing model, leading to a highly accurate and well-generalized final model. The general structure of XGBoost is depicted in Figure 2.

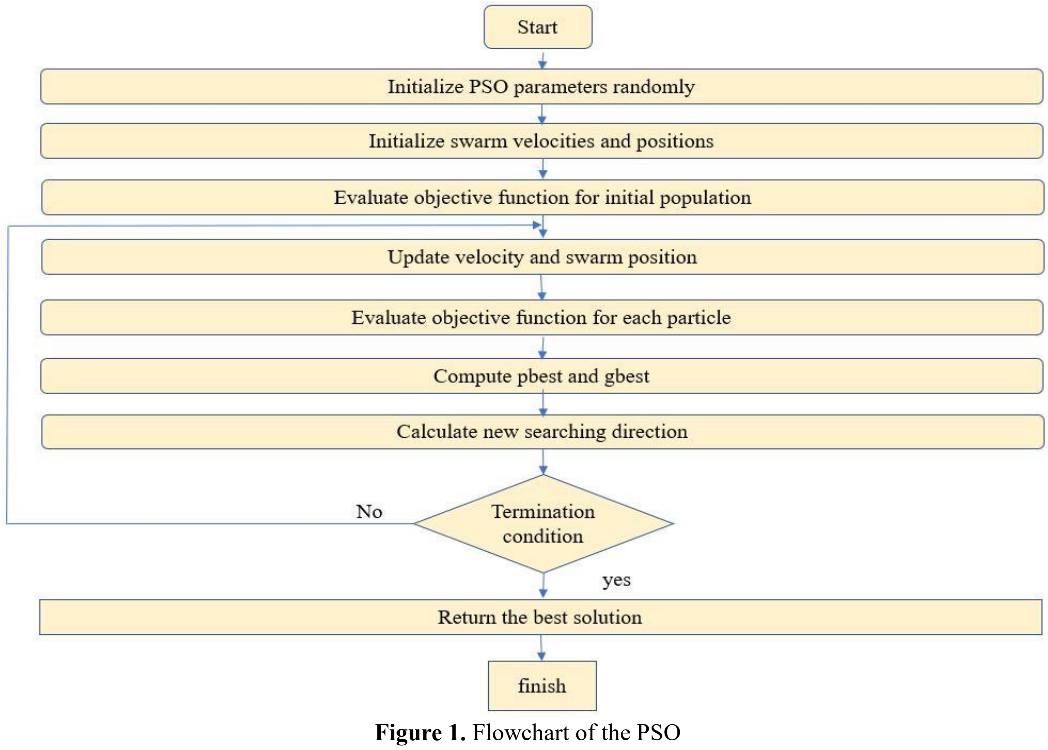

Figure 1. Flowchart of the PSO

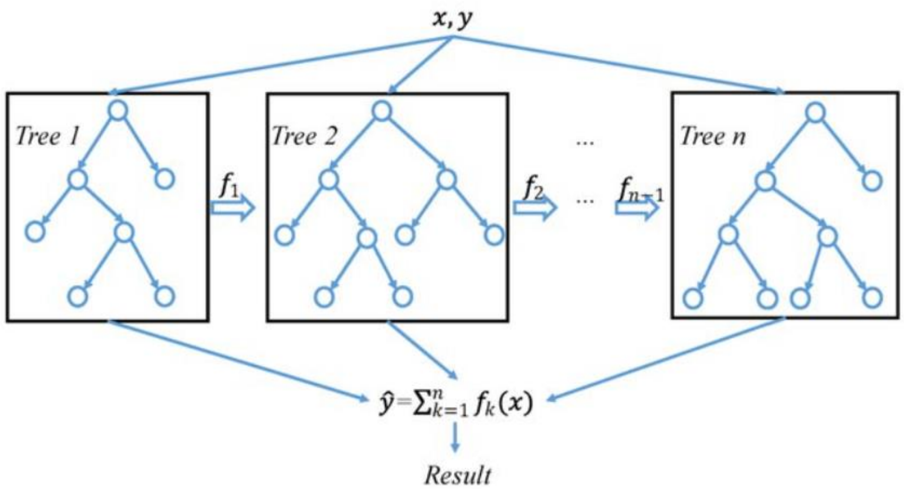

Figure 2. General structure of XGBoost [32]

Evaluation metrics

Several metrics can be employed to evaluate a machine learning model, and a few of them are presented below:

$$Precision = \frac{TP}{TP + FP} \quad (4)$$

$$Recall = \frac{TP}{TP + FN} \quad (5)$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (6)$$

$$F1 - score = \frac{TP}{TP + \frac{1}{2}(FP + FN)} \quad (7)$$

When a model makes a positive prediction with a positive primary value, it is considered a true positive (TP). Conversely, a true negative (TN) happens when the model predicts negatively with a negative primary value. False positives (FPs) are positive predictions with a negative primary value, while false negatives (FNs) are negative predictions with a positive primary value.

A confusion matrix serves as a commonly employed performance assessment tool in machine learning for evaluating the accuracy of a classification model. [33]. It presents a tabular representation of the model's predictions versus the real outcomes in a dataset. The matrix is divided into four quadrants: TP, TN, FP, and FN [33]. By comparing these values, different metrics such as recall, accuracy, precision, and F1 score are computed, offering a comprehensive understanding of the model's efficiency across different classes. The confusion matrix serves as a valuable diagnostic tool, aiding in the identification of areas where the model excels or struggles, thereby guiding refinement and optimization efforts [34].

Label encoding

The categorical features need to be converted into numerical representations before training the machine learning model [35]. This conversion is essential because most machine learning algorithms are designed to work with numerical data [35]. The LabelEncoder method is a valuable tool in machine learning for converting categorical data into a numerical format [36]. It assigns a unique integer to each category within a categorical variable, enabling algorithms to process the data efficiently [36]. This transformation simplifies the data representation and facilitates model training.

3. Result

Numerical results and discussion

In this section, an exploratory data analysis (EDA) is proposed to get some insights from the variables and their relationship and after that, a predictive model will be trained.

EDA

In the first step, the relationship between gender and sleep disorder is investigated and the result is shown in Figure 3.

Furthermore, an analysis for understanding the relationship between occupation and sleep disorder is conducted and the outcome is depicted in Figure 4.

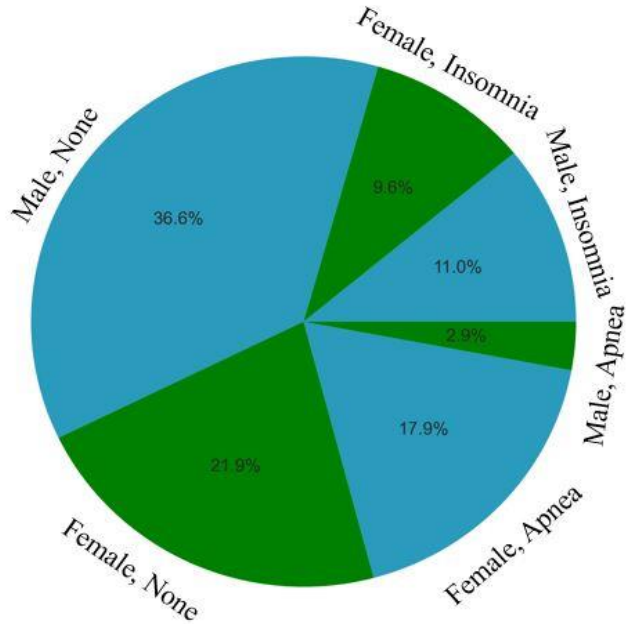

Figure 3. Relationship between gender and sleep disorder

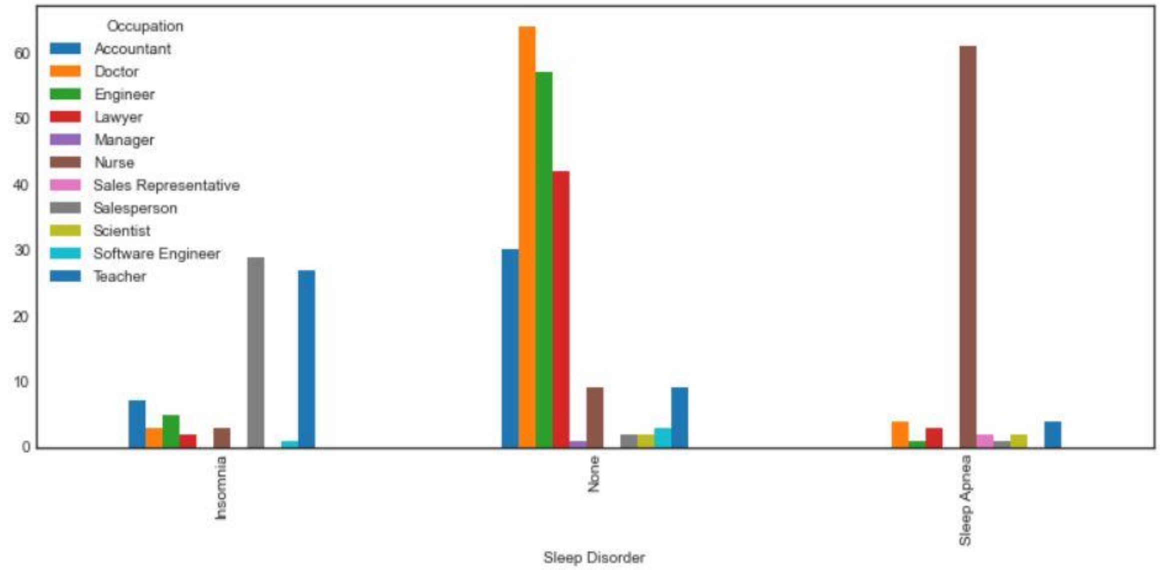

Figure 4. Relationship between occupation and sleep disorder

Based on Fig 4, doctors have normal sleep; nurses are the group that has the most sleep apnea problems, and salespersons have the most insomnia problems.

Next, an investigation is carried out to comprehend the connection between one's age, gender, and the occurrence of sleep disorders, with the results illustrated in Figure 5.

Finally, an examination is conducted to understand the correlation between an individual's weight and the presence of sleep disorders, and the findings are depicted in Figure 6.

Machine learning model

After analyzing the relationship between some of the variables and sleep disorders, the predictive model is trained based on the independent variables. For this purpose, after applying some preprocessing methods to the dataset, it was split into a training set and test set, to which 68% and 32% of the data are assigned respectively.

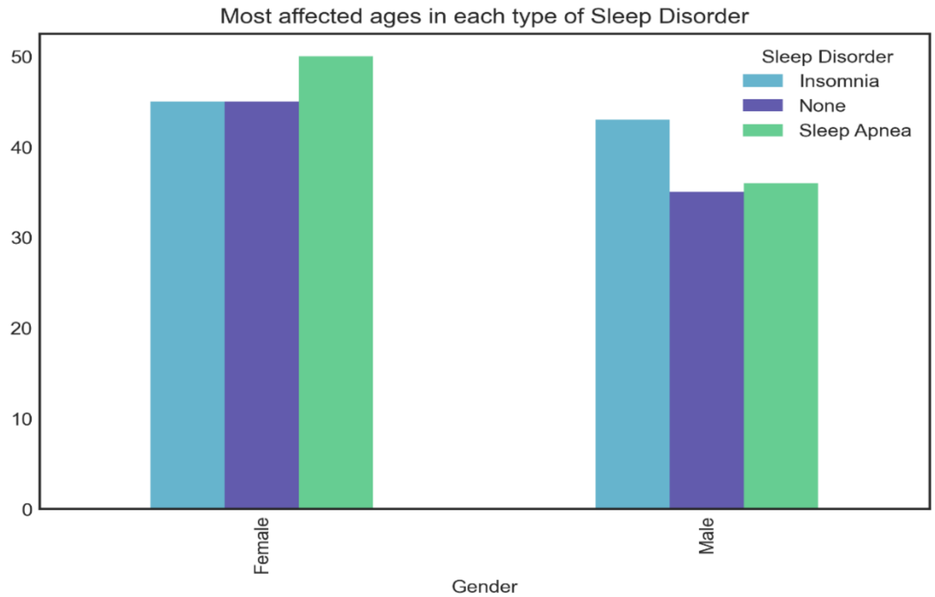

Figure 5. Relationship between one's age, gender, and sleep disorder

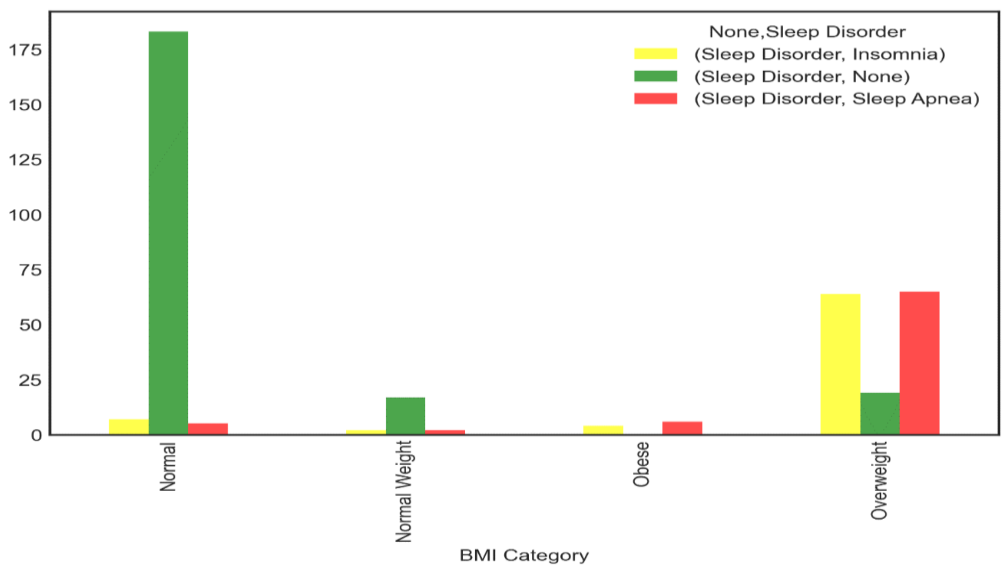

Figure 6. Relationship between BMI and sleep disorder

Some classification algorithms are utilized to build the machine learning model and the results are mentioned in Table 2. Also, the outcome of the confusion matrix analysis is depicted in Figure 7.

Based on Table 2 and Figure 7, the combination of the XGBoost classifier and PSO algorithm shows better performance than others. Therefore, it is chosen for building the model as the main algorithm.

Furthermore, a feature importance analysis is conducted to recognize the impact of each variable on the sleep disorder variable after the training model. The results are shown in Figure 8.

Based on Figure 8, it can be observed that one's occupation has the most impact on insomnia and BMI has the most effect on sleep apnea. Also, the other variables effect on the sleep disorder can be seen in the Figure 8.

Table 2. Evaluation's outcome and algorithms comparison

Algorithm	Accuracy (%)
Logistic regression	90.8
Decision Tree	88.3
Random Forest	89.5
Support vector	88.8
XGBoost	91.4
XGBoost + PSO	93.1

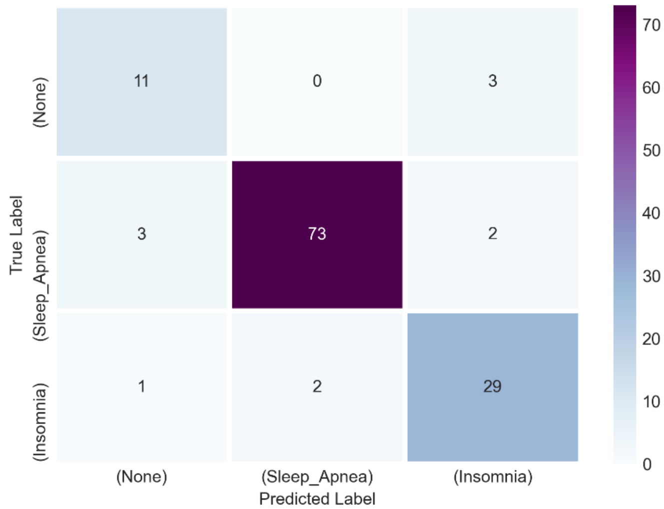

Figure 7. Confusion matrix result

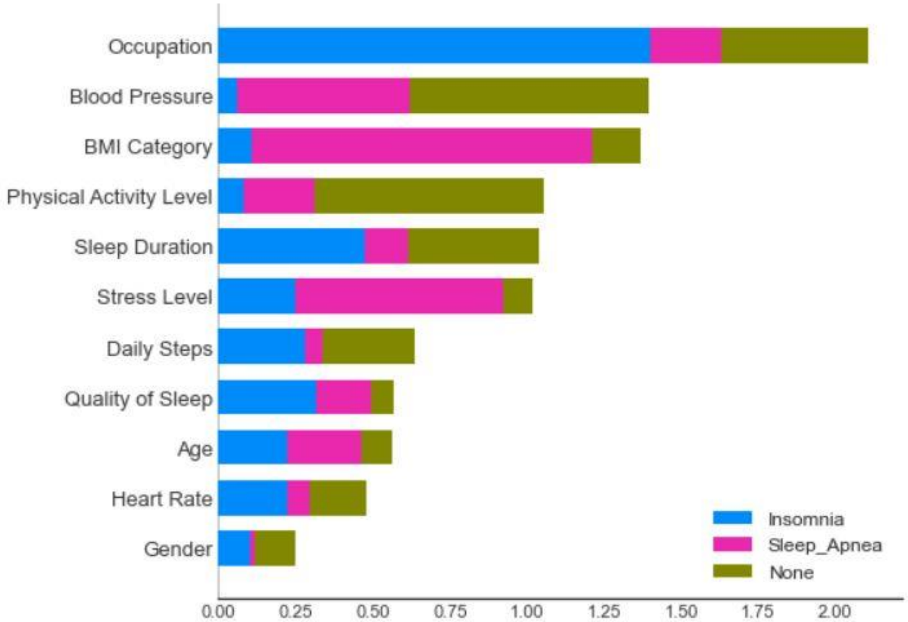

Figure 8. Feature importance analysis

4. Discussion

The implementation of a predictive model and the subsequent analysis of results contribute not only to the identification of existing issues but also to proactive measures for preventing potential problems. By leveraging the insights provided by the model, decision-makers can implement targeted interventions and wellness programs, fostering a preventive approach to employee well-being. This proactive strategy not only addresses current challenges but also helps create a healthier and more resilient workforce, ultimately boosting overall organizational performance and creating a positive work environment. Additionally, continuous monitoring and adjustment based on the model's predictions allow for adaptive strategies that can evolve with changing workplace dynamics, ensuring sustained improvements in both employee health and overall workplace efficiency. Some implications should be mentioned:

- There is a strong relationship between individual occupation and sleep disorders, as job-related stress, irregular work hours, and occupational demands can significantly disrupt sleep patterns and increase the risk of developing conditions like insomnia or sleep apnea. Therefore, the tasks should be assigned to employees appropriately.

- Individuals with higher or lower BMI categories, such as obesity or underweight, are often at increased risk for sleep disorders like sleep apnea and insomnia, respectively. Elevated blood pressure is commonly associated with sleep disorders like obstructive sleep apnea, where poor sleep quality or disruptions can contribute to hypertension. Thus, the decision-makers should make regular check-ups for employees to deal with these problems.

4. Conclusion

The effectiveness of a workplace and organization is significantly influenced by the pivotal factor of manpower. One key challenge impacting workforce efficiency is the prevalence of sleep disorders. Thus, this study employed data analytics techniques to delve into various physical and medical attributes of the manpower, aiming to extract valuable insights. Furthermore, a predictive model was developed through the integration of machine learning and PSO algorithms. The resultant model boasts an impressive accuracy of 93.1%, facilitating the prediction of sleep disorder types. This model showed a better performance in comparison with other papers such as 87% [17], 71%[19], and 86.27% [20]. The implementation of a predictive model enables decision-makers to identify and prevent potential issues, fostering a proactive approach to employee well-being through targeted interventions. Continuous monitoring allows for adaptive strategies, improving both employee health and organizational performance. As a consequence, the implementation of such programs contributes to enhanced efficiency and dynamism within workplaces and organizations, promoting overall well-being and productivity. Also, this research faced some limitations such as accessing more data and variables. Finally, for future research, other machine learning and/or deep learning algorithms can be utilized to increase the accuracy of the model; new features related to manpower can be investigated, and other manpower problems can be analyzed to increase the efficiency of the workplace.

Ethical Considerations

Compliance with ethical guidelines

There were no ethical considerations to be considered in this research.

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Author's contributions

Conceptualization and Supervision: Mohammad Noori; Methodology: Reza Amiri; Investigation, Writing – original draft, and Writing – review & editing: All authors; Data collection: Reza Amiri; Data analysis: Reza Amiri.

Conflict of interest

The Authors declare that there is no conflict of interest.

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