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Classification of Sleep Disorders Using Machine Learning Algorithms

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Abstract: This study aims to analyse the relationship between individuals' sleep health and lifestyle using machine learning algorithms. The Sleep Health and Lifestyle dataset used in the study includes variables such as age, gender, occupation, physical activity, stress level, and sleep duration. The data has been cleaned during the pre-processing stage and normalisation procedures have been applied. Subsequently, the classification of individuals' sleep quality was performed using the K-Nearest Neighbour (KNN), Random Forest, Support Vector Machines (SVM), and Artificial Neural Networks (ANN) algorithms. Model performance has been evaluated using metrics such as accuracy, F1-score, precision and sensitivity. In this study, the 5-fold cross-validation method was preferred to evaluate the model's performance in a more reliable and generalisable manner. The results show that ANN and Random Forest models achieve a higher accuracy rate compared to other algorithms. These findings reveal that lifestyle factors have a strong influence on predicting sleep quality.

Keywords: Machine Learning Algorithm, Sleep Disorders, Lifestyle Health

Introduction

Human beings need to work and rest throughout their lives. In order to work healthily and productively, he must pay attention to what he eats, drinks and how he rests. Sleep is very important for rest. If a person cannot get healthy sleep, their bodily functions cannot work properly either. Sleep health is a fundamental biological process that directly affects an individual's physical and mental quality of life. In order for both the body and mind to function healthily, it is recommended to sleep between 8 and 10 hours. As people age, this sleep duration may decrease slightly. In later years, some people may experience problems such as insomnia or waking up during sleep. This type of problem is referred to as sleep disorder. This disease takes a heavy toll on people both mentally and physically. The diagnosis of this disease can be made by looking at a specific time period. Nowadays, irregular sleep habits, a hectic work pace, stress and digital addictions are contributing to the increasing prevalence of sleep disorders. There are numerous studies in the literature examining the factors that affect sleep quality. For example, (Alnawwar et al, 2023). found that physical activity improves sleep quality and reduces symptoms of insomnia and restless sleep. Huang et al, (2025) demonstrated in their study that sleep duration and quality significantly increased in individuals who exercised regularly. Additionally, Godos et al, (2021) have conducted studies demonstrating the importance of food types in the relationship between diet and sleep. In light of these studies, the current research aims to predict sleep quality from individuals' lifestyle parameters using the Sleep Health and Lifestyle dataset. In this context, the original aspect of the study is the comparative analysis of four different machine learning algorithms and the fair evaluation of model performance using the stratified cross-validation method.

Numerous studies have been conducted in the literature on the analysis of variables affecting sleep health. Alnawwar MA et al, (2023) found that regular physical activity has numerous health benefits, including improved sleep quality and reduced symptoms of sleep disorders. Huang Y. et al, (2025) investigated the effects of exercise on sleep quality in the general population. Godos J. et al, (2021) investigated the relationship between diet and sleep quality. Koohsari MJ et al, (2023) found that prolonged sedentary periods are associated with insomnia and sleep disorders; the benefits of physical activity have been shown to partially offset the harm caused by sedentary behaviour. RM Merrill (2022) has demonstrated the relationship between stress and sleep disorders. GUR et al, (2024) analyse the effect of demographic characteristics such as gender, age and occupation, as well as lifestyle variables such as sleep duration, quality, physical activity levels and stress on sleep disorders using machine learning techniques in this study. This study (Ayan & Bilgin, 2024) aims to create a prediction model using the 'Sleep Health Lifestyle' dataset obtained from the Kaggle platform, evaluate this model using the Principal Component Analysis (PCA) method, the Naive Bayes method, and the Random Forest Trees method, and perform visualisations. Nazli et al, (2021) obtained heart rate variability (HRV) signals using R-peak information from electrocardiography signals divided into one-minute segments. Time and frequency domain features were determined from KHD signals, and apnoea classification was performed using the determined features with five different machine learning algorithms. In the study, the highest accuracy of 85.26% was obtained from the Random Forest algorithm, the highest precision of 78.08% from the K-Nearest Neighbour algorithm, and the highest selectivity of 91.4% from the Random Forest algorithm.

A literature review reveals numerous studies utilising machine learning models on physiological indicators and lifestyle factors affecting sleep health. These studies generally show that physical activity, nutrition, stress levels, sedentary lifestyles and demographic factors play a significant role in sleep quality and sleep disorders. Physical activity has been shown to improve sleep quality and reduce symptoms of sleep disorders. Similarly, it has been emphasised that diet has significant effects on sleep quality, and that increased stress levels also negatively affect sleep quality. Previous studies conducted on sleep disorders are summarized in Table 1.

Table 1. Studies conducted on sleep disorders

Study	Year	Method	Data Type	Key Findings
Alnawwar, M. A., et al,	2023	meta-analysis assessment	Systematic review; participants from various age groups	Physical activity improves sleep quality; it reduces insomnia and restless sleep symptoms.
Huang, Y., et al	2025	Regression analysis and survey evaluation	Cross-sectional; general population	Provides evidence of the effect of exercise on sleep quality
Godos, J., et al,	2021	PRISMA-based literature review	Systematic review; various age groups	It demonstrates the importance of food types in the relationship between diet and sleep.
Koohsari, M. J., et al,	2023	Multiple regression models	Observational; adult individuals	It demonstrates the importance of food types in the relationship between diet and sleep.
Merrill, R. M.	2022	Correlation and structural equation modelling	Cohort; 2,000 adults	It has quantitatively demonstrated the effect of stress on sleep quality and disorders.
Gur, Y.E. et al,	2024	machine learning and statistical analysis	Data from 374 participants on the Kaggle platform	The close relationship between the prevalence of sleep disorders and demographic factors
Ayan, S. et al,	2024	Principal Component Analysis (PCA) method	374-row variable dataset from the Kaggle platform	The effectiveness of PCA, Naive Bayes and ROA methods on sleep quality
Nazli, B. et al,	2021	Five different machine learning algorithms	ECG recordings of 70 people	The success of the KEK algorithm in apnoea classification

Methodology

The aim of this study is to classify sleep quality based on individuals' lifestyle variables using machine learning algorithms and to compare the performance of different machine learning algorithms (KNN, Random Forest, SVM, ANN). To develop a data-driven decision support system that enables the early prediction of sleep disorders using machine learning algorithms, thereby providing opportunities for early intervention and improving individuals' quality of life. Furthermore, unlike studies in the literature that are generally conducted with small samples, this research adopts a multivariate analysis approach using the Sleep Health and Lifestyle dataset and aims to obtain more reliable results through the stratified cross-validation method.

In this study, a machine learning-based classification model was developed on the Sleep Health and Lifestyle dataset. The workflow consists of data pre-processing, model creation, validation and performance evaluation stages. Missing values in the data have been imputed, and categorical variables have been converted using the one-hot encoding method. At the end of the training process, the performance of each model was compared using four different metrics. Figure 1 summarises the flow chart showing the general procedure of the study.

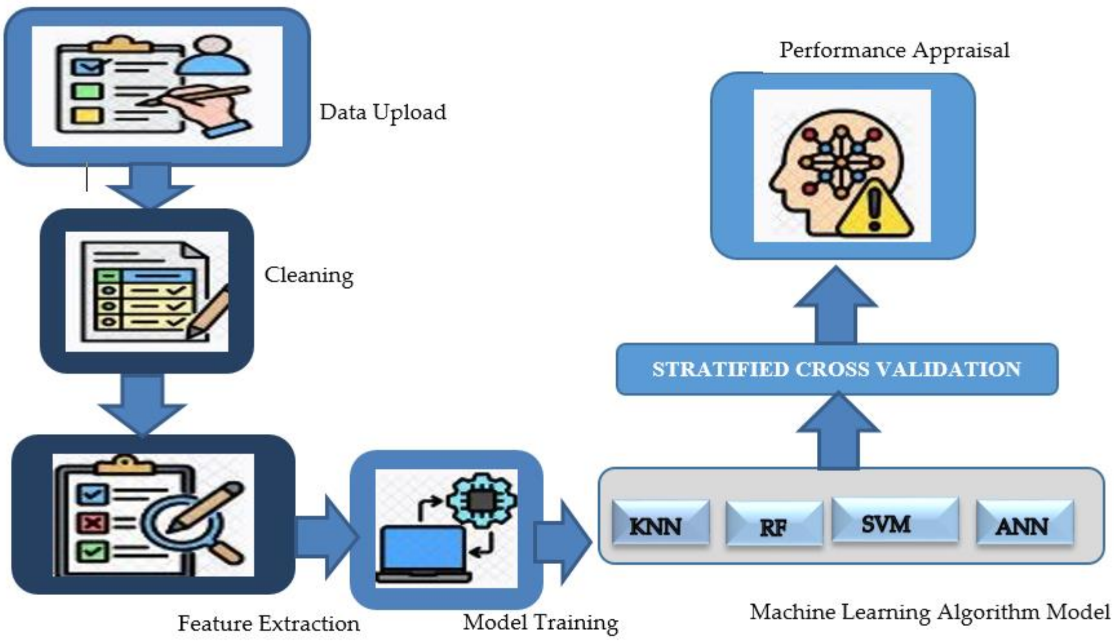

Figure 1. Flow diagram of the implemented model

Sleep Health and Lifestyle Dataset

The Sleep Health and Lifestyle dataset (kaggle sleep-health-and-lifestyle-dataset, 2025) contains variables such as individuals' demographic information, health habits, and sleep duration. In total, there are approximately 374 observations and 12 features. The target variable is defined as 'Sleep Disorder' (Normal, Sleep Apnoea, Insomnia). Table 2 presents the main characteristics and variables of the Sleep Health and Lifestyle Data Set used in this study. The stratified sampling method was applied to prevent an unbalanced class distribution in the data set. As the target variable is a classification problem, four commonly used classification algorithms have been applied. These are the K-Nearest Neighbour algorithm, Random Forest, Support Vector Machines, and Artificial Neural Networks algorithms.

Table 2. Characteristics of the Sleep Health and Lifestyle Data Set

Attirubutes	Values4	N
Gender	Male / Female	189 / 185
Age	27–59	374
Occupation	Nurse / Doctor / Engineer / Lawyer / Teacher / Accountant /	73 / 71 / 63 / 47 / 40 / 37 /
	Salesperson / Software Engineer / Scientist /	32 / 4 / 4 /
	Sales Representative / Manager	2 / 1
Sleep Duration	5.8–8.5 hours	374

Quality of Sleep	4–9	374
Physical Activity Level	30–90	374
Stress Level	3–8	374
BMI Category	Normal / Overweight / Normal Weight / Obese	195 / 148 / 21 / 10
Blood Pressure	130/85, 140/95, 125/80, 120/80, 115/75, 135/90, 140/90, 125/82,	99 / 65 / 65 / 45 / 32 / 27 / 4 / 4 /
	132/87, 128/85, 126/83, 115/78, 139/91, 142/92, 119/77, 135/88,	3 / 3 / 2 / 2 / 2 / 2 / 2 / 2 /
	129/84 / 128/84 / 131/86 / 117/76 / 130/86 / 118/75 / 121/79 / 122/80,	2 / 2 / 2 / 2 / 2 / 2 / 1 / 1 /
	118/76	1
Heart Rate	65–86 bpm	374
Daily Steps	3000–10000	374
Sleep Disorder	Sleep Apnea / Insomnia / None	78 / 77 / 219

The scatter plot matrix of all variables is illustrated in Figure 2. The relationships between features in the Sleep Health and Lifestyle Data Set are presented in Figure 3.

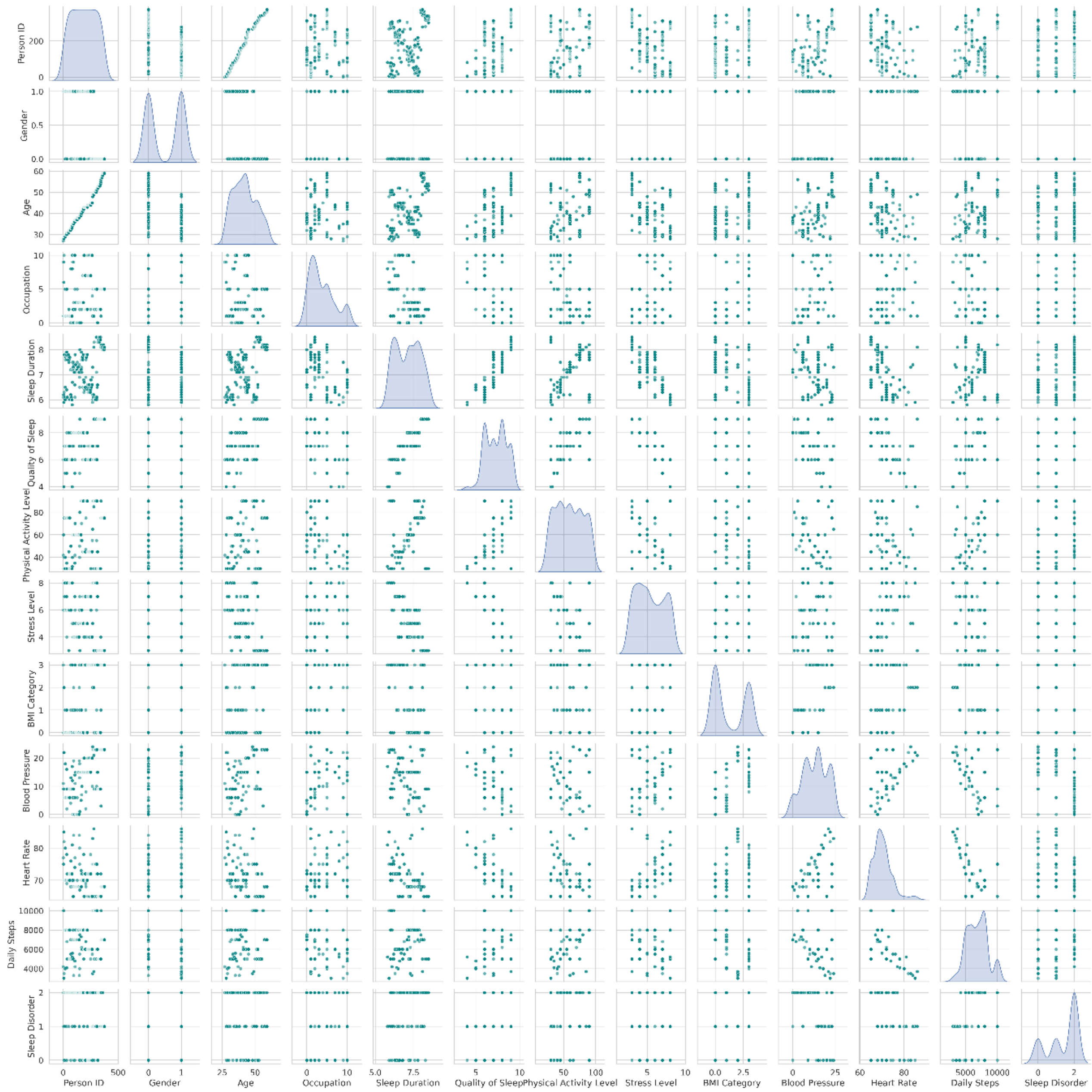

Figure 2. Scatter Plot matrix of All Veriables

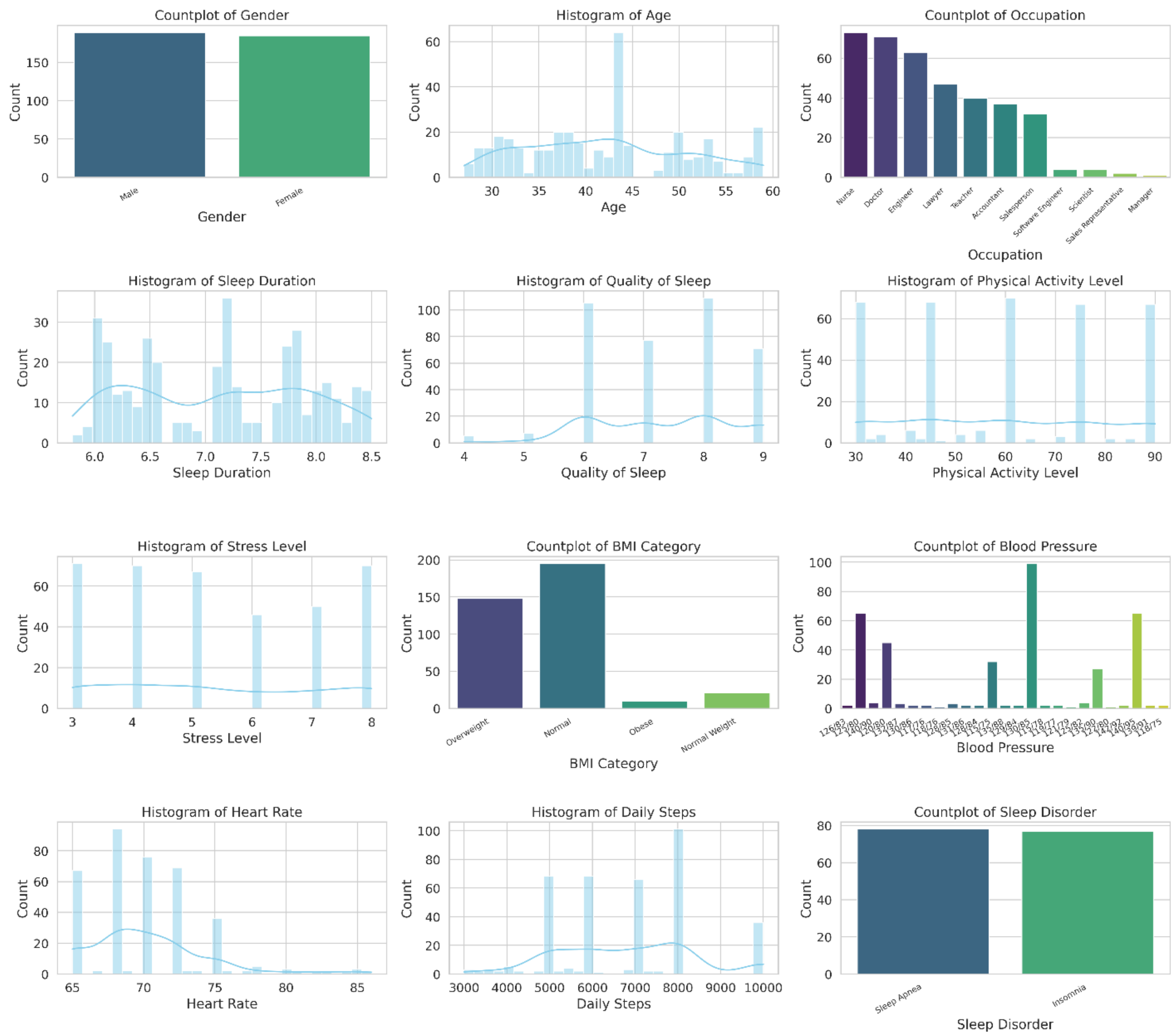

Figure 3. Relationships between features in the Sleep Health and Lifestyle Data Set

Machine Learning Algorithms

Machine learning involves automatically extracting patterns from data, modelling these patterns, and generalising them to new situations. Within this framework, numerous methods have been developed for various purposes such as classification, regression, clustering, and dimensionality reduction (Kursun & Koklu, 2025) (Unal et al, 2011) (Nazari et al, 2023). In this study, four different machine learning algorithms frequently used in the literature, namely K-Nearest Neighbours (KNN), Random Forest, Support Vector Machine (SVM) and Artificial Neural Network (ANN), were employed to evaluate the accuracy of the classification process.

K-Nearest Neighbord (KNN) Algorithm

The k-nearest neighbour method is an easy-to-use method among supervised learning models for problems such as classification and regression. (Kilci & Koklu, 2025) (Dertli & Koklu, 2025). A KNN classifier classifies new data by analysing K nearest neighbours (Koklu & Sabancı, 2016). The KNN algorithm classifies data by calculating the similarity between examples based on Euclidean distance. KNN is an example-based learning algorithm that classifies or predicts a new example based on its similarity to previously labelled examples. So the model does not establish a mathematical formula during 'learning'; it merely stores the data. When it is time to make a prediction, it looks at the K nearest neighbours to the new incoming data and makes a decision based on their labels. Due to its simple structure, it delivers effective results in low-dimensional data sets.

Random Forest (RF) Algorithm

Random forest is a machine learning model used to classify and predict data. For prediction based on a decision tree ensemble, majority vote or average is taken (Kilci & Koklu 2025). A collective learning method consisting of a combination of multiple decision trees. It prevents overfitting and has a high generalisation ability. First, random subsamples are taken from the data. Each tree is trained using samples randomly selected from the original data set. Each one uses only a subset of randomly selected features. Thus, the trees become different from one another. Finally, each tree makes its own prediction and the results are combined.

Support Vector Machine (SVM) Algorithm

Support Vector Machines are a supervised learning algorithm and a machine learning method widely used in classification and regression problems (Incekara et al, 2025). SVM is a powerful model for solving linear and non-linear classification problems. The data is classified using a hyperplane that maximises the class boundaries. Core functions are used to transform non-linear data into a higher-dimensional space for effective analysis (Kilci & Koklu, 2025). SVM classifies data using the maximum separation plane. It attempts to separate examples with the widest possible margin by determining the most appropriate boundary line or hyperplane between classes in a high-dimensional data space (Saritas et al, 2025) (Yildiz et al, 2024) (Al-doorı et al, 2021). The aim is to find a boundary that separates the two classes by the widest possible margin. The points on the boundary of this margin are the support vectors that determine the model's decision. In conclusion, SVMs can solve complex classification problems. Decision boundaries are determined by support vectors. The model has also been optimised by tolerating misclassifications with the tuning parameter (C) and ensuring high accuracy (Isik et al, 2024) (Yasar & Gölcük, 2025).

Artificial Neural Network (ANN) Algorithm

An Artificial Neural Network is a computer model that mimics the structure of the human brain and makes predictions based on the data processing process (Sabanci et al, 2015). This model is a computational system designed to model the human brain's learning and problem-solving abilities (Taspinar & Koklu, 2024) (Koklu et al, 2022). These supervised learning networks have an input layer, a hidden layer and an output layer. ANNs consist of artificial neurons connected in layers to extract patterns from data and perform classification, regression, recognition and prediction tasks. The network learns at each layer by processing information through neurons. Adam solver and ReLU activation functions are used for training. Artificial neural networks are commonly used to solve problems with high accuracy in complex classification and regression problems (Kursun et al, 2022).

Performance Metrics

The success of the models was evaluated using the metrics of accuracy, precision, recall, and F1-score. These metrics are particularly important in imbalanced classes, as they reflect the model's performance on each class rather than its overall accuracy. In the process of evaluating classification models, confusion matrices and metrics derived from them are widely applied, particularly in multi-class data structures (Kursun & Koklu, 2025). The confusion matrix is one of the fundamental statistical tools used to evaluate the performance of classification models (Kilci et al, 2025) (Tumer et al, 2025). The confusion matrix is shown in Table 3. This model, which is also used to evaluate the performance of deep learning models, is called a confusion matrix. This matrix divides the model's correct and incorrect classifications into four main categories: Table 3 shows the true positive (TP), true negative (TN), three-class confusion matrix, false positive (FP), and false negative (FN) data (Kilci et al, 2025).

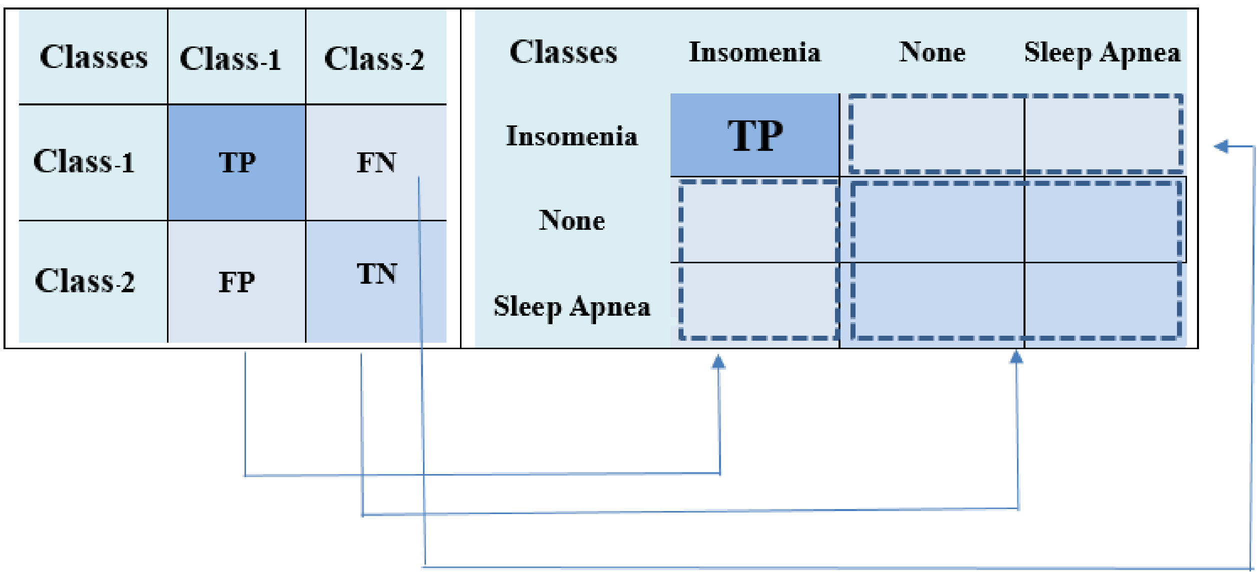

Figure 4. General structure of the confusion matrix

The calculation formulas obtained from the Confusion Matrix are given in Table 3.

Table 3. Performance metric formulas and explanations

Criterion	Formula	Explanation
Accuracy	$\frac{TP + TN}{TP + TN + FP + FN} x\, 100$	Overall accuracy rate of the model
Precision	$\frac{TP}{TP + FP} x\, 100$	How accurate positive predictions are
Recall	$\frac{TP}{TP + FN} x\, 100$	How many true positives are detected
F1 Score	$\frac{2TP}{2TP + FP + FN} x\, 100$	The harmonic mean of Precision and Recall

Stratified Cross Validation

The stratified cross-validation method was applied to account for class imbalance in the dataset. The k-fold cross-validation method involves randomly dividing the sample set into k equal-sized subgroups (folds). Here, the k value indicates how many parts the data set will be divided into (Cengel et al, 2025). For example, when k is set to 10, the data set is divided into 10 equal parts. In this case, nine subgroups are used as training data in each iteration, while the remaining subgroup is used as test data (Yasin et al, 2025). This approach enhances the model's generalisation ability by preserving the class ratios in each fold. The average performance of each model was obtained using 5-fold (k=5) cross-validation. This process is repeated k times, each time using a different subgroup as the test set. The final performance value is reported by taking the average of the results obtained (Ramezan et al, 2019).

Result and Discussion

In this section, various machine learning algorithms have been applied to classify sleep disorders into three different output classes: None, Sleep Apnoea, and Insomnia. During the classification process, the performance of models was comparatively evaluated using K-Nearest Neighbours, Random Forest, Support Vector Machine, and Neural Network algorithms. The training and prediction processes of the models utilised multi-dimensional data inputs including individual and physiological characteristics such as age, gender, occupation, physical activity level, stress level, blood pressure, heart rate, and daily step count.

Table 4. Classification results obtained using Random Forest

		Predicted		
	RF	**Insomenia**	**None**	**Sleep Apnea**
Actual	**Insomenia**	**64**	**7**	**6**
	None	**9**	**205**	**8**
	Sleep Apnea	**5**	**7**	**66**

Of the 77 examples belonging to the insomnia class, 64 were correctly classified, 7 were incorrectly assigned to the 'None' class, and 6 were incorrectly assigned to the 'Sleep Apnoea' class. This result indicates that the model generally correctly predicts insomnia cases, but that some confusion is present. In particular, the mixing of some insomnia data with the 'None' class may be due to symptom similarity or data imbalance. In the None (normal sleep) class, 205 out of 222 examples were correctly classified. 9 cases of insomnia and 8 cases of sleep apnoea were misdiagnosed. Although the accuracy rate is high in this class as well, some inconsistencies are observed. The model's high accuracy in identifying the 'None' class suggests that normal sleep samples have more distinct characteristics than the other two disorder types. The model's high accuracy in identifying the 'None' class suggests that normal sleep samples have more distinct characteristics than the other two disorder types. The confusion matrix results of the RF algorithm are presented in Table 4.

Table 5. Classification results obtained using KNN

		Predicted		
	KNN	**Insomenia**	**None**	**Sleep Apnea**
Actual	**Insomenia**	**63**	**9**	**5**
	None	**9**	**198**	**12**
	Sleep Apnea	**7**	**12**	**59**

Of the 77 examples belonging to the insomnia class, 63 were correctly classified, 9 were incorrectly labelled as 'None' and 5 as 'Sleep Apnoea'. This result indicates that the model largely correctly identifies insomnia data but experiences confusion, particularly with the 'None' class. This confusion may stem from the fact that insomnia symptoms exhibit characteristics that are partially similar to those of normal sleep patterns. In the

None" (normal sleep) class, 198 out of 219 examples were correctly predicted. 9 cases were misclassified as insomnia and 12 cases as sleep apnoea. This situation indicates that the model generally performs well in distinguishing normal sleep samples, but tends to misclassify some apnoea cases as 'None'. Such errors typically occur when there is symptom or feature overlap in the data set. Of the 78 examples belonging to the Sleep Apnoea class, 59 were correctly classified, 7 were incorrectly assigned to the insomnia class, and 12 were incorrectly assigned to the none class. The confusion matrix results of the KNN algorithm are presented in Table 5.

Table 6. Classification results obtained using SVM

		Predicted		
	SVM	**Insomenia**	**None**	**Sleep Apnea**
Actual	**Insomenia**	63	10	4
	None	7	207	5
	Sleep Apnea	6	5	67

Of the 77 examples belonging to the insomnia class, 63 were correctly classified, 10 were incorrectly predicted as 'None', and 4 were incorrectly predicted as 'Sleep Apnoea'. This result indicates that the model correctly identifies insomnia cases to a large extent, but experiences some confusion, particularly with the 'None' class. Such errors may occur because insomnia symptoms can sometimes resemble normal sleep characteristics. In the None (normal sleep) class, 207 out of 219 examples were correctly classified. 7 cases of insomnia and 5 cases of sleep apnoea were misclassified. This result demonstrates that the model successfully distinguishes normal sleep samples. The high classification accuracy in this class indicates that the model has learned the features representing the 'None' class well. Of the 78 examples belonging to the Sleep Apnoea class, 67 were correctly predicted. Six examples were incorrectly classified as insomnia and five as none. The confusion matrix results of the SVM algorithm are presented in Table 6.

Table 7. ANN algorithm confusion matrix results

		Predicted		
	ANN	**Insomenia**	**None**	**Sleep Apnea**
Actual	**Insomenia**	66	7	4
	None	4	209	6

Sleep Apnea	**4**	**5**	**69**

Table 7. ANN algorithm: 66 out of 77 examples belonging to the Insomnia class were correctly classified, 7 were incorrectly assigned to the 'None' class, and 4 were incorrectly assigned to the 'Sleep Apnoea' class. This result indicates that the model identifies insomnia cases with a high degree of accuracy, but experiences confusion with other classes in a small number of cases. In particular, incorrect assignments to the 'None' class may stem from the fact that insomnia symptoms in some individuals resemble normal sleep characteristics. In the None (normal sleep) class, 209 out of 219 examples were correctly predicted. Four examples were misclassified as insomnia, and six examples were misclassified as sleep apnoea. The accuracy rate in this class is quite high, and the model demonstrates strong performance in distinguishing normal sleep states. The low level of incorrect predictions indicates that the model generalises well to examples belonging to this class. In the Sleep Apnoea class, 69 out of 78 examples were correctly classified, 4 were incorrectly predicted as insomnia, and 5 were incorrectly predicted as none. The ANN algorithm confusion matrix results are presented in Table 7.

Experimental analyses have shown that SVM and ANN algorithms achieve higher accuracy rates compared to other methods. The SVM model and ANN model have achieved a 90% accuracy rate. The KNN and Random Forest models achieved 85% and 88% accuracy respectively. F1-score values also showed a similar trend, with SVM and ANN algorithms achieving higher values. Stratified cross-validation resulted in low variance, indicating the stability of the models. The performance metric results of the algorithms are presented in Table 8 and Figure 5.

Table 8. Algorithm performance metric results

Model	Acuracy	F1-Score	Precsion	Recall
KNN	85.561	82.601	82.596	82.623
RF	88.859	86.365	86.053	86.692
SVM	90.107	87.412	88.099	87.412
ANN	91.979	90.105	90.367	89.870

Figure 5. Performance metric results of the algorithms

Conclusion

This study compares the performance of KNN, Random Forest, Support Vector Machine and Artificial Neural Network models in classifying sleep disorders. The results obtained have revealed significant performance differences between the models. According to experimental results, the ANN model demonstrated the highest performance across all metrics, achieving 91.979% accuracy, 90.105% F1-score, 90.367% precision, and 89.870% recall. This situation demonstrates that ANN's ability to model non-linear relationships provides a significant advantage in complex, multi-class data structures such as sleep disorders. The SVM model achieved the second-best performance with an accuracy rate of 90.107%. High Precision (88.099%) and balanced Recall (87.412%) values demonstrate that SVM effectively distinguishes between classes. These results demonstrate that SVM is a powerful alternative, particularly for datasets with clearly defined class boundaries. The Random Forest model delivered a stable performance with an accuracy of 88.859% and an F1-score of 86.365%. Thanks to the ensemble learning approach, the RF model demonstrated a robust structure against overfitting but remained at lower accuracy values compared to ANN and SVM. The KNN model, however, demonstrated the lowest performance with an accuracy rate of 85.561%. It has been confirmed that neighbourhood-based approaches have limitations, particularly with large and complex data sets. This study examined the effects of lifestyle variables on sleep health using a machine learning approach. Results from machine learning algorithms have demonstrated that ANN and SVM models offer high accuracy in predicting sleep quality. This situation demonstrates that these models are more effective in capturing the non-linear relationships of complex and multi-dimensional lifestyle data. In future studies, the use of deep learning-based models with larger samples may increase the model's generalisation ability. Furthermore, the inclusion of additional factors such as stress, caffeine consumption and digital addiction in the model will enable more comprehensive analyses of the causes of sleep disorders. The findings generally indicate that deep learning-based ANN models are the most suitable approach for the automatic detection and classification of sleep disorders. However, considering the computational cost and model complexity, the SVM model can be considered a strong alternative in terms of performance–efficiency balance.

Conflicts of Interest: The authors declare no conflict of interest

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Availability of Data and Materials: This study uses a dataset obtained from Kaggle and the data can be accessed via the following link: https://www.kaggle.com/datasets/uom190346a/sleep-health-and-lifestyle-dataset

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