Applying machine learning algorithms for the classification of sleep disorders

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Abstract:

Sleep disorder classification is crucial in improving human quality of life. Sleep disorders and apnoea can have a significant influence on human health. Sleep-stage classification by experts in the field is an arduous task and is prone to human error. The development of accurate
machine learning algorithms (MLAs) for sleep disorder classification requires analysing, monitoring and diagnosing sleep disorders. This paper compares deep learning algorithms and conventional MLAs to classify sleep disorders. This study proposes an optimised method for the Classification of Sleep Disorders and uses the Sleep Health and Lifestyle Dataset publicly available online to
evaluate the proposed model. The optimisations were conducted using a genetic algorithm to tune the parameters of different machine learning algorithms. An evaluation and comparison of the proposed algorithm against
state-of-the-art machine learning algorithms to classify sleep disorders. The dataset includes 400 rows and 13
columns with various features representing sleep and daily activities. The k-nearest neighbours, support vector machine, decision tree, random forest and artificial neural network (ANN) deep learning algorithms were assessed. The experimental results reveal significant performance differences between the evaluated algorithms. The proposed algorithms obtained a classification accuracy of 83.19%, 92.04%, 88.50%, 91.15% and 92.92%,
respectively. The ANN achieved the highest classification accuracy of 92.92%, and its precision, recall and F1-score values on the testing data were 92.01%, 93.80% and 91.93%, respectively. The ANN algorithm achieved higher accuracy than other tested algorithms.

Introduction: Sleep disorder classification is crucial for improving human quality of life, as sleep disorders and apnoea can significantly influence human health. Sleep is a vital physiological function necessary for physical and mental health, helping to strengthen the body and consolidate brain functions and memories. Sleep quality affects cognitive functions, especially in children and older drivers who are at increased risk of accidents, and sleep deprivation can lead to health problems like heart disease, diabetes, and obesity.Traditionally, physicians, doctors, medical professionals, and experts must manually evaluate polysomnography (PSG) records to classify sleep stages. However, this manual classification is an arduous and
time-consuming task prone to human error, potentially leading to different assessments of sleep stages.To address these challenges, the development of accurate machine learning algorithms (MLAs) for sleep disorder classification is required, involving the analysis, monitoring, and diagnosis of sleep disorders. One study compares deep learning algorithms and conventional MLAs to classify sleep disorders, proposing an optimised method and using the Sleep Health and Lifestyle Dataset publicly available online to evaluate the proposed model.Furthermore, the increasing incidence of obstructive sleep apnea syndrome (OSAS) worldwide highlights the need for new screening methods to compensate for the shortcomings of PSG. PSG, while considered the traditional gold standard for diagnosing OSAS, requires overnight sleep in a laboratory and specialized personnel, leading to limited efficiency and potential disturbance of the subject's sleep. In response, there is a growing tendency to apply machine learning techniques in medical and healthcare fields due to their

ability to recognize and classify complex patterns in massive healthcare data, making them suitable for proposing prediction models for conditions like OSAS.

Result Analysis: The study "Applying Machine Learning Algorithms for the Classification of Sleep Disorders" evaluated the performance of various MLAs on the Sleep Health and Lifestyle Dataset.Without optimization, the accuracies achieved on the testing phase were: KNN (84.96%), SVM (64.6%), Decision Tree (86.73%), Random Forest (88.5%), and ANN (91.15%). The Artificial Neural Network (ANN) demonstrated the highest accuracy among the tested algorithms with default parameters.After applying a Genetic Algorithm (GA) for parameter optimization, the accuracies improved to: KNN (83.19%), SVM (92.04%), Decision Tree (88.50%), Random Forest (91.15%), and ANN (92.92%). With optimization, the ANN still achieved the highest accuracy (92.92%), but the Support Vector Machine (SVM) showed the most significant improvement, reaching 92.04%.The precision, recall, and F1-score for the optimized ANN were 92.01%, 93.80%, and 91.93%, respectively.Another study focused on predicting the severity of Obstructive Sleep Apnea Syndrome (OSAS) using data from 4,014 patients. They employed gradient boosting-based models and Random Forest, achieving high classification accuracies for different OSAS severity thresholds:88% for AHI ≥ 5,88% for AHI ≥ 15,91% for AHI ≥ 30.This study found LightGBM to show the best overall performance across severity classes, except for mild OSAS where CatBoost excelled.Several other reviewed studies in "Applying Machine Learning Algorithms..." also reported high accuracies using various MLAs and datasets for sleep disorder classification and sleep apnoea detection. For instance, CNNs achieved high accuracy on EEG spectrogram data, and Random Forest performed well on the ISRUC%-Sleep database using ECG data. Deep learning models combining CNN and LSTM also showed promising results.

Impact of Optimization:

The use of a Genetic Algorithm (GA) for hyperparameter tuning generally improved the performance of the MLAs in the primary study.A t-test analysis indicated that the improvement in accuracy with GA-optimized MLAs was statistically significant for SVM, Random Forest, and ANN.The study also explored using a grid search technique for optimizing the SVM, suggesting it could be even more effective than GA in terms of speed and results for that specific algorithm.

Dataset Characteristics and Limitations:

The primary study utilized the Sleep Health and Lifestyle Dataset, which contains 400 observations and 13 features related to sleep and daily habits.The study on OSAS severity prediction used a larger dataset of 4,014 patients with 33 features.The authors of "Applying Machine Learning Algorithms..." noted limitations of their study due to the relatively small size of the dataset and the fact that it was collected from only one sleep clinic, potentially introducing bias and limiting the generalizability of the results.The OSAS severity prediction study also acknowledged limitations such as data collection from a single center and the presence of missing values.

Comparison with Traditional Methods:

The introduction of "Applying Machine Learning Algorithms..." highlights that manual sleep stage classification using PSG records is arduous, time-consuming, and prone to human error.

The OSAS severity prediction study points out that PSG, the gold standard for diagnosis, is laborious, time-consuming, and expensive, motivating the exploration of machine learning-based screening methods.The results suggest that MLAs can achieve high accuracy in classifying sleep disorders and predicting OSAS severity, indicating their potential to complement or even replace traditional methods in certain contexts, especially for initial screening.

Literature Review:

Motivation for Applying Machine Learning:

Traditional methods of sleep disorder diagnosis, primarily relying on manual analysis of polysomnography (PSG) records, are arduous, time-consuming, and susceptible to human error. This creates a need for automated and more efficient techniques.The increasing prevalence of sleep disorders, such as obstructive sleep apnoea syndrome (OSAS), worldwide necessitates the development of new screening methods that can overcome the limitations of PSG, which includes its cost, requirement for specialized settings, and potential to disturb sleep.Machine learning, with its ability to recognize and classify complex patterns in large datasets, is well-suited to the intricate nature of physiological data related to sleep disorders.
This has led to a growing trend of applying MLAs in medical and healthcare fields for various diagnostic and predictive tasks.

Use of Consumer Sleep Technology (CST):

Several studies have explored the use of consumer sleep technology (CST) combined with MLAs for sleep classification. While PSG is considered the essential standard and more accurate, CST offers a more accessible and less expensive way to track sleep. MLAs can potentially improve the accuracy of sleep stage classification using CST data. However, there are limitations in applying raw signals with deep learning algorithms in this context.

Detection of Sleep Apnoea using ECG Signals:

Research has focused on using MLAs like SVM, Random Forest (RF), and deep learning algorithms to detect sleep apnoea from electrocardiogram (ECG) signals. Challenges in this area include the variability in ECG signals and the limited availability of large, diverse datasets for training robust models. However, studies have shown promising results, with SVM and deep learning-based neural networks performing well in detecting sleep apnoea from ECG data.

Classification using EEG Spectrograms:

MLAs have been applied to classify sleep stages using electroencephalogram (EEG) spectrograms. This approach aims to automate the time-consuming and error-prone process of manual sleep stage classification based on EEG signals. Challenges include low accuracy due to unbalanced datasets. Deep learning models, particularly Convolutional Neural Networks (CNNs) for feature extraction from EEG spectrograms and Recurrent Neural Networks (RNNs) like bidirectional Long Short-Term Memory (LSTM) for recognizing prediction sequences, have shown significant promise in this area, achieving high accuracies in some studies.

Prediction of OSAS Severity:Studies have utilized MLAs to predict the severity of obstructive sleep apnoea (OSA) syndrome using various patient data, including clinical measurements and questionnaire results. These studies often employ supervised and unsupervised learning techniques such as gradient boosting, RF, and K-means clustering. While achieving good classification accuracies, limitations like data collection from single centers and missing values need to be considered.

Datasets Used in Research:

The literature review highlights the use of various publicly available and private datasets for sleep disorder research, including the Sleep Health and Lifestyle Dataset, Apnoea-ECG Database, ISRUC%-Sleep database, PhysioNet ECG Sleep Apnoea v1.0.0 dataset, Wisconsin Sleep Cohort database, sleep-edf and sleep-edfx, and datasets from medical centers. The availability and characteristics of these datasets

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(e.g., size, features, bias) significantly influence the development and evaluation of MLAs.

Optimization Techniques:To improve the performance of MLAs, researchers have employed various optimization techniques, including Genetic Algorithms (GA) and Bayesian optimization, to tune model hyperparameters and select relevant features. The application of GA has shown promising results in enhancing the accuracy of sleep disorder classification models.

Overall Trends and Future Directions:The literature indicates a clear trend towards the automation of sleep disorder diagnosis and prediction using machine learning.Deep learning algorithms are increasingly being explored for their ability to learn complex patterns from various types of physiological signals.There is a growing recognition of the importance of addressing challenges related to data quality, availability, and bias to develop robust and generalizable models.Future research may focus on developing MLAs using unsupervised learning, assessing performance on new models, and comparing against existing state-of-the-art approaches.

Methodology: The main methodologies employed in the resources for sleep disorder classification and prediction involve several key steps:

Data Acquisition and Pre-processing: Studies utilize various datasets, including the **Sleep Health and Lifestyle Dataset**, the **OSAS dataset from Samsung Medical Center**, and other publicly available datasets like
Apnoea-ECG Database, **ISRUC%-Sleep database**, **PhysioNet ECG Sleep Apnoea v1.0.0**, and **sleep-edf/sleep-edfx** (mentioned in the "Related Work" sections).Pre-processing steps typically include **data cleaning**, handling missing values (mentioned in), and **encoding categorical variables** (implied by the use of features like 'Gender' and 'Occupation').Some studies perform **feature scaling** on numerical features.In the OSAS severity prediction study, the dataset was divided into **training (80%) and testing (20%) sets**, and **5-fold cross-validation** was used during training. The "Applying Machine Learning Algorithms..." study also used a split of the dataset into training (70%) and testing (30%).

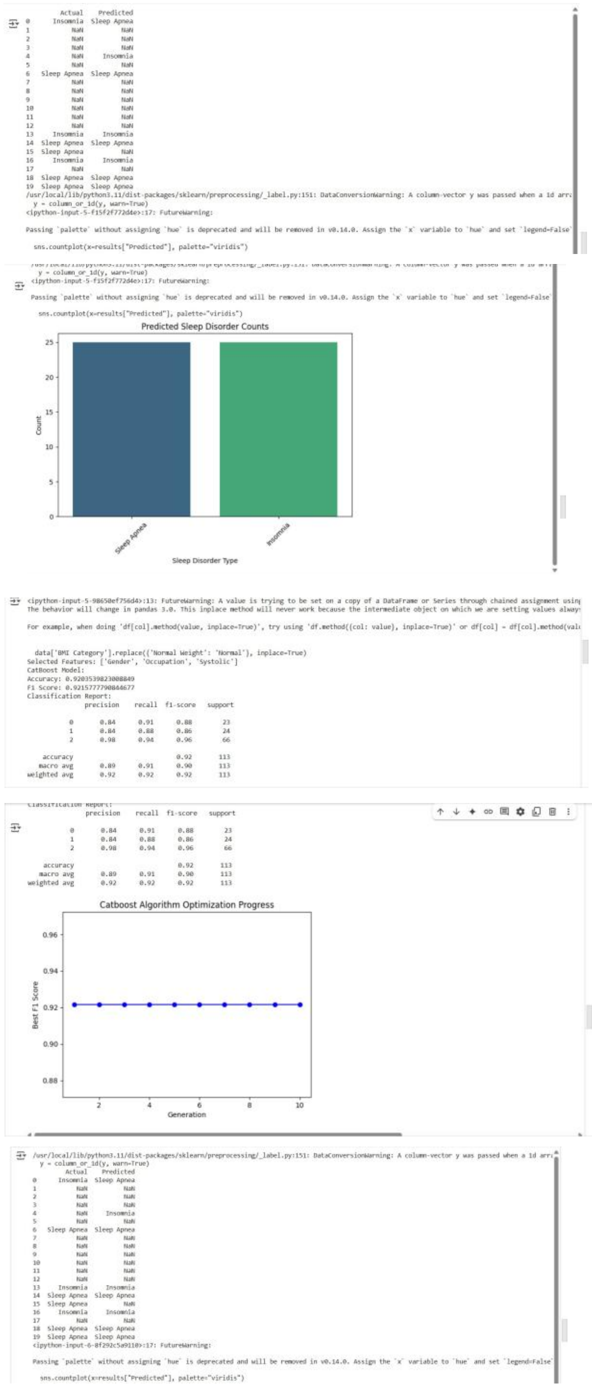
Feature Engineering (in some studies): The OSAS severity prediction study specifically mentions **feature engineering**, utilizing both medically researched methods (like weighted ESS and a formula for predicting AHI) and machine learning techniques (processing body measurement data to add body proportion features).The "Applying Machine Learning Algorithms..." paper calculates **feature importance** using techniques to score input features based on their influence on model accuracy.**Machine Learning Algorithm Implementation:**A variety of **conventional machine learning algorithms (MLAs)** are implemented, including:**K-Nearest Neighbors (KNN),Support Vector Machine (SVM),Decision Tree (DT),Random Forest (RF),Logistic Regression (LR)** (mentioned in the "Related Work"),**Gradient Boosting models (XGBoost, LightGBM, CatBoost),Quadratic Discriminant Analysis (QDA)** (in "paper 3.pdf" which references the base paper)**Deep learning algorithms** are also employed, primarily **Artificial Neural Networks (ANN)** and models involving **Convolutional Neural Networks (CNNs)** and **Long Short-Term Memory networks (LSTMs)**, particularly for EEG signal analysis.

Model Optimization:Hyperparameter tuning is a crucial part of the methodology. The "Applying Machine Learning Algorithms..." study uses a **Genetic Algorithm (GA)** to tune the parameters of different MLAs.The same study also mentions using a **grid search technique** specifically for optimizing the SVM.The OSAS severity prediction study utilized **Bayesian optimization** via Opuntia for hyperparameter tuning of the gradient boosting models and Random Forest.

Performance Evaluation: Model performance is evaluated using various metrics, including: **Classification Accuracy**, **Precision, Recall, F1-score, AUC (Area Under the ROC Curve)** (in the OSAS severity prediction study). **Confusion matrices** are used to visualize the classification results and identify misclassifications. **Statistical tests**, such as the **t-test** and the **Mann-Whitney U test** (in the OSAS study), are used to assess the statistical significance of the results and the impact of optimization techniques.

Comparison with Existing Methods/Studies: The methodologies often involve comparing the performance of the proposed MLAs and optimized models against **state-of-the-art machine learning algorithms** and, implicitly, against the limitations of traditional diagnostic methods like manual PSG analysis. Studies also compare their results with those of **previous research** in the field using similar datasets or approaches.

Results: Machine Learning Algorithms for Sleep Disorder Classification: The paper "Applying Machine Learning Algorithms for the Classification of Sleep Disorders" evaluated several machine learning algorithms (MLAs) and found significant performance differences between them. Without hyperparameter optimization using a Genetic Algorithm (GA), the accuracies on the testing set were: KNN: 84.96%, SVM: 64.6%, Decision Tree: 86.73%,
Random Forest: 88.5%, and ANN: 91.15%. The ANN achieved the highest accuracy in this initial evaluation. With hyperparameter optimization using a Genetic Algorithm (GA), the accuracies on the testing set improved for most algorithms: KNN: 83.19%, SVM: 92.04%, Decision Tree: 88.50%, Random Forest: 91.15%, and ANN: 92.92%. The ANN with GA achieved the highest classification accuracy of 92.92%, with a precision of 92.01%, recall of 93.80%, and an F1-score of 91.93% on the testing data.



The SVM performance significantly improved after optimization using both a GA and a grid search technique, achieving 92.04% accuracy with GA and an even more effective optimization with grid search (though the exact accuracy of grid search for SVM isn't explicitly stated numerically in the "Results" section). A t-test analysis showed statistically significant improvements in accuracy for SVM, Random Forest, and ANN after applying the GA for optimization, while KNN and Decision Tree did not show significant improvements.Confusion matrices provided insights into the classification performance of each model across the three sleep disorder categories (None, Apnoea, Insomnia), highlighting instances of correct classification and misclassification. For example, the ANN with GA correctly classified 61 instances of Class 1 (None), but misclassified 1 as Class 3 (Insomnia).Comparison with Other Studies: The authors compared their findings with existing literature.They noted that other researchers have used various MLAs and deep learning approaches for sleep disorder classification using different datasets and physiological signals like EEG and ECG.The proposed algorithm with GA optimization achieved better results than a recent study that used the same Sleep Health and Lifestyle Dataset.

OSAS Severity Prediction: The paper "Application of various machine learning techniques to predict obstructive sleep apnea syndrome severity" using a dataset of 4014 patients found high performance in predicting OSAS severity.Gradient boosting-based models (XGBoost, LightGBM, CatBoost) and Random Forest achieved high classification accuracies for three AHI thresholds (≥ 5, ≥ 15, ≥ 30): 88%,
88%, and 91%, respectively. LightGBM showed the best overall performance across the severity classes.Applying clustering before classification significantly improved prediction results for mild and moderate OSAS compared to without clustering.The approach of clustering with feature engineering and hyperparameter tuning showed the best results for moderate (87.84%) and severe (91.06%) OSAS prediction. For mild OSAS, clustering with feature engineering alone achieved the highest accuracy (88.16%).The study concluded that machine learning has significant potential for predicting OSAS severity, potentially serving as a screening method to prioritize patients for PSG.Limitations Acknowledged: Both studies acknowledged certain limitations.The Sleep Health and Lifestyle Dataset study noted the limited size of the dataset (400 rows) and its collection from a single online source, which might affect the generalizability of the results.The OSAS severity prediction study mentioned that the data was collected from one sleep clinic, potentially limiting generalizability to other populations. It also noted the presence of a considerable amount of missing values due to the retrospective nature of the study.

Conclusion:

The main conclusions from the resources are:Machine learning algorithms (MLAs), both conventional and deep learning, can be effectively used for sleep disorder classification. The study "Applying Machine Learning Algorithms for the Classification of Sleep Disorders" demonstrated that algorithms like Artificial Neural Networks (ANNs) can achieve high classification accuracy (up to 92.92% after optimization with a Genetic Algorithm) on the Sleep Health and Lifestyle Dataset. This suggests that MLAs can learn from sleep-related data to identify different sleep disorders without relying solely on expert-defined features.Hyperparameter optimization significantly improves the performance of MLAs for sleep disorder classification. The use of a Genetic Algorithm (GA) to tune the parameters of algorithms like SVM, Random Forest, and ANN led to statistically significant improvements in their classification accuracy.
This highlights the importance of optimization techniques in achieving the full potential of these algorithms.Deep learning algorithms, particularly ANNs, can outperform conventional MLAs in sleep disorder classification tasks when properly optimized.Machine learning techniques show significant potential for predicting the severity of Obstructive Sleep Apnea Syndrome (OSAS). The study "Application of various machine learning techniques to predict obstructive sleep apnea syndrome severity" achieved high classification accuracies (up to 91%) using gradient boosting models for different severity thresholds of OSAS. This indicates that machine learning could serve as a valuable screening tool to

complement or address the limitations of traditional diagnostic methods like polysomnography (PSG).Combining unsupervised learning (clustering) with supervised learning (classification) can enhance the prediction of OSAS severity. The OSAS severity prediction study found that building prediction models using clustering in conjunction with classification led to significantly superior performance for mild and moderate OSAS compared to using classification alone.Despite the promising results, limitations exist, such as the size and source of the datasets, which might affect the generalizability of the findings. Both studies acknowledged the need for larger and more diverse datasets to further validate and improve the developed models. Future work should focus on addressing these limitations and exploring the use of unsupervised learning methods further.

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