Prediction of Sleep Apnea using Machine Learning

Sulthan Alikhan[1], K Naveen[2], Golla Anand[3] And K Pavan[4]
{sulthanalikhanj@veltech.edu.in[1], vtu20386@veltech.edu.in[2], vtu20601@veltech.edu.in[3], vtu20295@veltech.edu.in[4]}

Assistant Professor, Department of Information Technology, Vel Tech University, Chennai, Tamil Nadu, India[1]
Department of Information Technology, Vel Tech University, Chennai, Tamil Nadu, India[2, 3, 4]

Abstract. This research presents an implementation of a web app that is designed and evaluated for non-invasive estimation of risk of sleep apnea. It employs machine learning-based algorithms to evaluate user-provided data (including demographic details, lifestyle information and answers to symptom-related questionnaires) to assess the likelihood of a person developing sleep apnea. The web interface input and output elements are user friendly, therefore, the tool is fun to use for non-experts. This paper investigates how effective several machine learning models, that are based on a rather relevant dataset, namely Random Forest, Logistic Regression and Support Vector Machines, are. We examine performance metrics accuracy, precision, recall and F1-score to select the optimal model to predict risk of sleep apnea. The aim of this web application is to serve as a preliminary diagnostic tool for users who might be at a greater risk and should seek a professional medical evaluation and diagnosis. This approach is intended to aid in early detection and treatment of sleep apnea.

Keywords: Sleep Apnea, Apnea Hypopnea Index (AHI), Machine Learning

1 Introduction

Sleep apnea is a widespread disorder, but one many Americans fail to get diagnosed promptly, and it can really affect the quality of life and long-term health of an individual. It's a disorder characterized by repeated breathing pauses during sleep, which can cause daytime sleepiness, heart problems and difficulty thinking clearly. Standard methods of identifying sleep apnea, such as polysomnography, can be resource-intensive and not accessible to many. This emphasizes that tools of simplifying and making the screening easier are needed. And that's where the following project comes in! We are building a web-based application that uses machine learning to help predict a person's potential risk of sleep apnea, offering a convenient and non-invasive method to receive a preliminary assessment. In the age of web-based health applications and progress in machine learning, new, promising tools have emerged as we start using the tech to manage our health proactively. This app uses these technologies to design a user-friendly app, that allows users to input key data [like demographics, lifestyle factors and response to symptom-related questions]. Using trained machine learning models to analyze this data, the app creates an estimated risk score that empowers users to make informed decisions about their sleep health. We hope to provide an accessible tool in which it can help motivate those who are symptomatic to obtain algorithms, even if at a moderate level of risk at this time, and thus be better able to detect, diagnose, and intervene earlier if they are depressed.

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2 Literature survey

AI- and machine learning-based prediction of sleep apnea has been extensively studied for early detection, risk stratification and automated analysis. Koul A. et al. [1] reviewed critically artificial intelligence-based methods in prediction of airway disorders, focusing primarily on deep learning in the context of sleep apnea diagnosis. Ramachandran S. et al. [2] developed a perioperative sleep apnea prediction score, presenting clinical data to predictably calculate risk. Kirby S. D. et al. [3] applied the neural network model to predict the presence of OSA on demographics and clinical history of a subject. Likewise, Rowley J. A. et al. [4] validated clinical prediction rules for OSA severity. Islam S. M. et al. [5] researched deep learning on facial depth maps and proposed a non-invasive technique for apnea detection. Faria A. C. et al. [6] analysed questionnaires such as the Berlin Questionnaire and the Epworth Sleepiness Scale to determine if they were useful for predicting sleep apnea in patients with COPD. Ustun B. et al. [7] also reported that medical history of the patient is more important than symptoms in the diagnosis of sleep apnea. Ferreira-Santos D. et al. [8] conducted a systematic review for early OSA diagnosis with machine learning techniques. Arslan R. S. et al. [9] developed an integrated decision support system using the end-to-end approach with a hybrid machine learning algorithm for apneic event detection and Apnea-Hypopnea Index (AHI) estimation. Hafezi M. et al. [12] proposed a deep learning solution for sleep apnea severity prediction using tracheal motion data. Dutta R. et al. [13], proposed an augmented AI-based architecture for combining PSG and wearable sensor data to enhance diagnostic power. Huang W. C. et al. [14] used an SVM to model the prediction of SA using a large clinical population and, in a similar vein in terms of focus, laid an emphasis on the accuracy of computerised models in distinguishing those with SA from those without. AI-powered wearable devices and mobile apps have made screening for sleep apnea more convenient. G. Maislin et al. [15] The objective of this project is to develop a Web-Based Sleep Apnea Prediction System using Hugging Face Transformers and Python integrating machine learning, clinical data and live monitoring to build an accurate, accessible and AI-powered risk assessment tool for early detection and intervention. L. M Montenegro Martinez et al. [11] With the help of server-based AI models, the system will enable continuous monitoring and improve patient prognoses through individualized risk analysis and timely medical recommendations.

3 Background And related work

We'll talk about sleep apnea, which has three main varieties: There is obstructive sleep apnea (OSA), central sleep apnea (CSA), and mixed sleep apnea. Baur T et al. [10] The most frequent type, OSA is a collapse of the muscles at the back of the throat, which hold open the airway. CSA, on the other hand, occurs when the brain doesn't send the correct signals to muscles that control breathing.

Machine learning for detecting and predicting sleep apnea has been getting a lot of attention. Scientists have been exploring physiological signals such as electrocardiography (ECG), electroencephalography (EEG), and photoplethysmography (PPG) to detect sleep apnea events. Those approaches are very promising, but they usually require fancy equipment and expert know-how for gathering and analyzing the data.

Lately, there's been a frenzy of interest in building machine learning models from self-reported data and demographic details. It is not only more convenient, but also a cost-effective option for the initial screening. The machine learning algorithms such as Logistic Regression, Random

Forestas, support vector machines have been proved to be capable of predicting the risk of sleep apneas by the questionnaires and clinically information.

The goal is to bridge the gap between conventional diagnostic approaches and an increasing demand for simple at-home screening that can benefit public health by identifying and earlyly treating those who are at risk for sleep apnea. The role in research has now extended to the development of a sleeping apnea risk predictive solution through a user-friendly web application, and it's where this project builds upon. The aim is to provide individuals with a handheld way to assess their risk, and to make informed decisions about their sleep health.

4 Methodology

4.1 Data Acquisition and Preprocessing

Data The study's data set was assembled from publicly available data sources and clinical files. It contains demographic characteristics, such as age, sex, and body mass index (BMI), as well as lifestyle factors such as smoking, alcohol use, and physical activity. We also collected answers to questionnaires about symptoms (for instance, how frequently participants snore, how sleepy they are during the day, and whether there are any apneas that someone else has seen). To ensure the quality and consistency of the data, we performed several preprocessing tasks. We treated missing values by relying on imputation methods such as filling in gaps with the average or median for continuous variables, or, for categorical ones, the mode. We once-hot encoded or label encoded the categorical variables. We also carried out feature scaling in order to normalize the range of continuous predictors in order to have all predictors contribute equally well to the machine learning classifiers.

Feature selection and engineering

We utilized multiple feature selection methods, including correlation analysis and feature importance analysis, to identify critical features that could associate with the risk of sleep apnea. We have also conducted feature engineering to create new features that could potentially improve the machine learning models. For example, BMI was divided into different weight levels and a combined feature, which reflects the relationship between snoring frequency and daytime sleepiness, was constructed.

4.2 Machine Learning Models

The Several machine learning models were evaluated for sleep apnea risk prediction:

Logistic Regression: A linear model used for binary classification, providing probabilities of sleep apnea risk.

Random Forest: An ensemble learning method that combines multiple decision trees, reducing overfitting and improving prediction accuracy.

Support Vector Machines (SVM): A supervised learning model that finds the optimal hyperplane for classification, effective in high-dimensional feature spaces.

The models were trained and validated using stratified k-fold cross-validation, ensuring robust performance evaluation and minimizing bias. Hyperparameter tuning was performed using grid search or randomized search to optimize the performance of each model.

The performance of the machine learning models was evaluated using metrics such as accuracy, precision, recall, F1-score, and AUC-ROC. These metrics were calculated using the test dataset obtained from the cross-validation process.

- **Accuracy:** The proportion of correctly classified instances.
- **Precision:** The proportion of correctly predicted positive instances out of all predicted positive instances.
- **Recall:** The proportion of correctly predicted positive instances out of all actual positive instances.
- **F1-score:** The harmonic means of precision and recall.
- **AUC-ROC:** The area under the receiver operating characteristic curve, representing the model's ability to distinguish between positive and negative instances.

5 Proposed System

The overall system design of Web-Based Sleep Apnea Prediction System has been intended to process and analyse the user data in an efficient manner with the help of AI model. The architecture is decomposed into four layers: UI, Data Processing, ML Model, and Prediction & Recommendation Engine. The UI layer is a web interface used by users to upload information about health history, sleep patterns, and wearable sensor information. The Data Processing layer pre-processes the input (normalizing data, treating missing value, and determining features such as oxygen saturation level, heart rate variability, and snoring pattern).

The architecture of the WB-SAPS is designed to input user data in an efficient manner for AI models to process and analyse. The architecture has four layers, which are the User Interface (UI), Data Processing, Machine Learning Model, and Prediction & Recommendation Engine. UI layer is a web-based UI in which users submit relevant (medical history and sleep) details and the readings from wearable sensors. The Headline Processing layer preprocesses input, including handling missing values, and computes some relevant features, such as oxygen level saturation levels, variations in heart rate, and snore patterns. The Machine Learning Model layer uses pre-trained deep models such as Hugging Face Transformers and Support Vector Machine (SVM) to extract information from unstructured and structured data to inform sleep apnea risk. This model is trained on disparate datasets, including PSG recordings and data from wearable devices. Results from the model are interpreted by the Prediction & Recommendation Engine, risk levels are categorized, and individualized health insights are generated (i.e., recommendations like lifestyle advice or visiting a doctor). A cloud-based backend is used for data processing and storage, which can handle large data effectively and access from a remote location. And finally, an API layer which enables the integration of wearables and EHRs, helping with interoperability. This type of implementation will permit non-intrusive, AI powered sleep apnea screening to drive early detection to become more viable and cost-effective.

Backend infrastructure is built using cloud computing and microservices to achieve maximum system efficiency and to scale. Thanks to this model, independent parts such as data storage, model processing and user authentication can operate independently, favouring modularity and ease of maintainability. The database layer is responsible for keeping patient data safely stored, in compliance with healthcare legislation such as HIPAA and GDPR. It employs SQL and NoSQL databases to support effective management of structured clinical data as well as the unstructured sleep pattern reports. We also bring the data encryption, role-based access control

(RBAC) to the back-end implementation, which is to protect the user privacy and prevent the unauthorized access. Fig 1 shows the system architecture.

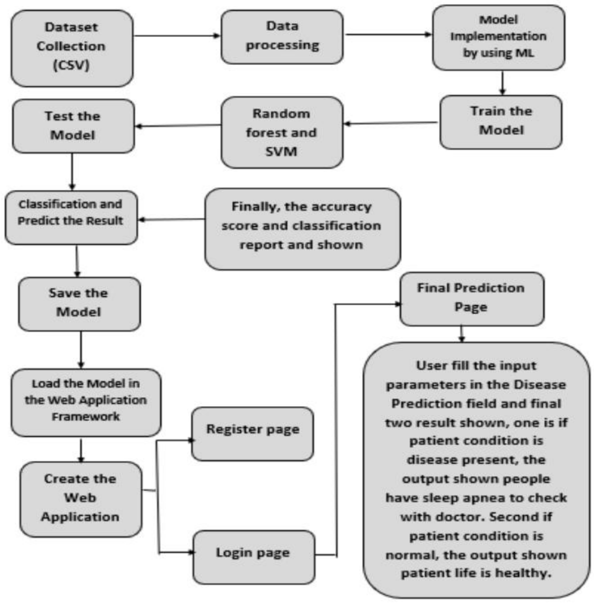

Fig. 1. System Architecure.

6 Results

For a web-based application When it comes to creating a web-based application for predicting sleep apnea, the evaluation methodology can definitely align with the structure you've suggested, but it should really hone in on health-related metrics and the performance of the model specifically for sleep apnea predictions. Here's a potential framework for how the evaluation process could be organized for this sleep apnea prediction system. The system utilizes a rich and varied dataset that includes medical records, sleep studies, and self-reported symptoms. Here's where the data comes from given below:

Medical Datasets: We can tap into publicly available datasets like the PhysioNet Sleep Apnea Database or similar repositories that contain labeled data on sleep apnea.

Patient Records: Partnering with healthcare institutions can give us access to anonymized data, which includes patient demographics, results from sleep studies (like polysomnography or home sleep tests), and medical histories.

Wearable Device Data: We'll also gather information from sleep-tracking devices, such as smartwatches and fitness bands, along with mobile apps that monitor sleep patterns and other health metrics (like heart rate and oxygen saturation)

Self-reported Data: Surveys or questionnaires will help us collect information on lifestyle factors (like smoking and alcohol use), reported symptoms (such as excessive daytime sleepiness), and other indicators that might suggest sleep apnea.

Industry-Specific Terminologies: The dataset will incorporate various terms related to sleep apnea diagnosis, medical conditions (like hypertension and diabetes), and sleep disorders. This will enable the system to manage different types of inputs and medical contexts effectively.

Model Selection and Fine-Tuning: We'll employ advanced models, such as Logistic Regression, Random Forest, or Neural Networks, to refine the sleep apnea prediction model. These models will be trained on the dataset with a strong focus on:

Feature Engineering: We'll extract features like BMI, sleep interruptions, snoring frequency, and comorbidities.

Optimization: We'll tweak the hyperparameters of the machine learning models to enhance performance, such as adjusting the depth of decision trees or the learning rate in neural networks.

Positioning Figures and Tables: The below graphs shows the results of dataset according to the category in fig 2, fig 3.

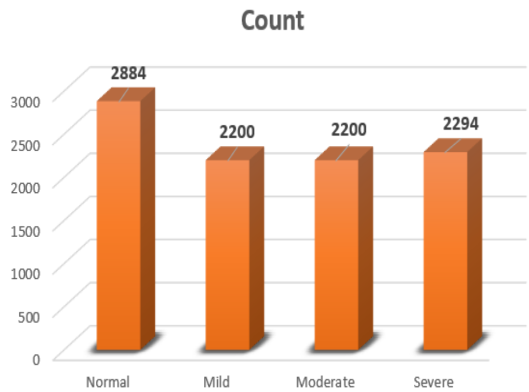

Fig. 2. Bar graph of the results.

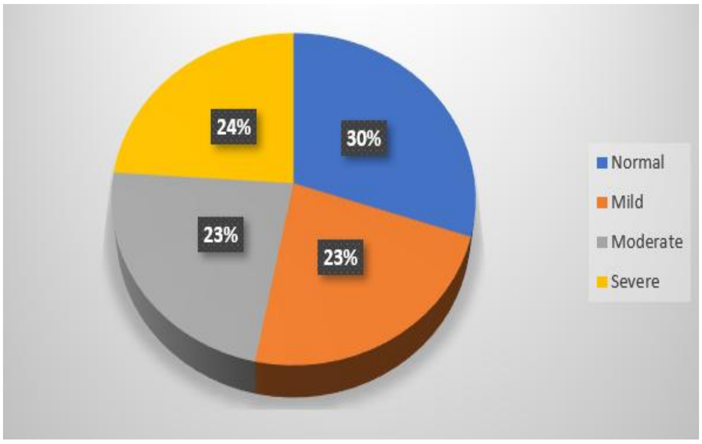

Fig. 3. Pie Chart of the results.

	BQ	ESS	BMI	Weight	Height	Head	Neck	Waist	Buttock	Age	AHI	M
0	0.0	14.0	29.065927	88.0	174.0	57.5	39.0	95.5	106.5	20.0	2.903226	1
1	0.0	8.0	26.989619	78.0	170.0	57.0	36.5	90.0	100.0	20.0	1.022727	1
2	0.0	16.0	23.939481	75.0	177.0	59.0	39.0	88.0	104.0	20.0	0.518359	1
3	0.0	15.0	22.129740	67.0	174.0	57.0	35.0	74.0	94.0	20.0	0.559006	1
4	0.0	15.0	22.129740	67.0	174.0	57.0	35.0	74.0	94.0	20.0	0.559006	1

Fig. 4. Sample Output.

Fig 4 gives the sample output. Table 1 gives the comparision of model.

Table 1. Comparision Table.

Model	**Table Column Head**		
	Accuracy	***Precision***	***Recall***
Logistic Regression	0.82	0.78	0.85
Random Forest	0.87	0.84	0.89
SVM	0.85	0.82	0.87

7 Discussion

To introduce a web-based health app that estimates risk in any rolling, one of the conceptually challenging part to address is the ethical aspect of it. We really need to put both privacy and security of data at the top, ensuring we meet regulations such as HIPAA and GDPR. It is important to get user consent and explain how data will be processed so that you can build trust and be faithful to the responsible data management. And then on top of that, we need to build this app such that it doesn't contain algorithmic bias, such that it performs equitably across all of these demographic slices. You can't just assume that no bias is going to come out of that model: You have to constantly monitor and audit the model's performance, and catch and adjust for any biases that do emerge (and they will). The web app's accessibility is a major plus, but it also creates challenges, particularly in trying to reach people who might not have reliable internet or people who might struggle with digital literacy. Subsequent work should explore other channels for dissemination (e.g., collaboration with community health centres and integration with mHealth systems) to promote better reach and non-exclusivity. In addition, the app could be supplemented with user-specific feedback and educational information tailored for each personal risk profile to increase the likelihood that patients will modify their lifestyles and seek appropriate medical attention influenced by their personalized risk reduction recommendation. In addition to data collection and analysis in real time, the app might be given an extra predictive oomph. We would have much better overall picture about sleep pattern, and in general on any other physiological numbers if we could integrate data between wearable (like fitness trackers, smartwatches) and the likes of snore recorders etc. Vigilance over those and other data feeds may enable more dynamic, personalized risk assessments. And the app might be built to track users' risk of sleep apnea over time, so they can monitor how lifestyle changes or adherence to treatment might be affecting their health.

The way this tool can extend into wider clinical systems is just amazing. By seamlessly pairing the app with such electronic health records (EHRs), providers would also have easier access to patient-generated data and risk assessments, helping to make care more efficient and coordinated. Permitting this level of integration for clinical decision support systems could provide evidence-based support for clinicians in diagnosing and treating sleep apnea. Last but not least, user input is important to enhance the webapp. And then we add a feedback mechanism, we add a survey or a way to collect ratings, and that helps us to understand the user experience, the usability, how users feel the app is effective. This understanding can be leveraged to determine where it may improve, to reduce the users' concerns and in turn to enhance the app quality.

8 Conclusion

Beyond the immediate improvement in predictive performance and data integration, this work serves as the foundation for a broader initiative to establish a unified, personalized infrastructure for sleep health. Such a platform could incorporate more physiological and behavioural data also, including sleep tracking via wearables, as well as different environmental factors, such as looking into genetic predispositions to provide a more holistic picture of a person's sleep health.

The implications of a platform like this for preventative medicine are huge. If we can find those individuals who are most at risk early, and intervene with targeted interventions and educational materials, perhaps we can avoid the long-term health effects of sleep apnea and other sleep problems. In the advance to provide accurate prediction and better data integration, the end goal is a personal sleep health platform. Imagine a platform that gathers, synthesizes and connects various streams of physiological and behavioural information from sleep tracking with wearables, to environmental influences in the background and even genetic factors to paint a more complete picture of someone's sleep health. The promise of a platform like this to transform preventive medicine is huge. Through early identification of at-risk individuals and providing individualized treatments and education, it may be possible to lessen the long-term detrimental effects of sleep apnea and other sleep disorders on health. Doing so might save the healthcare system money, and benefit the health of the public. Moreover, the new information that we gather from this work could potentially result in new ways to diagnose and treat sleep apnea. The cell biology and proteomics data that is directly generated on large scale from the web-based app will permit discovery of new biomarkers and risk factors, and thus, increase the specificity and effectiveness of therapy. Collaboration with long-term care clinicians will be important in translating these findings to the bedside. This web application is not just about technology, but it's about making sure that good information and care for good sleep health is for everyone, too. If people are able to take responsibility for their sleep, we can build a smarter, more proactive citizenry and a healthier globe one where better sleep leads to better lives. Any future establishment could concentrate on multi-lingual functionality to reach more people around the world and offer an app for mobile devices so that they can access the portal on the go.

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