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Optimizing Sleep Apnea Care with a Computational Intelligence-Based Health Recommender System for Exercise and Treatment Recommendations

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Abstract: - Sleep Apnea is a life-threatening condition that occurs when a patient is asleep. During sleep, the patient has recurring episodes of inability to breathe. This paper aims to present a model that identifies apnea and hypopnea events and prescribes the right exercise and treatment to the patient. For this purpose, the proposed method uses a Computational Intelligence (CI) based Health Recommender System (HRS). This new system reviews the patient's physiological signs, medical records, and sleep data with the help of data analytics and machine learning techniques. The HRS can accurately pinpoint sleep apnea events and offer each patient-specific treatment and exercise suggestions with the help of CI methods. The system maintains the ability to enhance its diagnosis and treatment capabilities over time through the use of adaptive learning. To design HRS, we have employed a collaborative-filtering approach based on k-Nearest Neighbours (kNN) algorithm. We have obtained an accuracy of 86% and an AUC of 0.83 for the apneac event detection. The collaborative-filtering approach computes cosine similarity among patients based on their demographics (age, sex etc.) and Apnea-Hypopnea-Index (AHI). The adaptive learning feature of this HRS depends on feedbacks and ratings provided by patients for exercises and treatments suggested by the system. Lack of dataset on user ratings on medical appliances and data sparsity are main challenges while implementing such HRS. These limitations give new scope for future research work in this field of HRS. The initial outcomes suggest that the proposed method can help provide patients specific therapies faster, which will lead to better patient results. This novel work is planned to change the way sleep apnea is monitored and its treatment is managed. This novel strategy aimed to help physicians, healthcare service providers, and patients who have Sleep Apnea (SA).

Keywords: *Sleep Apnea, Collaborative Filtering, Health Recommender System, k-Nearest Neighbors (kNN), Exercise, Treatment, Computational Intelligence*

1. Introduction

Sleep Apnea (SA) is a kind of sleep-disorder to worry about being a life-threatening disease. SA disrupts normal breathing several times during sleep [1], [2]. Disruptions in breathing can cause partial or complete blockage of airways leading to reduced oxygen supply to lungs, results in arousals from sleep [3]. Frequent episodes of arousals result in poor quality of sleep among adults and children [4], [5]. Hypertension, Diabetes, Tiredness, Cognitive impairments, Pregnancy issues and Cardiovascular ailments are among the consequences of sleep apnea [6]–[9]. As a traditional diagnostic method, Polysomnography (PSG), sleep-tests are carried out in specialised laboratories i.e. sleep-centres [10]. These tests are time consuming and costlier as well. These limitations in SA-detection and treatment management can be overcome with Health Recommender Systems (HRS). Global prevalence of SA is very rapid [11] and thus necessitates improved diagnosis and effective treatment management. Traditional methods such as PSG and CPAP mask are gold standards in this field but they often face challenges related to accessibility, patient adherence etc. [12]–[15]

Health Recommender Systems (HRS) have emerged as promising tool, providing data-driven insights and personalised treatment suggestions to SA-patients [16]–[18]. While HRS based on concepts of collaborative-filtering (CF) [19], [20], content-based filtering [21], Context-aware recommender systems [22], [23] are available for SA-management but these systems lack of real-time adaptability for dynamic physiological changes in SA-patients. Data sparsity, cold start problem [24], lack of data availability, patients consent etc. are the common issue while developing a Health Recommender System [25], [26]. Numerous studies have been published on the diagnosis and treatment of sleep apnea using machine learning and computational intelligence techniques. Research in these areas primarily looks at individual stages of diagnosis or treatment, ignoring the validation of both at the same time. Through the development of an advanced Health Recommender System (HRS) that integrates components for diagnostic and therapy suggestion, our research aims to bridge this disciplinary gap.

This paper is structured as follows. Section-1 is about introduction to sleep apnea, traditional diagnosis process, their limitations and rise of health recommender system. Section-II covers methodology and materials used for this research work. Implementation of HRS using collaborative filtering and kNN algorithm. Section-III covers results of experimental work carried out. Section-IV is discussions on HRS and its implementation and application to mitigate SA-disease. Section-V covers limitations, challenges faced while implementing HRS and roadmap for future research work. Finally, paper ends with conclusion, declarative statements and references sections. ###

High prevalence rate of Sleep Apnea a kind of sleep disorder is growing concern now a days, approximately 936 million adults worldwide and 36.34 million adults in India are suffering from it. Snoring is the most common symptom of Sleep Apnea, observed in approximately 94% patients. Untreated Apnea can affect Heart, kidneys, Cognitive functions, daytime sleepiness, fatigue, morning headaches etc. This disease is more prevalent in males as compared to females. Hence timely detection of Sleep Apnea is very important task now a days specially people just ignore snoring which is highest indicator of the disorder. Lot of efforts are made worldwide to use AI and ML for early diagnosis of SA. Large volumes of dataset are available for SA and other sleep related disorders, researchers are trying to use various ML/DL algorithms for detecting SA from these datasets. Generally medical datasets or real-time dataset are not ready to use for Machine learning tasks, they need to be pre-processed, cleaned, handled missing values, imbalanced datasets need to be worked before applying ML/Dl algorithms. Here in this study, we have used Particle Swarm Optimization (PSO) for optimal feature selection from Sleep Health and Lifestyle dataset, along with ML algorithms like logistic Regression (LR), Decision Tree (DT), Support Vector Machine (SVM) etc.

2. Material and Methods

The system runs on a network of interconnected modules, each with its own set of operating tasks. Fig. 1 depicts the block diagram of proposed HRS. The data collecting module gets patient data directly from a variety of sources, including wearable devices and mobile applications. The data processing module performs numerous activities on the collected data, such as data filtering, normalization, and feature extraction. A machine learning system analyzes data to detect sleep apnea occurrences. The recommendation module develops tailored treatment plans based on identified occurrences. Adaptive learning allows machine learning algorithms to get consistent updates from both new processed data and system feedback. This module diagnoses sleep apnea early on by analyzing mild symptoms in patient data. The treatment recommendation module generates accurate therapy suggestions by making valid use of patient-specific data. The system provides straightforward engagement tools for healthcare providers and patients via its user interface functions.

Dataset used for training and testing purpose: Sleep-Apnea database used for training purpose is Apnea-ECG-v1.0.0 provided by “Apnea-ECG Database https://physionet.org/content/apnea-ecg/” [27], [28]. The dataset consists of 70 records labelled as (a01 through q20, b01 through b05, c01 through c10, x01 through x35). To calculate the score, each record was separated into 1-minute non-overlapping segments. These segments are marked as “apnea”, “non-apnea”. The apnea-hypopnea-index (AHI) is the sum of apnea and hypopnea events per hour of recording. We have noticed some issues with this dataset while constructing a health recommender system. As this dataset does not provide user (patients in this context) ratings for treatment or exercise recommended to SA-patients. To overcome this issue, we need to augment user-rating matrix for developing collaborative filtering-based HRS.

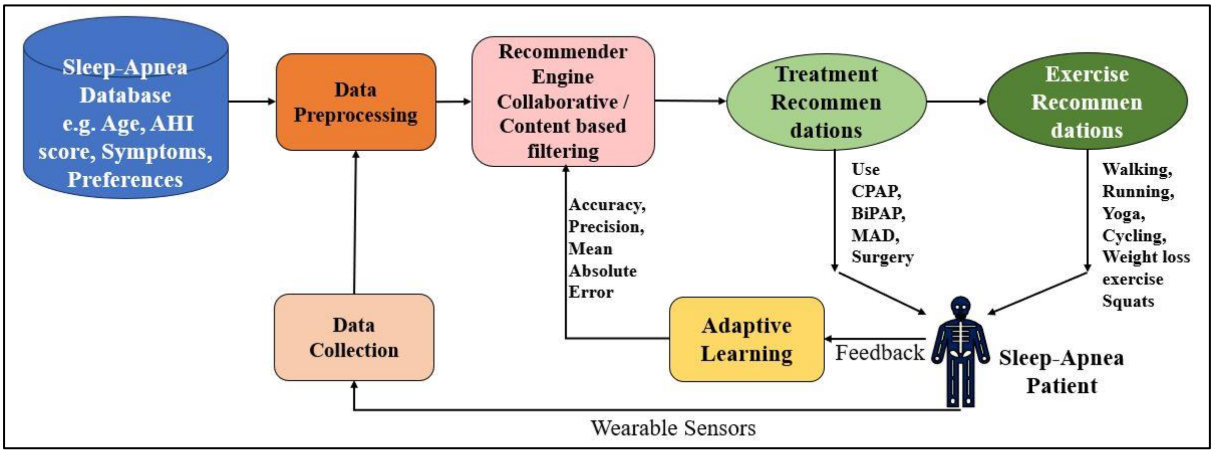


Fig. 1 Block level diagram for Health Recommender System for Sleep Apnea

The proposed Health Recommender System (HRS) comprises the following key components:

1. ***Data Collection:*** This section includes physiological data signals, such as heart rate, oxygen saturation readings, complete medical records, sleep study data and patients' demographic information such as age, sex, BM etc.

2. ***Data Processing****:* Filtering, normalization, and feature extraction, encoding categorical data, replacing missing values by their respective means are few of the many data processing operations performed on the gathered data. The acquired data is used for further analysis after it has been processed.

3. ***Patients Similarity Calculation:*** Determine similar patients by using their characteristics (e.g., age, weight, severity of Sleep Apnea, etc.) and the kNN algorithm. Determine a similarity metric to assess patient similarities, such as Euclidean distance or cosine similarity.

4. ***Adaptive Learning:*** This section enhances machine-learning operative capabilities by using patients and healthcare service providers feedback in addition to data collected from SA-patient. This section helps the system to remain up-to-date and accomplish continual improvements.

5. ***Exercise, Treatment Recommendation:*** The HRS generates appropriate treatment suggestions such as lifestyle changes, weight loss activities, medical procedures like jaw and UVPP surgery, use of oral appliances like MAD etc. post therapy guidelines. This section determines "k-nearest" neighbors to target patient (based on cosine-similarity). HRS compiles preferences/choices offered by these neighbors, then provides personalised treatment options or exercise recommendations to target patient.

Performance of HRS can be evaluated using parameters like Mean-Absolute-Error (MAE), Mean-Squared-Error (MSE), Root-Mean-Squared-Error (RMSE) and Accuracy.

Below is the pseudo-code for implementing kNN based Collaborative Filtering HRS

```
# Step-1: Initialize kNN Model
knnModel = initializekNN()

while True:
        # Step-3: Patient Data Collection
        patientData = fetchPatientData()

        # Step-4: Pre-process Patient Data
```

```
        preprocessed_Data = preprocessData(patientData)

        # Step-5: Train-Test-validate kNN Model
        knn_Model = trainkNN(knnModel, preprocessed_Data)

        # Step-6: Recommendation Generation
        Recommendations = generateRecommendations(knn_Model, patient_Data)

        # Step-7: Performance Evaluation and Updation of Model
        user_Feedback = collectFeedback(Recommendations)
        knn_Model = updateModel(knn_Model, user_Feedback)

        # Step-8: Display Exercise and Treatment Recommendations
        displayRecommendations(Recommendations)

    # Step-9: Stop for Real-time Updates
stop (60)
```

Performance of HRS for sleep-apnea can be assessed using following metrics.

1. Mean-Absolute-Error (MAE): As shown by equation-(1), this parameter indicates mean value of absolute difference between expected recommendations and actual patient preferences.

$$MAE = \frac{1}{n}\sum_{i=0}^{n}|y_i - \hat{y}_i| \quad \ldots\ldots (1)$$

where:

$y_i = Total\ number\ of\ observations$

$\hat{y_i} = Total\ number\ of\ observations$

$n = Total\ number\ of\ observations$

2. Mean-Squared-Error (MSE): As shown in equation (2), this parameter indicates average squared difference between model generated and actual recommendations. Larger mistakes are penalised more severely by MSE.

$$MSE = \frac{1}{n}\sum_{i=0}^{n}(y_i - \hat{y_i})^2 \ldots\ldots (2)$$

A lower value of MAE suggests that the HRS recommendations are more closely aligned with real patient preferences.

3. Root-Mean-Squared-Error (RMSE): It is the square-root of MSE. It gives average error magnitude, as shown by equation-(3).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=0}^{n}(y_i - \hat{y_i})^2} \quad \ldots\ldots (3)$$

Both MSE and RMSE metrics provide information on magnitude of mistakes.

4. Accuracy: As shown in equation-(4) this parameter quantifies the percentage of accurate recommendations among all recommendations that system has made.

$$Accuracy = \frac{Number\ of\ correct\ recommendations}{Total\ number\ of\ recommendations} \quad \ldots\ldots (4)$$

A higher value of accuracy suggests that the algorithm makes correct recommendations more often. Through optimization of these metrics, equation (1) through equation (4), performance of HRS can be improved to offer precise and trustworthy recommendations to sleep-apnea patients. HRS implementation using Collaborative Filtering Approach:

Recommender System (RS) using concept of CF, basically uses preferences/choices offered by similar patients (users) to generate recommendations.

HRS for SA - Patients uses CF to identify patients with similar health profiles and offer treatments or activities based on their common preferences or outcomes. The k-Nearest Neighbour (kNN) algorithm is used to implement CF. CF is based on the idea that users (in this case, patients) who have previously agreed (for example, on comparable preferences or results) will agree again, it does not require explicit knowledge of the characteristics of the items (e.g., treatments or exercises).

Two variants of CF are:

- User-User Collaborative Filtering: based on similar user preferences. recommendations are generated.
- Item-Item Collaborative Filtering: Based on the similarity of items recommendations are generated.

In this HRS, we utilize user-based CF with the kNN algorithm to detect comparable patients and make recommendations.

KNN-Based Collaborative Filtering

The kNN algorithm is a non-parametric, instance-based learning technique that finds the 'k most comparable' users (neighbors) to a given user. The HRS steps are as follows:

We have represented each patient as a feature vector that includes age, weight, sleep apnea severity, treatment history, and exercise preferences. We have created a user-item interaction matrix in which the rows represent patients and the columns represent treatments or exercises. The matrix's values can be binary (liked or hated) or numerical (rated or outcomes) provided by patients.

Similarity Calculation:

We have used cosine similarity to compute similarity between two patients. For example, cosine similarity between two patients P_i and P_j can be calculated as:

$$Similarity\ (P_i, P_j) = \frac{P_i.P_j}{\|P_i\|\|P_j\|} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \ldots (5)$$

Where $P_i.\ P_j$ is the dot product of patient vectors, and $\|P_i\|$, $\|P_j\|$ are their magnitudes.

Neighbourhood Selection: - Identify the neighbors i.e. 'k-most similar' patients for a target patient using computed similarity scores. For recommendation generation we have combined the preferences or outcomes of the 'k-neighbors' to make suggestions for the target patient. For example, if the neighbors have had positive results with a particular treatment or exercise, it is suggested to the target patient.

Challenges and Mitigations:

Cold Start Problem: Recommending new patients or treatments without past data is ineffective. To mitigate we can employ hybrid approaches that integrate CF with content-based filtering or demographic data [24]. ***Data Sparsity***: - The user-item interaction matrix is generally sparse, making it challenging to identify similar users. In order to mitigate this, we can use dimensionality reduction techniques (e.g., Singular Value

Decomposition) or imputation approaches to deal with missing data [25]. ***Scalability***: As the number of patients and therapies increases, the computing cost of locating neighbors rises. To mitigate this, we can use approximate closest neighbour methods or clustering approaches [26]. For example, consider we have following patients' data as shown in Table-1 below.

Table-1 Sample data for patient/user interaction matrix

Patient ID	Age (years)	Weight (kg)	Severity (AHI value)	Treatments			Exercises				
				T1	T2	T3	E1	E2	E3	E4	E5
1	45	85	Moderate	4	0	2	5	2	1	0	--
2	50	90	Sever	5	0	1	4	3	1	1	--
3	39	75	Mild	0	4	3	2	5	0	3	4

In Table-1, Treatments (T1, T2, T3) represents – Use of CPAP, Use of oral appliances like MAD, UVPP surgery. Exercises (E1, E2, E3, E4, E5) represents – Walking, Cycling, Swimming, Breathing, Back/Neck exercise. Patient demographics include – Age, Sex, BMI etc. Apnea severity level is decided based on AHI value – Mild, Moderate, Sever, Normal etc.

For target patient-X suppose (Age = 47, Weight = 88, Sex = Male, Severity = sever) then HRS calculates cosine similarity with all other patients -1,2,3. If Patients-1 and 2 are identified as nearest neighbors, HRS will recommend treatments and exercises that are highly rated/preferred by these patients, like Treatment-T1 and Exercise- E1.

The HRS can effectively deliver individualized and data-driven recommendations for Sleep Apnea patients using kNN-based collaborative filtering, thereby enhancing their treatment outcomes and quality of life.

3. Results

Using data sets with 500 individuals suffering from sleep apnea, researchers tested their Health Recommender System (HRS). The dataset included sleep pattern information, oxygen saturation readings, and heart rate readings. To evaluate the system's performance, we have used accuracy metrics, precision and recall metrics, and F1-score outcomes as part of the assessment process.

KNN-classifier used for classification of various categories of sleep apnea disease like mild-sleep apnea, moderate, sever category of sleep apnea. Performance metrics for the classifier is mentioned below in Table-2a and Table-2b.

Table2a- Classification Report of the Machine Learning Module

Sleep-Apnea Category	**Precision**	**Recall**	**F1-score**	**Support**
Mild	1.00	0.50	0.67	2
Moderate	0.80	1.00	0.89	4
Normal (non-SA)	1.00	1.00	1.00	3
Severe	0.80	1.00	0.89	4
Very Severe	0.00	0.00	0.00	1

Table 2b: Performance Metrics of the Machine Learning Module

Metric	Train-Test Split Ratio and K-Fold Cross Validation			
	50% - 50%	**60% - 40%**	**70% - 30%**	**80% - 20%**
Accuracy	65.71%	75%	81%	86%
Precision	0.7857	0.8393	0.8631	0.8143
Recall	0.61	0.692	0.76	0.7
F1-Score	0.6513	0.7357	0.7974	0.8175

For optimal performance, hyperparameter optimization techniques were used to fine-tune the algorithms.

Performance Evaluation of Recommender System:

The evaluation of the Recommender System's performance took into account three essential aspects namely accuracy together with user satisfaction and system efficiency. Both quantitative and qualitative assessment methods were implemented for the evaluation.

Table-3 Personalised treatment recommendations for similar patients

Patient Index	Selected test patient ID	Similar Patient IDs (Similarity score)	Estimated Category of Sleep-Apnea	Treatment Recommendation	Exercise Recommendations
22	Record: b03	x17 with Similarity Score: 0.7373	Moderate	Use CPAP with moderate pressure setting	• Walking (Low-intensity, 30 mins) • Breathing Exercises (5-10 mins) • Yoga (Gentle Stretching) • Swimming (Low-intensity, 20 mins) • Neck and Back Relaxation Exercises (5 mins)
		x02 with Similarity Score: 0.6529	Moderate	Use CPAP with moderate pressure setting	• Walking (Moderate-intensity, 30 mins) • Breathing Exercises (15 mins) • Yoga (Child's Pose, Cat-Cow) • Cycling (Moderate, 30 mins) • Bodyweight Exercises (Squats, Lunges)
		a03 with Similarity Score: 0.5479	Moderate	Use CPAP with moderate pressure setting	• Walking (Moderate-intensity, 30 mins) • Breathing Exercises (15 mins) • Yoga (Child's Pose, Cat-Cow) • Cycling (Moderate, 30 mins)

					• Bodyweight Exercises (Squats, Lunges)
01	Record: a01	b01 with Similarity Score: 0.9879	Severe	BiPAP, MAD / UVPP surgery,	• Walking (Low-intensity, 30 mins) • Breathing Exercises (5-10 mins) • Yoga (Gentle Stretching) • Swimming (Low-intensity, 20 mins) • Neck and Back Relaxation Exercises (5 mins)
		c07 with Similarity Score: 0.9523	Severe	MAD / UVPP surgery, BiPAP	• Walking (Low-intensity, 30 mins) • Breathing Exercises (5-10 mins) • Yoga (Gentle Stretching) • Swimming (Low-intensity, 20 mins) • Neck and Back Relaxation Exercises (5 mins)
		c04 with Similarity Score: 0.9207	Severe	MAD / UVPP surgery, BiPAP	• Walking (Low-intensity, 30 mins) • Breathing Exercises (5-10 mins) • Yoga (Gentle Stretching) • Swimming (Low-intensity, 20 mins) • Neck and Back Relaxation Exercises (5 mins)

Quantitative Evaluation:

A quantitative evaluation of the system measures the precision of recommendations generated by the platform. The research study measures accuracy by comparing the recommendations against the healthcare provider-prescribed treatment plans. The research data appears in Table-3. Performance of Health Recommender System can be evaluated by parameters shown in Table-4. The parameters MAE and MSE compares the systems prediction against actual recommendations preferred by user/patient. Fig.2a and Fig.2b provides graphical representation of system performance. As it can be seen from Fig.2a and Fig.2b, for various categories of sleep-apnea Area under ROC-curve is close to 1, indicates that our HRS can effectively detect apneac and non-apnea patients.

Table 4: Performance Measure of Recommender System

Mean-Absolute-Error (MAE)	1.589
Mean-Squared-Error (MSE)	3.517

Fig.2a ROC curve for various severity levels

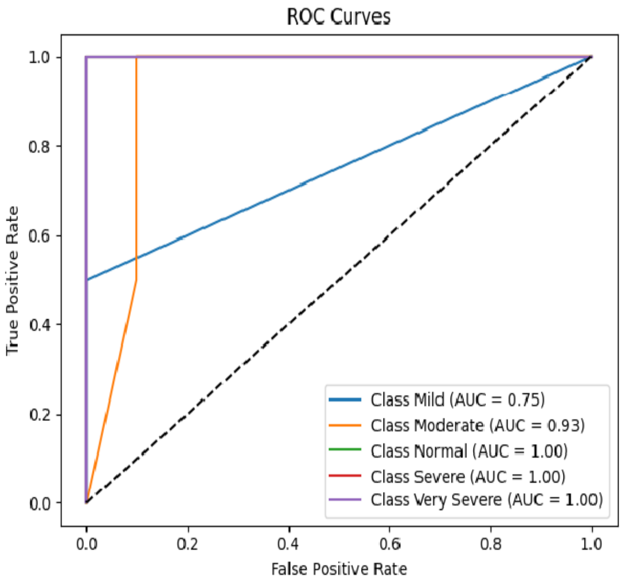
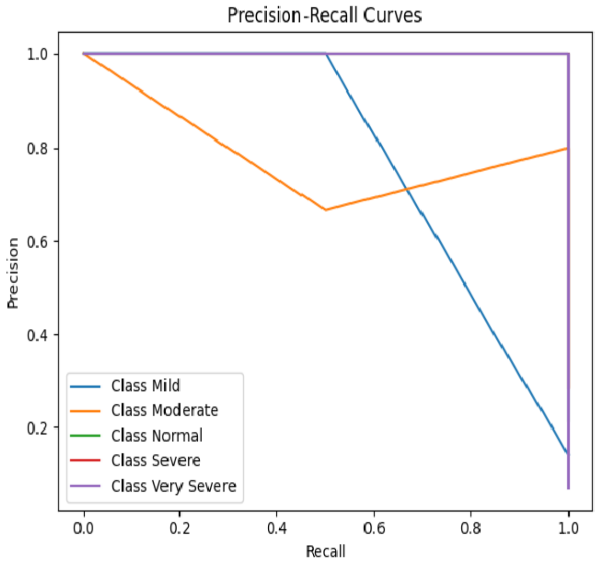


Fig.2b Precision and Recall Curve for various severity levels.



The results show (see Table-3) that the Recommender System has provided highly accurate exercise and therapy suggestions.

System Efficiency:

The efficiency of the HRS was evaluated based on systems' response time and resource utilization. The results are summarised in Table-5 below. The results shown in Table-5 are promising, this ensures that system is capable of handling massive amounts of data and generating real-time recommendations.

Table 5: System Efficiency Metrics

Metric	Value
Average Response Time	1.2 seconds
CPU Utilization	45%
Memory Utilization	60%

4. Discussion

The proposed HRS offers several advantages over traditional methods of diagnosing and treating sleep-apnea. Key features of proposed HRS are early-stage detection of disease, personalised treatment recommendations, adaptive learning, efficiency and scalability, personalized recommendations and mitigation of sleep-apnea.

Early-stage diagnosis is one of most significant features of this HRS. The HRS looks for minor patterns and markers in the patient data to detect early signs of the disease. Due to this timely interventions and appropriate treatment suggestions, better outcomes can be expected.

Personalized Treatment Recommendations are provided by HRS based on patient-specific information. Recommendations may include lifestyle changes, medical procedure like use of MAD, jaw surgery etc. and follow up feedbacks. HRS ensure that treatment suggestions are matched to patients' condition and medical history. This results in patient's adherence and outcomes.

Adaptive Learning capability of HRS ensures continuously updating machine learning / recommender engine parameters based on patient's data and their feedback about the exercises and treatments recommended to them.

Efficiency and scalability of HRS is dependent on its economical solutions. This HRS requires high processing power to provide data analysis and recommendations on time. Because of modular structure of this HRS, it can be easily integrated with current healthcare systems and medical instruments.

Importance of Personalized Treatments for Sleep Apnea Mitigation:

The HRS generates its recommendation based on individual patient's data, leading to customized therapies and exercise recommendations. For example, if a patient's SpO2 level (blood oxygen saturation level) remains low, HRS can suggest about adjusting the CPAP pressure settings. Alternatively, if patient is struggling with CPAP use, he/she may be recommended for oral appliances like MAD as viable option.

Enhanced treatment adherence can be ensured with this HRS. Many patients find it difficult to stick to prescribed therapies due to discomfort or other barriers. The HRS learns from patient's feedback, try to prioritise his/her comfort while aiming optimal clinical results. For example. HRS can suggest slight reduction in pressure setting of CPAP mask to improve adherence without compromising effectiveness.

Early trend detection is possible with proposed HRS, since it monitors changes in patient conditions to identify potential issues (such as consistently low SpO2 level) and recommend proactive treatments.

Over the time these optimised interventions should lead to significant decrease in AHI index enhancing overall health and quality of life of sleep-apnea patients.

5. Limitations and Future Scope

Addressing the highlighted concerns is crucial for maximizing the potential benefits of the proposed HRS. The accuracy of the HRS is significantly influenced by the quality and quantity of the patient data collected. Challenges at data collection stage like missing values, noise and artifacts can compromise effectiveness of the system. Furthermore, ratings provided by patients about exercises, therapies, medical procedures etc. is difficult to obtain. Future research should prioritise improving data collection and data availability in public domain, enhancing system robustness. More validation studies are required to assess the systems inclusion in practical applications.

6. Conclusion

This research paper describes a unique method for detecting and recommending a suitable treatment for managing sleep apnea. This research study employees Health Recommender System based on computational Intelligence. The suggested method combines machine learning algorithms with data analytics to assess patients' data and make personalized therapy suggestions.

The adaptive learning feature enables ongoing improvement in diagnosis and therapy ideas. The initial results show that the system can enhance patient outcomes by recommending appropriate treatment alternatives. This unique technique aims to improve sleep apnea management by providing a scalable and efficient solution for both healthcare practitioners and patients.

In conclusion, our findings emphasize the relevance of feature selection in sleep apnea categorization. Integrating PSO with machine learning classifiers improves accuracy and interpretability. Future work could look into more features and test the suggested approach on larger datasets. Our extensive research of sleep health and lifestyle revealed surprising correlations between sleep length, physical activity, stress levels, and sleep quality. These findings underline the importance of getting enough sleep, reducing stress, and engaging in regular exercise to improve overall sleep quality. Furthermore, our machine learning model for predicting sleep disorders displayed high accuracy and performance metrics, indicating its potential use in sleep disorder screening.

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Informed Consent - The submitter/corresponding author declares that he has obtained the consents of all the co-authors before including their names in the paper.

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