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Original Article

Obstructive Sleep Apnea Severity Prediction Model GUI using Anthropometrics

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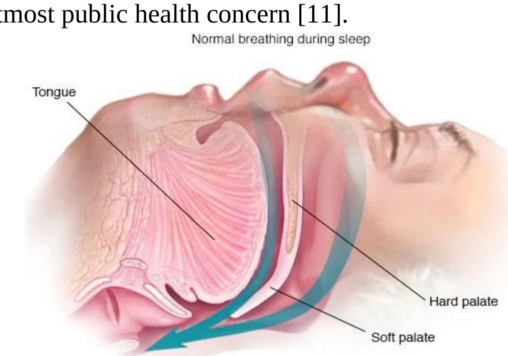
Abstract *- It is still challenging to anticipate the austerity of obstructive sleep apnea (OSA) in clinical practice. Polysomnography (PSG) has been widely used for predicting OSA, but it is expensive. To tackle the challenge, in this work, a Machine Learning (ML) approach was used to create a predictive model for determining OSA severity level, and a web application was created based on the ML model, where anyone can check their level of OSA. Instead of PSG, anthropometrics such as weight, height, waist circumference, head, etc., can be used to predict OSA severity. Moreover, these parameters are very cheap and easy to measure. To validate this methodology, 5245 records from the TMUH (Taipei Medical University Hospital) sleep center dataset are employed, which has the physical body characteristics along with the age and gender of the patients. To evaluate the model, supervised machine learning classifiers were implemented to predict the OSA severity. Random Forest classifier performed well on processed data with an accuracy of 91%. With the help of a random forest model pickle file, a web application has been developed to classify the OSA severity based on anthropometrics.*

Keywords – *Anthropometrics, Obstructive sleep apnea, Polysomnography, Supervised machine learning classifier, Web application .*

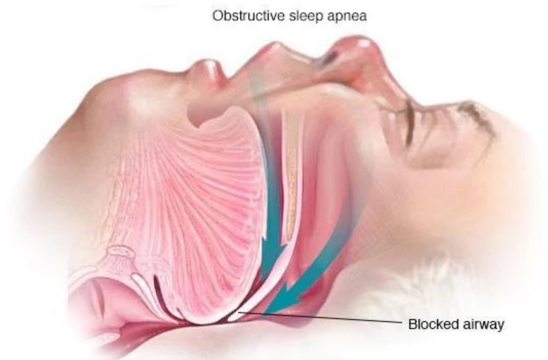
1. Introduction

OSA is a persistent sleeping disorder. Adult women experience OSA at a rate of 4%, compared to adult men, who experience it at a rate of 9% in the united states, whereas 23% of women and 50% of men got affected in Switzerland [1,2]. It is a global disorder. Due to upper airway collapse, breathlessness, and sleep fragmentation, patients with OSA will have sluggish breathing while sleeping, resulting in non-restorative sleep, excessive daytime drowsiness, and fatigue [3, 4]. Moreover, growing data suggests that OSA is associated with a wide range of disorders, including cardiovascular disease, neurocognitive impairment, and stroke. OSA has also been linked to several public disasters [5,6]. Despite the fact that OSA has received a lot of importance nowadays, many people (approximately 80-90 percent of all patients) continue to go undiagnosed and untreated [1,8]. Normal breathing occurs when there is no blocked airway during sleep, as shown in Figure 1, and OSA occurs when there is a blocked airway during sleep [4].

OSA is diagnosed based on the existence of pertinent medical symptoms and scientific proof of sleep-disordered breathing. When OSA is suspected, the lab will use polysomnography as a first-line diagnostic procedure. The multichannel signals that have been recorded can be used to extract information on sleep quality, respiratory issues, and anomalous gas exchange patterns [44]. Although polysomnography is a common procedure and the best method for diagnosis, it is neither practical nor cost-effective for screening purposes. It takes more time and involves more work because it needs a whole sleep laboratory and skilled personnel. Because of these requirements, it is labour-intensive and takes more time. A portable device replaces polysomnography, called tiny polygraphy, for diagnosing OSA. Although it takes less time, patients must still meet specific requirements, including a high pre-test likelihood of having a normal condition to the severe state of OSA and the absence of any medical comorbidities or sleeping-related issues [10]. Given OSA's wide-ranging effects on public health, developing a novel and efficient method for screening patients is of utmost public health concern [11].



a)



b)

Fig. 1 (a) Breathing without apnea, (b) Breathing with apnea

In the context of primary care, a number of surrogates have been created to achieve the screening goal utilizing a range of clinical prediction techniques and values that evaluate the most common OSA signs and indications. Examples include the BQ (Berlin questionnaire), SBQ (STOP-Bang questionnaire), and SACS (Sleep Apnea Clinical Score). A fresh approach is necessary because of the increasing heterogeneity of communities at this stage of globalization, which may restrict the efficiency of these questionnaire screenings. Anthropometric traits significantly influence the degree of OSA severity. A frequent measurement is body fat composition in diagnosing OSA [12, 13].

Physical body features, such as the waist-to-hip ratio, waist-to-height ratio, neck-to-waist ratio, and waist circumference, have been associated with the severity of OSA. It was recently discovered that new models for gender-specific OSA features are needed after researchers examined the anthropometrics of OSA patients by examining gender-oriented alterations in the tissue known as adipose with its distribution. It is essential to consider giving prime importance to the OSA detection models built based on anthropometrics. These anthropometric features are generally available and straightforward to gather in the outpatient context [14–18].

According to sources and research, no extensive study has examined the potential for combining different body shape profiles to screen OSA severity. These physical body characteristics, aka anthropometrics, are suitable for building an OSA prediction model with a minimized monetary and psychological load on patients. Numerous studies have been conducted on the characteristics of supervised machine-learning techniques that may extract complex correlations between parameters [19–27]. Various ML models have been developed to detect cancers at early stages [28-30], but very few researchers focused on OSA prediction. Some ML models have been created to predict the severity of OSA based on anthropometrics [45], but very few articles have compared the performance of the classifiers used in a model. Some research articles have used the same dataset used in this work. But no one had manipulated the dataset to analyze the performance of the models. In this work, some modifications were done to the dataset, each dataset type was tested in a model, and the best dataset processing mechanism was found. Even though a machine learning (ML) model has been created to predict the severity degree of OSA, its use in actual scenarios remains one of the largest challenges. To address that problem, a Graphical user Interface (GUI) has been developed with an ML model in the background to predict the OSA severity.

2. Materials and Methods

The TMUH database was used to acquire patient information. Patients aged between 20 and 80 suspected of having sleep apnea were included in the TMUH database. The database contains information on age, gender, weight, height, ESS (Epworth Sleepiness Scale), BQ, and PSG examination data. Anthropometric measurements such as the neck, head, buttock, and waist circumferences were measured at the sleep lab before beginning the PSG [45]. The BQ is divided into three main categories: snoring, daytime drowsiness or fatigue, hypertension, and obesity. These three divisions are separated into categories for severe, moderate, mild, and normal conditions. With a BQ score of 0, the patient is thought to be at low risk, while a BQ value of 1 indicates that the patient is at high risk [32]. Patients from the ASIAN continent make up the majority of this dataset.

2.1. Block Diagram

Figure 2 represents the flow diagram of the entire workflow of this work. A detailed explanation regarding the used dataset is given in 2.1.1.

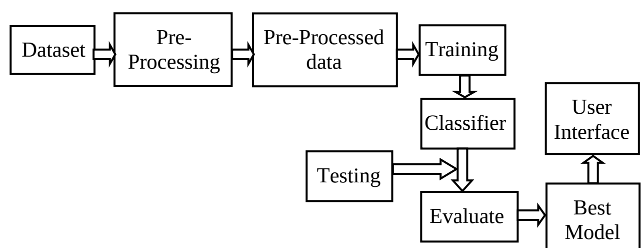


Fig. 2 Block Diagram

2.1.1. Dataset

The TMUH dataset contains 5241 patient records with 11 medical features from 3999 men and 1242 women. The dataset includes a target column called status that depends on all 10 medical features and forecasts the patient's OSA severity. Table 1 displays the Apnea Hypopnea Index (AHI) index for OSA severity.

Table 1. OSA Severity Condition

OSA Severity	AHI
Severe	≥ 30
Moderate	15 ≤ AHI < 30
Mild	5 < AHI < 15
Normal	< 5

2.1.2. Preprocessing

Pre-processing is the phase in which a clean dataset is generated. The clean dataset is the dataset free of outliers, object data types, not number (NAN) values, and missing values. This stage is very prevalent and most important while building an ML model. Before training the model, preprocessing should be mandatorily done to get the proper results. Some records were removed if all the fields of that record were not filled. Figure 3 illustrates the preprocessing steps used in this work.

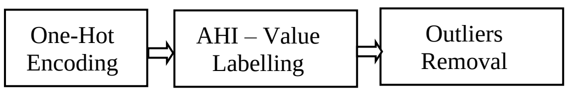


Fig. 3 Preprocessing Steps

One Hot Encoding

Due to the heterogeneous data types in the TMUH dataset, the gender label contains object data like M and F, while the other labels have numerical data. The ML algorithms do not support the object data type during the evaluation phase. It must therefore be either deleted or changed to a numerical data type. The dataset will suffer data loss if it is eliminated. In most cases, this is the prime mistake that most developers make. It must be transformed into a numerical data type to avoid data loss. The gender labels M and F are changed into 0 and 1 via one-hot encoding, accordingly. Tables 2 and 3 show the sample dataset before and after applying one hot encoding.

Table 2. Before One Hot Encoding

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

Table 3. After One Hot Encoding

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

Table 4. Before Labelling

	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

Table 5. After Labelling

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

AHI Value Labeling

The AHI values don't have a label that can help classify the OSA level. If AHI values are not labeled into proper classes, the ML model does not perform well in predicting the severity of OSA, as AHI values have many numbers. Labelling has been done based on the severity level to address this issue. Based on the AHI measurement, TMUH has assigned the severity status. In this work, the same has been taken into account. The severity of OSA is labeled in the following Table 6. Table 4 and 5 represents the AHI values before and after labeling.

Table 6. AHI Labelling

OSA Severity	AHI	Labeling (Status)
Severe	≥ 30	3
Moderate	$15 \leq \text{AHI} < 30$	2
Mild	$5 < \text{AHI} < 15$	1
Normal	< 5	0

After labeling, the outliers are removed. Outliers are values not in a particular field's permissible range. Ex: if a value in the age field is given as 500, then it is an outlier of that particular field, as 500 cannot be a valid entry in that field. The records that have these kinds of outlier data should be deleted.

Unbalanced Dataset (Original TMUH dataset)

The original dataset has 5245 patient records; after preprocessing, the records have become 5208. The 5208 records have been divided into four categories based on the AHI index. The original dataset has been treated as an imbalanced dataset because the count of each category varies a lot, as shown in Figure 4.

The unbalanced dataset was subjected to classification, and a high percentage of misclassification occurred, which is evident in Figure 4. The performance of the classifiers may appear to be good, but when a fresh batch of data is applied to the model, it'll almost mislead the model and classify the results incorrectly [33,34].

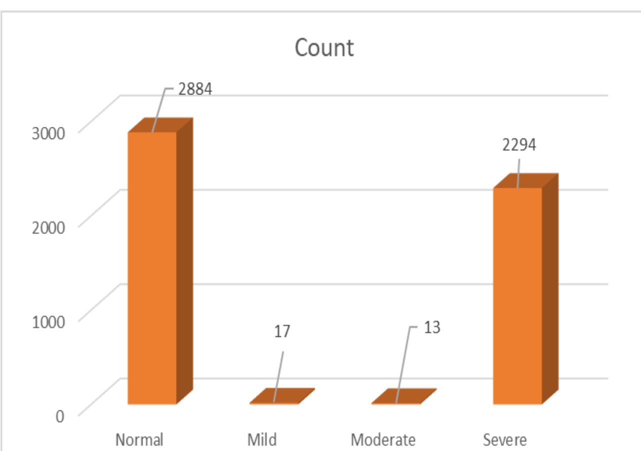


Fig. 4 Count of AHI levels in an Imbalanced dataset

To overcome the above-stated problem, the input dataset should be balanced. Any method or process can be followed to fabricate a normal dataset into a balanced dataset. Here two methods were trained & tested; then, one method was selected as the best method to construct a balanced dataset. That balanced dataset has been considered to train the ML model, which is the base of the UI page. Under-sampling and oversampling can be done to convert an imbalanced dataset into a balanced dataset.

Under-sampling and oversampling can be done to convert an imbalanced dataset into a balanced dataset.

a) Under-Sampled Dataset (Modified TMUH dataset)

In this case, the preprocessed dataset is subjected to under-sampling to create a balanced dataset. The under-sampling was done with the help of a random under-sampler technique. Using this technique, the records in the dataset will get into the minimum count such that a new dataset is created, which down-samples the 5241 records and randomly collect 13 records for each AHI severity level to make it a balanced dataset. So, the count of normal and severe levels is down-sampled to 13 records from 2884 and 2294, respectively. Figure 5 shows the count of AHI levels in the new dataset.

The under-sampled dataset has not provided the best results even though the dataset is balanced. This dataset has not performed well compared to the imbalanced dataset because the count of AHI level severity is minimal and cannot train the model more efficiently. Due to less count, the classifiers do not perform well Fig shows the accuracy of this dataset's classifiers.

b) Over-Sampled Dataset (Modified TMUH dataset)

The synthetic Minority Over-sampling Technique (SMOTE) [35,36] was used to increase the number of data records in the mild and moderate AHI labels to the count of 2200 each so that the resultant dataset resembles a balanced dataset. The total number of records needed in the mild and moderate categories is fixed at 2200 randomly, as the other categories also have a similar number of records.

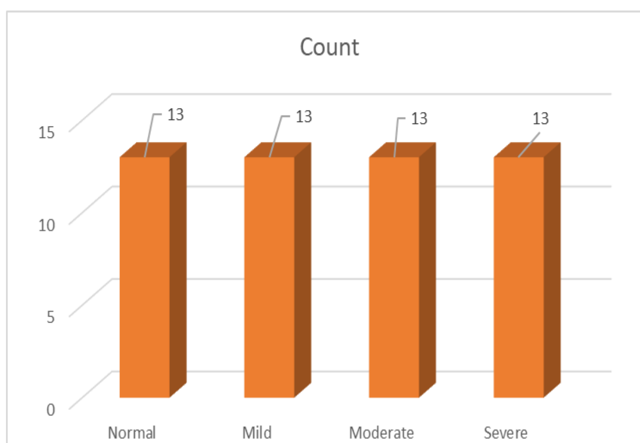


Fig. 5 Count of AHI levels in Under-sampled dataset

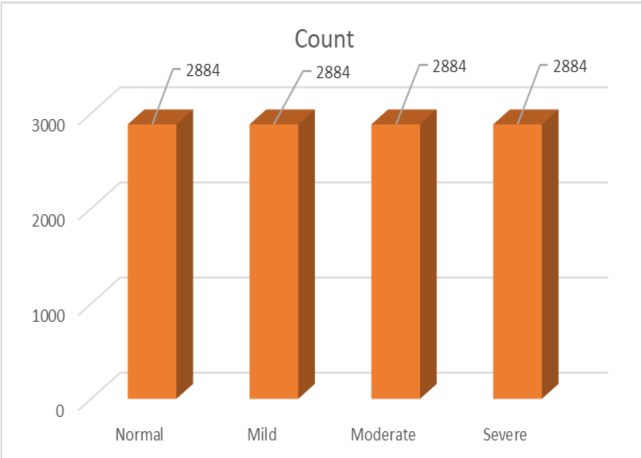


Fig. 6 Count of AHI levels in Over-sampled dataset

This SMOTE technique adds duplicate values in the mild and moderate categories as the number of records in these two categories is much lesser than in the other two. These duplicate values do not match the original values but will fall inside the original data range. After using the SMOTE technique, a new dataset with 9578 records was created. The number of records in the Normal and Severe categories remained the same as in the original dataset. Still, the number of records in the Mild and Moderate categories increased to 2200 and 2200, respectively. Figure 6 shows the count of each category.

This dataset has added advantage; it provides the result when applied to any classifier because all the categories have an equal count of records and has more count of classifying the model more efficiently. This dataset is considered for deploying UI because it shows the best results compared to the other two datasets, which is evident in Table 7.

2.1.3. Train-Test Split

To assess the model, the preprocessed data must be divided into train and test sets [33]. The model was trained using training data, and its performance was assessed using test data. The ideal train-test splitting percentage for maximizing the classifier's performance cannot be predicted by a specified function. A trial-and-error method has been used to determine the best train-test split percentage for all the classifiers considered in this work. The accuracy percentage based on various train-test split ratios for the random forest classifier, which is named the best classifier for this dataset in the results, is shown in Figure 7. The considered train test split percentage starts from 60:40 and ends at 90:10. The Model was overfitted when the ratio 90:10 was considered; hence 80:20 has been considered as the optimal train test split ratio.

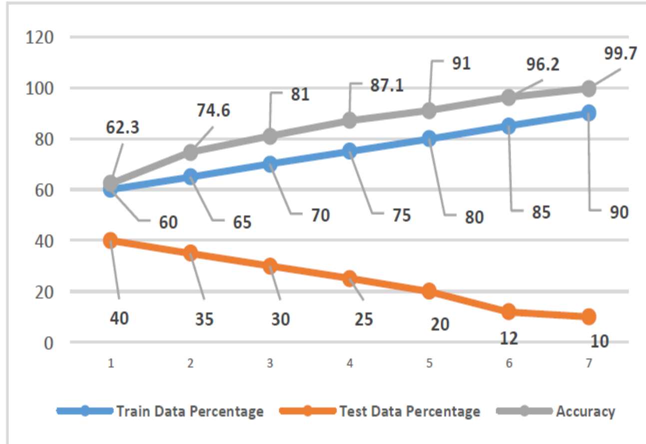


Fig. 7 Train & Test Data split with the corresponding Accuracy

2.1.4. Classifier

A classifier in machine learning is an algorithm that automatically organizes data into one or more categories. Seven supervised classifiers were employed in [38,39]. The seven classifiers are:

- K-Nearest Neighbor
- Logistic Regression
- Extra Tress Classifier
- Support Vector Machine
- Random Forest
- Decision Tree
- Gaussian NB

2.1.5. Performance Metrics

Metrics for machine learning are used to assess how well a model works [40,47]. The essential goal of a learning model is to generalize unexplored data properly. Performance metrics can be utilized to determine how successfully a model generalizes to new data. Five metrics are used in this work to assess the test data and determine the model's performance: accuracy, precision, recall, F1 score, and time.

2.1.6. Best Model

The best classifier is selected based on performance criteria, and the model built with the best and most potent classifier is termed the best model. That best model is used as the background for the UI page.

2.1.7. User Interface

The web page, known as the user interface (UI), interacts with users and provides them with the desired outcomes based on the UI's design. A web framework named flask has been utilized to create the backend of the user interface for classifying the severity of apnea. Typically written in Python, it is a tiny web framework. Flask Framework Instance, which is app. run and app. route, is needed to create a flask framework. A pickle file has been made for the best model, and the flask server will use this pickle file. The implementation of the classifier and its performance metrics will be dumped into the pickle file. Hyper Text Markup Language (HTML) and Cascading Style Sheets (CSS) were used to design the UI's front end. The web application can be accessed by the following link https://osaprediction.herokuapp.com.

HTML

The most well-known and often used markup language for creating websites is Hyper Text Markup Language. When an HTML file is submitted to a server, the set of markup codes or symbols is coded, preserved, and used to display the web page's text and graphics on the internet.

CSS

The appearance of the HTML file can be described using a style sheet called Cascading Style Sheets. The CSS file supports a website's backdrop, fonts, layout, and color scheme.

Web Application

A web application (or web app) is software that operates on a web server instead of computer-based software programs that function locally on the device's operating system (OS). The user accesses web apps through a web browser with an active network connection. The online application developed here is user-friendly and straightforward to understand. The Heroku platform was used to deploy the web application for creating links.

3. Results

In this section imbalanced dataset, under-sampled dataset and over-sampled dataset were considered as case-1, case-2, and case-3, respectively.

3.1. Accuracy

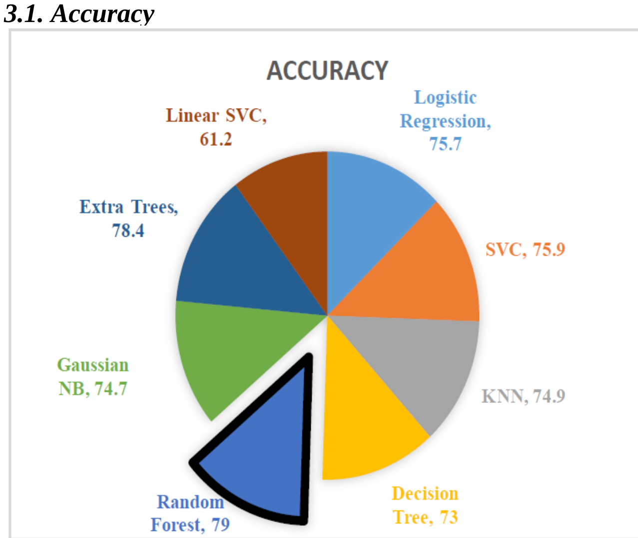


Fig. 8 Accuracy of the different classifiers for an imbalanced dataset

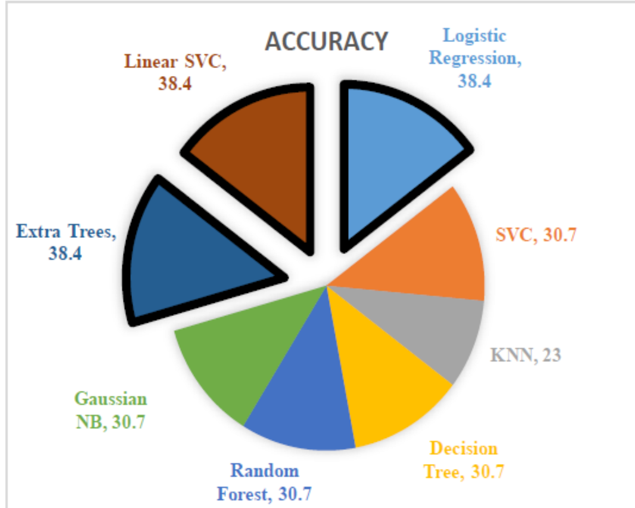


Fig. 9 Accuracy of the different classifiers for the under-sampled dataset

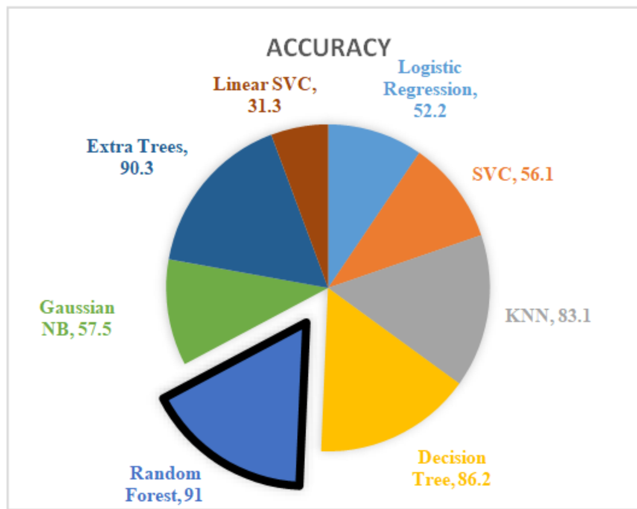


Fig. 10 Accuracy of the different classifiers for over-sampled dataset

The above charts state that in cases 1 and 3 random forest classifier has performed well, and the majority of the classifiers have the highest accuracy in case 3. Even though some classifiers provide some good results in case-1, due to misclassification in AHI levels, it is not considered to be a good dataset. The misclassification can be seen in the confusion matrix of all the dataset cases for top-performed classifiers in Figures 11, 12 and 13. So, as a result, the best model to use in the UI can be decided by using the classifier performance metric results of case-3.

3.2. Confusion Matrix of the Classifiers

The confusion matrix for the top-performed classifiers in each dataset type was considered. This performance metric alone gives the maximum information regarding the classifiers' performance [42]. Figures 11 and 12 show that the AHI category records were misclassified either in the normal or severe category. Figure 13 shows some misclassifications in its records, which is negligible since a significantly smaller number of records were misclassified. Therefore, Oversampled dataset with a random forest classifier considers the best ML model for this problem.

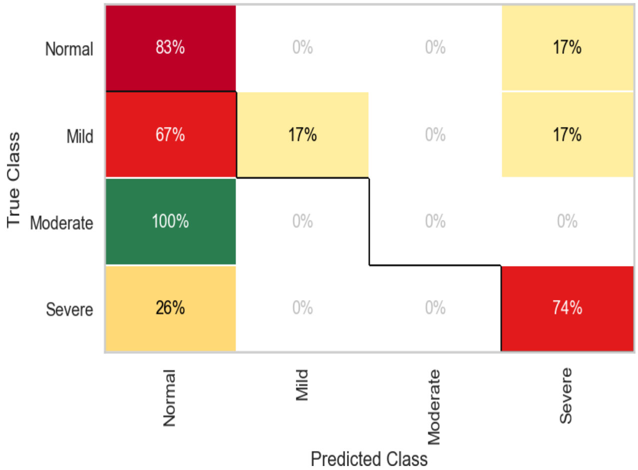


Fig. 11 Performance of Random Forest for imbalanced dataset

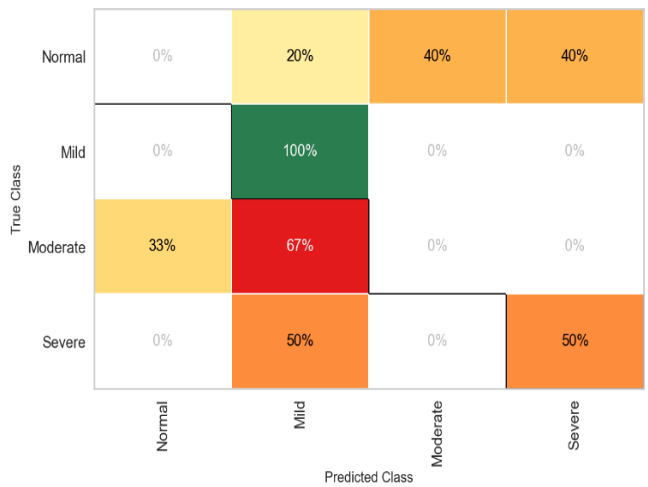


Fig. 12 Performance of Random Forest for Under-sampled dataset

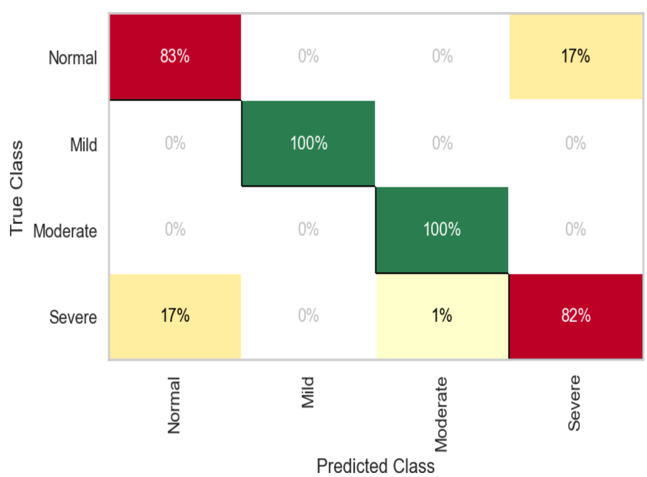
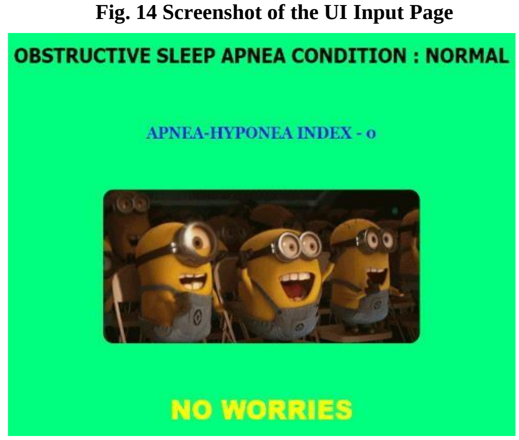


Fig. 13 Performance of Random Forest for Over-sampled dataset

3.3. UI Results

A user interface has been developed with the help of a flask server [43]. The flask server will have the ML model with the best-performed classifier. The python script is used as a base to create the flask server.

Fig. 14 Screenshot of the UI Input Page



a)

b)

Fig. 15 Sample screenshot of the UI output page

Table 7 shows that the random forest classifier has performed well, so the random forest pickle file has been used to develop a web application.

The user interface is developed in such a way that the user should enter values for all required fields before clicking the submit button. If the user missed entering the data in any field, the interface shows a pop-up message to enter the value that the user has not entered. If the user has entered any value outside the field range, one pop-up will be opened to indicate the user has entered the value within the permissible range. So that illogical entries can be avoided. Once the user enters all the values in the fields, they can click on the submit button at the bottom. Then with these field values as input, the ML model will be executed, and the stage of OSA will be predicted and displayed with an emoji related to the four stages.

Normal, mild, moderate and severe are the four severity levels, out of which one criterion of OSA will be displayed in the result page based on the provided input values. The sample result page of all the severity levels is displayed in the below figures.

Table 7. The performance metrics of different classifiers for all three datasets.

Dataset	Classifiers	Accuracy	Precision	Recall	F1-Score	Time Taken
Imbalanced	Random Forest	61.2	**79**	**79**	**79**	1.22
	Decision Tree	73	73	73	73	0.06
	Extra Trees	**78.4**	78	78	78	0.89
	Logistic Regression	75.7	75	76	75	0.3
	SVC	75.9	75	76	76	1.42
	KNN	74.9	74	75	75	0.11
	Gaussian NB	74.7	74	75	75	**0.02**
	Linear SVC	61.2	75	61	57	1.22
Under-sampled	Random Forest	30.7	15	38	25	0.09
	Decision Tree	30.7	21	38	25	0.01
	Extra Trees	**38.4**	19	38	25	0.15
	Logistic Regression	**38.4**	19	38	25	0.02
	SVC	30.7	18	42	23	**0.007**
	KNN	23	17	26	20	0.019
	Gaussian NB	30.7	**56**	38	**31**	0.014
	Linear SVC	30.7	19	**50**	28	0.02
Over-sampled	**Random Forest**	**91**	**91**	**91**	**91**	0.82
	Decision Tree	83.1	86	90	86	**0.04**
	Extra Trees	90.3	90	86	90	0.57
	Logistic Regression	52.2	52	52	51	0.38
	SVC	56.1	58	56	55	3.87
	KNN	83.1	83	83	82	0.11
	Gaussian NB	57.5	58	58	57	0.57
	Linear SVC	31.3	30	31	21	1.32

4. Conclusion and Future Scope

The supervised classification algorithms were implemented in this work for classifying the OSA severity. Eight different classifiers were used in this work to execute the classification process. Compared to the imbalanced dataset, the original and under-sampled datasets provide poor classification results. The metrics such as accuracy, precision, recall, and f1 score are inferior, whereas the time taken to complete the execution of classification is very less compared to the former. Therefore, the time consumption is improved a bit. The over-sampled dataset is preferred to attain good classification results as it gives perfect accuracy and other parameters while classifying the OSA class. The over-sampled dataset alone provided the best results for the majority of the classifiers when compared with the imbalanced and under-sampled datasets. The classifiers trained & tested with an over-sampled dataset produce an average accuracy of 68.07% (average of accuracies of all eight classifiers), which is less than the average accuracy of the classifiers trained & tested with imbalanced default dataset as it produces an average accuracy of 71.87%, but way greater than the average accuracy of the classifiers trained & tested with an under-sampled dataset which is 31.66%. Though the imbalanced dataset improves average accuracy, it fails in the confusion matrix as many false positives and false negatives can be witnessed in mild and moderate cases. Therefore, an over-sampled dataset provides a better option which holds an upper hand in confusion matrix results. Random forest classifiers provide better performance metrics compared to all the classifiers used in all three dataset cases. The point to be noted is that the “Tree” based classifiers work too well in the over-sampled balanced dataset compared to the vector-based classifiers.

The SMOTE technique helps in providing the best results for the classifiers. Detecting the OSA and its stage based on anthropometrics proves to be way cheaper than detecting the same using polysomnography data. Throughout the world, polysomnography is the popular method used to detect OSA, but anthropometrics slowly finds its way into OSA diagnosis. This work will be a torch bearer for building a model with the anthropometric dataset. Some works that use anthropometrics don’t deal with the SMOTE technique to create the oversampled dataset and don’t load the ML model into a web-based application. If the same technique can be used for some other parameters, such as polysomnography data or EEG signal, it can be a game changer in the OSA diagnosis. Physicians can feed the data, and the machine will do the rest.

Moreover, it performs decently well in classifying the OSA. The user interface will be a handy aid for both patients as well as doctors to identify the stage of OSA of a patient with their body characteristics. This work can be extended with optimization techniques like bio-inspired algorithms to enhance the classification process. This work concentrates on the dataset where only the data has been collected from the ASIAN region. In future, the same model can be tried and tested with data from different geographical regions.

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