Investigation on the impact of COVID-19 on Sleep Quality

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Abstract -A SARS (Severe Acute Respiratory Syndrome) epidemic known as covid spread around the world in 2019 and afflicted nearly all regions, causing both physical and mental anguish. In the early stages of the pandemic, mortality and inflation rates were high, forcing people to stay at home wherever they were in the world and forcing the closure of all activities. Many people were psychologically and physically impacted by disruption of daily routines, social exclusion, and isolation, which resulted in sleep disorders such insomnia and restlessness. The health index decreased as a result of the poor sleep. The major goal of this study is to examine the factors influencing sleep quality in individuals with and without covid. To do this, supervised machine learning algorithms will be used, along with sampling strategies to enhance model performance.

Keywords: Regression, classification, supervised learning, machine learning, covid, sleep quality, oversampling, and undersampling.

I. Introduction

Adults from all socioeconomic classes and backgrounds have experienced great stress and tension as a result of the covid outbreak, which caught everyone off guard. Many people now have disrupted busy routines, unpredictable behaviour, and rapidly rising levels of anxiety as a result of social exclusion, school and university closures, remote workers, isolation, widely dispersed job cuts at the workplace, the ongoing risk to healthcare professionals, and worry about positive test results [1]. All of these elements may make insomnia and other sleep-related problems worse. Covid confinement practices have influenced a variety of psychological issues, such as anxiety, dread, and insomnia. It is well known that stressful situations have negative psychological effects on people as well as negative physical and mental effects [2]. Examining the factors that contributed to stress and sleep issues during the covid outbreak may also help us better understand how the mind works and advance the medical system as a whole. Finding out whether there is a connection between the covid outbreak shutdown and markers such poor sleep, stress, depression, and restlessness is the main goal of this endeavour [3].

In reaction to the covid epidemic, numerous studies have been conducted to ascertain how it has affected people's health as well as their sleep patterns, among other things. Several people's mental health has gotten worse as a result of the preventative measures taken in response to the epidemic. This study uses widely used questionnaires, including variants of the SSRS, GAD7, SARS [4], and PSQI.

II. Review of the literature

In the Chinese city of Wuhan, Covid debuted in 2019. It spread over Hubei Province and other parts of China quite swiftly, having an impact on over 110 countries. During that time, SARS-CoV-2 was formally referred to as the cause of acute respiratory syndrome (SARS syndrome) by the WHO (World Health Organization) [5]. The nations have been severely damaged by this disease. However, psychologically speaking, people who received this early form of support were confronted with feelings like uncertainty, dread, anger, and irritability that could quickly lead to tension, tedium, and/or discomfort [6].

The stress of worrying about nearly inevitable health risks and social alienation brought on by having to manage academics from home seems to have had a major negative impact in the case of people with children on daily activities and nightly sleep [7]. There have been debates about how stress may alter sleeping patterns throughout the pandemic. Excessive cognitive worry and physical attentiveness when exposed to stress may disrupt sleep, according to the factor impacting hypothesis of insomnia, which is based on an auto cycle [8].

Numerous studies [9] have explored the effects of the covid pandemic on sleep duration and the factors that contribute to such effects. Recent research conducted a contextual analysis to understand the lack of sleep even during the covid epidemic. According to the research, there is a combined incidence rate of 36.7% of insomnia worldwide, with covids accounting for the majority of cases (73.8%), followed by medical professionals (34.0%) and the general population (31.3%) [10]. A randomized research on covid patients revealed that the illness also causes sleeping issues and emotional anguish.

III. proposed project

Data for this study was gathered from a dependable source and further pre-processed into the necessary format. The processed dataset was subjected to data analysis and data visualisation in order to identify the key features that might serve as the best feature vector for the development of the supervised Machine Learning (ML) model on this data. The training dataset was used to develop and train "three Machine Learning models." The best optimal model was ultimately determined by testing all of these trained models against test data and evaluating them using various regression criteria. Additionally, the features were examined so that their significance to sleep quality could be determined and appropriate preventive measures could be taken. Each stage is thoroughly detailed in the following section.

1V. Dataset Description

The dataset utilised in this study of sleep analysis during covid time has 4,417 rows and 98 total attributes. The dataset has been analysed by Boston College academics [15] and made available for use by the general public at redcap online survey. The original dataset has also been expanded with new columns. These qualities include several elements that affect the quantity and quality of sleep.

The collected processed data was split into train and test data after acquisition. Different Machine Learning models that were employed in this study's implementation were trained using train data. On the test data, the models were evaluated. For training and testing, this data was split 80:20, respectively.

I. **Methodology**:

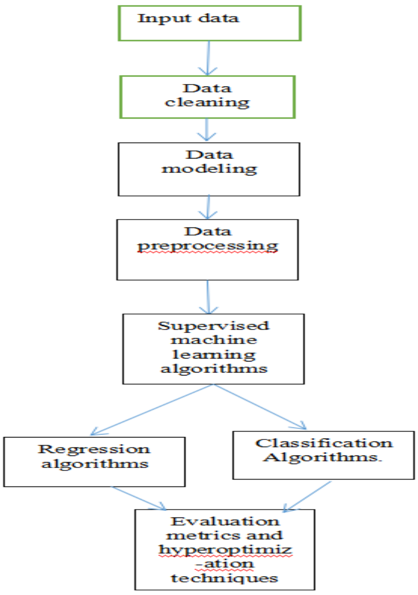

Fig 1. Methodology to perform machine learning algorithms.

In this problem it is important to analyse the worry scale using histogram.

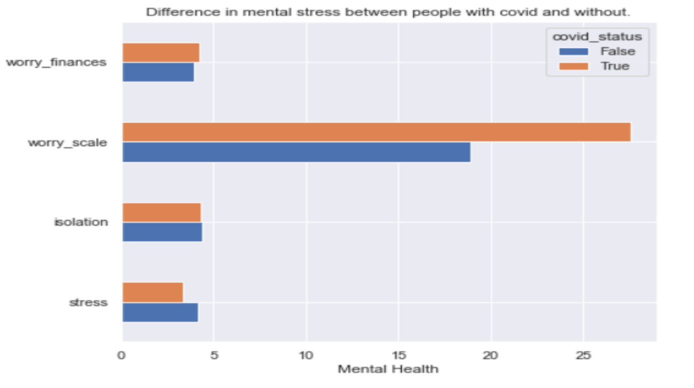

Fig 2. Analysis on mental health in people with and without covid.

According to the problem from our dataset it is essential to carry out analysis on mental health attributes.

1) The “Worry_finances” attribute represents people with covid status has higher score which indirectly impacts on quality of sleep.

2) The “Worry scale” represents people with covid status has high score.

3) As the “isolation” and “stress” attributess dominated by people without covid.

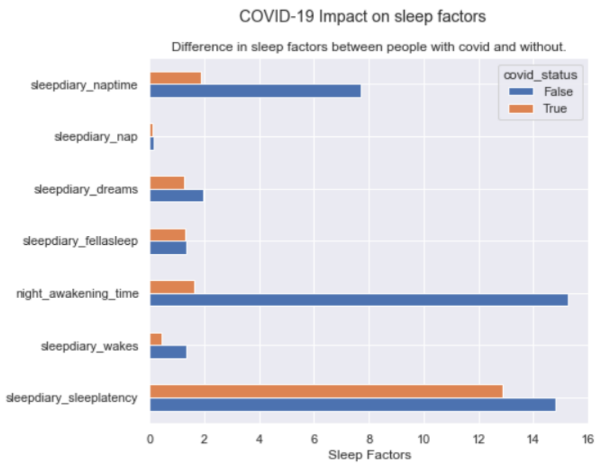

Fig 3. Analysis on sleepdairy columns and worryy scale.

As far as our dataset is concerned, sleep factors play a major role to analyse quality of sleep impact during covid pandemic.

1) The “sleep dairy nap time” attribute describes the number of times an individual napped and from the figure it is clearly exhibited that people with covid status false has the highest sleep dairy nap time.

2) The “sleep dairy nap” attribute explains whether each individual napped on the previous day or not and considering our findings, it shows that people with covid status false has the highest sleep nap time.

3) The “considering sleep dairy dreams” attribute indicates that people with covid false has highest dreams remembered during their sleep.

4) The “sleep dairy fell asleep” attribute represents the difficulty level of sleep and both categories have almost the same minutes but some of the sleep columns performances are largely depending upon the other attributes as well.

	covid_status	total_sleep_time	difficulty_falling_asleep	virtually_socialization_min	prop_exercise	stress_level	isolation_level	worry_level	panas_level	depre
0	False	7.638	1.347	51.912	0.509	4.290	4.390	18.888	44.997	
1	True	7.427	1.312	38.500	0.067	3.367	4.312	27.562	33.812	

Fig 4. Aggregation of all sleep columns in people with and without covid.

Aggregation of each attribute with respect to covid status columns help us to identify overall sleep duration.

1) People with covid status true has lower total sleep time which impacts quality of sleep.
2) People with covid status true has less virtual socialization which affects their sleep.
3) Proper exercise minutes denotes time spent for exercise by people with covid status false has higher number of minutes.
4) Level of depression is higher in people with covid status true is one factor disturbs quality of sleep.

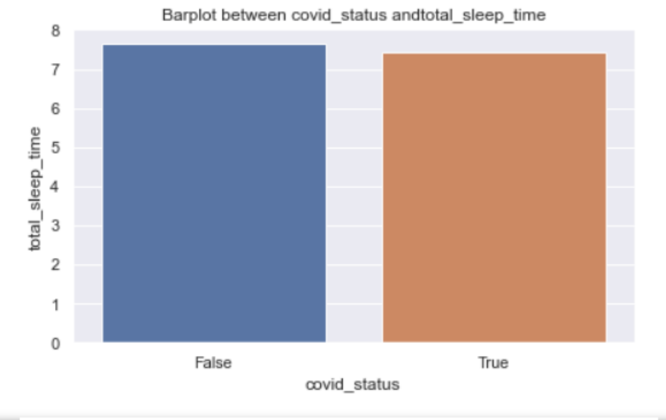

Fig 5. Analysis of total sleep time and covid status columns.

The bar plot shown in Figure 5 clearly exhibits that total sleep time for people with covid status false.

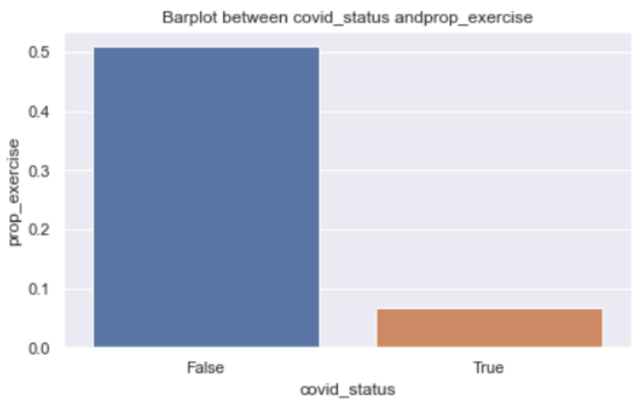

Fig 6. Analysis of proper exercise and covid status.

From Figure 6, proper exercise minutes are higher in people without covid, indicating effects on quality of sleep on people with covid.

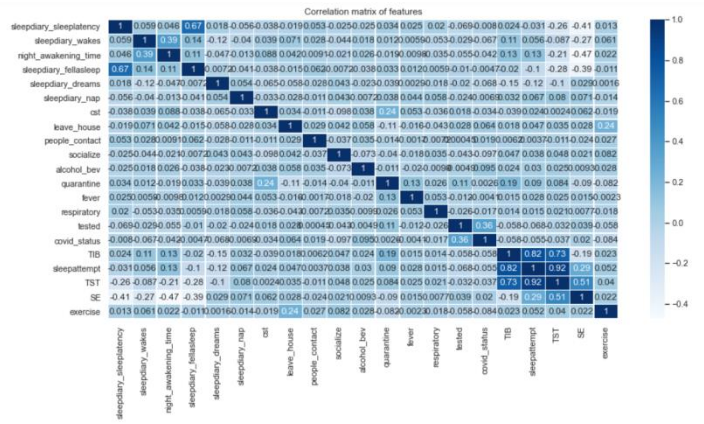

Fig 7. Correlation among feature variables.

Correlation among important variables helps us to determine the most correlated variables to extract the feature selection.

As shown in the correlation plot presented in Figure 7, these are mostly correlated features to perform machine learning algorithms.

1) Sleep efficiency and covid status are chosen as target variable when compared among all the other attributes.
2) 'sleepdiary_sleeplatency', 'sleepdiary_wakes', 'night_awakening_time', 'sleepdiary_fellasleep', 'sleepdiary_dreams',
3) 'sleepdiary_nap', 'cst', 'leave_house', 'people_contact', 'socialize', 'alcohol_bev',

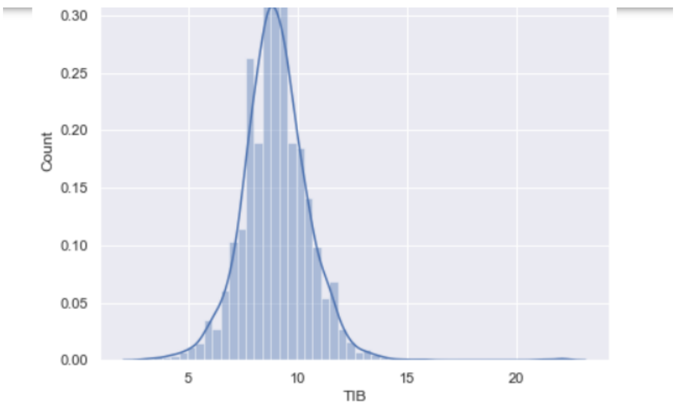

Fig 8. Normal distribution curve in TIB attribute.

From Figure 8, the TIB feature with mean and standard deviation curves almost fit into the normally distributed curves suitable for training model.

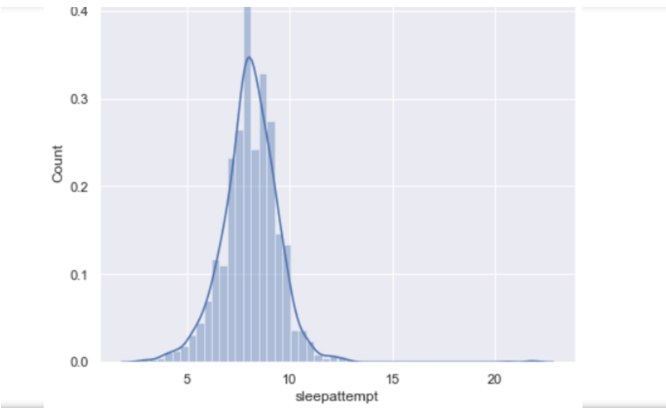

Fig 9. Normal distribution curve in sleepattempt feature.

From Figure 9, the sleepattempt feature with mean and standard deviation curves almost fit into the normally distributed curves suitable for training model.

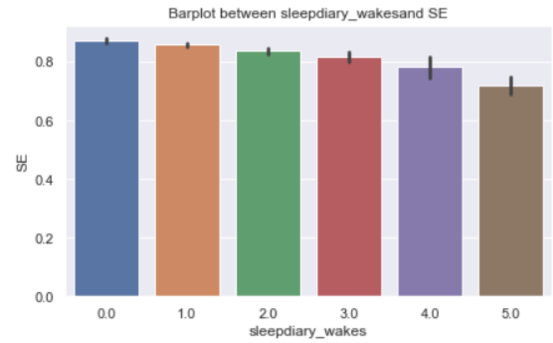

Fig 10. Histogram analysis in sleepdairy_wakes with respect to sleep efficiency target variable.

From the above bar plot shown in Figure 10, as sleepdairy_wakes decrease with increase in sleep efficiency which shows clear impact on quality of sleep.

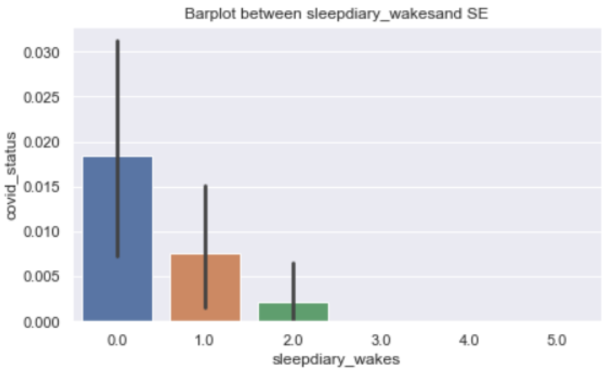

Fig 11. Histogram analysis in sleepdairy_wakes with covid_status column.

From the bar plot presented in Figure 11, as sleepdairy_wakes decrease with increase in covid status which shows clear impact on quality of sleep.

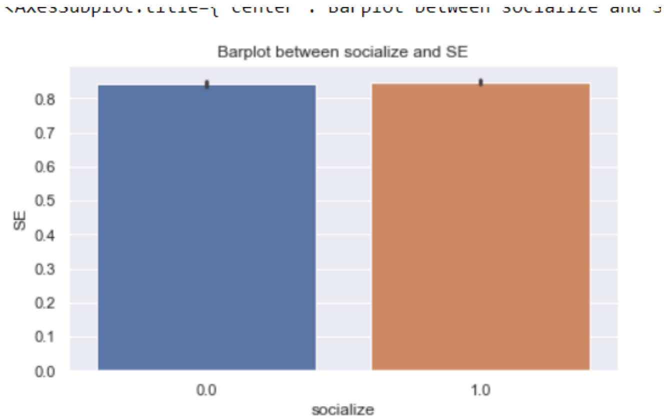

Fig 12. Histogram analysis on socialization and sleep efficiency columns.

Figure 12 shows that socialization does not impacts the sleep efficiency as the ratio is almost same.

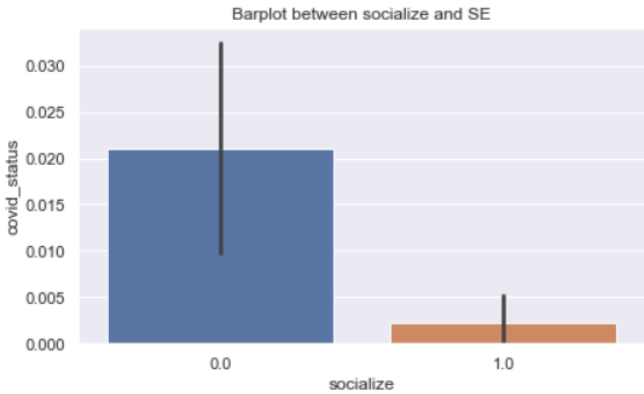

Fig 13. Histogram analysis on socialization and covid_status
Figure 13 shows that socialization does impacts the covid_status the ratio is lower for with covid.

VI.CHOOSING TARGET AND FEATURE VARIABLES FOR MACHINE LEARNING ALGORITHMS.

After performing exploratory and correlation analysis found these are independent variables 'sleepdiary_sleeplatency','sleepdiary_wakes', 'night_awakening_time', 'sleepdiary_fellasleep', 'sleepdiary_dreams', 'sleepdiary_nap', 'cst', 'leave_house', 'people_contact', 'socialize', 'alcohol_bev', 'quarantine', 'fever', 'respiratory', 'tested','covid_status','TIB','sleepattempt', 'TST', ,'exercise'.

In order to know the performance and effect of sleep quality, the "covid status" column was divided into two feature variables: one is covid positive with class '0's, and the other is covid negative with class '1's, respectively and to avoid bias in our analysis.
Sleep efficiency 'SE' is found as target variable which is calculated from 'time in bed' and 'total sleep time' columns.

A) DATA PREPROCESSING TECHINIQUE

Using standard scalar as pre-processing method to avoid biasing in feature and target variables because it scales mean and standard deviation suitable as input to machine learning algorithms.

VIII. TESTS AND EVALUATION

APPLYING MACHING LEARNING ALGORITHMS

SUPERVISED LEARNING ALGORITHMS

LINEAR REGRESSION

A linear regression model is used to establish and identify a linear relationship between independent variables and target variables. As in this problem linear regression is more effective in processing continues variables and helps to identify effects of input variables on target variable represented by the equation [12].

$$Y - = B0 + B1X1 + B2X2 + B3X3 + \ldots\ldots + BnXn$$

From the above equation,
Y= target variable
B= coefficients of each input feature
X= multiple input features.

A) DECSION TREE REGRESSION AND CLASSIFICATION

Since we have multiple features, a decision tree is effective in dealing with non-linear data unlike linear regression. A decision tree learns from each training node to predict the class of the target variable. It learns from each feature and finally predict the class when it reaches the 'leaf' node. It is mainly utilized in optimization of error [12].

B) RANDOM FOREST REGRESSION AND CLASSIFICATION

A random forest regression and classification model is more effective when dealing with multiple features as input. This is relevant especially in this problem with multiple input features trains each decision tree with each sample data and the final prediction of target variable is overall mean of all decision trees forming best possible prediction of target variable in regression model.
In classification, the model that considers only the highest number of voting from various decision trees is known as 'BOOTSTRAP'.

C) APPLYING MACHINE LEARNING MODELS ON COVID POSITIVE DATA

	models	score	MAE	MSE	RMSE
0	LinearRegression	100.000000	0.026849	0.001571	0.039641
1	DecisionTreeRegressor	100.000000	0.091963	0.011618	0.107786
2	RandomForestRegressor	79.837865	0.099220	0.012997	0.114002

Fig 14. Comparison of regression models in covid positive data.

D).APPLYING MACHINE LEARNING ALGORITHMS ON COVID NEGATIVE DATA

	models	score	MAE	MSE	RMSE
0	LinearRegression	91.820735	0.014117	0.000571	0.023898
1	DecisionTreeRegressor	100.000000	0.009915	0.000442	0.021022
2	RandomForestRegressor	99.436489	0.006301	0.000249	0.015787

Fig 15. Comparison of regression models in covid negative data.

	Predicted Sleep Quality	Actual Sleep Quality
1551	0.956356	0.962579
561	0.820866	0.814815
621	0.930718	0.931373

Fig 16. Comparison of actual and predicted values in covid negative data.

In order to evaluate the model accuracy, MSE, MAE and RMSE were implemented as our evaluation metrics to calculate the error between actual and predicted values [11].

MAE (Mean absolute error) calculates the difference between actual and predicted from the mean differences of the input data [12].MSE (Mean squared error) calculates the mean squares of error between actual and predicted values [13].RMSE (Root mean squared error) calculates the coefficients of input values to define quality of fit with actual values [14].

E) COMPARING QUALITY OF SLEEP EFFICIENCY IN BOTH COVID POSITIVE AND NEGATIVE DATA

IS Quality of Sleep is Better in people without COVID

```
print('Quality of sleep wihtout Covid')
pickled_model = pickle.load(open('rfr.pkl', 'rb'))
pickled_model.predict([[ 1.        , 15.        , 2.        , 7.        , 2.        ,
         0.        , 0.        , 0.        , 0.        , 0.        ,
         1.        , 1.        , 20.       , 0.        , 0.        ,
         0.        , 0.        , 0.        , 0.        , 5.        ,
         2.        , 6.08333333, 0.        , 5.5       , 0.        ,
         5.13333333, 1.        , 22.       , 50.       ,
        23.        , 0.        , 4.        , 30.       , 4.        ,
        35.        ]])

Quality of sleep wihtout Covid

array([0.81617644])
```

```
print('Quality of sleep with Covid')
ps_model = pickle.load(open('lr_pos.pkl', 'rb'))
ps_model.predict([[ 1.        , 15.        , 2.        , 7.        , 2.        ,
         0.        , 0.        , 0.        , 0.        , 0.        ,
         1.        , 1.        , 20.       , 0.        , 0.        ,
         0.        , 0.        , 0.        , 0.        , 5.        ,
         2.        , 6.08333333, 0.        , 5.5       , 0.        ,
         5.13333333, 1.        , 22.       , 50.       ,
        23.        , 0.        , 4.        , 30.       , 4.        ,
        35.        ]])

Quality of sleep with Covid

array([0.41470693])
```

Fig 17. Prediction of sleep quality in people with and without covid.

From the results presented in Figures 14, 15, 16 and 17, the models that had the best performance with high accuracy and low error from evaluation metrics are random forest regressor from people without covid data and linear regression from people with covid data.

Finally, predicting our model from random input variables to find quality of sleep it was clearly predicted that people with covid achieved low quality of sleep of 0.41 when compared with people without covid of 0.81.

F) APPLYING CLASSIFICATION ALGORITHMS ON COVID NEGATIVE SLEEEP DATA

BAGGING CLASSIFIER

A bagging classifier is a group of predictions that interpret base classifiers for every random subset of actual input values and predicting random subsets using aggregation or mean values to make the final prediction of a target variable. In this scenario, since we have multiple input variables used to predict the target variable implementing, the bagging classifier reduces the variance and minimizes the cost function of actual and predicted values by bagging random subsets of each input data.

```
BaggingClassifier()


accuracy score 0.97709049255441
Cross-val-score= 0.9667881529889824


roc_auc_score 0.974996735866301


              precision    recall  f1-score   support

           0       0.93      0.97      0.95       207
           1       0.99      0.98      0.98       666

    accuracy                           0.98       873
   macro avg       0.96      0.97      0.97       873
weighted avg       0.98      0.98      0.98       873
```

Fig 18. Evaluation metrics on covid negative data classification.

```
[[200   7]
 [ 15 651]]


AxesSubplot(0.125,0.808774;0.62x0.0712264)
```

Fig 19. Confusion matrix, and ROC-AUC curve.

Performing evaluation metrics like accuracy, precision, recall and f1-score with high score
ROC (Receiver Operating Characteristic Curve), mainly utilized to evaluate the prediction of true positives and false positive rate, achieved 0.97 accuracy.

	Model	cvs	score	rocscore
0	GradientBoostingClassifier	96.656089	97.021764	95.384515
1	RandomForestClassifier	89.756608	93.356243	88.154459
2	BaggingClassifier	96.678815	97.709049	97.499674
3	LogisticRegression	97.617716	97.250859	95.534665
4	DecisionTreeClassifier	94.088119	95.532646	94.242068

Fig 20. Comparison of classification model on covid negative dataset.

From Figure 20, Bagging classifier and logistic regression models perform with high accuracy.

	Predicted Sleep Quality	Actual Sleep Quality
1551	1	1
561	1	1
621	1	1

Fig 21. Comparison of actual and predicted sleep quality on covid negative data.

From Figure 21, actual and predicted values of target variable 'SE' people without covid achieves good quality of sleep.

```
print('Quality of sleep wihtout Covid')
pickled_model = pickle.load(open('bc.pkl', 'rb'))
pickled_model.predict([[ 0.        , 1.        , 30.        , 2.        , 7.        ,
        2.        , 0.        , 0.        , 8.        , 7.        ,
        0.        , 1.        , 1.        , 20.       , 0.        ,
        0.        , 0.        , 0.        , 0.        , 5.        ,
        2.        , 0.08333333, 0.        , 5.5       , 0.        ,
        5.13333333, 1.        , 22.       , 30.       , 23.       ,
        0.        , 4.        , 30.       , 9.        , 35.
        ]])

Quality of sleep wihtout Covid

array([1])
```

Fig 22. Prediction of quality of sleep in covid negative data.

By choosing bagging classifier to predict target variable using random input values achieved an array of '1' represents people without covid has good quality of sleep.

G) APPLYING MACHINE LEARNING ALGORITHMS ON COVID POSITIVE DATA
DECISION TREE

```
DecisionTreeClassifier()


accuracy score 1.0
Cross-val-score= 1.0


roc_auc_score 1.0


              precision    recall  f1-score   support

           0       1.00      1.00      1.00         2
           1       1.00      1.00      1.00         4

    accuracy                           1.00         6
   macro avg       1.00      1.00      1.00         6
weighted avg       1.00      1.00      1.00         6
```

Fig 23. Evaluation metrics on covid positive data classification.

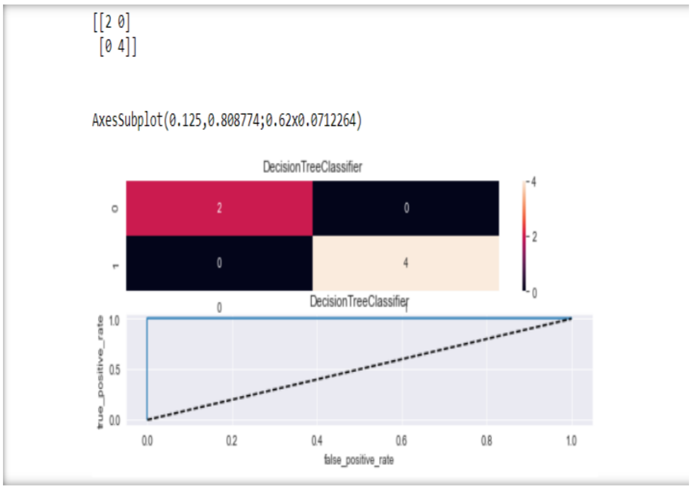

Fig 24. Confusion matrix, ROC-AUC curve.
Performing evaluation metrics like accuracy, precision, recall and f1-score with high score respectively.
ROC achieved 1.00 accuracy.

	Model	cvs	score	rocscore
0	RandomForestClassifier	92.5	66.666667	50.0
1	BaggingClassifier	100.0	100.000000	100.0
2	LogisticRegression	92.5	66.666667	50.0
3	DecisionTreeClassifier	100.0	100.000000	100.0

Fig 25. Comparison of classification model on covid positive dataset.

From Figure 25, the machine learning algorithms bagging classifier and decision algorithms performed well.

	Predicted Sleep Quality	Actual Sleep Quality
27	1	1
15	1	1
23	1	1
17	0	0

Fig 26. Comparison of actual and predicted sleep quality on covid positive data
From Figure 26, actual and predicted values prove that the people with actual sleep quality ‘0’ having predicted value ‘0’ which represents bad quality of sleep in people with covid.

H) PERFORMING OVER SAMPLING AND UNDER SAMPLING TECHNIQUES ON COVID NEGATIVE DATA

As far as over sampling and under sampling on covid positive data concerned, since the data set covid positive data has very less number of samples that is only 30 values, which is not either suitable for over sampling and under sampling. In order to avoid biasing as well as to reduce loss of important data,. it is better not to perform sampling techniques on covid positive data but covid negative has considerable amount of samples. in order to prove even the model performance is more accurate by implementing over sampling and under sampling techniques using SMOTE (Synthetic Minority Over-Sampling Technique) which performs synthetic samples by arbitrarily sampling the features from events in the minority class known as over sampling.

Unlikely, under sampling is performed when the data has more sufficient class needs to be balanced with the minority class.

I) UNDER SAMPLING

Decision Tree Classifier

```
dc.fit(X_train_ures,y_train_ures)              # fitting data to train the model
y_pred3 = dc.predict(x_test)                 # making prediction on test data
print(confusion_matrix(label_test,y_pred3))    # printing confusion matrix
print(accuracy_score(label_test,y_pred3))      # printing accuracy score
print(classification_report(label_test,y_pred3)) # printing classification report
```

```
[[198  14]
 [ 24 637]]
0.9564719358533792
              precision    recall  f1-score   support

           0       0.89      0.93      0.91       212
           1       0.98      0.96      0.97       661

    accuracy                           0.96       873
   macro avg       0.94      0.95      0.94       873
weighted avg       0.96      0.96      0.96       873
```

Fig 27. Evaluation metrics on under sampling data classification.

Performing evaluation metrics like accuracy, precision, recall and f1-score with high scores respectively.
ROC achieved 95 percent accuracy.

	Predicted Sleep Quality	Actual Sleep Quality
3452	1	1
224	0	1
3551	1	1

Fig 28. Comparison of actual and predicted sleep quality on covid positive data.
From Figure 28, actual and predicted values of the people without covid achieves good quality of sleep.

J) OVER SAMPLING

Random Forest Classifier

```
rfc.fit(X_train_res,y_train_res)         # fitting data to train the model

y_pred3 = rfc.predict(x_test)              #predicting test data
print(confusion_matrix(label_test,y_pred3))    # printing confusion matrix
print(accuracy_score(label_test,y_pred3))          # printing accuracy score
print(classification_report(label_test,y_pred3))     # printing classification report
```

```
[[183  29]
 [ 24 637]]
0.9392898052691867
              precision    recall  f1-score   support

           0       0.88      0.86      0.87       212
           1       0.96      0.96      0.96       661

    accuracy                           0.94       873
   macro avg       0.92      0.91      0.92       873
weighted avg       0.94      0.94      0.94       873
```

Fig 29. Evaluation metrics on over sampling data.

Performing evaluation metrics like accuracy, precision, recall and f1-score with high scores respectively.
ROC achieved 98 percent accuracy.

:

	Predicted Sleep Quality	Actual Sleep Quality
3452	1	1
224	1	1
3551	1	1
2854	1	1
1952	1	1

Fig 30. Comparison of actual and predicted sleep quality on covid positive data.

From the Figure 30, actual and predicted values of the people without covid achieves good quality of sleep.

K) FEATURE IMPORTANT SCORE

Feature important score using random forest classifier to identify the important input features impacts on the target variable 'sleep efficiency of people without covid and people with covid.

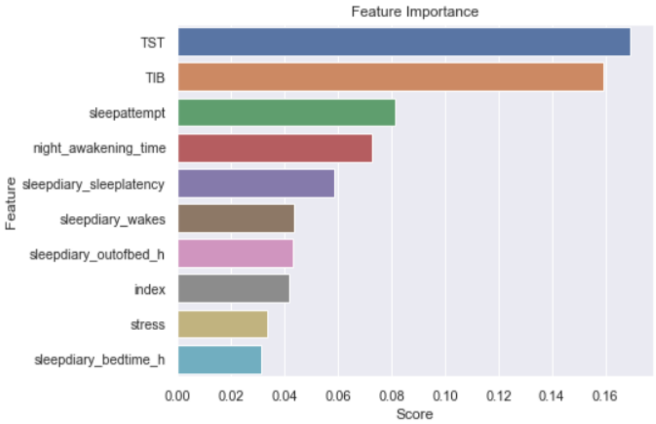

Fig 31. Feature important score and its impact on quality of sleep.

From Figure 31, it is clearly shown that the top two features that is 'Time in bed' and 'Total sleep time' shows impact on people with covid and people without covid.

IX OBSERVATIONS AND CONCLUSIONS

After reviewing all regression and classification models clearly shows that people with covid effected their quality of sleep and people without covid has good quality of even after performing oversampling and under sampling.decision tree and bagging classifier achieved high accuracy and low error.

In feature with more features and good quality of data helps us to generate morefactors effecting quality of sleep using feature important score technique

X. References:

[1] Pilcher, J., Dorsey, L., Galloway, S. and Erikson, D., 2022. *Social Isolation and Sleep: Manifestation During COVID-19 Quarantines*.

[2]Anbarasi, L. & Jawahar, Malathy & Ravi, Vinayakumar & Cherian, Sherin & Shreenidhi, S. & Sharen, H.. (2022). Machine learning approach for anxiety and sleep disorders analysis during COVID-19 lockdown. Health and Technology. 12. 10.1007/s12553-022-00674-7.

[3]Anbarasi, L.J., Jawahar, M., Ravi, V. *et al.* Machine learning approach for anxiety and sleep disorders analysis during COVID-19 lockdown. *Health Technol.* **12**, 825–838 (2022). https://doi.org/10.1007/s12553-022-00674-7

[4] Choudhry, A., Shahzeen, F., Choudhry, S., Batool, N., Murtaza, F., Dilip, A., Rani, M. and Chandnani, A., 2022. *Impact of COVID-19 Infection on Quality of Sleep*.

[5] World Health Organization (2020). Mental health and psychosocial considerationsduring the COVID-19 outbreak. (No. WHO/2019-nCoV/MentalHealth/2020.1). Geneva: World Health Organization

[6] Brooks, S. K., Webster, R. K., Smith, L. E., Woodland, L., Wessely, S., Greenberg, N., et al. (2020). The psychological impact of quarantine and how to reduce it: rapid review of the evidence. Lancet 395, 912–920. doi: 10.1016/S0140-6736(20) 30460-8

[7] Altena, E., Baglioni, C., Espie, C. A., Ellis, J., Gavriloff, D., Holzinger, B., et al. (2020). Dealing with sleep problems during home confinement due to the COVID-19 outbreak: Practical recommendations from a task force of the European CBT-I Academy. J. Sleep Res. 4:e13052. doi: 10.1111/jsr.13052

[8] Morin, C. M., Stone, J., Trinkle, D., Mercer, J., and Remsberg, S. (1993). Dysfunctionalbeliefs and attitudes about sleep among older adults with and without insomnia complaints. Psychol. Aging 8, 463–467. doi: 10.1037//0882- 7974.8.3.463

[9]] Jahrami H, BaHammam AS, Bragazzi NL, Saif Z, Faris M, Vitiello MV. Sleep problems during the COVID-19 pandemic by population: a systematic review and meta-analysis. Journal of Clinical Sleep Medicine 2021;17:299–313.

[10] Huang C, Huang L, Wang Y, et al. 6-month consequences of COVID-19 in patients discharged from hospital: a cohort study. The Lancet 2021;397(10270):220–32. doi: 10.1016/S0140-6736(20)32656-8.

[11] Raghuvanshi, M., 2016. Knowledge and Awareness: Linear Regression. *Educational Process: International Journal*, 5(4), pp.279-292.

[12] G, M., 2021. Accuracy Analysis for Logistic Regression Algorithm and Random Forest Algorithm to Detect Frauds in Mobile Money Transaction. *Revista Gestão Inovação e Tecnologias*, 11(4), pp.1228-1240.

[13] Han, X. and Clemmensen, L., 2014. On Weighted Support Vector Regression. *Quality and Reliability Engineering International*, 30(6), pp.891-903.

[14] Hernández-Orallo, J., Ferri, C., Lachiche, N., Martínez-Usó, A. and Ramírez-Quintana, M., 2015. Binarised regression tasks: methods and evaluation metrics. *Data Mining and Knowledge Discovery*, 30(4), pp.848-890.

[15] Cunningham TJ, Fields EC, Kensinger EA. Boston College daily sleep and well-being survey data during early phase of the COVID-19 pandemic. Sci Data. 2021 Apr 16;8(1):110. doi: 10.1038/s41597-021-00886-y. PMID: 33863920; PMCID: PMC8052376.

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