Project Report

1. **Project Title: Sleep Efficiency**
2. **Data Set Name: Sleep Efficiency**
3. **Data Set Source: Kaggle**
4. **Data set Link: https: Sleep Efficiency Dataset**
5. **Data Set Description:** The dataset contains information about a group of test subjects and their sleep patterns. *The dataset consists of 15 columns and 618 rows.*

   Variable description along with data type:

   - *Independent Variables:*
     i. Subject ID: Unique identifier for each test subject (categorical)
     ii. Age: Age of each subject (numeric)
     iii. Gender: Gender of each subject (categorical)
     iv. Bedtime: Time when the subject goes to bed each day (datetime)
     v. Wakeup time: Time when the subject wakes up each day (datetime)
     vi. Sleep duration: Total amount of time each subject slept in hours (numeric)
     vii. REM sleep percentage: Percentage of time spent in REM sleep (numeric)
     viii. Deep sleep percentage: Percentage of time spent in deep sleep (numeric)
     ix. Light sleep percentage: Percentage of time spent in light sleep (numeric)
     x. Awakenings: Number of times each subject wakes up during the night (numeric)
     xi. Caffeine Consumption: Information about each subject's caffeine consumption in the 24 hours prior to bedtime (categorical)
     xii. Alcohol Consumption: Information about each subject's alcohol consumption in the 24 hours prior to bedtime (categorical)
     xiii. Smoking Status: Information about each subject's smoking status (categorical)
     xiv. Exercise Frequency: Information about each subject's exercise frequency (categorical)

   - *Dependent Variable:*
     i. Sleep efficiency: Proportion of time spent in bed that is actually spent asleep (numeric)

   Missing Values:
   1. Total missing values: 91
   2. Missing values in Caffeine Consumption: 36
   3. Missing values in Alcohol Consumption: 21
   4. Missing values in Awakenings: 27

5. Missing values in Exercise: 7

6. **Description of Work Done:**
The project involves predicting sleep efficiency based on various factors using different feature selection techniques and regression algorithms. Initially, the dataset is preprocessed by removing unnecessary columns and imputing missing values. Categorical variables are converted to factors, and the data is split into training and testing sets.

   i. *Feature Selection Techniques:*
   The project explores multiple feature selection methods, including Lasso Regression, ANOVA, Recursive Feature Elimination (RFE), and Forward Feature Selection. These techniques help identify the most relevant predictors for the sleep efficiency prediction model.

   ii. *Regression Algorithms: Several regression algorithms are employed to build predictive models:*
      - *Random Forest: A robust ensemble learning method capable of capturing complex interactions and nonlinear relationships in the data.*
      - *Gradient Boosting: Another ensemble method that builds multiple weak learners sequentially, focusing on the errors of the previous models.*
      - *SVR (Support Vector Regression): A regression model that uses support vector machines to map input data to high-dimensional feature spaces.*
      - *Decision Trees: A simple yet powerful non-parametric model that partitions the feature space into segments to make predictions.*

   iii. *Model Training and Evaluation:*
   Each regression model is trained on the selected features and evaluated using performance metrics such as R-squared, RMSE (Root Mean Squared Error), and MAE (Mean Absolute Error). These metrics provide insights into how well the models are capturing the variance in sleep efficiency and making accurate predictions.

7. **Literature Survey:**

Project Report

					Data Preprocessing						
Sr. No.	Title	Author	Year of Journal	Dataset used	Outlier	NA	Class Balance	Feature selection	Algorithm	Evaluation parameters	Findings
1	A Survey of Sleep Methods	Vanessa Ibáñez, Josep Silva, and Omar Cauli	2018	The dataset used in the document is a survey on sleep questionnaires and diaries, and it did not use raw data. The authors conducted a comprehensive review and analysis of existing literature, studies, and tools related to sleep assessment methods						he document discusses various evaluation parameters for sleep assessment methods, including sensitivity, specificity, and accuracy. It provides a critical discussion about	The document presents a comprehensive literature review on sleep assessment methods, focusing on questionnaires, diaries, hardware devices, and contactless methods. It discusses the inclusion and exclusion criteria for selecting relevant studies, the process of study selection, and data extraction. The authors emphasize the need for validation studies to support
2	A Study Based on ML-Based Sleep model using lifelog data	Jiyong Kim and Minseo Park	2023	Samsung Galaxy Watch	Logistic regression Stacking models	NA	Good sleep,Bad Sleep, Intemediate Sleep	LASSO ,Two step categiroziation	Linear model, Logistic Model	Sleep duration, Sleep timing, Sleep efficiency	The study develops a sleep habit scoring model using wearable device data to objectively evaluate sleep habits' impact on health, finances, and insurance. Employing machine learning, the model categorizes sleep states into good, intermediate, and bad, with the study detailing methodology, results, and potential applications.
3	Representation of temporal sleep dynamics: Review and synthesis of the literature	LWA Harmans,IAN Huijben	2022	PSG recordings,fMRI data,Slee measurements collected from wearables	NA	NA	Wakefulness, Rapid eye movements Sleep, various stages of non-rapid eye movements	EEG Signal, spectral power of EEG Signal	Long short term memory cell (LSTM),	Clinical relevance in distinguishing healthy sleepers from individuals with sleep disorders.	This document reviews different methods for representing temporal sleep dynamics, highlighting strengths, limitations, validation needs, clinical relevance, and interpretability. It emphasizes
4	Global Research Output on Sleep Research in	M.L., A.R.M., and G.E. V.	2020	The dataset used for the bibliometric analysis of sleep research in athletes was retrieved from the Scopus database and analyzed using Microsoft Excel 2013, SPSS v20, and VOSViewer program.	NA		NA	The feature selection process involves using regularization models such as LASSO to identify important features and discard irrelevant	The algorithm used in the study is a stacking ensemble model, incorporating machine learning and deep learning algorithms, to predict sleep	The evaluation parameters for the sleep habit score model include AUROC, K-S statistic, and Gini Coefficient, which are used to assess the	The findings of the study include the proposal of an objective daily sleep habit score calculation method, the use of a logistic regression model to generate sleep habit scores for good and bad sleep, and the application of ensemble machine learning to generate sleep habit scores for
5	Athletes from 1966 to 2019: A Bibliometric Analysis	Tarek Lajnef a , Sahbi Chaibi a , Perrine Ruby b , Pierre-Emmanuel Aguera b , Jean-Baptiste Eichenlaub c , Mounir Samet a , Abdennaceur Kachouri a,d , Karim Jerbi b,e,	2015	polysomnographic (PSG) records in 15 healthy subjects aged 29.2 ± 8 years, which were collected at the DyCog Lab of the Lyon Neuroscience Research Center (Lyon, France) as part of a larger study exploring cognition during sleep (Eichenlaub et al., 2012, 2014; Ruby et al., 2013a,b).				Forward sequencial selection, t test	Hierarchical Clustering, Multi-class Support vector Machine, k-fold Cross validation	Specificity, sensitivity, and overall accuracy assess classification performance.	Accuracy, with a mean specificity, sensitivity, and overall accuracy of approximately 92%, 74%, and 88%, respectively.
6	A review of automated sleep disorder detection	Shuting Xua , Oliver Faust, Seoni Silvia , Subrata Chakraborty, Prabal Datta Barua, Hui Wen Loh, Heather Elphick, Filippo Molinari, U. Rajendra Acharya	12 June 2023	Some other public datasets are involved in those papers, such as the Shiga University of Medical Science hospital (SUMS), the Rio Hortega University Hospital dataset (RHUH), from universities or hospitals.					ML methods like decision trees, SVM, k-NN, random forests, and DL techniques such as CNNs, RNNs, LSTMs		
7	Sleep–wake stages classification and sleep efficiency estimation using single-lead electrocardiogram	Mourad Adnane, ZHongwei Jiang, ZHonghong Yan	January 2012,	MIT/BIH Polysomnographic Database (MITBPD); (Ichimaru & Moody, 1999).				SVM recursive features elimination (SVM-RFE) method is applied to the initially extracted 12 features.	SVM and SVM-RFE algorithms used for sleep-wake stage classification.	Evaluation parameters include accuracy, classification error, and sleep efficiency estimation.	Mean classification accuracy: 79.31% (12 features), 79.99% (10 features); Cohen's kappa: κ = 0.41 (12 features), κ = 0.43 (10 features); average sleep efficiency error: 4.52% (12 features), 4.64% (10 features).
8	An Investigation of Data Mining Based Automatic Sleep Stage Classification Techniques	Thakerng Wongsirichot, Nittida Elz, Supasit Kajkamhaeng, Wanchai Nupinit, and Narongrit Sridonthong	International Journal of Machine Learning and Computing, Vol. 9, No. 4, August 2019	Sleep Heart Health Study (SHHS) Dataset			Low accuracy of the S1 sleep stage classification, indicating potential class imbalance issues	Maximum, minimum, average, kurtosis, and standard deviation.	Decision Trees, Random Forests, Neural Network, and k-Nearest Neighbors	Accuracy, precision, recall, specificity, and F-measure.	k-Nearest Neighbors achieved the highest accuracy at 83.76%
9	A Study on ML-Based Sleep Score Model Using Lifelog Data	Jiyong Kim 1 and Minseo Park	12 January 2023	Samsung Galaxy Devices		KNN			1.XGBoost 2. LightGBM 3. CatBoost 4. TabNet neural network model for prediction.		Suggest correlations between sleep characteristics, sleep states, and lifestyle factors, with recommendations for future research to enhance sleep scores and contribute to overall lifestyle evaluation.

Project Report

11	Modified Bald Eagle Search Algorithm With Deep Learning-Driven Sleep Quality Prediction for Healthcare Monitoring Systems	RANA ALABDAN 1, HANAN ABDULLAH MENGASH 2, MOHAMMED MARAY 3, FAIZ ALOTAIBI4, SITELBANAT ABDELBAGI 5, AND AHMED MAHMUD6	28 November 2023,	sleep dataset from the Kaggle repository					Modified Bald Eagle Search Algorithm with Deep Learning-Driven Sleep Quality Prediction (MBES-DLSQP)	The sleep quality detection outcomes of the MBES-DLSQP method on 80% of TRP and 20% of TSP. The experimental outcome denotes that the MBES-DLSQP system effectually recognizes the sleep classes. On 80% of TRP, the MBES-DLSQP system	The experimental outcomes, with a high accuracy of 98.33%, highlight the potential and promising performance of the MBES-DLSQP method. 8.33% whereas the MWHMSQP-ODL, MLP, CNN, LR, RNN, and LSTM models obtain decreased accuy of 97.50%, 92.46%, 92.01%, 92.21%, 93.08%, and 91.67%, respectively.
12	Sleep Efficiency May Predict Depression in a Large Population-Based Study	Bin Yan1,2 *, Binbin Zhao2 , Xiaoying Jin2 , Wenyu Xi 2 , Jian Yang1,2, Lihong Yang1 and Xiancang Ma2 *	13 April 2022	Sleep Heart Health Study (SHHS) datasets				Sleep efficiency (SE) Wake after sleep onset (WASO) Sleep fragmentation index (SFI) Arousal index (ArI)		Sleep efficiency (SE) Wake after sleep onset (WASO)	Sleep efficiency (SE) and wake after sleep onset (WASO) are associated with the incidence of depression. The relationship between SE and depression is more pronounced in men. Improving sleep may help reduce the risk of depression.
13	Measuring Sleep Efficiency: What Should the Denominator Be?	David L. Reed, PhD1 ; William P. Sacco, PhD	2016					Inconsistency in defining sleep efficiency (SE) causes confusion. SE refers to total sleep time (TST) compared to time spent attempting to sleep. Non-sleep related activities in bed should not be included in SE.		Sleep efficiency, duration of sleep episode, sleep onset episode, Total sleep Time, Time attempting to sleep after final awakening (TASAFA).	Using DSE as the SE denominator yields higher SE levels than using TIB. Distinguishing between sleep and non-sleep related activities in bed is important for conditioning models of insomnia.
14	Sleep Regularity and Predictors of Sleep Efficiency and Sleep Duration in Elite Team Sport Athletes	Shona L. Halson1,2* , Rich D. Johnston1,2,3, Laura Piromalli4 , Benita J. Lalor5 , Stuart Cormack2,5, Gregory D. Roach6 and Charli Sargent	2022					The study examined sleep regularity in a large cohort of elite athletes. Sleep regularity was measured using the sleep regularity index (SRI). Regular sleepers had greater sleep efficiency and less variability in sleep time.	The study used the Actiwatch algorithm to score sleep and wake times. The sensitivity of the algorithm was set at medium, with a threshold activity count of 40.	Sleep regularity index (SRI), Sleep efficiency and total sleep time were important contributors to sleep quality. Bedtime, sleep onset time, and sleep offset time	Athletes in the study had an average sleep duration of more than 8 hours. The median sleep regularity index was 85.1. Regular sleepers had significantly better sleep efficiency.

Project Report

15	Factors involved in sleep efficiency: a population-based study of community-dwelling elderly persons	Sophie Desjardins1, *, , Sylvie Lapierre1 , Carol Hudon2 and Alain Desgagné3	15 Feb 2019					Factors associated with poor sleep efficiency in elderly persons Sex differences in factors affecting sleep efficiency Certain factors have no significant		Sleep efficiency is defined as the ratio of total sleep time to time in bed.	Factors associated with poor sleep efficiency in elderly persons were identified. Pain, nocturia, sleep medication use, and awakening from bad dreams were strongly associated with sleep efficiency below 80%.
16	Modified Bald Eagle Search Algorithm With Deep Learning-Driven Sleep Quality Prediction for Healthcare Monitoring Systems	RANA ALABDAN 1, HANAN ABDULLAH MENGASH 2, MOHAMMED MARAY 3, FAIZ ALOTAIBI4, SITELBANAT ABDELBAGI 5, AND AHMED MAHMUD6	28 November 2023,	sleep dataset from the Kaggle repository					Decision Trees, Random Forests, Neural Network, and k-Nearest Neighbors		The experimental outcomes, with a high accuracy of 98.33%, highlight the potential and promising performance of the MBES-DLSQP method.
17	INTEGRATION OF FEATURE SELECTION TECHNIQUES USING A SLEEP QUALITY DATASET FOR COMPARING REGRESSION ALGORITHMS			Kaggle				SelectKBest, Principal Component Analysis (PCA), Recursive Feature Elimination (RFE), Chi-squared test, Mutual Information	Linear regression, Ridge regression, Lasso Regression and Random Forest Regressor.	Linear Regression, Lasso Regression,Ridge RegressionRandom Forest Regressor,Mean Squared Error (MSE),R Squared Error (RSE)	

`Literature Review

8. **Data Preprocessing:** *Four major preprocessing steps are being followed in the project which include the following:*

   1. *Loading dataset:*

      Loading dataset into a file/variable 'f' using ***'read.csv ()'*** *command.*

   2. *Removing unnecessary columns:*

      Removing unnecessary columns includes "Bedtime", "Wakeup time", "ID" as they are date-time type of variable and don't affect the Sleep Efficiency factor.

   3. *Missing Values:*

      Columns which include missing values are initially found and consists of "Awakenings", "Caffeine Consumption", "Alcohol Consumption", and "Exercise Frequency".

      The next step involves imputing the missing values with mean of the entire column respectively

   4. *Conversion of categorical variables:*

      Categorical variables are converted into factors as 1 and 2 which include "Gender" and "Smoking Status

9. Feature Selection: *Feature selection techniques are applied to select the most relevant features for predicting Sleep Efficiency. Feature selection methods comprises of Recursive Feature Selection (RFE), Lasso Regression, Analysis of Variance (ANOVA) and Forward Feature Selection.*

i. Recursive Feature Elimination (RFE):

- *Recursive Feature Elimination is a wrapper method that recursively selects subsets of features and evaluates their performance using a machine learning model.*
- *The algorithm starts with all features and evaluates their importance based on some criterion (e.g., coefficients in linear models, feature importance in tree-based models).*
- *It then removes the least important feature(s) and repeats the process until the desired number of features is reached.*
- *RFE provides a ranking of features based on their importance and can be used to identify the optimal subset of features for a given machine learning task.*

Feature	Coefficient
Light.sleep.percentage	2.475934
Deep.sleep.percentage	2.450623
Awakenings	1.289569
Alcohol.consumption	0.4742709
Age	0.3545051
Smoking.status	0.2636254
Exercise.frequency	0.1638683
REM.sleep.percentage	0.133295
Sleep.duration	0.1226135
Caffeine.consumption	0.06987856

ii. *Lasso Regression:*

- *Lasso (Least Absolute Shrinkage and Selection Operator) is a regularization technique that penalizes the absolute size of feature coefficients. As a result, it pushes less influential features' coefficients towards zero, effectively eliminating them from the model.*
- *Lasso feature selection is particularly useful when dealing with high-dimensional datasets with many potentially irrelevant features.*
- *It automatically selects the most relevant features by shrinking the coefficients of less important features towards zero.*

Feature	Coefficient
Age	0.911025544
Smoking Status	-0.043096079
Awakenings	-0.034987054
Caffeine Sleep Percentage	-0.006090499
Light Sleep Percentage	-0.005803604
Sleep duration	0.004398362
Exercise frequency	0.002966852
REM Sleep Percentage	0.001597183
Gender	0.000974335
Caffeine Consumption	0.000103843
Deep Sleep Percentage	0

iii. *Analysis of Variance (ANOVA):*

- *ANOVA (Analysis of Variance) is a statistical technique used to determine whether there are statistically significant differences between the means of two or more groups.*
- *In the context of feature selection, ANOVA is applied to each feature individually to assess whether it contributes significantly to the target variable's variability.*
- *Features with high F-statistics and low p-values are considered significant and retained, while those with low F-statistics and high p-values are discarded.*

Feature	Coefficient
Deep.sleep.percentage	9.79E-139
Awakenings	1.40E-38
Smoking.status	2.78E-11
Age	8.11E-08
Alcohol.consumption	0.006516754
REM.sleep.percentage	0.02809321
Sleep.duration	0.1476042
Exercise.frequency	0.171884
Gender	0.2355469
Caffeine.consumption	0.2546618

iv. *Forward Feature Selection:*

- *Forward Feature Selection is a greedy search algorithm that iteratively builds a model by adding one feature at a time based on some criterion, such as the improvement in model performance.*
- *The algorithm starts with an empty set of features and iteratively adds the feature that provides the greatest improvement in model performance until no further improvement is observed.*
- *Forward FS is computationally efficient and easy to implement, making it suitable for datasets with a relatively small number of features.*

Features	Coefficient
Age	1
Sleep.duration	-0.103164293
REM.sleep.percentage	0.0694031
Light.sleep.percentage	-0.030106567
Awakenings	-0.0250294
Caffeine.consumption	-0.182968785
Alcohol.consumption	0.04040126
Exercise.frequency	0.06991375
Gender Male	0.22667581
Gender Female	-0.23159756
Smoking.status Yes	0.04587878
Smoking_status No	-0.04587878

10. **Algorithms Implemented:**

i.*Decision Tree:*

- A decision tree is a flowchart-like tree structure where an internal node represents a feature, the branch represents a decision rule, and each leaf node represents the outcome.
- Decision trees are straightforward to understand and interpret, making them suitable for visualization
- In this project, the rpart package is used to build a Decision Tree model with the specified features.

ii.*Random Forest:*

- *Random Forest is an ensemble learning method that constructs a multitude of decision trees at training time and outputs the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees.*
- *Random Forest improves the accuracy and reduces overfitting compared to a single decision tree by averaging multiple decision trees.*
- *In this project, the randomForest package is used to build a Random Forest model with the specified features.*

iii.*Support Vector Regression (SVR):*

- *Support Vector Regression is a regression algorithm that uses the same principles as Support Vector Machines (SVM) for classification but applies them to regression problems.*
- *SVR identifies the hyperplane that best fits the data such that the margin between the hyperplane and the data points is maximized.*
- *In this project, the e1071 package is used to build an SVR model with the specified features.*

iv.*Gradient Boosting:*

- *Gradient Boosting is an ensemble learning technique where multiple weak learners (typically decision trees) are sequentially trained, with each subsequent model correcting the errors of its predecessor.*
- *Gradient Boosting iteratively minimizes a loss function by adding weak learners, which makes it less prone to overfitting.*
- *In this project, the gbm package is used to build a Gradient Boosting model with the specified features.*

Code*:*

```
# Load required libraries
library(caret)
library(rpart)
library(randomForest)
library(e1071)
library(gbm)
library(Metrics)
# Read the dataset
f <- read.csv("Sleep_Efficiency_Updated.csv")
# Remove unnecessary columns
f <- f[, -which(names(f) %in% c("Bedtime", "Wakeup.time", "ID"))]
# Check for missing values and impute missing values with mean
f$Awakenings[is.na(f$Awakenings)] <- mean(f$Awakenings, na.rm = TRUE)
f$Caffeine.consumption[is.na(f$Caffeine.consumption)] <- mean(f$Caffeine.consumption, na.rm = TRUE)
f$Alcohol.consumption[is.na(f$Alcohol.consumption)] <- mean(f$Alcohol.consumption, na.rm = TRUE)
f$Exercise.frequency[is.na(f$Exercise.frequency)] <- mean(f$Exercise.frequency, na.rm = TRUE)
# Convert categorical variables to factors
f$Gender <- as.factor(f$Gender)  # Male: 1, Female: 0
f$Smoking.status <- as.factor(f$Smoking.status)  # Yes: 1, No: 0
```

Project Report

```
# Train/test split
set.seed(123)
train_index <- sample(1:nrow(f), 0.7 * nrow(f))
train_data <- f[train_index, ]
test_data <- f[-train_index, ]
#----
ctrl <- rfeControl(functions = rfFuncs, method = "cv", number = 5)
rfe_profile <- rfe(x = train_data[, -which(names(train_data) == "Sleep.efficiency")],
          y = train_data$Sleep.efficiency,
          sizes = c(1:ncol(train_data) - 1),
          rfeControl = ctrl)
# Get the selected features
selected_features <- predictors(rfe_profile)
# Train a Random Forest model on the selected features
rf_model <- randomForest(Sleep.efficiency ~ ., data = train_data[, c(selected_features,
"Sleep.efficiency")])
# Extract variable importance scores
importance_scores <- importance(rf_model)
# Sort importance scores in descending order
sorted_importance <- importance_scores[order(importance_scores, decreasing = TRUE), ]
# Print importance scores
# print(as.list(sorted_importance))
selected_col<- names(sorted_importance)[1:8]
#-------
# Random Forest Model
rf_model <- randomForest(Sleep.efficiency ~ ., data = train_data[, c(selected_col, "Sleep.efficiency")])
# Evaluate model
rf_predictions <- predict(rf_model, newdata = test_data[, selected_col])
```

```
# Calculate Residual Sum of Squares (RSS) for each model
rf_rss <- sum((rf_predictions - test_data$Sleep.efficiency)^2)

# Calculate Total Sum of Squares (TSS)
mean_y <- mean(test_data$Sleep.efficiency)
tss <- sum((test_data$Sleep.efficiency - mean_y)^2)
# Calculate R-squared for each model
rf_r_squared <- 1 - (rf_rss / tss)
# Print R-squared for each model
cat("Random Forest R-squared:", rf_r_squared, "\n")
```

11. Shiny app:

```
library(shiny)
library(randomForest)
f <- read.csv("Sleep_Efficiency_Updated.csv")
# Load the random forest model from the .rds file
rf_model <- readRDS("rf_model.rds")
f$Smoking.status <- as.factor(f$Smoking.status)
# Define UI
ui <- fluidPage(
  titlePanel("Sleep Efficiency Calculator"),
  sidebarLayout(
    sidebarPanel(
      numericInput("light_sleep", "Light Sleep Percentage:", value = 20, min = 0, max = 100),
      numericInput("deep_sleep", "Deep Sleep Percentage:", value = 30, min = 0, max = 100),
      numericInput("awakenings", "Number of Awakenings:", value = 2, min = 0),
      numericInput("alcohol_consumption", "Alcohol Consumption:", value = 2, min = 0),
      numericInput("age", "Age:", value = 30, min = 0),
      selectInput("smoking_status", "Smoking Status:", choices = c("Yes", "No")),
      numericInput("exercise_frequency", "Exercise Frequency:", value = 3, min = 0),
      numericInput("rem_sleep", "REM Sleep Percentage:", value = 20, min = 0, max = 100),
      actionButton("calculate_button", "Calculate Sleep Efficiency")
    ),
```

```
  mainPanel(
    h3("Results"),
    verbatimTextOutput("sleep_efficiency_result")
   )
  )
)

server <- function(input, output) {
  observeEvent(input$calculate_button, {
   # Convert selectInput choice to 1 or 0

   # Prepare input data
   input_data <- data.frame(
     Light.sleep.percentage = input$light_sleep,
     Deep.sleep.percentage = input$deep_sleep,
     Awakenings = input$awakenings,
     Alcohol.consumption = input$alcohol_consumption,
     Age = input$age,
     Smoking.status = factor(input$smoking_status, levels = c("Yes", "No")),
     Exercise.frequency = input$exercise_frequency,
     REM.sleep.percentage = input$rem_sleep
   )

   # Print input data for debugging
   print(input_data)

   # Predict sleep efficiency using the random forest model
   sleep_efficiency <- predict(rf_model, newdata = input_data)

   # Output sleep efficiency result
   output$sleep_efficiency_result <- renderText({
     paste("Predicted Sleep Efficiency:", sleep_efficiency)
   })
  })
}


# Run the application
shinyApp(ui = ui, server = server)
```

Project Report

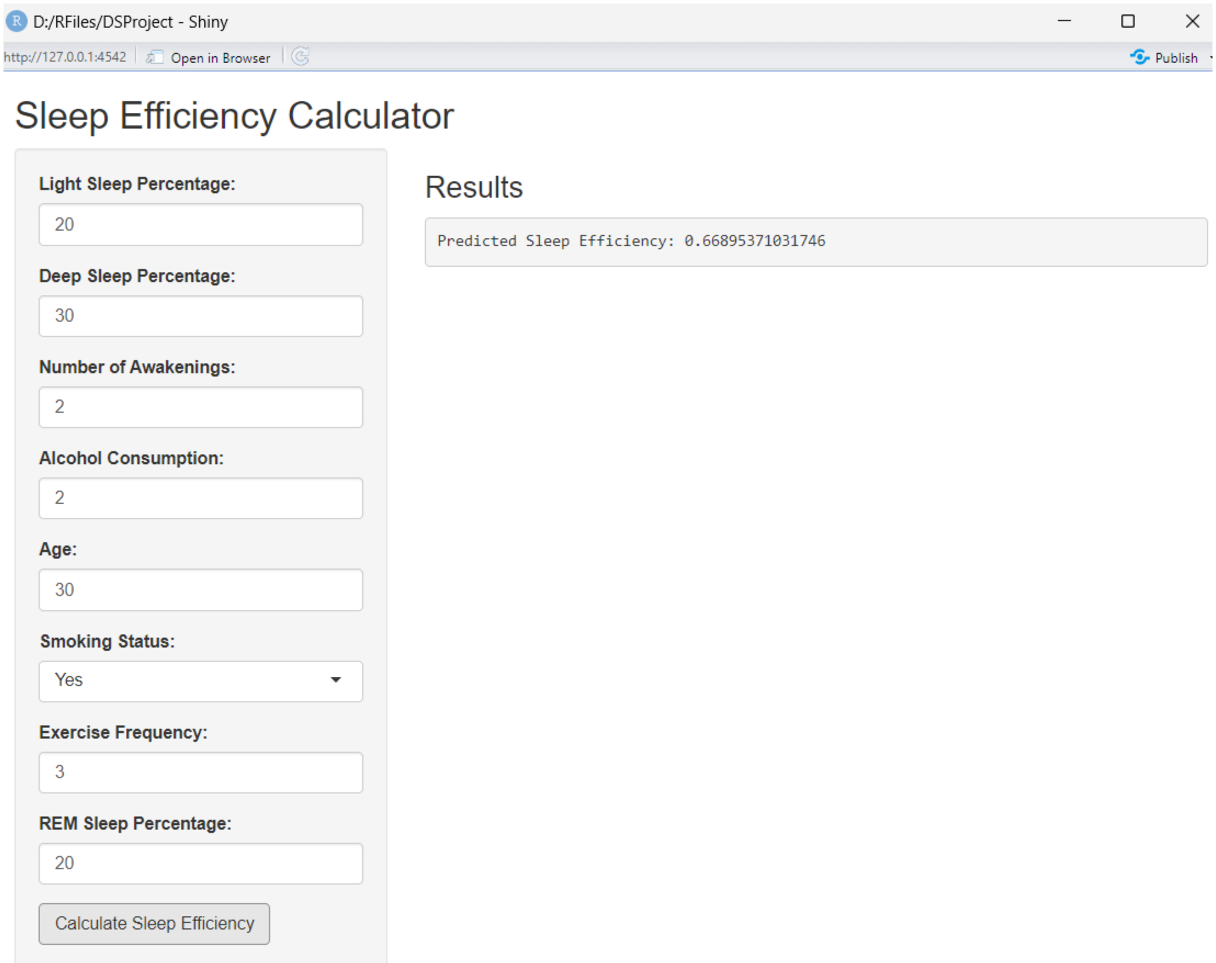


Image: Shiny App UI (along with some calculated values and its output)

12. Evaluation Parameters:

Evaluation parameters provide different perspectives on model performance. It calculated for each of the machine learning models (Decision Tree, Random Forest, SVR, Gradient Boosting) to compare their performance in predicting sleep efficiency based on the selected features.

i.RMSE:

- *RMSE is a commonly used metric to evaluate the accuracy of regression models.*
- *It measures the average magnitude of the errors between predicted values and actual values.*
- *RMSE is calculated by taking the square root of the mean of the squared differences between predicted and actual values.*
- *Lower RMSE values indicate better model performance, with a value of 0 representing perfect predictions.*

ii.MAE:

- *MAE is another metric for evaluating the accuracy of regression models.*
- *It measures the average absolute difference between predicted values and actual values.*
- *MAE is calculated by taking the mean of the absolute differences between predicted and actual values.*
- *Lower MAE values indicate better model performance.*

iii.R-Squared:

- *R-squared is a statistical measure that represents the proportion of variance in the dependent variable (target) that is explained by the independent variables (features) in the model.*
- *It ranges from 0 to 1, where 0 indicates that the model does not explain any variability in the target variable, and indicates that the model perfectly explains the variability.*
- *R-squared values closer to 1 indicate better model fit, while values closer to 0 indicate poor model fit.*
- *R-squared can be interpreted as the percentage of the variance in the target variable that is accounted for by the independent variables.*

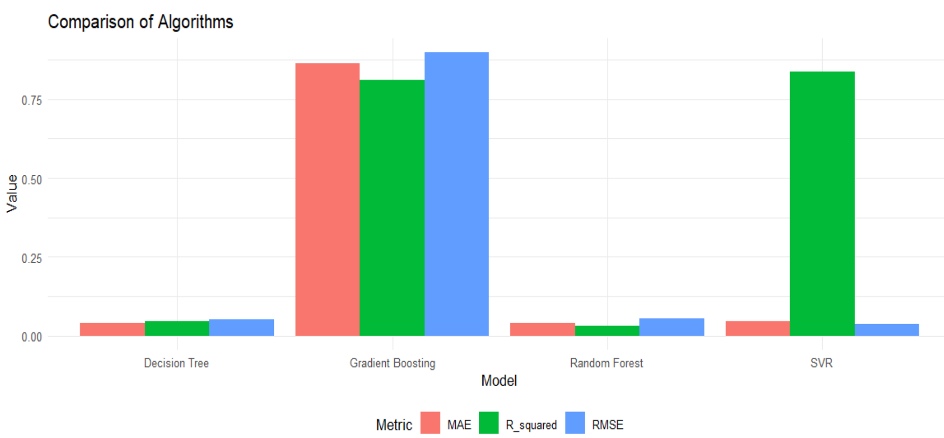
Lower RMSE and MAE values and higher R-squared values indicate better predictive performance of the models.

Project Report

_13._ Results and Discussions:

i. *Experiment: Algorithms without any feature selection methods.*

Algorithms \Evaluation Parameters	R-Squared	RMSE	MAE
DT	0.8386299	0.0510072	0.0395892
RF	0.8980748	0.0405378	0.0315786
SVR	0.8644608	0.0467468	0.0360256
GB	0.8108494	0.0552235	0.0448295

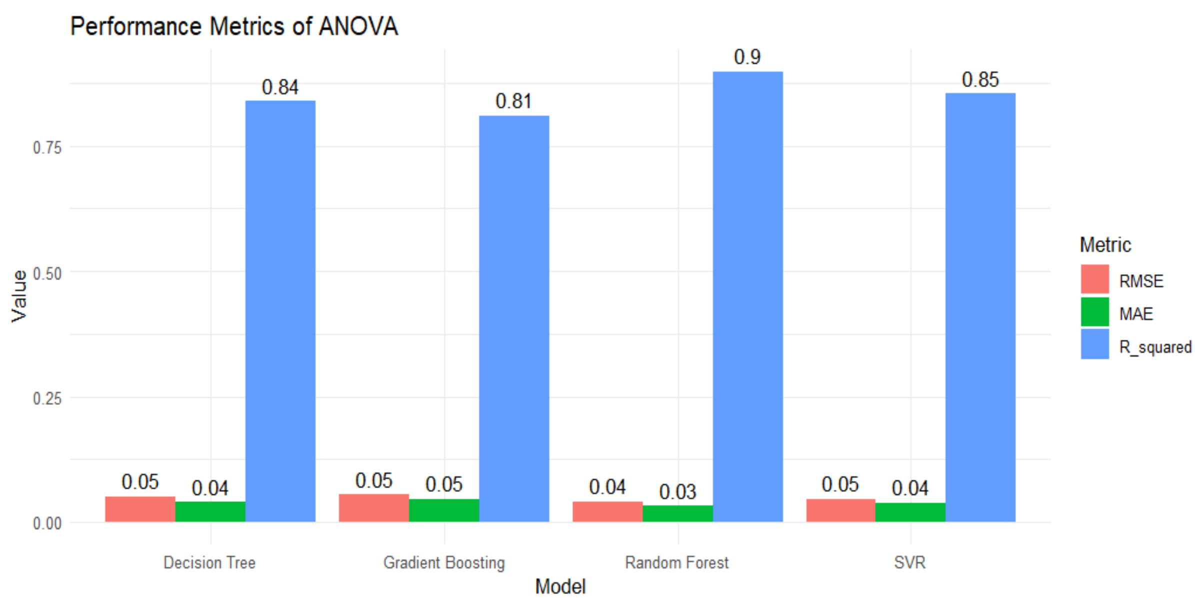


Algorithms are evaluated without any feature selection methods *ii. Experiment: Algorithms with Lasso Regression feature selection method using all the variables.*

Algorithms \Evaluation Parameters	R-Squared	RMSE	MAE
DT	0.8386299	0.03958917	0.05100718
RF	0.8897944	0.03252333	0.04215234
SVR	0.8402972	0.03870235	0.050743
GB	0.8077984	0.04534769	0.05566706

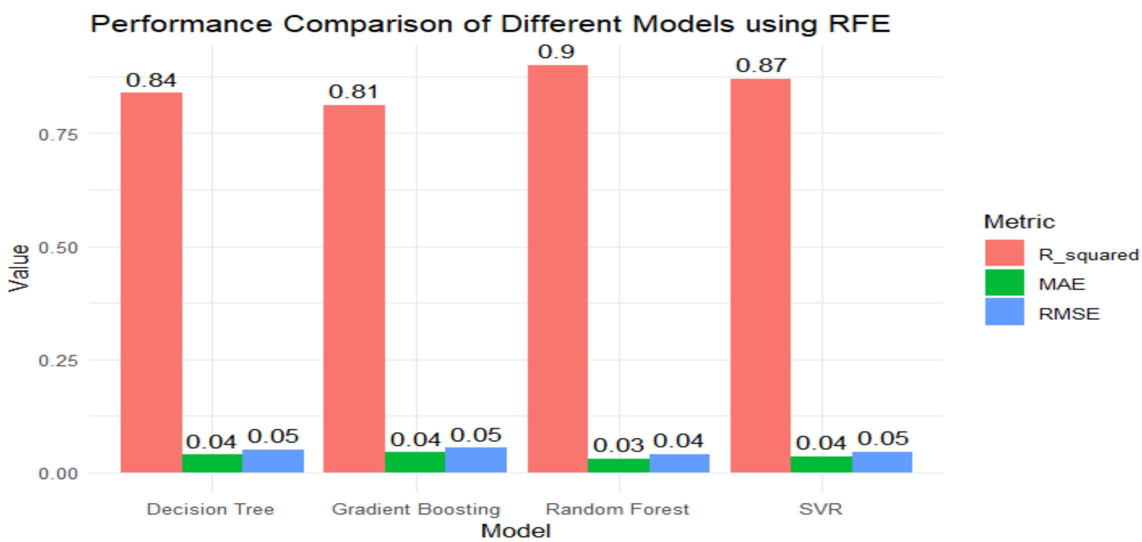
iii. Experiment: Algorithms with ANOVA feature selection method using all the variables.

Algorithms \Evaluation Parameters	R-Squared	RMSE	MAE
DT	0.8386299	0.03958917	0.05100718
RF	0.8982078	0.03145493	0.04345587
SVR	0.8546201	0.03804044	0.05224341
GB	0.8098832	0.04536163	0.05580576



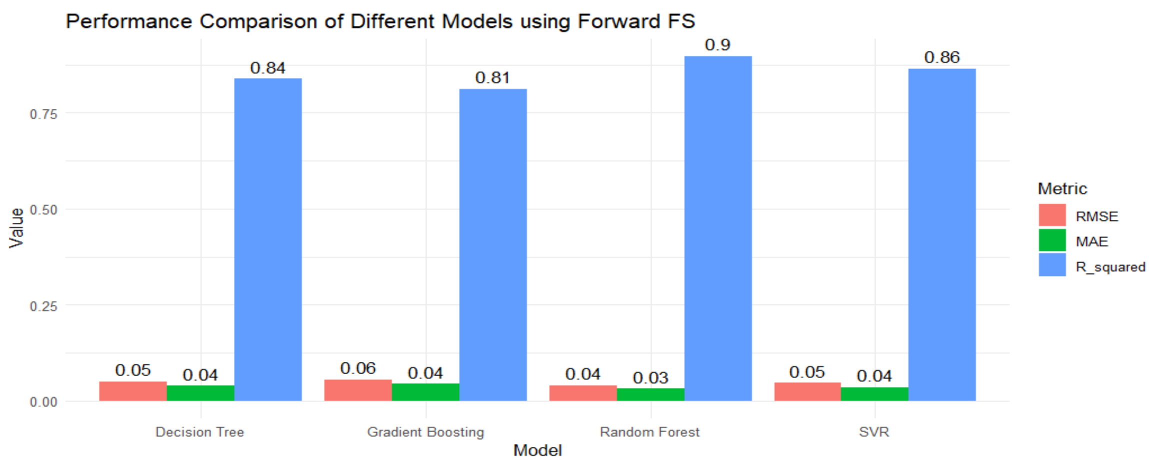
iv. *Experiment: Algorithms with RFE feature selection method using all the variables.*

Algorithms \Evaluation Parameters	R-Squared	RMSE	MAE
DT	0.8386299	0.03958917	0.05100718
RF	0.9001484	0.03097975	0.04012337
SVR	0.8705219	0.0355086	0.04568967
GB	0.8126672	0.0448281	0.05495747



v. *Experiment: Algorithms with Forward feature selection method using all the variables.*

Algorithms \Evaluation Parameters	R-Squared	RMSE	MAE
DT	0.8386299	0.03958917	0.05100718
RF	0.8971596	0.03179588	0.04071943
SVR	0.8644608	0.03602563	0.04674684
GB	0.8115416	0.04484214	0.05512233



vi. Experiment: Algorithms with Lasso feature selection method using different number of the variables.

	Algorithms	R-Squared	MAE	RMSE
5	Decision Tree	0.8386299	0.03958917	0.05100718
	Random Forest	0.8206704	0.04404145	0.05377072
	SVR	0.8341263	0.0398274	0.05171405
	Gradient Boosting	0.8043706	0.04592306	0.05616126
6	Decision Tree	0.8386299	0.03958917	0.05100718
	Random Forest	0.8818027	0.03391238	0.04365395
	SVR	0.8448462	0.03788762	0.05001509
	Gradient Boosting	0.8058991	0.04540295	0.05594143
7	Decision Tree	0.8386299	0.03958917	0.05100718
	Random Forest	0.899596	0.03172168	0.0402342
	SVR	0.8602179	0.03619004	0.04747288
	Gradient Boosting	0.8099104	0.04499346	0.05536037
8	Decision Tree	0.8386299	0.03958917	0.05100718
	Random Forest	0.8913242	0.03194344	0.04185875
	SVR	0.8363151	0.03933639	0.05137172
	Gradient Boosting	0.8059412	0.04524087	0.05593536
9	Decision Tree	0.8386299	0.03958917	0.05100718
	Random Forest	0.8878153	0.03273276	0.04252915
	SVR	0.8287564	0.03992389	0.05254446
	Gradient Boosting	0.8055061	0.04547221	0.05599804

vii. *Experiment: Algorithms with ANOVA feature selection method using different number of the variables.*

	Algorithms	R-Squared	MAE	RMSE
5	Decision Tree	0.8386299	0.03958917	0.05100718
	Random Forest	0.8222243	0.04339198	0.05353724
	SVR	0.05463274	0.04148923	0.05463274
	Gradient Boosting	0.05660358	0.04608853	0.05660358
6	Decision Tree	0.8386299	0.03958917	0.05100718
	Random Forest	0.8826169	0.03322187	0.04033001
	SVR	0.8307131	0.03945961	0.04598407
	Gradient Boosting	0.8057428	0.04520479	0.0547953
7	Decision Tree	0.8386299	0.03958917	0.05100718
	Random Forest	0.879896	0.03350434	0.04115451
	SVR	0.8368838	0.03874966	0.04530165
	Gradient Boosting	0.7991878	0.04599598	0.05471283
8	Decision Tree	0.8386299	0.03958917	0.05100718
	Random Forest	0.894505	0.03185454	0.04033001
	SVR	0.855286	0.03770485	0.04598407
	Gradient Boosting	0.808464	0.04489698	0.0547953
9	Decision Tree	0.8386299	0.03958917	0.05100718
	Random Forest	0.8983192	0.03102132	0.05377072
	SVR	0.8521046	0.03816008	0.05171405
	Gradient Boosting	0.8128277	0.04458619	0.05616126

viii. *Experiment: Algorithms with RFE feature selection method using different number of the variables.*

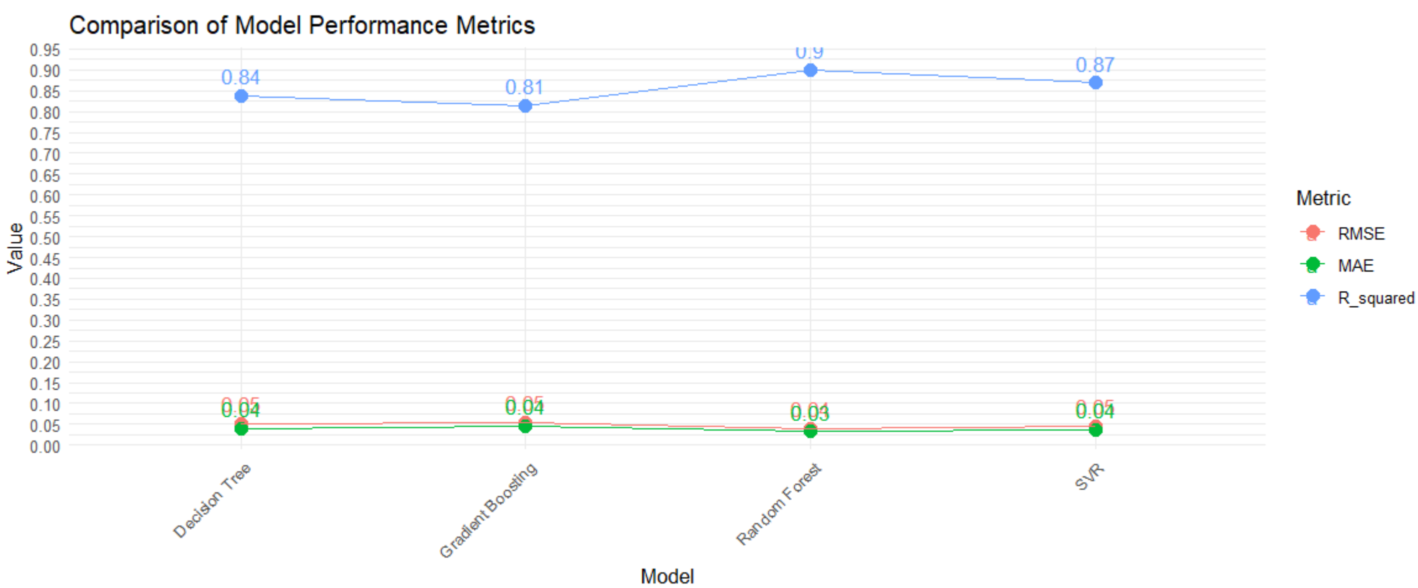
	Algorithms	R-Squared	MAE	RMSE
5 Variables	Decision Tree	0.8157928	0.04448673	0.05449706
	Random Forest	0.846305	0.04054931	0.04977941
	SVR	0.8013448	0.04331001	0.05659392
	Gradient Boosting	0.8002754	0.04629332	0.05674604
6 Variables	Decision Tree	0.8386299	0.03958917	0.05100718
	Random Forest	0.880324	0.03377912	0.04392618
	SVR	0.8448462	0.03788762	0.05001509
	Gradient Boosting	0.8048293	0.04525645	0.05609538
7 Variables	Decision Tree	0.8386299	0.03958917	0.05100718
	Random Forest	0.8949502	0.03223263	0.04115451
	SVR	0.8727117	0.03558851	0.04530165
	Gradient Boosting	0.8143313	0.04439003	0.05471283
8 Variables	Decision Tree	0.8386299	0.03958917	0.05100718
	Random Forest	0.8991172	0.03176168	0.04033001
	SVR	0.8688479	0.03530871	0.04598407
	Gradient Boosting	0.8137712	0.0441578	0.0547953
9 Variables	Decision Tree	0.8386299	0.03958917	0.05100718
	Random Forest	0.8996232	0.03101658	0.04022874
	SVR	0.8704227	0.03521038	0.04570717
	Gradient Boosting	0.8144273	0.0443134	0.05469868

ix. *Experiment: Algorithms with Forward feature selection method using different number of the variables.*

	Algorithms	R-Squared	MAE	RMSE
5	Decision Tree	0.6450164	0.06516263	0.07565262
	Random Forest	0.6980616	0.05772118	0.06977165
	SVR	0.6584758	0.05888257	0.07420456
	Gradient Boosting	0.6606533	0.06300075	0.07396762
6	Decision Tree	0.6450164	0.06516263	0.07565262
	Random Forest	0.748825	0.0514089	0.06363675
	SVR	0.6624466	0.05857591	0.07377191
	Gradient Boosting	0.6824886	0.06135903	0.07154832
7	Decision Tree	0.6450164	0.06516263	0.07565262
	Random Forest	0.7474923	0.05135135	0.06380536
	SVR	0.6721603	0.05828064	0.07270271
	Gradient Boosting	0.6727316	0.06187535	0.07263934
8	Decision Tree	0.8157928	0.04448673	0.05449706
	Random Forest	0.8607046	0.03657309	0.04739016
	SVR	0.7948335	0.04414834	0.05751393
	Gradient Boosting	0.7971472	0.0461	0.05718871
9	Decision Tree	0.8157928	0.04448673	0.05449706
	Random Forest	0.8675632	0.03542589	0.04620875
	SVR	0.8008699	0.0435612	0.05666153
	Gradient Boosting	0.7999108	0.04557091	0.05679782

x. *Experiment: Decision Tree and Random Forest Algorithms with RFE and ANOVA feature selection method using all the variables.*

		ANOVA			RFE		
	Algorithms	**R-Squared**	**MAE**	**RMSE**	**R-Squared**	**MAE**	**RMSE**
5	Decision Tree	0.8386299	0.03958917	0.05100718	0.8157928	0.04448673	0.05449706
	Random Forest	0.8222243	0.04339198	0.05353724	0.846305	0.04054931	0.04977941
6	Decision Tree	0.8386299	0.03958917	0.05100718	0.8386299	0.03958917	0.05100718
	Random Forest	0.8826169	0.03322187	0.04033001	0.880324	0.03377912	0.04392618
7	Decision Tree	0.8386299	0.03958917	0.05100718	0.8386299	0.03958917	0.05100718
	Random Forest	0.879896	0.03350434	0.04115451	0.8949502	0.03223263	0.04115451
8	Decision Tree	0.8386299	0.03958917	0.05100718	0.8386299	0.03958917	0.05100718
	Random Forest	0.894505	0.03185454	0.04033001	0.8991172	0.03176168	0.04033001
9	Decision Tree	0.8386299	0.03958917	0.05100718	0.8386299	0.03958917	0.05100718
	Random Forest	0.8983192	0.03102132	0.05377072	0.8996232	0.03101658	0.04022874
All	Decision Tree	0.8386299	0.03958917	0.05100718	0.8386299	0.03958917	0.05100718
	Random Forest	0.8982078	0.03145493	0.04345587	0.9001484	0.03097975	0.04012337



14. Conclusions:

- *In the final model of Sleep Efficiency prediction, we have Random Forest regression model trained on a dataset containing sleep efficiency data after feature selection using Recursive Feature Elimination (RFE) with a Random Forest algorithm. The model aims to predict sleep efficiency based on various predictors such as age, sleep duration, awakenings, caffeine consumption, smoking status, gender, and other factors which affect sleep patterns.*
- *The choice of Random Forest as the algorithm is chosen due to its ability to handle non-linear relationships and interactions between features effectively, making it suitable for capturing complex patterns in the data. R-squared is chosen as the evaluation metric because it provides an indication of the proportion of variance in the dependent variable (sleep efficiency) explained by the independent variables (predictors) and provides near 0.9 values whereas MAE and RMSE need near 0 value and here they fail to do so.*
- *Selecting eight variables through RFE allows for a balance between model complexity and performance, aiming to capture the most relevant predictors as we aim to keep minimum columns and highest prediction accuracy. Additionally, RFE helps in identifying the subset of features that contribute the most to the model's predictive accuracy, leading to improved interpretability and potentially better generalization to unseen data.*
- *Overall, the Random Forest model with RFE-selected features achieves a satisfactory level of performance, as indicated by the obtained R-squared value, providing valuable insights into factors influencing sleep efficiency.*

References:

[1] Ibáñez, Vanessa, Josep Silva, and Omar Cauli. "A survey on sleep assessment methods." *PeerJ* 6 (2018): e4849.

[2] Kim, Jiyong, and Minseo Park. "A Study on ML-Based Sleep Score Model Using Lifelog Data." *Applied Sciences* 13, no. 2 (2023): 1043.

[3] Hermans, Lieke WA, Iris AM Huijben, Hans van Gorp, Tim RM Leufkens, Pedro Fonseca, Sebastiaan Overeem, and Merel M. van Gilst. "Representations of temporal sleep dynamics: Review and synthesis of the literature." *Sleep Medicine Reviews* 63 (2022): 101611.

[4] Lastella, Michele, Aamir Raoof Memon, and Grace E. Vincent. "Global research output on sleep research in athletes from 1966 to 2019: a bibliometric analysis." *Clocks & sleep* 2, no. 2 (2020): 99-119.

[5] Lastella, Michele, Aamir Raoof Memon, and Grace E. Vincent. "Global research output on sleep research in athletes from 1966 to 2019: a bibliometric analysis." *Clocks & sleep* 2, no. 2 (2020): 99-119.

[6] Xu, Shuting, Oliver Faust, Silvia Seoni, Subrata Chakraborty, Prabal Datta Barua, Hui Wen Loh, Heather Elphick, Filippo Molinari, and U. Rajendra Acharya. "A review of automated sleep disorder detection." *Computers in Biology and Medicine* 150 (2022): 106100.

[7] Adnane, Mourad, Zhongwei Jiang, and Zhonghong Yan. "Sleep–wake stages classification and sleep efficiency estimation using single-lead electrocardiogram." *Expert Systems with Applications* 39, no. 1 (2012): 1401-1413.

[8] Wongsirichot, Thakerng, Nittida Elz, Supasit Kajkamhaeng, Wanchai Nupinit, and Narongrit Sridonthong. "An investigation of data mining based Automatic Sleep Stage Classification techniques." *International Journal of Machine Learning and Computing* 9, no. 4 (2019): 520-526.

[9] Kim, Jiyong, and Minseo Park. "A Study on ML-Based Sleep Score Model Using Lifelog Data." *Applied Sciences* 13, no. 2 (2023): 1043.

[10] Kalintha, Wasin, Takafumi Kato, and Ken–ichi Fukui. "SleepAge: sleep quality assessment from nocturnal sounds in home environment." *Procedia Computer Science* 176 (2020): 898-907.

[11] Alabdan, Rana, Hanan Abdullah Mengash, Mohammed Maray, Faiz Alotaibi, Sitelbanat Abdelbagi, and Ahmed Mahmud. "Modified Bald Eagle Search Algorithm With Deep Learning-Driven Sleep Quality Prediction for Healthcare Monitoring Systems." *IEEE Access* 11 (2023): 135385-135393.

[12] Yan, Bin, Binbin Zhao, Xiaoying Jin, Wenyu Xi, Jian Yang, Lihong Yang, and Xiancang Ma. "Sleep efficiency may predict depression in a large population-based study." *Frontiers in Psychiatry* 13 (2022): 838907.

[13] Reed, David L., and William P. Sacco. "Measuring sleep efficiency: what should the denominator be?." *Journal of clinical sleep medicine* 12, no. 2 (2016): 263-266.

[14] Halson, Shona L., Rich D. Johnston, Laura Piromalli, Benita J. Lalor, Stuart Cormack, Gregory D. Roach, and Charli Sargent. "Sleep regularity and predictors of sleep efficiency and sleep duration in elite team sport athletes." *Sports Medicine-Open* 8, no. 1 (2022): 79.

[15] Desjardins, Sophie, Sylvie Lapierre, Carol Hudon, and Alain Desgagné. "Factors involved in sleep efficiency: a population-based study of community-dwelling elderly persons." *Sleep* 42, no. 5 (2019): zsz038.

[16] Alabdan, Rana, Hanan Abdullah Mengash, Mohammed Maray, Faiz Alotaibi, Sitelbanat Abdelbagi, and Ahmed Mahmud. "Modified Bald Eagle Search Algorithm With Deep Learning-Driven Sleep Quality Prediction for Healthcare Monitoring Systems." *IEEE Access* 11 (2023): 135385-135393.

[17] Tanuku, Sai Rohith, and Venkat Tummala. "Integration of Feature Selection Techniques using a Sleep Quality Dataset for Comparing Regression Algorithms." *arXiv preprint arXiv:2303.02467* (2023).