Research Article

Feature Selection Intent Machine Learning based Conjecturing Workout Burnt Calories

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Abstract: As we know that running is the victor for most calories burned per hour. Stationary bicycling, running, and swimming are fabulous choices as well. HIIT works out are too incredible for burning calories. After a HIIT workout, your body will proceed to burn calories for up to 24 hours. Forecasting the workout burnt calories still remains an open challenge as the changes in the environmental calamity and body health. The machine learning strategies can predict the burnt out calories for the course of exercise done by a body. With this background, we have utilized Exercise dataset extracted from UCI Machine Learning repository for predicting the workout burnt calories. The forecasting of burnt calories rate are achieved in four ways. Firstly, the data set is preprocessed with Feature Scaling and missing values. Secondly, exploratory feature examination is done and the scattering of target highlight is visualized. Thirdly, the raw data set is fitted to all the regressors and the execution is dissected before and after scaling. Fourth, the raw data set is subjected to feature selection axioms like Anova test, Correlated Feature, Variance Based and KBest Feature based methods and are fitted to all the regressors and the performance is analyzed before and after feature scaling. The execution is done using python language under Spyder platform with Anaconda Navigator. Experimental results shows that the Decision Tree and Gradient Boosting regressor tends to retain 99% before and after feature scaling for the Anova test, Correlated Feature, Variance Based and KBest Feature based methods.

Keywords: Machine learning, feature scaling, undersampling, precision, accuracy, classification

1. Introduction

Since most individuals will not go to such lengths, utilize your gauge of calories burned as a base point to track your workouts. In case you ordinarily burn a certain number of calories during a certain sort of workout, you will increment that number to burn more calories or diminish it on the off chance that you are feeling burned out or overtrained. Rather like counting calories in your nourishment can assist you reach your weight misfortune objectives, so can knowing how numerous calories you're burning during work out. An experienced exerciser will burn less calories since his or her body has gotten to be more proficient at work out. Not getting a satisfactory sum of rest can cause you to burn less calories. Not as it were will you are feeling more exhausted and conceivably work out less, but a need of rest can too diminish your digestion system as well.

2. Background

This book say that each person burn 2,000 calories a day. And in case we work out and cut carbs, we'll lose more weight. In this paradigm-shifting book, Herman Pontzer uncovers for the primary time how human digestion system really works so that ready to at last oversee our weight and progress our wellbeing [1]. Agreeing to customary wage measures, nineteenth century American and British mechanical laborers were two to four times as affluent as destitute individuals in creating nations nowadays. Shockingly, in any case, todays destitute are less hungry than yesterday's well off mechanical specialists. I gauge the request for calories of American and British mechanical specialists utilizing the 1888 taken a toll of Living Study and discover that the assessed calorie versatilities for both American and British families are more prominent than calorie versatility gauges for families in show day creating nations. The outcomes are vigorous to estimation mistake, unreported nourishment utilization, and circuitous estimation inclination. This finding suggests considerable dietary advancements among the destitute within the twentieth century [2]. To bolster the individuals wellbeing condition from their calories lopsidedness conditions and slim down conditions and after that turn our information wellness into a enormous wellbeing applications .Based on the chart which shows the nourishment expended by the individual. The sensors makes a difference to calculate the calories admissions and burnt amid the workout .The individual will too be an everyday Calories Objectives which keeps track of the people admissions .Besides specialists cannot degree the genuine movement we utilize data such as expends more and less calories behind. It requires more classification of the information [3].

The expanded utilization of innovations like Machine Learning , Information Mining has made the man sluggish , which expanded the wellbeing issues within the modern world .The realization features a stage is best SST approach to utilized and wear preparing , sst which is Keen Don Preparing. Since the SST has experienced a burst development towards this SST preparing [4]. Weight compounds the metabolic reaction to basic ailment and increments the chance for overloading complications due to its comorbidities. Hypocaloric, high-protein sustenance treatment manages the hospitalized quiet with weight the opportunity to attain net protein anabolism with a decreased hazard of overloading complications. The intent of this audit is to supply the hypothetical system for advancement of a hypocaloric high-protein regimen, logical prove to back this mode of treatment, and interesting contemplations for its utilize in specialized subpopulations [5].

This paper gives an efficient writing survey of shrewd wear preparing, displaying 109 recognized thinks about. Shrewdly information investigation strategies are displayed, which are right now utilized within the field of Shrewd Wear Preparing (SST). Wear spaces in which SST is as of now utilized are displayed, and stages of training are distinguished, beside the development of SST strategies [6]. This paper proposes a nourishment calorie and nutrition estimation framework that can offer assistance patients and dietitians to degree and oversee day by day nourishment intake. Our framework is built on food picture handling and employments dietary reality tables. The sum of calories from a food’s picture by measuring the volume of the nourishment parcels from the picture and using dietary truths tables to degree the sum of calorie and nutrition within the food [7].

This paper proposes a machine-learning-based approach to foresee the sum of calories from nourishment pictures. To begin with, we distinguish the sort of the nourishment thing within the picture. Moment, we gauge the measure of the nourishment thing in grams. It foresee the amount of calories within the shot nourishment thing. All these three stages are based simply on directed machine learning. We appear that this pipelined approach is exceptionally successful in foreseeing the sum of calories in a nourishment thing as compared to pattern approaches which straightforwardly predicts the sum of calories from the image [8]. This paper construct a rainstorm predictor using ANN and construct electrical storm predictor. The created ANN demonstrate is based on one of the neural organize design called multilayer perceptron organize (MLPN) model. The change in forecast of these imperative climate marvels is exceedingly incapacitated due to need of mesoscale observations [9]. It construct a precipitation predictor by using neural systems and construct a precipitation predictor. This paper proposed nearby precipitation expectation based on NNs utilizing meteorological information gotten from the site of the JMA [10].

3. Proposed Work

The Exercise dataset with 8 independent variables and 1 dependent variable has been used for implementation. The prediction of burnt out calories is done with the following contributions.

(i) Firstly, the data set is preprocessed with Feature Scaling and missing values.
(ii) Secondly, exploratory feature examination is done and the scattering of target highlight is visualized.
(iii) Thirdly, the raw data set is fitted to all the regressors and the execution is dissected before and after scaling.
(iv) Fourth, the raw data set is subjected to feature selection axioms like Anova test, Correlated Feature, Variance Based and KBest Feature based methods and are fitted to all the regressors and the performance is analyzed before and after feature scaling.
(v) Fifth, performance analysis is done using metrics like MAE, MSE, EVS, RScore and running time. Fig. 1 shows the overall workflow of this work

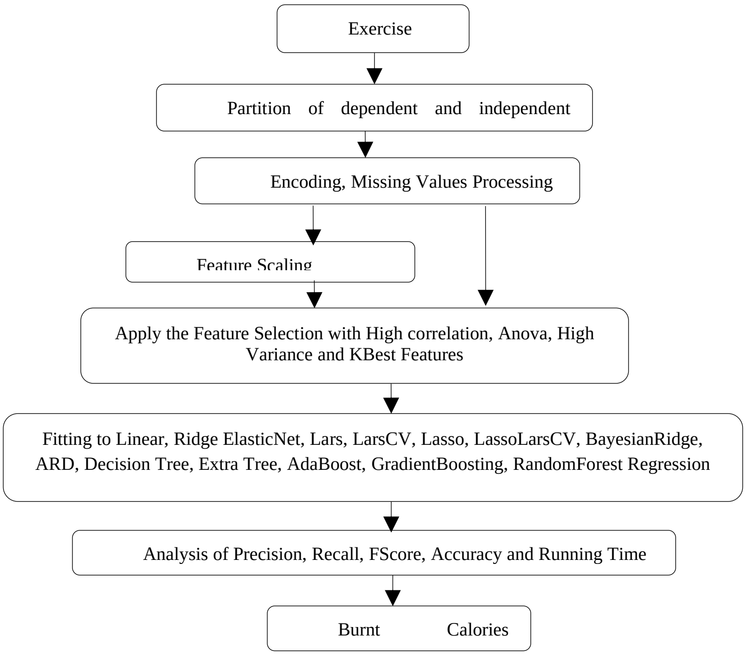
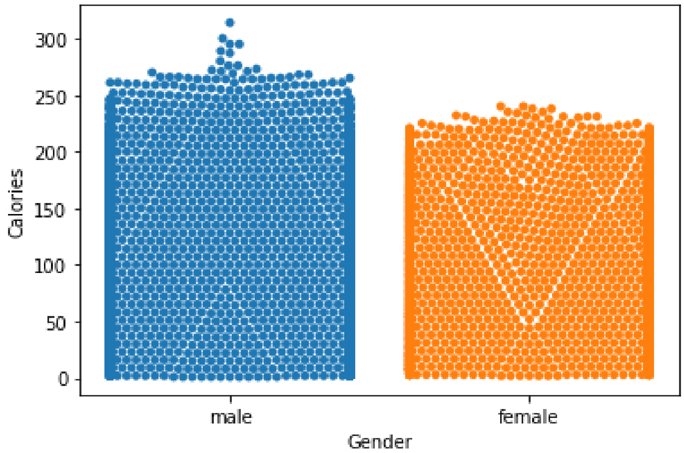


Fig.1. Overall workflow of the system.

4. Exploratory Data Analysis

The Exercise dataset extricated from the UCI machine learning store is utilized for usage. The dataset comprises of 15,000 person information with 8 autonomous highlights (User_ID, Gender, Age, Height, Weight, Duration, Heart Rate, Body Temperature) and 1 Target "Calories". The code is implemented with python under Anaconda Navigator with Spyder IDE. The data set is splitted with 80:20 for training and testing dataset. Fig.2. shows the target feature analysis. The correlation of the features is shown in Fig. 3.



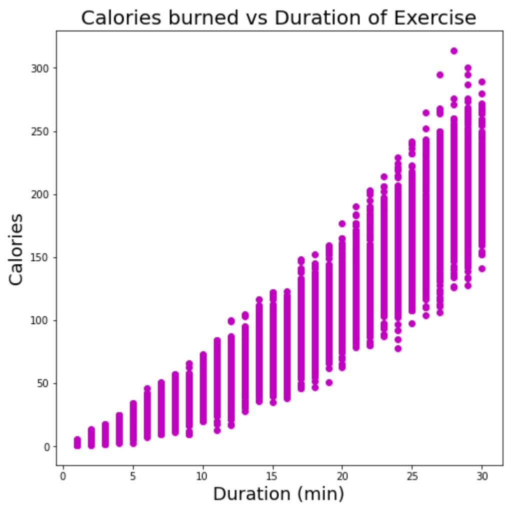


Fig.2. Target feature analysis with respect to Gender and Duration of the Exercise dataset

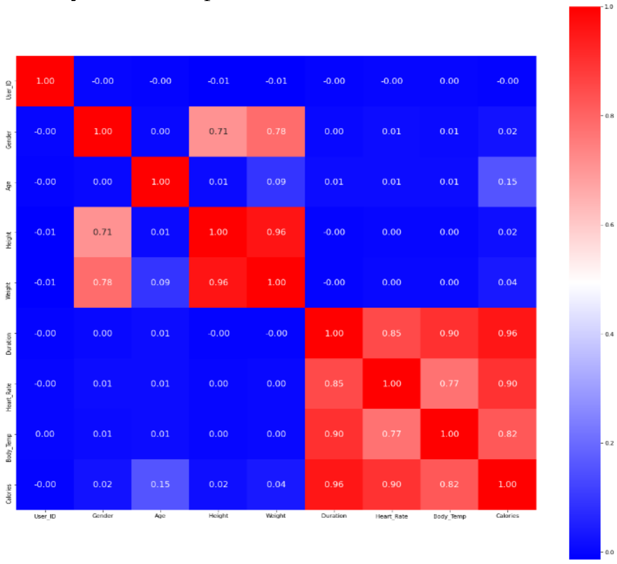


Fig.3. Feature Correlation of the Exercise dataset

5. Implementation and Discussion

The raw data set is fitted to all the regressors like Linear Regression, Ridge Regression, ElasticNet Regression, Lars Regression, LarsCV Regression, Lasso Regression, LassoLarsCV Regression, BayesianRidge, ARDRegression, Decision Tree Regression, Extra Tree Regression, AdaBoost Regression, GradientBoosting Regression and RandomForest Regression with and without the presence of feature scaling and performance is shown in Table 1 and Table 2, the RScore and the running time comparison is shown in Figure. 4 - 5.

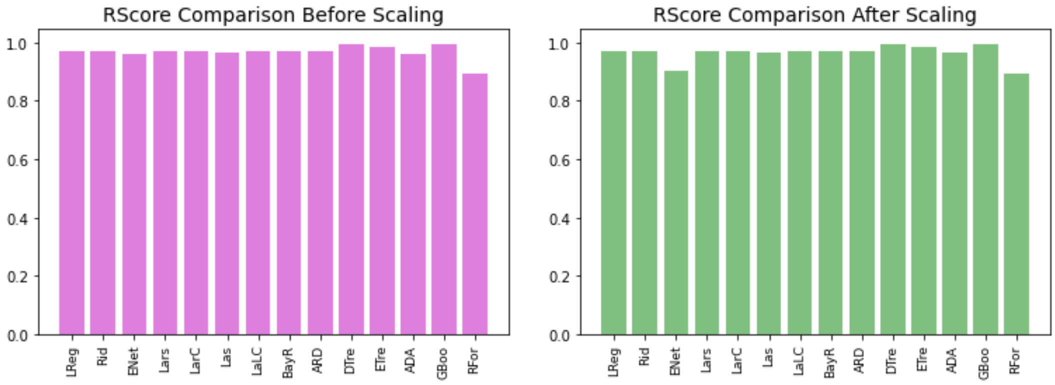


Fig.4. RScore Analysis of raw dataset before and after feature scaling

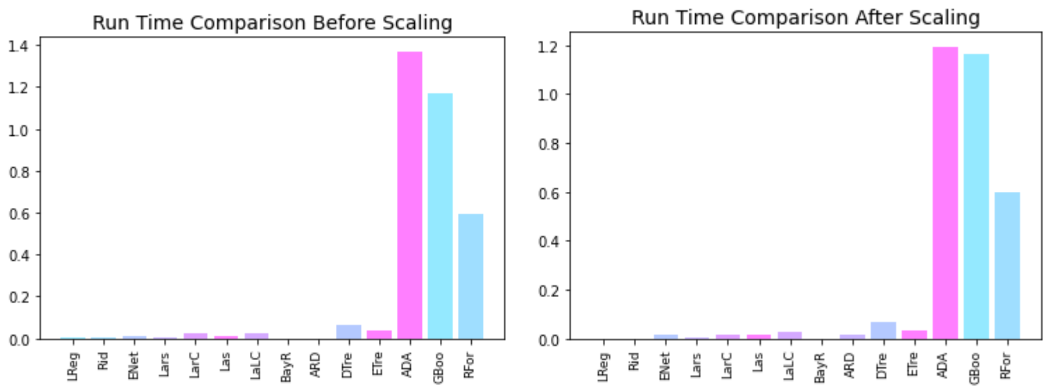


Fig.5. Response time analysis of raw dataset before and after feature scaling

Table 1. Regressor performance of the raw dataset before scaling

Regressor	EVS	MSE	MAE	RScore	Running Time (ms)
Linear	0.97	118.82	8.09	0.97	0.00

Ridge	0.97	118.82	8.09	0.97	0.01
ElasticNet	0.96	142.56	9.02	0.96	0.01
Lars	0.97	118.82	8.09	0.97	0.00
LarsCV	0.97	118.82	8.09	0.97	0.03
Lasso	0.97	127.87	8.44	0.97	0.01
LAssoLarsCV	0.97	118.82	8.09	0.97	0.03
Bayesian	0.97	118.82	8.09	0.97	0.00
ARd	0.97	118.76	8.09	0.97	0.00
DecisionTree	0.99	29.13	3.53	0.99	0.06
ExtraTree	0.99	55.19	4.47	0.99	0.04
AdaBoost	0.97	143.52	9.56	0.96	1.37
GradientBoost	1.00	13.31	2.65	1.00	1.17
RandomForest	0.89	417.79	15.73	0.89	0.60

Table 2. Regressor performance of the raw dataset after scaling

Regressor	**EVS**	**MSE**	**MAE**	**RScore**	**Running Time (ms)**
Linear	0.97	118.82	8.09	0.97	0.00
Ridge	0.97	118.82	8.09	0.97	0.00
ElasticNet	0.91	364.90	14.70	0.91	0.02
Lars	0.97	118.82	8.09	0.97	0.00
LarsCV	0.97	118.82	8.09	0.97	0.02
Lasso	0.96	138.90	8.70	0.96	0.02
LAssoLarsCV	0.97	118.82	8.09	0.97	0.03
Bayesian	0.97	118.82	8.09	0.97	0.00
ARd	0.97	118.77	8.09	0.97	0.02
DecisionTree	0.99	29.04	3.52	0.99	0.06
ExtraTree	0.99	55.19	4.47	0.99	0.03
AdaBoost	0.97	138.25	9.43	0.96	1.20
GradientBoost	1.00	13.31	2.65	1.00	1.16
RandomForest	0.89	417.79	15.73	0.89	0.60

6. Feature Selection Results and Performance Analysis

The raw data set is subjected to feature selection to find the important features with anova test anlaysis. The resampled dataset after anova is fitted to all the regressors with and without the presence of feature scaling and performance is shown in Table 3 and Table 4, the accuracy and the running time comparison is shown in Fig. 6 - 7.

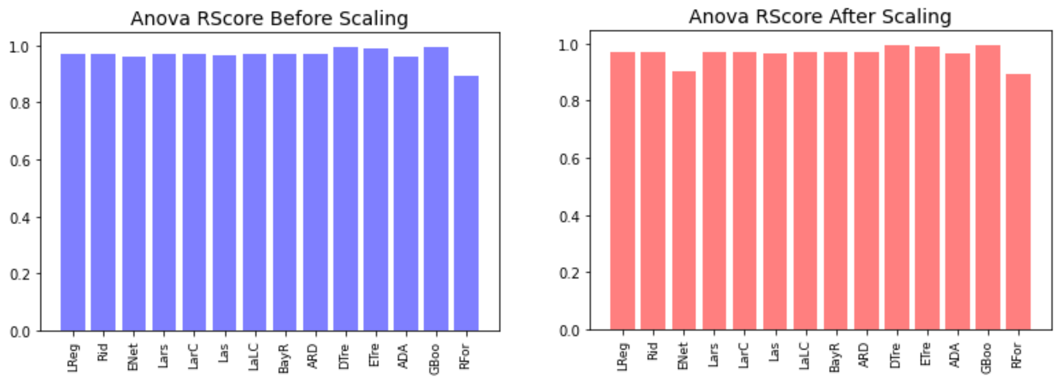


Fig.6. RScore Analysis of ANOVA dataset before and after feature scaling

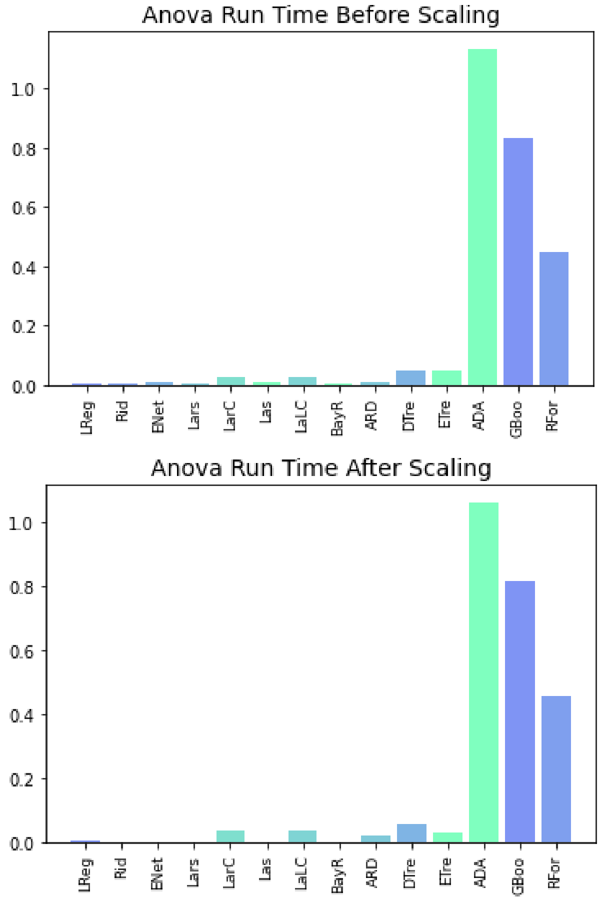


Fig.7. Response time analysis of ANOVA dataset before and after feature scalin

Table 3. Regressor performance of the ANOVA dataset before scaling

Regressor	**EVS**	**MSE**	**MAE**	**RScore**	**Running Time (ms)**
Linear	0.97	118.79	8.09	0.97	0.00
Ridge	0.97	118.79	8.09	0.97	0.00
ElasticNet	0.96	142.56	9.02	0.96	0.01
Lars	0.97	118.79	8.09	0.97	0.01
LarsCV	0.97	118.79	8.09	0.97	0.03
Lasso	0.97	127.86	8.44	0.97	0.01
LAssoLarsCV	0.97	118.79	8.09	0.97	0.03
Bayesian	0.97	118.79	8.09	0.97	0.01

ARd	0.97	118.76	8.09	0.97	0.01
DecisionTree	0.99	26.70	3.35	0.99	0.05
ExtraTree	0.99	32.21	3.66	0.99	0.05
AdaBoost	0.97	143.52	9.56	0.96	1.14
GradientBoost	1.00	13.39	2.66	1.00	0.83
RandomForest	0.89	417.79	15.73	0.89	0.45

Table 4. Regressor performance of the ANOVA dataset after scaling

Regressor	**EVS**	**MSE**	**MAE**	**RScore**	**Running Time (ms)**
Linear	0.97	118.79	8.09	0.97	0.00
Ridge	0.97	118.79	8.09	0.97	0.00
ElasticNet	0.91	364.90	14.70	0.91	0.00
Lars	0.97	118.79	8.09	0.97	0.00
LarsCV	0.97	118.79	8.09	0.97	0.03
Lasso	0.96	138.90	8.70	0.96	0.00
LAssoLarsCV	0.97	118.79	8.09	0.97	0.03
Bayesian	0.97	118.79	8.09	0.97	0.00
ARd	0.97	118.76	8.09	0.97	0.02
DecisionTree	0.99	26.48	3.33	0.99	0.06
ExtraTree	0.99	32.21	3.66	0.99	0.03
AdaBoost	0.97	138.25	9.43	0.96	1.07
GradientBoost	1.00	13.39	2.66	1.00	0.81
RandomForest	0.89	417.79	15.73	0.89	0.46

The raw data set is subjected to feature selection to find the important features with correlation analysis. The resampled dataset after removing the high correlated features as shown in Fig.8 and is fitted to all the regressors with and without the presence of feature scaling and performance is shown in Table 5 and Table 6, the accuracy and the running time comparison is shown in Fig. 9 - 10.

HighCorrelatedFeatures_todrop - List (3 elements)

Index	Type	Size	
0	str	1	Weight
1	str	1	Body_Temp
2	str	1	Calories

Fig.8. High correlated Features of Exercise Dataset

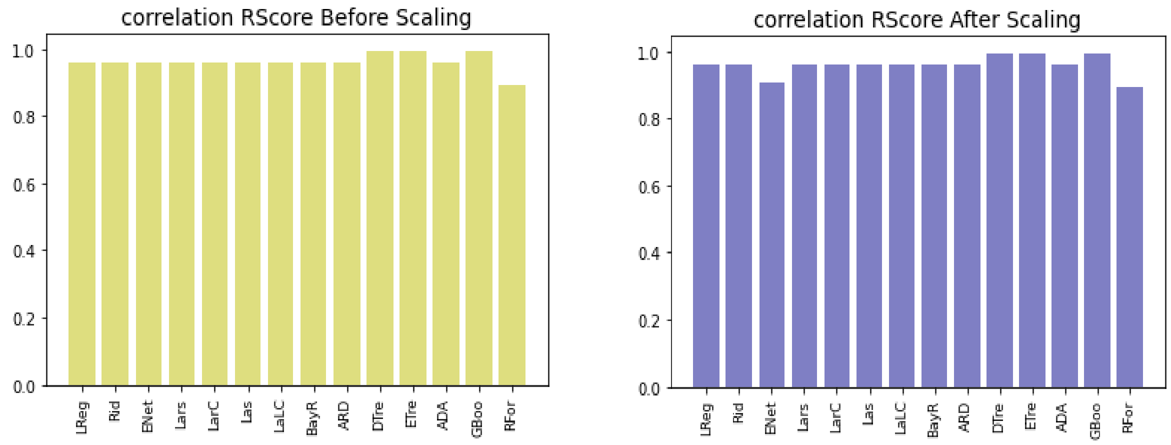


Fig.9.RScore Analysis of correlated Free dataset before and after feature scaling

Table 5. Regressor performance of the correlated Free before scaling

Regressor	**EVS**	**MSE**	**MAE**	**RScore**	**Running Time (ms)**
Linear	0.96	148.83	9.25	0.96	0.01
Ridge	0.96	148.83	9.25	0.96	0.00
ElasticNet	0.96	149.30	9.25	0.96	0.01
Lars	0.96	148.83	9.25	0.96	0.01
LarsCV	0.96	148.83	9.25	0.96	0.03
Lasso	0.96	148.93	9.24	0.96	0.00
LAssoLarsCV	0.96	148.83	9.25	0.96	0.02
Bayesian	0.96	148.84	9.25	0.96	0.01
ARd	0.96	148.84	9.25	0.96	0.00
DecisionTree	0.99	25.31	3.27	0.99	0.06
ExtraTree	0.99	23.51	3.10	0.99	0.04
AdaBoost	0.97	162.18	10.20	0.96	1.12
GradientBoost	1.00	16.60	2.94	1.00	0.65
RandomForest	0.89	417.79	15.73	0.89	0.36

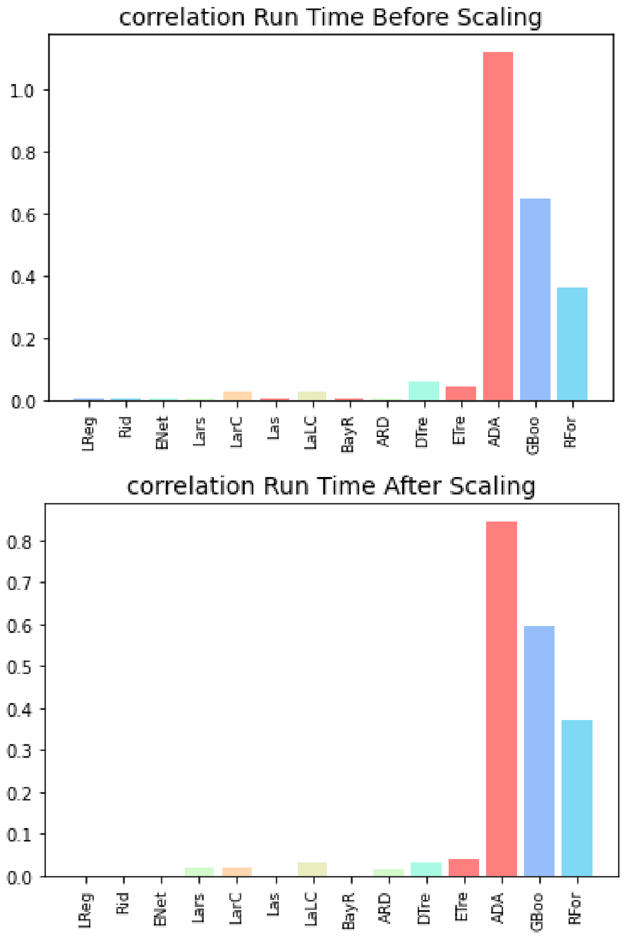


Fig.10. Response time analysis of correlated Free dataset before and after feature scaling

Table 6. Regressor performance of the correlated Free dataset after scaling

Regressor	**EVS**	**MSE**	**MAE**	**RScore**	**Running Time (ms)**
Linear	0.96	148.83	9.25	0.96	0.00
Ridge	0.96	148.84	9.25	0.96	0.00
ElasticNet	0.91	358.65	14.51	0.91	0.00
Lars	0.96	148.83	9.25	0.96	0.02
LarsCV	0.96	148.83	9.25	0.96	0.02
Lasso	0.96	151.93	9.21	0.96	0.00
LAssoLarsCV	0.96	148.83	9.25	0.96	0.03
Bayesian	0.96	148.84	9.25	0.96	0.00
ARd	0.96	148.84	9.25	0.96	0.02
DecisionTree	0.99	25.37	3.27	0.99	0.03
ExtraTree	0.99	23.51	3.10	0.99	0.04
AdaBoost	0.97	163.20	10.22	0.96	0.85
GradientBoost	1.00	16.60	2.94	1.00	0.60
RandomForest	0.89	417.79	15.73	0.89	0.37

The raw data set is subjected to feature selection to find the important features with Variance anlaysis. The resampled dataset after removing high variance features is fitted to all the regressors with and without the presence of feature scaling and performance is shown in Table 7 and Table 8, the accuracy and the running time comparison is shown in Fig. 11 - 12.

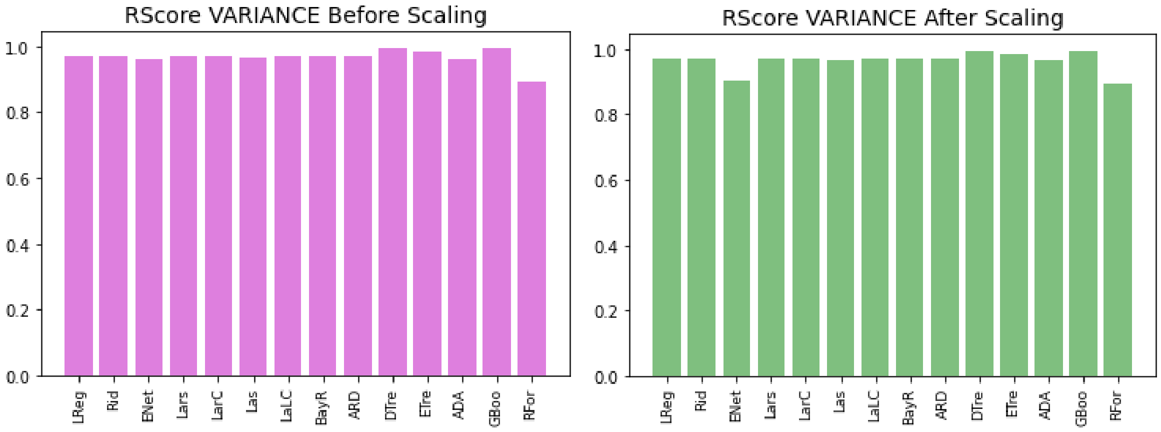


Fig. 11. RScore Analysis of variance free dataset before and after feature scaling

Fig.12. Response time analysis of variance free dataset before and after feature scaling

Table 7. Regressor performance of the variance free dataset before scaling

Regressor	**EVS**	**MSE**	**MAE**	**RScore**	**Running Time (ms)**
Linear	0.97	118.82	8.09	0.97	0.01
Ridge	0.97	118.82	8.09	0.97	0.00
ElasticNet	0.96	142.56	9.02	0.96	0.01
Lars	0.97	118.82	8.09	0.97	0.01

LarsCV	0.97	118.82	8.09	0.97	0.05
Lasso	0.97	127.87	8.44	0.97	0.01
LAssoLarsCV	0.97	118.82	8.09	0.97	0.03
Bayesian	0.97	118.82	8.09	0.97	0.00
ARd	0.97	118.76	8.09	0.97	0.01
DecisionTree	0.99	29.13	3.53	0.99	0.08
ExtraTree	0.99	55.19	4.47	0.99	0.04
AdaBoost	0.97	143.52	9.56	0.96	1.40
GradientBoost	1.00	13.31	2.65	1.00	1.18
RandomForest	0.89	417.79	15.73	0.89	0.64

Table 8. Regressor performance of the variance free dataset after scaling

Regressor	**EVS**	**MSE**	**MAE**	**RScore**	**Running Time (ms)**
Linear	0.97	118.82	8.09	0.97	0.00
Ridge	0.97	118.82	8.09	0.97	0.01
ElasticNet	0.91	364.90	14.70	0.91	0.00
Lars	0.97	118.82	8.09	0.97	0.01
LarsCV	0.97	118.82	8.09	0.97	0.03
Lasso	0.96	138.90	8.70	0.96	0.00
LAssoLarsCV	0.97	118.82	8.09	0.97	0.04
Bayesian	0.97	118.82	8.09	0.97	0.01
ARd	0.97	118.77	8.09	0.97	0.02
DecisionTree	0.99	29.04	3.52	0.99	0.08
ExtraTree	0.99	55.19	4.47	0.99	0.03
AdaBoost	0.97	138.25	9.43	0.96	1.25
GradientBoost	1.00	13.31	2.65	1.00	1.18
RandomForest	0.89	417.79	15.73	0.89	0.61

The raw data set is subjected to feature selection to find the important features with KBest Feature test anlaysis. The resampled dataset after KBest Features and is fitted to all the regressors with and without the presence of feature scaling and performance is shown in Table 9 and Table 10, the accuracy and the running time comparison is shown in Fig. 13 - 14.

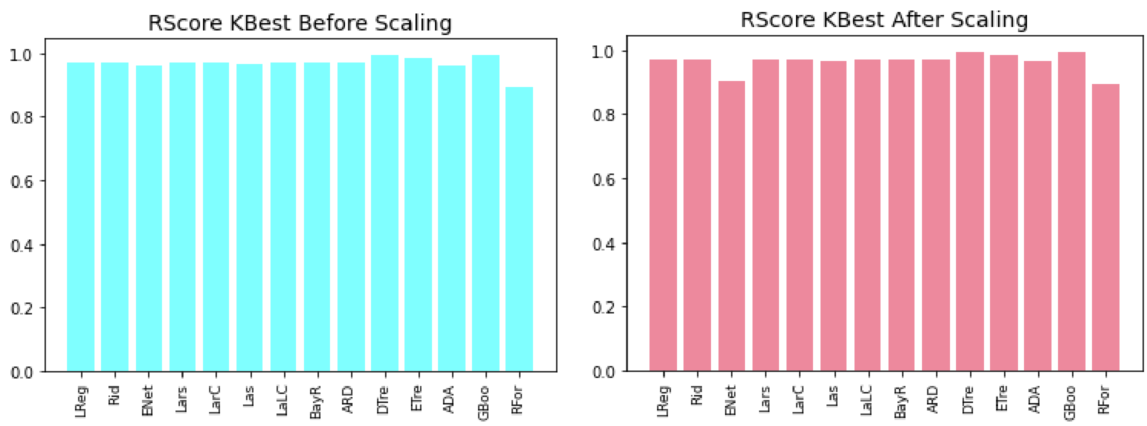


Fig.13. RScore Analysis of KBest dataset before and after feature scaling

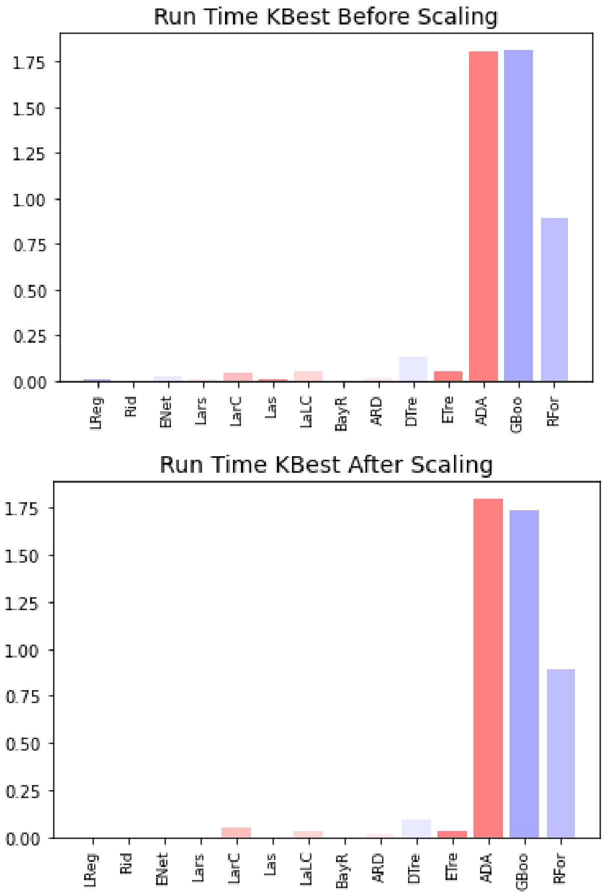


Fig.14. Response time analysis of KBest dataset before and after feature scaling

Table 9. Regressor performance of the KBest dataset before scaling

Regressor	**EVS**	**MSE**	**MAE**	**RScore**	**Running Time (ms)**
Linear	0.97	118.82	8.09	0.97	0.02
Ridge	0.97	118.82	8.09	0.97	0.01
ElasticNet	0.96	142.56	9.02	0.96	0.02
Lars	0.97	118.82	8.09	0.97	0.01
LarsCV	0.97	118.82	8.09	0.97	0.08
Lasso	0.97	127.87	8.44	0.97	0.02
LAssoLarsCV	0.97	118.82	8.09	0.97	0.05
Bayesian	0.97	118.82	8.09	0.97	0.00
ARd	0.97	118.76	8.09	0.97	0.02
DecisionTree	0.99	29.13	3.53	0.99	0.11
ExtraTree	0.99	55.19	4.47	0.99	0.05
AdaBoost	0.97	143.52	9.56	0.96	1.90
GradientBoost	1.00	13.31	2.65	1.00	1.84
RandomForest	0.89	417.79	15.73	0.89	0.93

Table 10. Regressor performance of the KBest dataset after scaling

Regressor	**EVS**	**MSE**	**MAE**	**RScore**	**Running Time (ms)**
Linear	0.97	118.82	8.09	0.97	0.00

Ridge	0.97	118.82	8.09	0.97	0.00
ElasticNet	0.91	364.90	14.70	0.91	0.00
Lars	0.97	118.82	8.09	0.97	0.00
LarsCV	0.97	118.82	8.09	0.97	0.05
Lasso	0.96	138.90	8.70	0.96	0.00
LAssoLarsCV	0.97	118.82	8.09	0.97	0.05
Bayesian	0.97	118.82	8.09	0.97	0.01
ARd	0.97	118.77	8.09	0.97	0.02
DecisionTree	0.99	29.04	3.52	0.99	0.10
ExtraTree	0.99	55.19	4.47	0.99	0.03
AdaBoost	0.97	138.25	9.43	0.96	1.78
GradientBoost	1.00	13.31	2.65	1.00	1.78
RandomForest	0.89	417.79	15.73	0.89	0.93

The MI value associated with FTest feature analysis for the exercise dataset is shown in Fig. 15.

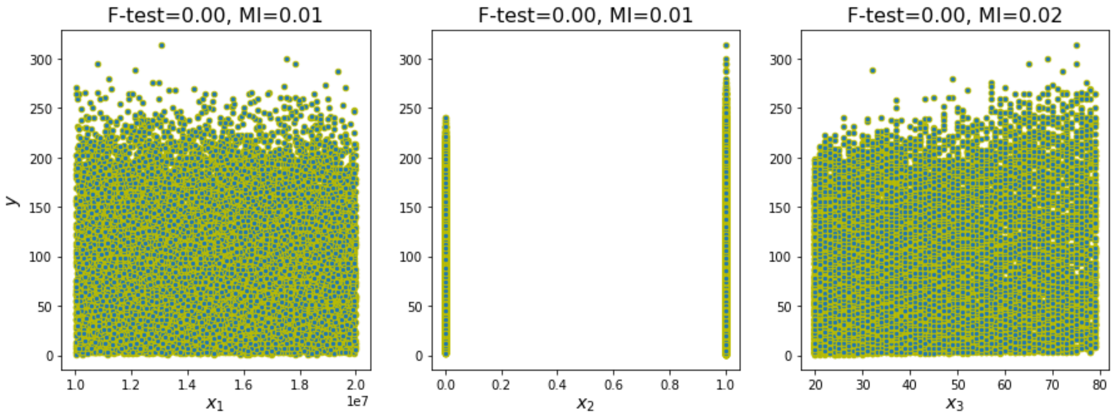


Fig.15. MI value analysis of FTest of Exercise Dataset

The MI Value for the KBest Feature analysis with mutual information and Feature regression is shown in Fig. 16.

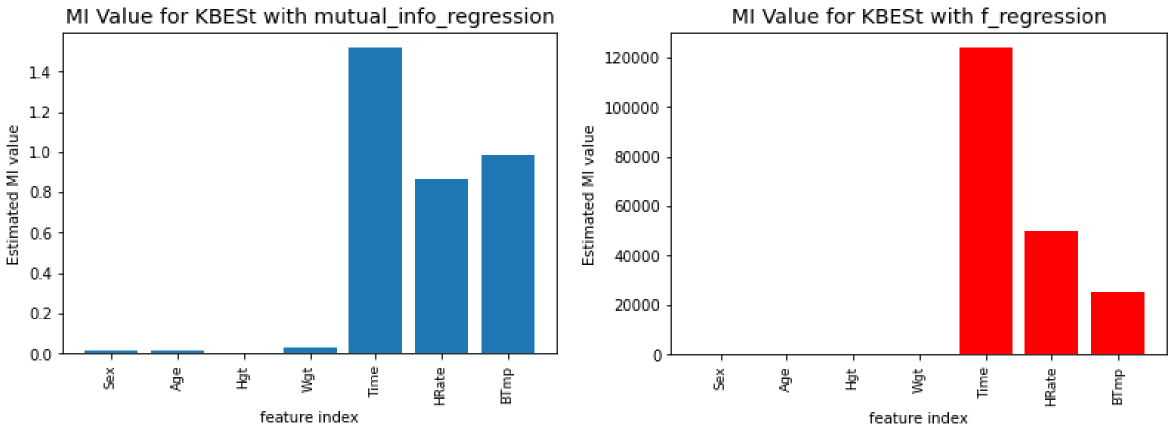


Fig.16. MI value analysis of KBest with mutual information and feature regression of Exercise Dataset

7. Conclusion

An attempt is made to find the performance analysis of the exercise dataset in forecasting the workout burnt calories by applying various feature selection methods with High correlation, High Variance, Anova Test analysis and KBest Feature analysis. The MI value for the Kbest feature for feature regression and mutual information regression also examined and visualized. The correlation of each features in the dataset is extricated and the distribution of target variable with respect to gender and duration is analysed. Experimental results shows that the Decision Tree and Gradient Boosting regressors tends to retain 99% before and after feature scaling for the Anova test, Correlated Feature, Variance Based and KBest Feature based methods.

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