

Estimation of obesity levels based on eating habits and physical condition

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01

Introduction

Brief introduction to the
dataset for this project



Obesity dataset from UCI Machine learning Repository



This dataset includes data for the obesity levels in individuals from the countries of Mexico, Peru and Columbia, and also data for eating habits and physical condition.

About the Dataset



2111 datas 17 variables

```
$ Gender           : chr  "Female" "Female" "Male" "Male" ...
$ Age              : num  21 21 23 27 22 29 23 22 24 22 ...
$ Height           : num  1.62 1.52 1.8 1.8 1.78 1.62 1.5 1.64 1.78 1.72 ...
$ Weight           : num  64 56 77 87 89.8 53 55 53 64 68 ...
$ family_history_with_overweight: chr  "yes" "yes" "yes" "no" ...
$ FAVC             : chr  "no" "no" "no" "no" ...
$ FCVC             : num  2 3 2 3 2 2 3 2 3 2 ...
$ NCP              : num  3 3 3 3 1 3 3 3 3 3 ...
$ CAEC             : chr  "Sometimes" "Sometimes" "Sometimes" "Sometimes" ...
$ SMOKE            : chr  "no" "yes" "no" "no" ...
$ CH20             : num  2 3 2 2 2 2 2 2 2 2 ...
$ SCC              : chr  "no" "yes" "no" "no" ...
$ FAF              : num  0 3 2 2 0 0 1 3 1 1 ...
$ TUE              : num  1 0 1 0 0 0 0 0 1 1 ...
$ CALC             : chr  "no" "Sometimes" "Frequently" "Frequently" ...
$ MTRANS           : chr  "Public_Transportation" "Public_Transportation" "Public_Transportation" "Walking" ...
$ NObeyesdad       : chr  "Normal_Weight" "Normal_Weight" "Normal_Weight" "Overweight_Level_I" ...
```

About the Dataset

Eating habits



FAVC

Frequent consumption of high caloric food



FCVC

Frequency of consumption of vegetables



NCP

Number of main meals



CAEC

Consumption of food between meals



CH2O

Consumption of water daily



CALC

Consumption of alcohol



Physical condition

SCC

Calories consumption monitoring



FAF

Physical activity frequency



TUE

Time using technology devices



MTRANS

Transportation



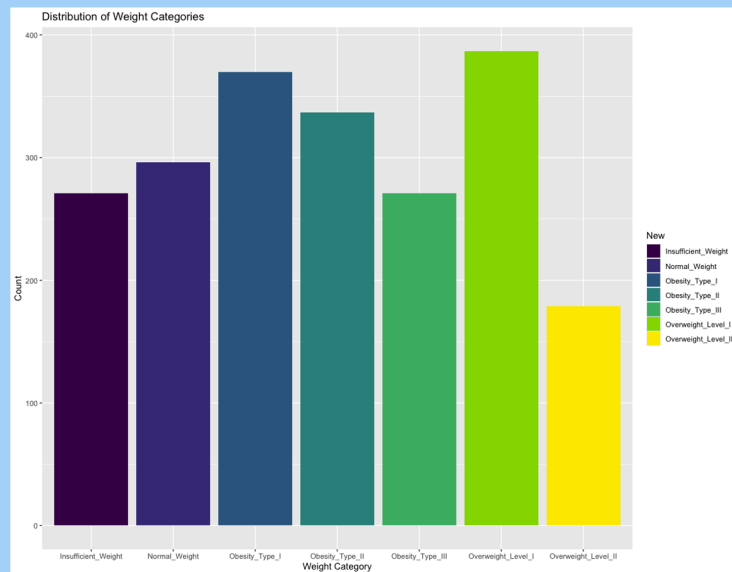
Other Variables: Gender, Height, Weight, NObeyesdad

About the Dataset

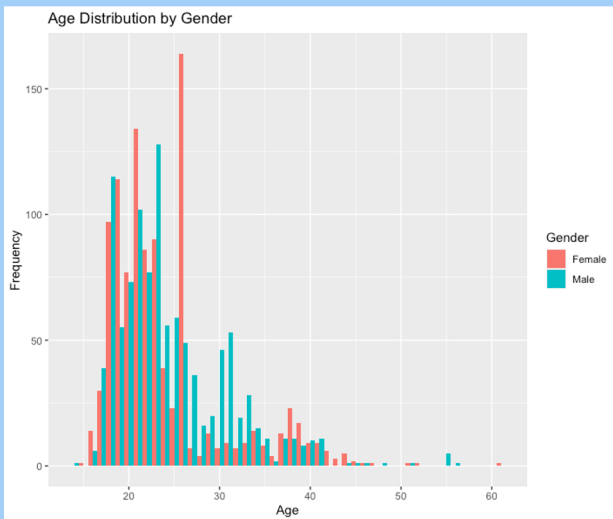


Obesity Level Category (Recategorized)

- Underweight: Less than 18.5
- Normal: 18.5 to 24.9
- Overweight I: 25.0 to 27.9
- Overweight II: 28 to 29
- Obesity I: 30.0 to 34.9
- Obesity II: 35.0 to 39.9
- Obesity III: Higher than 40

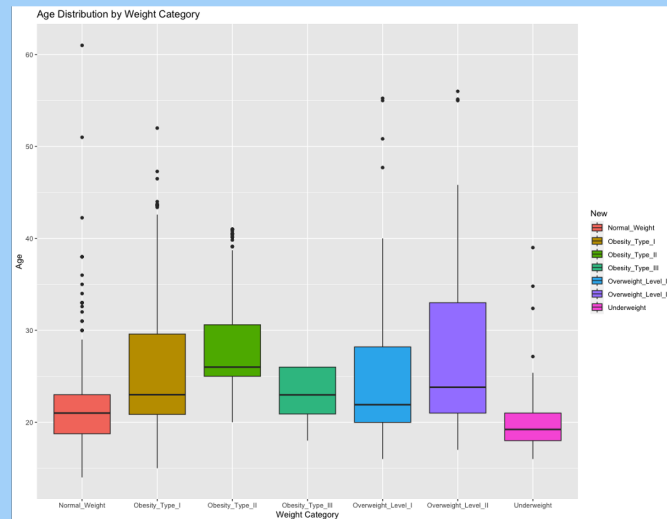


About the Dataset



Age Distribution by Gender

The histogram provides how ages are distributed.
The height of the bars indicates the count of individuals within each age group.



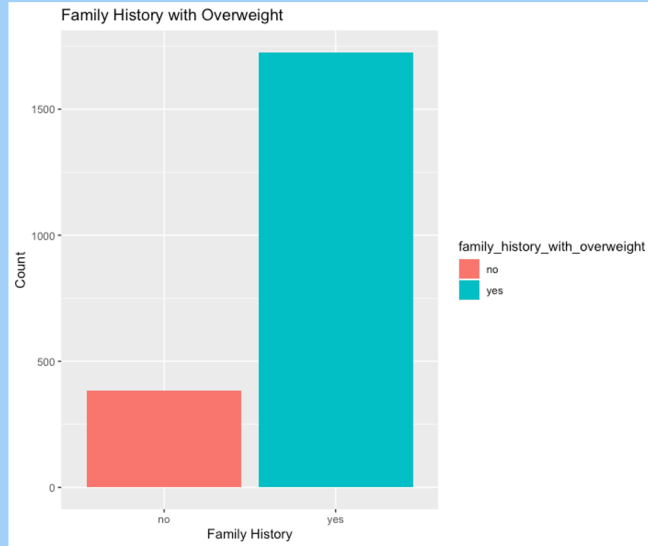
Age Distribution by Weight Category

We've got seven categories on obesity which are calculated by BMI.

About the Dataset



Family History with Overweight

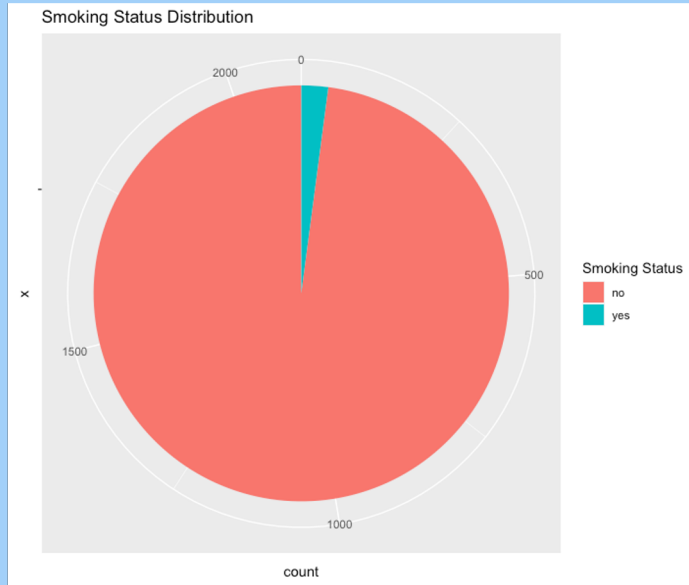


- Yes: 1726 records
- No: 385 records

About the Dataset



Smoking Status Distribution

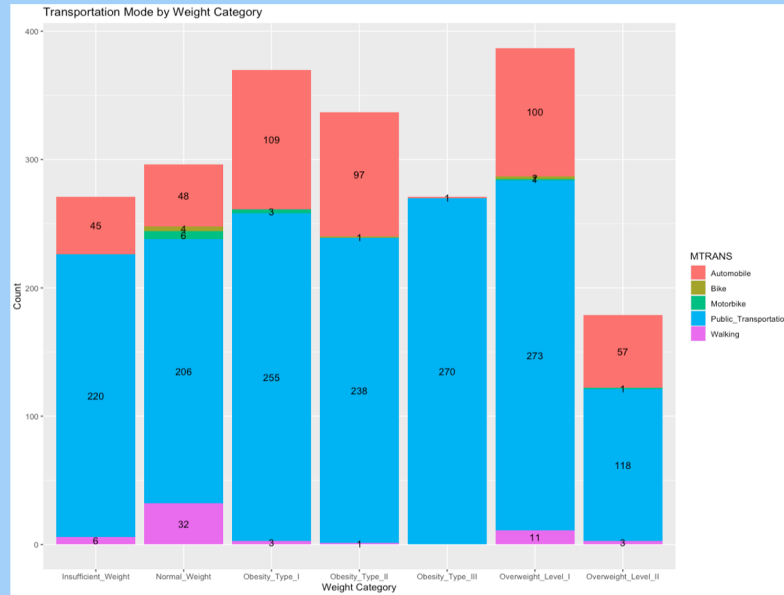


- Yes: 44 records
- No: 2067 records

About the Dataset



Transportation Mode by Weight Category





02

ANOVA

Uncover significant variations in variables
among diverse obesity categories

ANOVA



FCVC

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
New	2	68.2	34.10	146.2	<2e-16 ***
Residuals	835	194.8	0.23		

NCP

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
New	2	10.8	5.386	10.11	4.58e-05 ***
Residuals	835	444.7	0.533		

CH2O

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
New	2	35.67	17.837	49.77	<2e-16 ***
Residuals	835	299.25	0.358		

FAF

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
New	2	40.5	20.267	25.71	1.46e-11 ***
Residuals	835	658.2	0.788		

TUE

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
New	2	9.33	4.664	14.1	9.49e-07 ***
Residuals	835	276.20	0.331		

CAEC

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
New	2	157.5	78.76	99.2	<2e-16 ***
Residuals	835	663.0	0.79		

CALC

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
New	2	40.45	20.225	91.05	<2e-16 ***
Residuals	835	185.48	0.222		

Post Hoc Tests



```
Fit: aov(formula = FCVC ~ New, data = data_selected)
```

\$New

	diff	lwr
Normal_Weight-Insufficient_Weight	-0.1358790	-0.2312201
Obesity_Type_III-Insufficient_Weight	0.5271320	0.4297117
Obesity_Type_III-Normal_Weight	0.6630109	0.5676698
	upr	p adj
Normal_Weight-Insufficient_Weight	-0.04053785	0.0024636
Obesity_Type_III-Insufficient_Weight	0.62455229	0.0000000
Obesity_Type_III-Normal_Weight	0.75835205	0.0000000

Post Hoc Tests



FCVC

	p adj
Normal_Weight-Insufficient_Weight	0.0024636
Obesity_Type_III-Insufficient_Weight	0.0000000
Obesity_Type_III-Normal_Weight	0.0000000

FAF

	p adj
Normal_Weight-Insufficient_Weight	0.9169894
Obesity_Type_III-Insufficient_Weight	0.0000000
Obesity_Type_III-Normal_Weight	0.0000000

NCP

	p adj
Normal_Weight-Insufficient_Weight	0.0107079
Obesity_Type_III-Insufficient_Weight	0.3039238
Obesity_Type_III-Normal_Weight	0.0000355

TUE

	p adj
Normal_Weight-Insufficient_Weight	0.0050222
Obesity_Type_III-Insufficient_Weight	0.0000005
Obesity_Type_III-Normal_Weight	0.0614452

CH20

	p adj
Normal_Weight-Insufficient_Weight	0.8501884
Obesity_Type_III-Insufficient_Weight	0.0000000
Obesity_Type_III-Normal_Weight	0.0000000

CAEC

	p adj
Normal_Weight-Insufficient_Weight	0.9909276
Obesity_Type_III-Insufficient_Weight	0.0000000
Obesity_Type_III-Normal_Weight	0.0000000

CALC

	p adj
Normal_Weight-Insufficient_Weight	0.0003389
Obesity_Type_III-Insufficient_Weight	0.0000000
Obesity_Type_III-Normal_Weight	0.0000009

Post Hoc Tests



Frequency of eating vegetables

Obesity_Type_III > Insufficient_Weight > Normal

Number of main meals

Obesity_Type_III = Insufficient_Weight > Normal

Consumption of water daily

Obesity_Type_III > Insufficient_Weight = Normal

Physical activity frequency

Insufficient_Weight = Normal > Obesity_Type_III

Consumption of food between meals

Insufficient_Weight > Normal = Obesity_Type_III

Time using technology devices

Insufficient_Weight = Normal > Obesity_Type_III

Consumption of alcohol

Obesity_Type_III > Normal > Insufficient_Weight



03

Model

Comparing different models'
predictions and accuracy

Steps



Data Splitting & Feature Selection

80% training 20% testing
Selected the top 10 features

Decision Tree Model

rpart library

Random Forest Model

randomForest library

ROC Curves

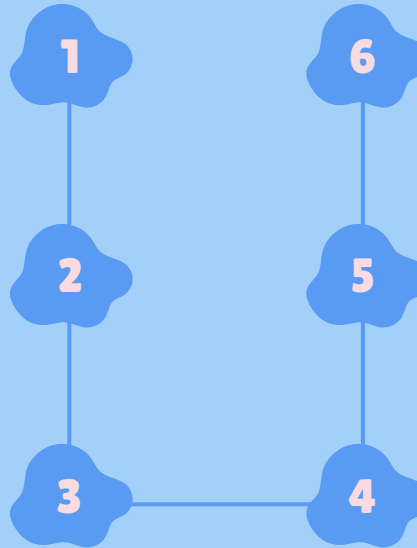
pROC library
Visualize the performance of our models

Model Evaluation

Using confusion matrices and
calculate accuracy

SVM Model

e1071 library



Models



Feature Selection

Variables	Accuracy	Kappa	AccuracySD	KappaSD	Selected
10	0.9137	0.8984	0.02144	0.02522	*
16	0.9090	0.8929	0.02489	0.02927	

The top 5 variables (out of 10):

Weight, Height, Age, FCVC, Gender

[1] "Weight"	"Height"	"Age"
[4] "FCVC"	"Gender"	"CH2O"
[7] "TUE"	"NCP"	"FAF"
[10] "family_history_with_overweight"		

Selected the top ten features by running RFE with Random Forest

Models



Decision Tree

```
[1] "Decision Tree Confusion Matrix:"
```

```
> print(dt_conf_matrix)
```

dt_predictions	Insufficient_Weight	Normal_Weight	Obesity_Type_I	Obesity_Type_II	Obesity_Type_III
Insufficient_Weight	50	11	0	0	0
Normal_Weight	4	38	0	0	0
Obesity_Type_I	0	0	58	2	0
Obesity_Type_II	0	0	11	64	2
Obesity_Type_III	0	0	0	1	52
Overweight_Level_I	0	10	2	0	0
Overweight_Level_II	0	0	3	0	0

dt_predictions	Overweight_Level_I	Overweight_Level_II
Insufficient_Weight	0	0
Normal_Weight	5	0
Obesity_Type_I	0	2
Obesity_Type_II	0	0
Obesity_Type_III	0	0
Overweight_Level_I	64	16
Overweight_Level_II	8	17

Decision Tree Accuracy: 0.816666666666667

Models



Random Forest

```
[1] "Random Forest Confusion Matrix:"  
> print(rf_conf_matrix)
```

rf_predictions	Insufficient_Weight	Normal_Weight	Obesity_Type_I	Obesity_Type_II	Obesity_Type_III
Insufficient_Weight	50	2	0	0	0
Normal_Weight	4	51	0	0	0
Obesity_Type_I	0	0	69	3	0
Obesity_Type_II	0	0	1	64	1
Obesity_Type_III	0	0	0	0	53
Overweight_Level_I	0	6	2	0	0
Overweight_Level_II	0	0	2	0	0

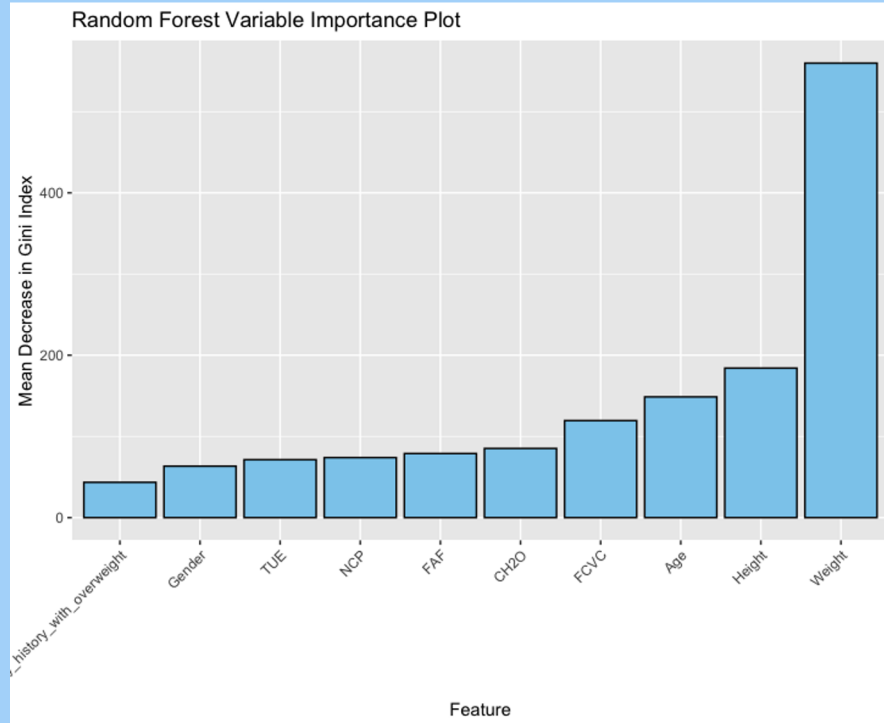
rf_predictions	Overweight_Level_I	Overweight_Level_II
Insufficient_Weight	0	0
Normal_Weight	6	0
Obesity_Type_I	0	0
Obesity_Type_II	0	0
Obesity_Type_III	0	0
Overweight_Level_I	69	10
Overweight_Level_II	2	25

Random Forest Accuracy: 0.907142857142857

Models



Random Forest



Models



Support Vector Machine

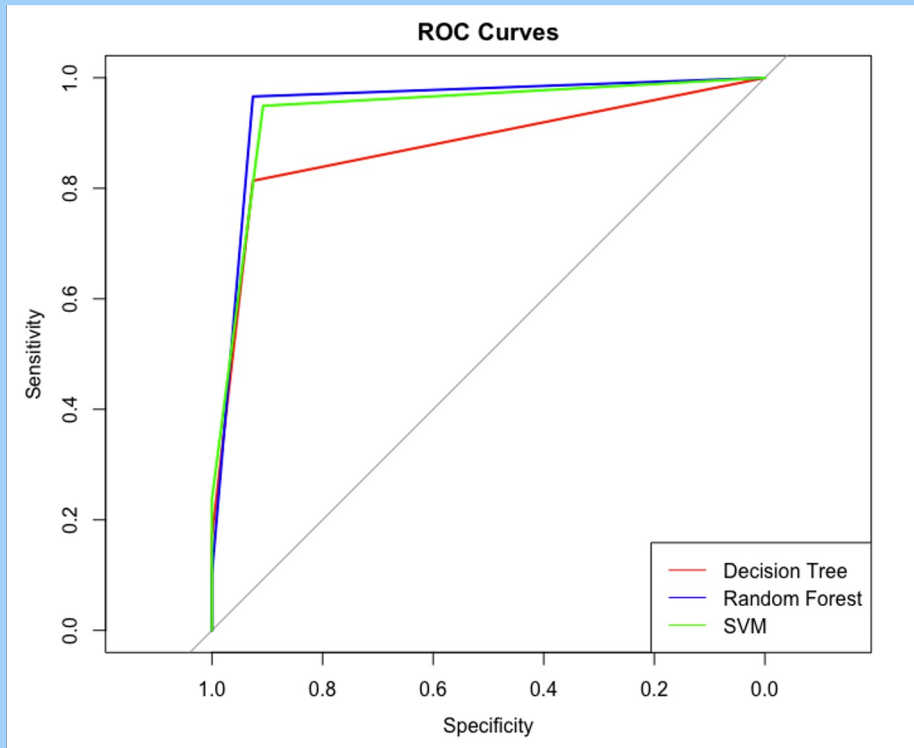
```
[1] "SVM Confusion Matrix:"  
> print(svm_conf_matrix)
```

svm_predictions	Insufficient_Weight	Normal_Weight	Obesity_Type_I	Obesity_Type_II	Obesity_Type_III
Insufficient_Weight	49	3	0	0	0
Normal_Weight	5	42	0	0	0
Obesity_Type_I	0	0	66	0	0
Obesity_Type_II	0	0	4	66	2
Obesity_Type_III	0	0	0	1	52
Overweight_Level_I	0	14	1	0	0
Overweight_Level_II	0	0	3	0	0

svm_predictions	Overweight_Level_I	Overweight_Level_II
Insufficient_Weight	0	0
Normal_Weight	4	0
Obesity_Type_I	0	4
Obesity_Type_II	0	0
Obesity_Type_III	0	0
Overweight_Level_I	70	17
Overweight_Level_II	3	14

SVM Accuracy: 0.854761904761905

ROC Curves



Random Forest Model has the highest accuracy.

	Decision Tree	Random Forest	SVM
Accuracy	0.816667	0.9071429	0.8547619
AUC	0.8760201	0.9497803	0.9392655

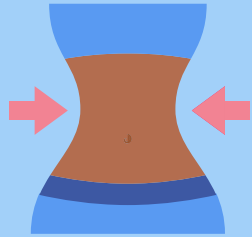


04

Conclusion

Conclusions for the project

Conclusions



Conclusion A

For Physical Activity Frequency and Number of Main Meals, no significant difference is observed between Obesity and Insufficient Weight. However, a significant difference exists between Obesity and Normal Weight.

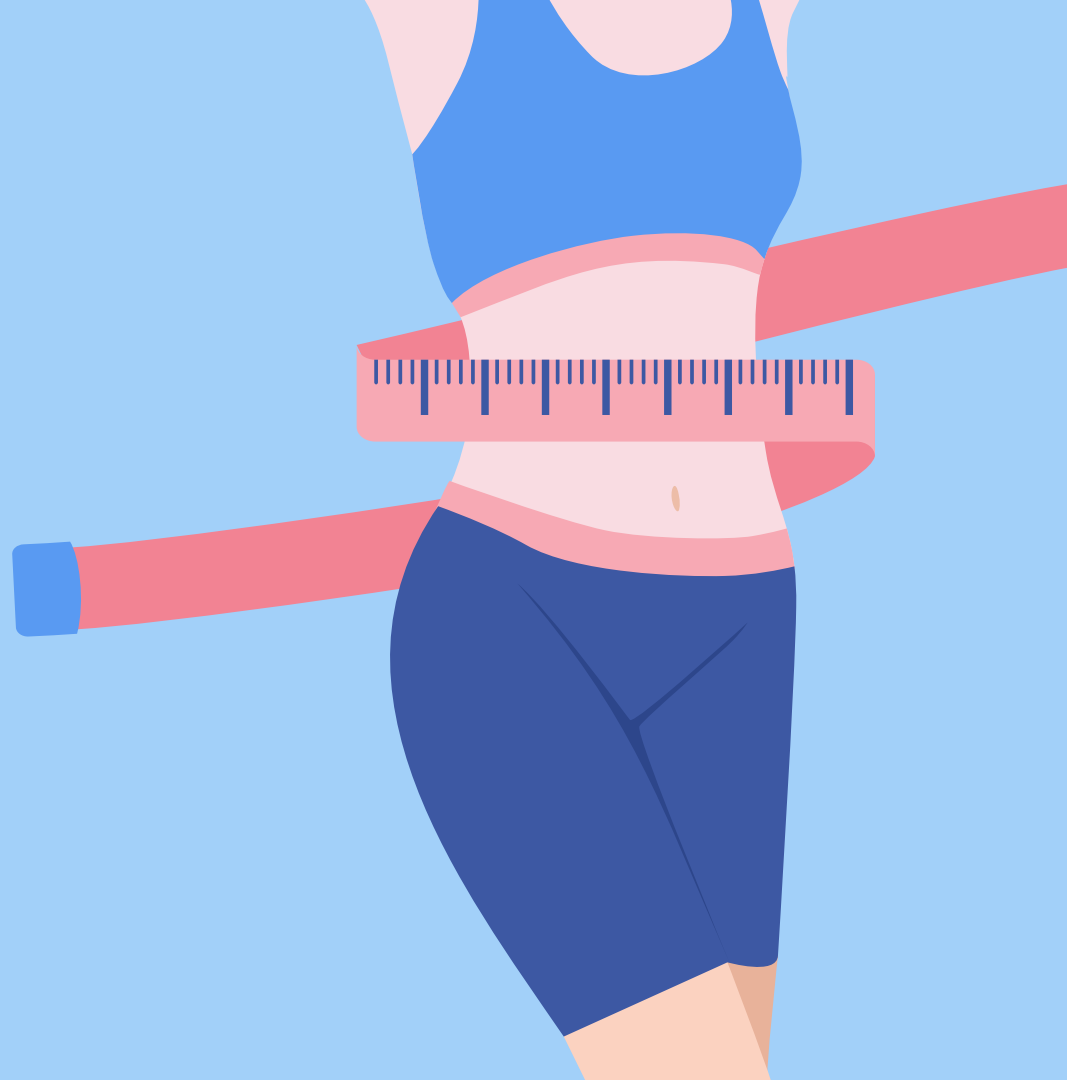


Conclusion B

Random Forest Model appears to be the most accurate among the three, suggesting that its ensemble nature helps improve predictive performance.

Thanks!

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05

Response

Response to questions received

Response to Questions

Figure 1

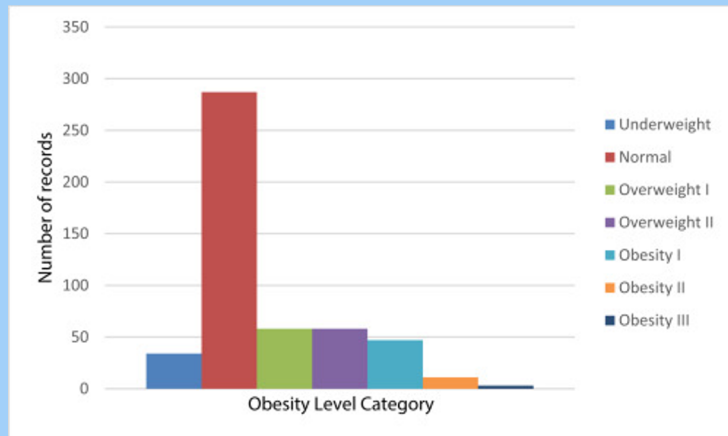
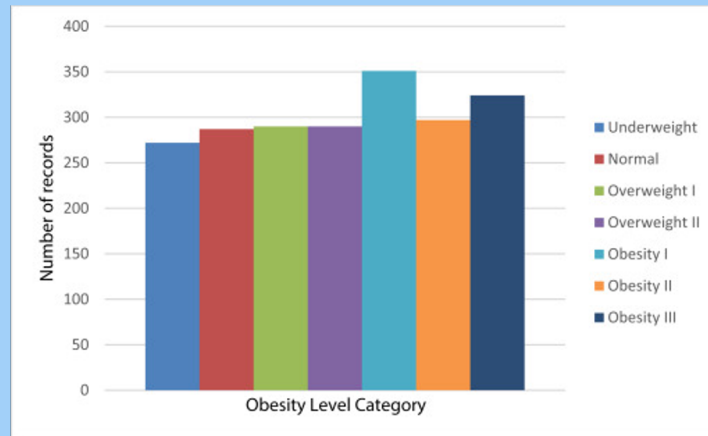


Figure 2



According to the paper in the data set, the original data was also unbalanced. Since we found that the data classification was incorrect when pre-processing the data, we reclassified the data but the data was slightly unbalanced. According to the original literature, after the labeling process was finished, the categories of obesity levels were unbalanced (Fig. 1), and this presented a learning problem for the data mining methods since it would learn to identify correctly the category with most records compared with the categories with less data. After the balancing class problem was identified, synthetic data was generated, up to 77% of the data, using the tool Weka and the filter SMOTE. Although the data we reclassified did not have serious data imbalance problems , but according to the literature, if the above method is used, there is a chance that the model accuracy can be improved.