Project1_VenkataKanaparthi

January 9, 2022

0.1 Problem Statement

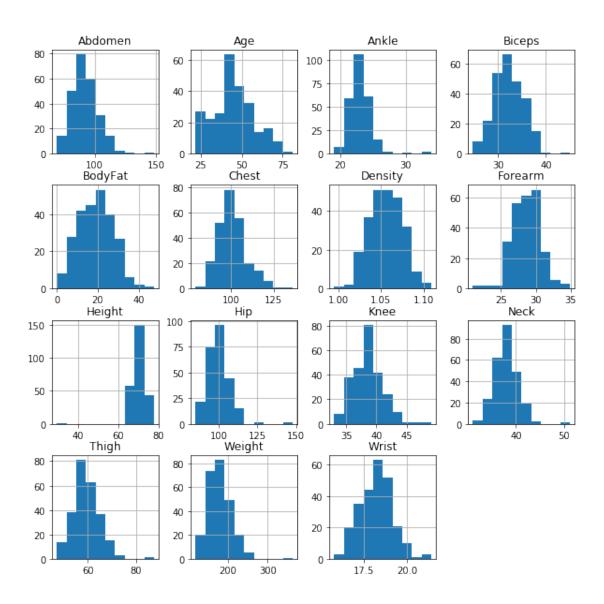
The terms "overweight" and "obesity" refer to body weight that is greater than what is considered normal or healthy for a certain height. Overweight is generally due to extra body fat. However, overweight may also be due to extra muscle, bone, or water. This would impact the health and there are many other diseases caused by extra body fat. We would be creating a model to predict the body fat based on some parameters. We would like to determine whether the person is obese or not in this project.

```
[1]: # Import necessary libraries
     import pandas as pd
     import numpy as np
     import matplotlib.pyplot as plt
     import seaborn as sns
     import scikitplot as skplt
     from imblearn.over_sampling import SMOTE
     from sklearn.feature selection import VarianceThreshold
     from sklearn.feature_selection import SelectKBest
     from sklearn.feature_selection import f_classif
     from sklearn.dummy import DummyClassifier
     from sklearn.model_selection import RepeatedStratifiedKFold
     from sklearn.metrics import
     -classification_report,confusion_matrix,ConfusionMatrixDisplay,roc_auc_score,accuracy_score
     from sklearn.metrics import auc,make_scorer,precision_recall_curve,log_loss
     from sklearn.model_selection import cross_val_score
     from numpy import mean, std
     from sklearn.preprocessing import StandardScaler
     from sklearn.pipeline import Pipeline
     from sklearn.covariance import EllipticEnvelope
     from sklearn.ensemble import IsolationForest
     from sklearn.decomposition import PCA
     from sklearn.cross_decomposition import PLSRegression
     from sklearn.preprocessing import PowerTransformer, Normalizer
     from sklearn.feature_selection import mutual_info_regression
     from sklearn.inspection import permutation_importance
     from sklearn.linear_model import Ridge, Lasso, ElasticNet, LinearRegression
     from sklearn.model_selection import train_test_split, cross_val_score, __
      →LeaveOneOut
```

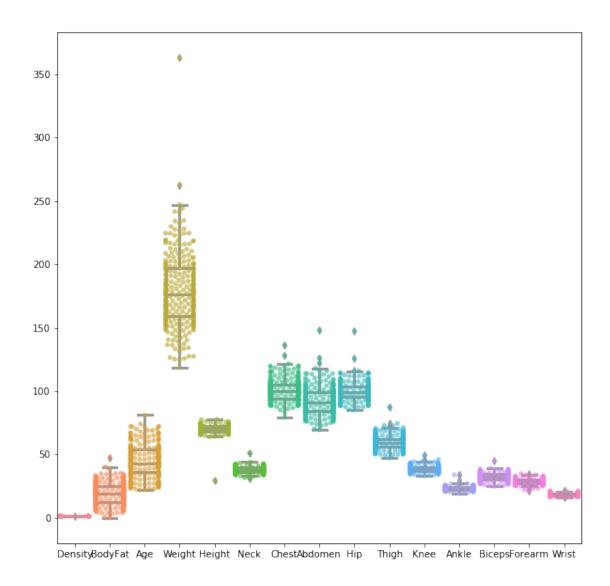
```
from sklearn.ensemble import RandomForestRegressor
     from sklearn.pipeline import make_pipeline
     from sklearn.compose import TransformedTargetRegressor
     from sklearn.metrics import r2 score, mean squared error, make scorer
     from sklearn.model_selection import RandomizedSearchCV
     from scipy.stats import skew, kurtosis
     from tqdm import tqdm
[2]: # Load data into a dataframe
     bodyfat_df = pd.read_csv("bodyfat.csv")
     bodyfat df.head(10)
[2]:
        Density
                BodyFat
                              Weight
                                       Height
                                               Neck Chest
                                                            Abdomen
                                                                       Hip
                                                                            Thigh \
                          Age
        1.0708
                    12.3
                           23 154.25
                                        67.75
                                               36.2
                                                      93.1
                                                               85.2
                                                                      94.5
                                                                             59.0
                           22 173.25
        1.0853
                     6.1
                                        72.25
                                               38.5
                                                      93.6
                                                               83.0
                                                                      98.7
                                                                             58.7
     1
        1.0414
                                                                      99.2
                    25.3
                           22 154.00
                                        66.25
                                              34.0
                                                      95.8
                                                               87.9
                                                                             59.6
     3
        1.0751
                    10.4
                           26 184.75
                                        72.25
                                              37.4 101.8
                                                               86.4 101.2
                                                                             60.1
                                                      97.3
        1.0340
                    28.7
                           24 184.25
                                        71.25 34.4
                                                                     101.9
                                                                             63.2
     4
                                                              100.0
     5
        1.0502
                    20.9
                           24 210.25
                                        74.75 39.0 104.5
                                                               94.4 107.8
                                                                             66.0
     6
        1.0549
                    19.2
                           26 181.00
                                        69.75 36.4 105.1
                                                               90.7
                                                                    100.3
                                                                             58.4
                    12.4
                                              37.8
                                                               88.5
                                                                      97.1
     7
        1.0704
                           25 176.00
                                        72.50
                                                      99.6
                                                                             60.0
     8
        1.0900
                    4.1
                           25 191.00
                                        74.00 38.1 100.9
                                                               82.5
                                                                      99.9
                                                                             62.9
        1.0722
                    11.7
                           23 198.25
                                        73.50 42.1
                                                      99.6
                                                               88.6 104.1
                                                                             63.1
       Knee
             Ankle
                   Biceps Forearm
                                      Wrist
     0 37.3
               21.9
                       32.0
                                27.4
                                       17.1
     1 37.3
               23.4
                      30.5
                                28.9
                                       18.2
     2 38.9
               24.0
                      28.8
                                25.2
                                       16.6
     3 37.3
               22.8
                      32.4
                                29.4
                                       18.2
     4 42.2
               24.0
                      32.2
                                27.7
                                       17.7
     5 42.0
               25.6
                      35.7
                                30.6
                                       18.8
     6 38.3
               22.9
                      31.9
                                27.8
                                       17.7
     7 39.4
               23.2
                      30.5
                                29.0
                                       18.8
     8 38.3
               23.8
                      35.9
                                31.1
                                       18.2
     9 41.7
               25.0
                       35.6
                                30.0
                                       19.2
    EDA and Outlier Detection
[3]: # Check the dimension of the table
     print("The dimension of the table is: ", bodyfat_df.shape)
     # What type of variables are in the table
     print("Describe Data")
     print(bodyfat_df.describe())
    The dimension of the table is:
                                    (252, 15)
    Describe Data
                          BodyFat
                                                   Weight
                                                               Height
              Density
                                          Age
                                                                              Neck \
    count 252.000000 252.000000 252.000000 252.000000 252.000000 252.000000
```

```
19.150794
                                  44.884921
                                                            70.148810
                                                                         37.992063
mean
         1.055574
                                              178.924405
std
         0.019031
                      8.368740
                                  12.602040
                                               29.389160
                                                             3.662856
                                                                          2.430913
                      0.000000
                                  22.000000
                                              118.500000
                                                            29.500000
                                                                         31.100000
min
         0.995000
25%
                                  35.750000
                                              159.000000
                                                            68.250000
                                                                         36.400000
         1.041400
                     12.475000
                                  43.000000
50%
         1.054900
                     19.200000
                                              176.500000
                                                            70.000000
                                                                         38.000000
75%
                     25.300000
                                  54.000000
                                              197.000000
                                                            72.250000
         1.070400
                                                                         39.425000
         1.108900
                     47.500000
                                  81.000000
                                              363.150000
                                                            77.750000
                                                                         51.200000
max
             Chest
                       Abdomen
                                                                 Knee
                                                                             Ankle
                                        Hip
                                                   Thigh
count
       252.000000
                    252.000000
                                 252.000000
                                              252.000000
                                                           252.000000
                                                                        252.000000
       100.824206
                     92.555952
                                  99.904762
                                               59.405952
                                                            38.590476
                                                                         23.102381
mean
std
         8.430476
                     10.783077
                                   7.164058
                                                5.249952
                                                             2.411805
                                                                          1.694893
        79.300000
                     69.400000
                                  85.000000
                                               47.200000
                                                            33.000000
                                                                         19.100000
min
25%
                     84.575000
                                                                         22.000000
        94.350000
                                  95.500000
                                               56.000000
                                                            36.975000
50%
        99.650000
                     90.950000
                                  99.300000
                                               59.000000
                                                            38.500000
                                                                         22.800000
75%
       105.375000
                     99.325000
                                 103.525000
                                               62.350000
                                                            39.925000
                                                                         24.000000
       136.200000
                    148.100000
                                 147.700000
                                               87.300000
                                                            49.100000
                                                                         33.900000
max
           Biceps
                       Forearm
                                      Wrist
       252.000000
                    252.000000
                                 252.000000
count
mean
        32.273413
                     28.663889
                                  18.229762
std
         3.021274
                      2.020691
                                   0.933585
min
        24.800000
                     21.000000
                                  15.800000
25%
                     27.300000
        30.200000
                                  17.600000
50%
        32.050000
                     28.700000
                                  18.300000
75%
                     30.000000
        34.325000
                                  18.800000
        45.000000
                     34.900000
                                  21.400000
max
```

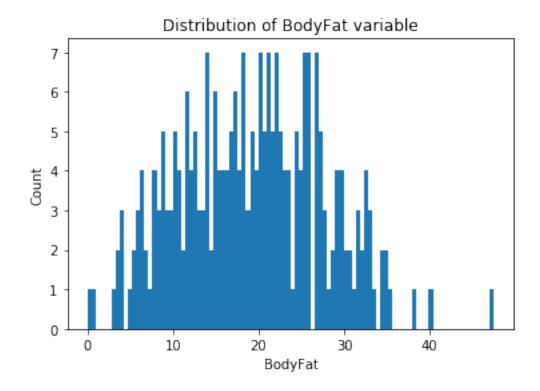
- [4]: # Check if any missing values
 np.sum(np.sum(bodyfat_df.isna()))
- [4]: 0
- [5]: bodyfat_df.hist(figsize=(10,10))
 plt.show()



```
[6]: import warnings
warnings.filterwarnings('ignore')
plt.figure(figsize=(10,10))
sns.boxplot(data=bodyfat_df,color="white",linewidth=3)
sns.swarmplot(data=bodyfat_df,s=5,alpha=0.65)
plt.show()
```

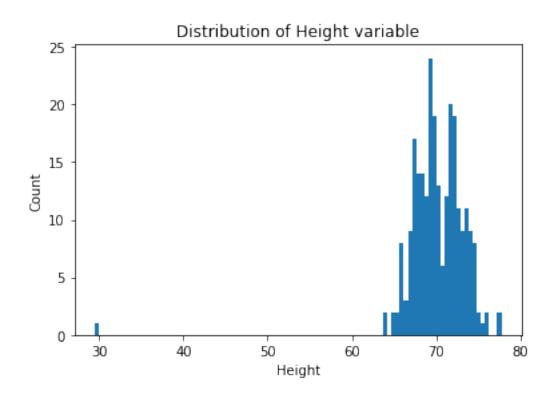


```
[7]: # Plot histogram to identify any outlier that is visual to eye
plt.hist(bodyfat_df['BodyFat'], bins=100)
plt.ylabel('Count')
plt.xlabel('BodyFat')
plt.title('Distribution of BodyFat variable');
```

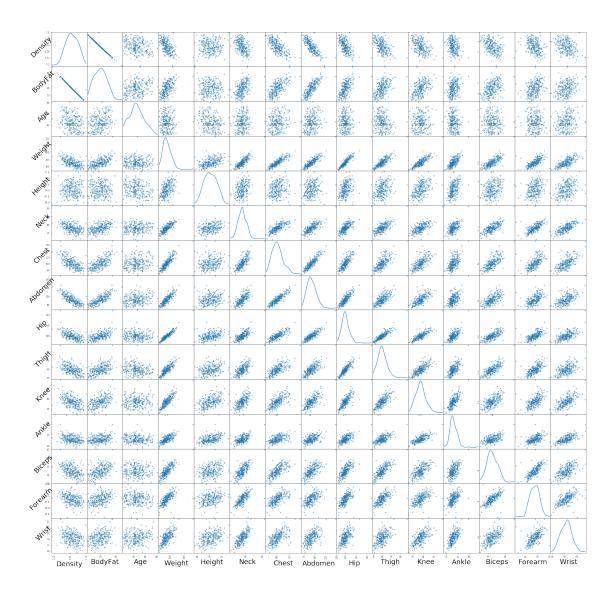


The values of 0 and 0.7 are not possible to achieve and we can delete them.

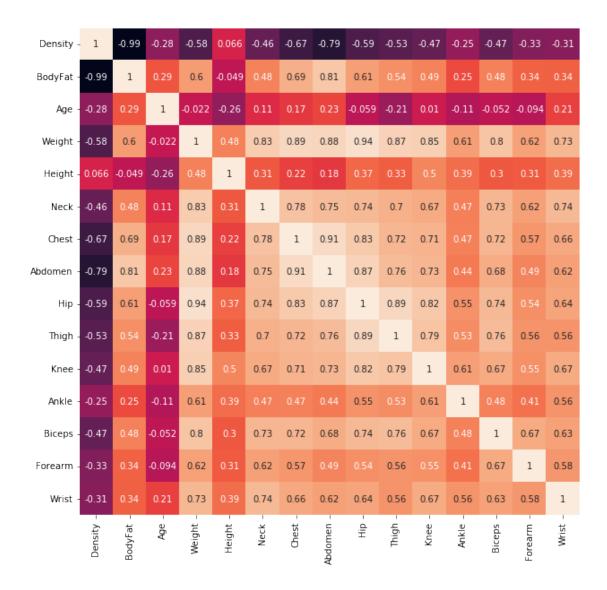
```
[8]: bodyfat_df.loc[bodyfat_df['BodyFat'] < 1]
 [8]:
           Density
                     BodyFat
                              Age
                                   Weight
                                            Height
                                                    Neck
                                                           Chest
                                                                  Abdomen
                                                                             Hip
                                                                                  Thigh \
      171
            1.0983
                         0.7
                               35
                                   125.75
                                              65.5
                                                    34.0
                                                            90.8
                                                                     75.0
                                                                            89.2
                                                                                   50.0
      181
            1.1089
                         0.0
                               40
                                   118.50
                                              68.0
                                                    33.8
                                                            79.3
                                                                     69.4
                                                                           85.0
                                                                                   47.2
           Knee
                 Ankle
                         Biceps
                                 Forearm
                                           Wrist
           34.8
                   22.0
                           24.8
                                    25.9
                                            16.9
      171
           33.5
                                    24.6
      181
                  20.2
                           27.7
                                            16.5
     bodyfat_df1 = bodyfat_df.drop(bodyfat_df[bodyfat_df['BodyFat'] < 1].index)</pre>
[10]: # Plot histogram to identify any outlier that is visual to eye
      plt.hist(bodyfat_df['Height'], bins=100)
      plt.ylabel('Count')
      plt.xlabel('Height')
      plt.title('Distribution of Height variable');
```



```
[11]: bodyfat_df1.loc[bodyfat_df1['Height'] < 35]</pre>
[11]:
          Density
                    BodyFat
                             Age
                                  Weight
                                           Height
                                                   Neck
                                                          Chest
                                                                 Abdomen
                                                                             Hip
                                                                                  Thigh \
      41
            1.025
                       32.9
                              44
                                    205.0
                                             29.5
                                                   36.6
                                                          106.0
                                                                    104.3
                                                                           115.5
                                                                                    70.6
                        Biceps
                Ankle
                                Forearm
                                          Wrist
      41 42.5
                  23.7
                          33.6
                                    28.7
                                           17.4
     It looks like an outlier in the dataset, so I will delete this observation as well.
[12]: bodyfat_df1 = bodyfat_df1.drop(bodyfat_df1.loc[bodyfat_df1['Height'] < 35].
       →index)
[13]: # Scatter plot of the variables
      axes = pd.plotting.scatter_matrix(bodyfat_df1, figsize=(35, 35), s=75,__
       →diagonal='kde')
      for ax in axes.flatten():
          ax.set_ylabel(ax.get_ylabel(), fontsize=25, rotation=45)
          ax.set_xlabel(ax.get_xlabel(), fontsize=25)
```



```
[14]: # Correlation of the variables
  f,ax = plt.subplots(figsize=(10,10))
  sns.heatmap(bodyfat_df1.corr(),annot=True,cbar=False,ax=ax)
  plt.show()
```



Based on the scatter plot and the correlation heatmap it looks like there is a perferct linear relationship between Density and BodfFat variable. Since fat percentage and body density are synonymous, I will drop density and use only the circumference measurements to predict body fat percentage.

Also age doesn't determine the body fat of a person, so will drop Age variable also from the dataset

```
[15]: y = bodyfat_df1['BodyFat']
      x = bodyfat_df1.drop(columns=['BodyFat', 'Density', 'Age'])
      print(x)
           Weight
                    Height
                                           Abdomen
                                                                           Ankle
                                                                                  Biceps
                            Neck
                                   Chest
                                                       Hip
                                                            Thigh
                                                                    Knee
           154.25
                                                                                     32.0
     0
                     67.75
                            36.2
                                    93.1
                                              85.2
                                                      94.5
                                                              59.0
                                                                    37.3
                                                                            21.9
     1
           173.25
                     72.25
                            38.5
                                    93.6
                                              83.0
                                                      98.7
                                                              58.7
                                                                    37.3
                                                                            23.4
                                                                                     30.5
     2
           154.00
                     66.25
                            34.0
                                    95.8
                                              87.9
                                                      99.2
                                                              59.6
                                                                    38.9
                                                                            24.0
                                                                                     28.8
     3
           184.75
                     72.25
                                                                                     32.4
                            37.4
                                   101.8
                                              86.4
                                                     101.2
                                                              60.1
                                                                    37.3
                                                                            22.8
```

```
•••
                                   •••
         134.25
                   67.00 34.9
                                 89.2
                                          83.6
                                                        49.6 34.8
                                                                     21.5
                                                                             25.6
     247
                                                 88.8
     248 201.00
                   69.75 40.9
                                108.5
                                         105.0 104.5
                                                        59.6 40.8
                                                                     23.2
                                                                             35.2
     249 186.75
                   66.00 38.9
                                111.1
                                         111.5 101.7
                                                        60.3 37.3
                                                                     21.5
                                                                             31.3
                                                        56.0 41.6
     250 190.75
                   70.50 38.9 108.3
                                         101.3
                                                 97.8
                                                                     22.7
                                                                             30.5
                   70.00 40.8 112.4
                                         108.5 107.1
     251 207.50
                                                        59.3 42.2
                                                                     24.6
                                                                             33.7
          Forearm Wrist
     0
             27.4
                   17.1
     1
             28.9
                    18.2
     2
             25.2
                    16.6
     3
             29.4
                    18.2
     4
             27.7
                  17.7
     . .
              •••
     247
             25.7
                    18.5
     248
             28.6
                    20.1
             27.2
                    18.0
     249
     250
             29.4
                    19.8
     251
             30.0
                    20.9
     [249 rows x 12 columns]
[16]: x_train, x_test, y_train, y_test = train_test_split(x,y,test_size=0.
      \hookrightarrow2, random_state=42)
[17]: # Details of training dataset
      print("Shape of x_train dataset: ", x_train.shape)
      print("Shape of y_train dataset: ", y_train.shape)
      print("Shape of x_test dataset: ", x_test.shape)
      print("Shape of y_test dataset: ", y_test.shape)
     Shape of x_train dataset: (199, 12)
     Shape of y_train dataset:
                                (199.)
     Shape of x_test dataset:
                               (50, 12)
     Shape of y test dataset: (50,)
[18]: # Feature selection using SelectKBest feature selection
      skbest = SelectKBest(k=10)
      skbest.fit(x train,y train)
      x_train_skbest=skbest.transform(x_train)
      x_test_skbest=skbest.transform(x_test)
      x_train_skbest.shape
[18]: (199, 10)
[19]: # 10 best features using SelectKBest
      best_features = SelectKBest(score_func=f_classif, k=10)
```

4

184.25

71.25 34.4

97.3

100.0 101.9

63.2 42.2

24.0

32.2

```
fit = best_features.fit(x_train,y_train)
df_scores = pd.DataFrame(fit.scores_)
df_columns = pd.DataFrame(x_train.columns)
feature_scores = pd.concat([df_columns, df_scores],axis=1)
feature_scores.columns = ['Feature_Name','Score'] # name output columns
print(feature_scores.nlargest(10,'Score')) # print 10 best features
```

```
Feature_Name
                   Score
4
       Abdomen 3.809316
3
         Chest 2.662361
5
           Hip 2.475324
         Weight 2.117462
0
2
          Neck 1.948599
6
         Thigh 1.768280
9
        Biceps 1.545362
7
          Knee 1.457433
1
        Height 1.193745
         Wrist 1.139133
11
```

Looks like Abdomen, Chest, Hip and Weight plays a major part when compared to the other features

Model Evaluation

```
def evaluate_model(pipe, X, y):
    y_pred, y_true = np.empty(len(y)), np.empty(len(y))
    loo = LeaveOneOut()
    for i, (train_idx, test_idx) in tqdm(enumerate(loo.split(X)), total=len(y)):
        X_train, X_test = X.iloc[train_idx], X.iloc[test_idx]
        y_train, y_test = y.iloc[train_idx], y.iloc[test_idx]
        y_pred[i] = pipe.fit(X_train, y_train).predict(X_test)[0]
        y_true[i] = y_test
    return r2_score(y_true, y_pred), np.sqrt(mean_squared_error(y_true, y_pred))
```

```
pipe = get_pipeline(PCA(n_components=6), model=LinearRegression())
model_score, score_std = get_model_score(pipe=pipe, data_x=x, data_y=y, cv=5)
r2, rmse = evaluate_model(pipe, x, y)
```

```
print('Linear Regression Model Score: ', model_score)
print('Linear Regression SD Score: ',score_std)
print('R Square: ', r2)
print('Root Mean Sqaure: ', rmse)
```

100% | 249/249 [00:10<00:00, 24.40it/s]

Linear Regression Model Score: 0.4760618237463552 Linear Regression SD Score: 0.2588001654989154

R Square: 0.5842677076011253

Root Mean Sqaure: 5.277296230935636

```
pipe = get_pipeline(PCA(n_components=6), model=RandomForestRegressor())
model_score, score_std = get_model_score(pipe=pipe, data_x=x, data_y=y, cv=5)
r2, rmse = evaluate_model(pipe, x, y)
print('Random Forest Regressor Model Score: ',model_score)
print('Random Forest Regressor SD Score: ',score_std)
print('R Square: ', r2)
print('Root Mean Sqaure: ', rmse)
```

100% | 249/249 [01:13<00:00, 3.40it/s]

Random Forest Regressor Model Score: 0.4713688065398777 Random Forest Regressor SD Score: 0.22240534030226908

R Square: 0.5808876913007635

Root Mean Sqaure: 5.298705727658999

Linear Regression is providing a better accuracy when compared with Random Forest. So, I would like to choose Linear Regression model in calcualting the BodyFat for a provided data

```
def predict_loo(model, X, y):
    y_pred, y_true = np.empty(len(y)), np.empty(len(y))
    loo = LeaveOneOut()
    for i, (train_idx, test_idx) in tqdm(enumerate(loo.split(X)), total=len(y)):
        X_train, X_test = X.iloc[train_idx], X.iloc[test_idx]
        y_train, y_test = y.iloc[train_idx], y.iloc[test_idx]
        y_pred[i] = model.fit(X_train, y_train).predict(X_test)[0]
        y_true[i] = y_test
    return y_pred, y_true
```

```
[25]: final_model = get_pipeline(model=LinearRegression())
y_pred, y_true = predict_loo(final_model, x, y)
```

```
100% | 249/249 [00:09<00:00, 26.54it/s]
```

These are some random measurements which would be given as input to provide the bodyfat of a person

```
[26]: measurements = np.array([165, 180, 38.5, 102.5, 90, 55.2, 38.3, 26.3, 32.5, 29.
```

```
[27]: prediction = final_model.predict(measurements)[0]
print(f'The prediction for body fat percent is {prediction:.1f}%.')
```

The prediction for body fat percent is 17.3%.